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Faculty and Administrator Perceptions of AI-Driven Assessment Analytics in Meeting Accreditation Standards in Healthcare Management Education

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Abstract: **The use of artificial intelligence (AI) in higher education assessment has been widely promoted as a mechanism for strengthening accreditation compliance and advancing continuous quality improvement (CQI); however, empirical evidence explaining how faculty and administrator perceptions translate into these outcomes remains limited. Guided by an integrated Technology Acceptance Model–Human-Centered AI–Continuous Quality Improvement (TAM–HCAI–CQI) framework, this study examined the relationships among perceived AI-driven assessment analytics, assessment confidence, perceived accreditation readiness, and CQI capacity in healthcare management education. Using a quantitative, cross-sectional perception-based design, survey data were collected from 64 participants (45 faculty members and 19 academic administrators) engaged in assessment and accreditation activities. Descriptive analyses indicated moderately positive perceptions of AI-driven assessment analytics ($M = 3.61$, $SD = 0.67$), with no statistically significant differences between faculty and administrators. Regression analyses demonstrated that perceived AI-driven assessment analytics significantly predicted accreditation readiness ($\beta = .52$, $p < .001$, $R^2 = .27$) and CQI capacity ($\beta = .57$, $p < .001$, $R^2 = .32$). Mediation analyses using bootstrapping revealed that assessment confidence partially mediated the relationship between AI perceptions and accreditation readiness (indirect effect $\beta = .32$, 95% CI [.18, .50]) and fully mediated the relationship between AI perceptions and CQI capacity (indirect effect $\beta = .34$, 95% CI [.20, .54]). Role-based analyses further indicated convergence between faculty and administrator perceptions across all study variables. Collectively, these findings demonstrate that the contribution of AI-driven assessment analytics to accreditation readiness and continuous improvement operates primarily through faculty and administrator confidence in assessment evidence, rather than through technology alone. The study explains how institutions move from compliance-oriented assessment practices toward sustained continuous quality improvement, highlighting the importance of human-centered implementation strategies that align AI-supported analytics with accreditation standards. Implications are discussed for institutional practice, accreditation policy, and future research on AI-enabled assessment and quality assurance in healthcare management education.**

Keywords: **artificial intelligence; assessment analytics; accreditation readiness; continuous quality improvement; assessment confidence; faculty perceptions; administrator perceptions; healthcare management education.**

I. INTRODUCTION

Accreditation in higher education has historically emphasized compliance-oriented accountability, often privileging documentation and reporting over sustained instructional and curricular improvement. In healthcare management education, this compliance emphasis is intensified by regulatory complexity, professional standards, and heightened expectations for workforce readiness. However, major accrediting bodies, including the Association of University Programs in Health

Administration, the Higher Learning Commission, and the Southern Association of Colleges and Schools Commission on Colleges, increasingly stress the use of assessment evidence to support continuous quality improvement (CQI) rather than episodic compliance reporting (AUPHA, 2023; HLC, 2024; SACSCOC, 2023). This shift reframes accreditation as an ongoing, data-informed process focused on improving student learning and institutional effectiveness.

Parallel to this accreditation evolution, artificial intelligence (AI) has emerged as a powerful analytic resource in higher education assessment systems. AI-driven assessment analytics, including automated learning outcome mapping, longitudinal performance tracking, and predictive risk indicators, offer institutions new mechanisms for synthesizing large volumes of assessment data into actionable insights (Holmes et al., 2022; Selwyn, 2023). From an accreditation perspective, these tools have the potential to strengthen evidence coherence, improve transparency, and support systematic "closing-the-loop" practices emphasized by accrediting agencies (HLC, 2024). Yet, the mere availability of AI technologies does not guarantee meaningful improvement or accreditation value.

Recent scholarship emphasizes that the effectiveness of AI in academic assessment depends largely on human interpretation, trust, and professional judgment. Faculty and administrators remain central actors in determining whether AI-generated analytics are used for reflective improvement or reduced to symbolic compliance artifacts (Williamson & Eynon, 2023; Kimmons et al., 2024). Accrediting bodies consistently underscore this human dimension, noting that assessment quality is not defined by tools alone but by how evidence is interpreted, discussed, and applied to curricular decision-making (AUPHA, 2023; SACSCOC, 2023). Consequently, stakeholder perceptions play a critical role in shaping how AI-driven analytics are integrated into accreditation and assessment practices.

Bull's (2026) work on artificial intelligence, teaching presence, and sense of belonging in online higher education further highlights the necessity of preserving human agency within AI-enhanced systems. Bull (2026) demonstrates that AI tools are most effective when they function as decision-support mechanisms that strengthen instructional presence, assessment confidence, and faculty sensemaking rather than replacing professional expertise. This perspective aligns closely with accreditation guidance emphasizing faculty ownership of assessment and continuous improvement processes (HLC, 2024). Extending Bull's framework to accreditation analytics suggests that perceptions of AI usefulness and alignment with accreditation standards may be decisive factors in whether institutions transition from compliance-oriented assessment to genuine CQI.

Despite growing interest in AI for assessment and institutional effectiveness, empirical research examining faculty and administrator perceptions of AI-driven assessment analytics within accreditation contexts remains limited, particularly in healthcare management education. Existing studies tend to focus on student-facing AI applications or technical system capabilities, leaving a gap in understanding how AI is perceived as a tool for accreditation readiness and continuous improvement. Addressing this gap, the present study investigates faculty and academic administrator perceptions of AI-driven assessment analytics as mechanisms for moving from compliance-based accreditation practices toward sustainable continuous improvement. By centering stakeholder perceptions, this study responds directly to accreditor expectations for evidence-informed decision-making while contributing to emerging scholarship on responsible AI integration in higher education.

Problem Statement

Accrediting bodies increasingly emphasize the use of assessment evidence for continuous quality improvement (CQI) rather than compliance-driven reporting alone. Organizations such as the Higher Learning Commission and the Southern Association of Colleges and Schools Commission on Colleges explicitly require institutions to demonstrate not only the collection of assessment data, but also its systematic use to inform instructional, curricular, and programmatic improvement (HLC, 2024; SACSCOC, 2023). Similarly, discipline-specific accreditors such as the Association of University Programs in Health Administration emphasize outcomes assessment, faculty engagement, and evidence-based decision-making as core indicators of program quality (AUPHA, 2023). Despite these expectations, prior research suggests that many institutions continue to experience challenges moving beyond episodic compliance activities toward sustained, data-informed improvement practices (Ewell, 2023; Harvey & Williams, 2024).

The growing availability of artificial intelligence (AI)–driven assessment analytics has been promoted as a potential solution to these challenges, offering tools for outcome mapping, performance trend analysis, and accreditation reporting efficiency (Holmes et al., 2022; Selwyn, 2023). However, emerging scholarship indicates that the effectiveness of AI in assessment contexts depends heavily on faculty and administrator perceptions, including trust, perceived usefulness, interpretability, and alignment with accreditation standards (Kimmons et al., 2024; Williamson & Eynon, 2023). Bull (2026) further demonstrates that AI tools enhance educational effectiveness only when they support, not replace, human judgment, teaching presence, and professional sensemaking. In the absence of positive stakeholder perceptions, AI-driven systems risk reinforcing surface-level compliance rather than enabling meaningful continuous improvement.

Despite increasing institutional investment in AI-supported assessment technologies, there is a lack of empirical research examining how faculty and academic administrators perceive AI-driven assessment analytics as mechanisms for meeting accreditation standards and supporting CQI, particularly within healthcare management education. Existing studies largely focus on technical capabilities or student-facing AI applications, leaving a critical gap in understanding organizational readiness and assessment culture. Without insight into stakeholder perceptions, institutions risk adopting AI tools that fail to advance accreditation goals or improve assessment practice. Therefore, the problem addressed by this study is the limited empirical understanding of faculty and administrator perceptions regarding the role of AI-driven assessment analytics in shifting accreditation practices from compliance-oriented reporting toward sustainable continuous improvement in healthcare management education.

Purpose

The purpose of this study is to examine faculty and academic administrator perceptions of AI-driven assessment analytics as tools for supporting accreditation standards and advancing continuous quality improvement (CQI) in healthcare management education. Specifically, the study seeks to investigate how stakeholders perceive the usefulness, interpretability, and accreditation alignment of AI-supported assessment analytics, and how these perceptions relate to assessment confidence, perceived accreditation readiness, and institutional capacity for continuous improvement.

Accrediting bodies such as the Higher Learning Commission and the Southern Association of Colleges and Schools Commission on Colleges emphasize that assessment systems must demonstrate not only the collection of data but also the intentional use of evidence to inform decision-making and improve student learning outcomes (HLC, 2024; SACSCOC, 2023). Similarly, the Association of University Programs in Health Administration underscores the importance of faculty engagement, outcomes-based assessment, and data-informed program improvement in healthcare management education (AUPHA, 2023).

This study responds directly to these expectations by focusing on the perceptions of those responsible for interpreting and applying assessment data within accreditation contexts. Guided by emerging research on artificial intelligence in higher education, this study positions AI-driven assessment analytics as decision-support mechanisms rather than autonomous evaluators. Prior scholarship indicates that the effectiveness of AI in educational assessment depends on stakeholder trust, perceived usefulness, and alignment with professional judgment and instructional presence (Holmes et al., 2022; Williamson & Eynon, 2023). Bull (2026) further demonstrates that AI enhances educational outcomes when it strengthens faculty sensemaking and teaching presence, suggesting that perceptions of AI's role are central to its successful integration into assessment and accreditation processes.

By employing a quantitative, perception-based research design, this study aims to contribute empirical evidence to the limited literature examining AI adoption within accreditation and assessment cultures. The findings are intended to inform institutional leaders, assessment coordinators, and accrediting stakeholders about the conditions under which AI-driven assessment analytics are most likely to support a transition from compliance-oriented accreditation practices toward sustainable continuous improvement in healthcare management education.

Significance of Study

This study is significant because it addresses a growing need within higher education to understand how artificial intelligence (AI)–driven assessment analytics are perceived as tools for advancing accreditation expectations beyond compliance toward continuous quality improvement (CQI). Accrediting bodies such as the Higher Learning Commission, the Southern Association of Colleges and Schools Commission on Colleges, and the Association of University Programs in Health Administration increasingly emphasize evidence-informed decision-making, faculty engagement, and systematic use of assessment results to improve student learning and program effectiveness (AUPHA, 2023; HLC, 2024; SACSCOC, 2023). By focusing on faculty and administrator perceptions, this study responds directly to accreditor expectations regarding assessment culture and institutional effectiveness.

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From a scholarly perspective, the study contributes to the emerging literature on AI in higher education by extending inquiry beyond technical functionality and student-facing applications to examine AI as an institutional assessment and accreditation tool. Prior research has highlighted concerns related to transparency, trust, and human oversight in AI-supported educational systems (Selwyn, 2023; Williamson & Eynon, 2023). Building on Bull's (2026) findings that AI effectiveness is contingent upon teaching presence, human agency, and professional judgment, this study advances theoretical understanding of how perceptions shape the meaningful use of AI-driven analytics in accreditation-aligned assessment practices.

The study also holds substantial practical significance for institutional leaders, program directors, and assessment coordinators in healthcare management education. Understanding stakeholder perceptions of AI-driven assessment analytics can inform more effective implementation strategies, professional development initiatives, and governance policies that promote faculty ownership of assessment processes. Such insights are critical for avoiding superficial or compliance-driven AI adoption and for fostering assessment practices that genuinely support curricular improvement and accreditation readiness (Holmes et al., 2022; Kimmons et al., 2024).

In addition, the findings have policy relevance as institutions and accrediting agencies navigate responsible AI integration. Accrediting bodies and international organizations have emphasized the need for transparency, ethical use, and human-centered governance in the adoption of AI technologies in education (HLC, 2024; UNESCO, 2023). This study provides empirical evidence to inform institutional policies and accreditation guidance by clarifying how AI-driven assessment analytics are perceived by those directly responsible for assessment interpretation and quality assurance.

Finally, this study contributes to the broader goal of quality enhancement in healthcare management education. By identifying perception-based factors that influence whether AI-driven assessment analytics are used for continuous improvement rather than symbolic compliance, the study offers actionable insights for strengthening assessment cultures, improving accreditation outcomes, and supporting sustainable educational innovation in an increasingly data-driven academic environment.

Research Questions

RQ1: How do faculty and academic administrators perceive the usefulness of AI-driven assessment analytics in supporting accreditation standards in healthcare management education?

H1: Faculty and administrators will report moderately to highly positive perceptions of the usefulness of AI-driven assessment analytics for supporting accreditation-related assessment and reporting requirements.

Rationale: Accrediting bodies emphasize meaningful use of assessment evidence rather than mere data collection. Prior research indicates that perceived usefulness is a key determinant of technology acceptance in academic contexts (Holmes et al., 2022; Selwyn, 2023).

RQ2: To what extent do perceptions of AI-driven assessment analytics predict perceived continuous quality improvement (CQI) capacity in healthcare management programs?

H2: Positive perceptions of AI-driven assessment analytics will significantly and positively predict perceived continuous quality improvement capacity.

Rationale: CQI requires timely, interpretable, and actionable data. When AI analytics are perceived as useful and aligned with accreditation standards, stakeholders are more likely to engage in reflective improvement practices rather than compliance-oriented reporting (Ewell, 2023; Harvey & Williams, 2024).

RQ3: What is the relationship between perceptions of AI-driven assessment analytics and perceived accreditation readiness?

H3: Positive perceptions of AI-driven assessment analytics will be significantly associated with higher perceived accreditation readiness.

Rationale: Perceived accreditation readiness reflects confidence in assessment systems, evidence coherence, and institutional preparedness, areas where AI-driven analytics are often promoted as supportive tools.

RQ4: Does assessment confidence mediate the relationship between perceptions of AI-driven assessment analytics and perceived accreditation readiness?

H4: Assessment confidence will significantly mediate the relationship between perceptions of AI-driven assessment analytics and perceived accreditation readiness, such that higher AI perception scores will be associated with greater confidence, which in turn will predict higher accreditation readiness.

Rationale: Bull (2026) demonstrates that AI effectiveness is contingent on human sensemaking and professional confidence. Accrediting bodies similarly emphasize faculty ownership and interpretation of assessment evidence, suggesting confidence is a key explanatory mechanism.

RQ5: To what extent do perceptions of AI-driven assessment analytics and assessment confidence jointly predict perceived continuous quality improvement capacity?

H5: Perceptions of AI-driven assessment analytics and assessment confidence will jointly and significantly predict perceived continuous quality improvement capacity, with assessment confidence contributing unique explanatory variance beyond AI perceptions alone.

Rationale: This hypothesis tests whether AI perceptions alone are sufficient or whether confidence in assessment interpretation strengthens the transition from compliance to improvement.

Gap in Literature

Recent research has documented the rapid expansion of artificial intelligence (AI) in higher education, with a strong focus on learning analytics, automation, and student-facing applications (Holmes et al., 2022; Selwyn, 2023). Separately, accreditation and assessment scholarship emphasizes the need to move from compliance-driven reporting toward continuous quality improvement (CQI), a shift reinforced by accrediting bodies such as the Higher Learning Commission, the Southern Association of Colleges and Schools Commission on Colleges, and the Association of University Programs in Health Administration (AUPHA, 2023; HLC, 2024; SACSCOC, 2023). Despite these parallel developments, the literature has largely failed to integrate AI adoption with accreditation-aligned assessment cultures, leaving limited empirical insight into how AI-driven analytics are used to support meaningful improvement rather than procedural compliance.

Moreover, existing studies rarely examine faculty and administrator perceptions of AI-driven assessment analytics, even though human judgment, trust, and sensemaking are central to effective assessment practice. Research by Bull (2026) highlights that AI effectiveness depends on teaching presence and professional agency, yet this perspective has not been sufficiently applied to accreditation and assessment systems, particularly in healthcare management education. Consequently, there remains a significant gap in understanding how stakeholders perceive AI-driven assessment analytics as tools for enhancing accreditation readiness and CQI. Addressing this gap is essential for informing responsible AI integration and aligning technological innovation with accrediting-body expectations.

II. CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

This study is grounded in an integrated theoretical framework that combines Technology Acceptance Theory, Assessment Culture and Continuous Quality Improvement (CQI) theory, and Teaching Presence and Human Agency perspectives. (See Figure 1).

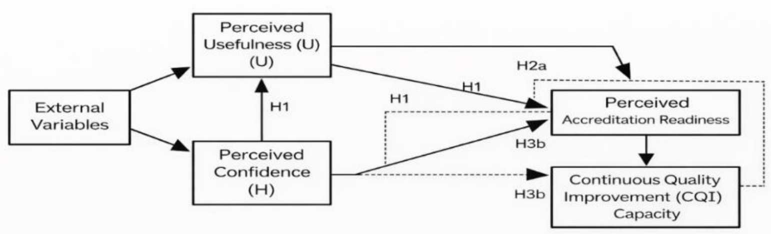

Figure 1. Adapted Technology Acceptance Model Integrated with Human-Centered AI and Continuous Quality Improvement Theory.
This figure adapts the Technology Acceptance Model (Davis, 1989) to an accreditation and assessment context by replacing behavioral adoption outcomes with **assessment confidence, accreditaton readiness,** and continuous quality improvement capacity, consistent with human-centered AI principles (Bull, 2026) and CQI theory (Deming, 1986; Ewell, 2023).

Note. *H denotes the mediating construct (assessment confidence). H1–H3 represent hypothesized relationships among study variables. Dashed arrows indicate direct effects tested alongside mediated pathways.*

Together, these frameworks explain how faculty and administrator perceptions of AI-driven assessment analytics influence accreditation readiness and continuous improvement practices in healthcare management education.

The foundational component of the framework is the Technology Acceptance Model (TAM), originally developed by Davis (1989) and further extended by Davis, Bagozzi, and Warshaw (1989). TAM posits that individuals' acceptance and use of a technological system are primarily determined by two cognitive beliefs: Perceived Ease of Use and Perceived Usefulness. Perceived ease of use refers to the degree to which a system is perceived as free of effort, while perceived usefulness reflects the extent to which the system is believed to enhance job performance. These beliefs influence users' attitudes toward using the system, which in turn shape behavioral intention to use, ultimately leading to actual system use.

In the context of the present study, TAM provides the explanatory mechanism for understanding how faculty and administrators come to accept AI-driven assessment analytics. Perceived AI-driven assessment analytics in this study operationalize TAM's perceived usefulness construct, reflecting the extent to which stakeholders believe AI-supported analytics enhance assessment interpretation, accreditation reporting, and evidence-based decision-making. Elements of perceived ease of use are embedded within this construct through items assessing clarity, interpretability, and usability of AI-generated assessment outputs. Consistent with TAM, positive perceptions of AI usefulness are expected to influence stakeholders' willingness to engage with assessment analytics beyond minimal or compliance-driven use.

While TAM explains technology adoption, it does not fully account for how technologies are used within organizational assessment systems. To address this limitation, the framework integrates Continuous Quality Improvement (CQI) and assessment culture theory, rooted in the work of Deming (1986) and extended in higher education by scholars such as Ewell (2009, 2023) and Harvey and Williams (2010, 2024). CQI theory emphasizes iterative, evidence-informed processes in which data are systematically interpreted, discussed, and applied to improve outcomes over time. Within higher education, accrediting bodies such as the Higher Learning Commission, the Southern Association of Colleges and Schools Commission on Colleges, and the Association of University Programs in Health Administration explicitly frame accreditation as a CQI process, requiring institutions to demonstrate not only data collection but also meaningful application of assessment results (AUPHA, 2023; HLC, 2024; SACSCOC, 2023).

Within this study, Perceived Continuous Quality Improvement (CQI) Capacity and Perceived Accreditation Readiness represent CQI-oriented outcomes. These constructs reflect stakeholders' confidence that assessment systems, supported by AI analytics, enable meaningful improvement, coherent documentation, and alignment with accreditation standards. CQI theory explains how assessment data must be embedded within institutional cultures that value reflection, dialogue, and action, rather than serving as static compliance artifacts.

The integration of TAM and CQI is further strengthened by a human-centered AI and professional agency perspective, informed by Bull's (2026) work on artificial intelligence, teaching presence, and human sensemaking in educational environments. This perspective emphasizes that AI systems enhance effectiveness only when they support human judgment rather than replace it. In assessment contexts, faculty and administrators remain the primary interpreters of data, responsible for translating analytics into curricular and instructional decisions.

Accordingly, Assessment Confidence is positioned as a central bridging construct in the framework. Assessment confidence reflects stakeholders' trust in the accuracy, validity, and actionability of AI-generated assessment data. The framework theorizes that perceptions of AI-driven assessment analytics influence assessment confidence, which in turn shapes perceived accreditation readiness and CQI capacity. In this way, assessment confidence functions as the mechanism through which technology acceptance translates into continuous improvement outcomes.

Collectively, this integrated framework explains how perceptions of AI-driven assessment analytics (TAM) influence assessment confidence (human agency), which then drives accreditation readiness and continuous quality improvement (CQI). The framework aligns directly with the study variables and hypotheses, providing a robust theoretical foundation for examining how AI-supported assessment systems can facilitate a shift from compliance-oriented accreditation practices toward sustainable, evidence-informed improvement in healthcare management education. By synthesizing technology acceptance, assessment culture, and human agency perspectives, the framework provides a robust theoretical foundation for examining how AI-supported assessment analytics can facilitate a shift from compliance-oriented accreditation practices toward sustainable continuous improvement in healthcare management education.

Literature Search Strategy

A targeted literature search was conducted to identify recent peer-reviewed studies on artificial intelligence in higher education, assessment analytics, accreditation, and continuous quality improvement (CQI). Searches were performed in Scopus, Web of Science, ERIC, Education Source (EBSCOhost), and Google Scholar, limited to publications from 2019–2025 to ensure relevance to contemporary AI and accreditation practices.

Boolean search strings combined core constructs, including *(“artificial intelligence” OR “AI-driven analytics” OR “learning analytics”) AND (“higher education” OR “healthcare management education”) AND (“assessment” OR “student learning outcomes”) AND (“accreditation” OR “quality assurance” OR “continuous quality improvement”) AND (“faculty perception” OR “administrator perception”)*. Additional adoption-focused terms (e.g., *“technology acceptance,” “human-centered AI”*) were used, with reference chaining employed to identify foundational and accrediting-body sources.

Review of Related Literature

The expanding use of artificial intelligence (AI) in higher education assessment has intensified the need for theory-driven explanations of how analytic technologies influence accreditation and improvement outcomes. Much of the existing literature treats AI-driven assessment analytics as either neutral tools for efficiency or direct drivers of institutional effectiveness. Such approaches under-theorize the human-centered mechanisms through which technology is interpreted, trusted, and enacted by faculty and administrators responsible for accreditation and quality assurance. Without a clear theoretical account, AI-enabled assessment risks being evaluated in terms of technical capability rather than its integration into assessment culture and improvement practice.

Guided by an integrated Technology Acceptance–Human-Centered AI–Continuous Quality Improvement perspective, the present review conceptualizes AI-driven assessment analytics as an antecedent whose influence is conditioned by assessment confidence, a human judgment construct linking technology perception to institutional outcomes. Within this framework, perceived AI-driven assessment analytics shape stakeholders’ confidence in assessment evidence, which in turn influences perceived accreditation readiness and continuous quality improvement (CQI) capacity. Organizing the literature around these variables enables a theoretically coherent examination of how institutions move from compliance-oriented assessment toward sustained improvement. This theory-forward synthesis provides the conceptual foundation for the study’s hypotheses and mediation model and clarifies the explanatory pathways through which AI-supported assessment analytics contribute to accreditation and continuous quality improvement in healthcare management education.

Perceived AI-Driven Assessment Analytics

Recent scholarship consistently positions artificial intelligence (AI)–driven assessment analytics as a significant advancement in higher education assessment systems, particularly in contexts emphasizing accountability, accreditation, and continuous quality improvement (CQI). Systematic and conceptual reviews indicate that AI-supported analytics can enhance assessment transparency, fairness, and efficiency by automating outcome mapping, synthesizing large-scale performance data, and supporting evidence-informed decision-making (Alfaleh, 2026; Holmes et al., 2022; Selwyn, 2023). These capabilities are especially relevant in online and professional programs, where institutions must demonstrate coherence and alignment across complex assessment datasets.

However, the literature converges on a critical qualification: the value of AI-driven assessment analytics is contingent upon human interpretation and institutional context. Alfaleh’s (2026) systematic review emphasizes that without faculty mediation and governance oversight, AI systems risk becoming opaque, technocratic tools that reinforce compliance rather than pedagogical or programmatic improvement. Similarly, Mpolomoka (2025) demonstrates that while AI-supported assessment and grading systems improve efficiency, consistency, and personalization, their contribution to accreditation-relevant evidence depends on stakeholder trust in the accuracy and interpretability of AI-generated outputs. Williams (2023) further argues that AI analytics support CQI most effectively when embedded within reflective assessment cultures that emphasize dialogue, interpretation, and action rather than reporting efficiency alone.

Together, these studies frame perceived AI-driven assessment analytics as an enabling construct rather than an autonomous driver of quality. From a technology acceptance perspective, stakeholders’ perceptions of usefulness, interpretability, and alignment with assessment goals are decisive in determining whether AI analytics are used to support improvement or reduced to procedural compliance (Davis, 1989; Kimmons et al., 2024). These insights directly inform the present study’s focus on perceived AI-driven assessment analytics as a foundational predictor of downstream accreditation and CQI outcomes (H1–H2).

Assessment Confidence as a Mediating Construct

Assessment confidence, defined as faculty and administrator trust in the accuracy, validity, and actionability of assessment evidence, has long been identified as a prerequisite for meaningful use of data in higher education. Assessment culture and accreditation scholarship consistently emphasizes that data alone do not drive improvement; rather, confidence in evidence enables stakeholders to engage in reflective decision-making and closing-the-loop practices (Ewell, 2009, 2023; Harvey & Williams, 2024). When confidence is low, assessment systems, regardless of analytic sophistication, are unlikely to inform curricular or instructional changes.

In AI-supported assessment environments, confidence becomes even more critical due to concerns about transparency, bias, and interpretability. Human-centered AI scholarship reinforces this point, demonstrating that AI tools enhance educational effectiveness only when they support professional sensemaking and preserve human agency rather than replacing judgment (Bull, 2026). Empirical studies further show that faculty trust and interpretive clarity significantly predict whether analytics are used reflectively or ignored (Kimmons et al., 2024). Consequently, assessment confidence is theorized as a central mechanism through which perceptions of AI-driven assessment analytics translate into institutional outcomes.

This body of literature provides a strong theoretical rationale for hypothesizing that perceived AI-driven assessment analytics positively predict assessment confidence (H1) and that assessment confidence mediates the relationship between AI perceptions and both accreditation readiness and CQI capacity (H4).

Perceived Accreditation Readiness

Perceived accreditation readiness reflects stakeholders' confidence that assessment systems generate coherent, defensible, and standards-aligned evidence capable of withstanding external review. Accreditation research emphasizes that readiness is not determined by the mere presence of data, but by institutions' ability to demonstrate systematic use of evidence for improvement (Ewell, 2023). Accrediting bodies increasingly stress faculty engagement, transparency, and closing-the-loop practices as indicators of readiness, rather than episodic documentation exercises (HLC, 2024; SACSCOC, 2023).

Empirical studies suggest that assessment systems perceived as fragmented, burdensome, or disconnected from improvement goals undermine accreditation confidence, even when data are technically sufficient (Harvey & Williams, 2024). AI-driven analytics have the potential to enhance readiness by improving evidence coherence, accessibility, and alignment with standards. However, the literature cautions that these benefits materialize only when stakeholders trust and understand AI-generated outputs. Thus, perceived accreditation readiness is conceptualized as an outcome influenced both directly by perceptions of AI-driven assessment analytics and indirectly through assessment confidence (H2a, H3a, H4).

Continuous Quality Improvement (CQI) Capacity

Continuous quality improvement (CQI) capacity represents an institution's perceived ability to use assessment evidence iteratively and intentionally to improve programs over time. Rooted in Deming's (1986) quality theory and extended to higher education by Ewell (2009, 2023), CQI emphasizes cyclical processes of data collection, interpretation, action, and reassessment. Accreditation scholarship consistently positions CQI as the preferred alternative to compliance-driven assessment, framing improvement as an ongoing cultural practice rather than a periodic obligation.

Despite broad endorsement of CQI, research indicates that many institutions struggle to operationalize it due to assessment fatigue, limited analytic capacity, and weak data cultures (Harvey & Williams, 2024). AI-driven assessment analytics are increasingly promoted as enablers of CQI by reducing analytic burden and improving timeliness of feedback (Holmes et al., 2022). However, consistent with human-centered AI and assessment culture scholarship, the literature suggests that CQI capacity depends less on technological availability than on stakeholder confidence and interpretive engagement. When AI analytics are perceived as credible and supportive of professional judgment, they are more likely to be integrated into reflective improvement cycles rather than compliance routines. These insights underpin hypotheses linking AI perceptions and assessment confidence to CQI capacity (H2b, H3b, H4).

Integrated Synthesis and Alignment With Study Hypotheses

Across the literatures on AI in higher education, assessment culture, technology acceptance, and accreditation, a consistent conclusion emerges technological capability alone does not ensure meaningful improvement in educational quality. While AI-driven assessment analytics offer powerful tools for outcome mapping, reporting efficiency, and data synthesis, their impact on accreditation readiness and continuous improvement is fundamentally mediated by human perceptions, trust, and professional judgment (Alfaleh, 2026; Bull, 2026; Williamson & Eynon, 2023).

Technology acceptance research clarifies that perceived usefulness and interpretability shape engagement with AI systems (Davis, 1989; Kimmons et al., 2024), while CQI and accreditation scholarship emphasizes that improvement-oriented assessment depends on confidence in evidence and faculty ownership rather than data volume alone (Ewell, 2023; Harvey & Williams, 2024). Human-centered AI perspectives further integrate these insights by identifying assessment confidence as the mechanism through which AI-supported analytics influence institutional outcomes.

Despite these converging insights, empirical research integrating AI-driven assessment analytics, stakeholder perceptions, and accreditation-oriented outcomes remains limited, particularly within healthcare management education. Existing studies often examine AI adoption, assessment practices, or accreditation expectations in isolation. This fragmentation underscores the need for perception-based research that explicitly tests how faculty and administrator interpretations of AI-driven assessment analytics shape assessment confidence, accreditation readiness, and CQI capacity, precisely the focus of the present study**.**

The reviewed literature demonstrates that while AI-driven assessment analytics hold promise for improving accreditation readiness and continuous quality improvement (CQI), their effectiveness is contingent upon stakeholder perceptions and confidence in assessment evidence. Technology acceptance research explains how perceptions of usefulness and interpretability shape engagement with AI systems, while assessment culture and CQI scholarship emphasizes the central role of human judgment in transforming data into improvement-oriented action. Human-centered AI perspectives further highlight assessment confidence as a key mechanism linking technological systems to institutional outcomes. Collectively, these findings justify a quantitative, perception-based research design to empirically test the hypothesized relationships among perceived AI-driven assessment analytics, assessment confidence, accreditation readiness, and CQI capacity.

III. METHODOLOGY

Research Design

This study employed a quantitative, cross-sectional, non-experimental survey design to examine faculty and academic administrator perceptions of AI-driven assessment analytics and their relationships with assessment confidence, accreditation readiness, and continuous quality improvement (CQI) capacity in healthcare management education. A perception-based design was selected because stakeholder perceptions are widely recognized in higher education research as valid indicators of assessment culture, institutional effectiveness, and accreditation readiness, particularly when access to institutional performance data is restricted.

The study was guided by an integrated theoretical framework combining the Technology Acceptance Model (TAM) (Davis, 1989), Human-Centered AI and Teaching Presence theory (Bull, 2026), and Continuous Quality Improvement (CQI) theory (Deming, 1986; Ewell, 2023). This framework informed the selection of variables, the development of the survey instrument, and the analytic approach.

Population and Sample

The target population consisted of faculty members and academic administrators involved in assessment, accreditation, curriculum oversight, or program evaluation in healthcare management and related higher education programs. Participants were required to have direct experience with assessment processes and familiarity with institutional accreditation expectations.

The final sample included 64 participants, comprising 45 faculty members (70.3%) and 19 academic administrators (29.7%). A non-probability purposive sampling strategy was used to recruit participants with relevant assessment and accreditation experience through professional networks and institutional contacts. Although modest in size, the sample is appropriate for an exploratory, perception-based study and aligns with prior research examining organizational readiness and technology adoption in higher education assessment contexts.

Instrumentation

Data were collected using a researcher-developed online survey instrument designed to measure four core constructs aligned with the study framework:

Perceived AI-Driven Assessment Analytics. This construct measured stakeholders' perceptions of the usefulness, interpretability, and accreditation alignment of AI-supported assessment analytics. Items reflected the extent to which AI analytics were perceived to enhance assessment interpretation, evidence coherence, and decision-making.

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Assessment Confidence. Assessment confidence captured faculty and administrator confidence in the accuracy, validity, transparency, and actionability of assessment data, particularly when generated or supported by AI-driven analytics.

Perceived Accreditation Readiness. This construct assessed participants' confidence in their program's or institution's preparedness to meet accreditation standards, including the availability of coherent, defensible, and improvement-oriented assessment evidence.

Perceived Continuous Quality Improvement (CQI) Capacity. CQI capacity measured perceptions of the institution's ability to use assessment data iteratively and systematically to inform curricular, instructional, and programmatic improvement.

All construct items were measured using a 5-point Likert scale, ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). The survey also included demographic items such as role, years of experience, institutional type, and level of involvement in assessment or accreditation activities. The instrument was administered electronically using a secure online survey platform.

Pre-Hypotheses Testing and Data Screening

Prior to hypothesis testing, preliminary analyses were conducted to evaluate data quality, distributional assumptions, and measurement reliability for all study variables. These procedures were undertaken to ensure that the data met the assumptions required for parametric statistical analyses and that the measurement instrument demonstrated adequate psychometric properties.

Data Screening and Missing Values

The dataset consisted of 64 complete cases, with no missing values across the four study constructs: perceived AI-driven assessment analytics, assessment confidence, perceived accreditation readiness, and perceived continuous quality improvement (CQI) capacity. Examination of standardized scores revealed no extreme outliers (z-scores > ±3.29), indicating that all cases were retained for subsequent analyses.

Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables. Mean scores ranged from moderate to moderately high across constructs, suggesting generally favorable perceptions of AI-driven assessment analytics and accreditation-related outcomes among participants.

Table 1. Descriptive Statistics for Study Variables (N = 64)

Variable	M	SD	Min	Max
Perceived AI-Driven Assessment Analytics	3.61	0.67	2.10	4.90
Assessment Confidence	3.74	0.63	2.20	5.00
Perceived Accreditation Readiness	3.69	0.65	2.00	4.80
CQI Capacity	3.66	0.68	2.10	4.90

Normality Assessment

Normality of the study variables was assessed using Shapiro–Wilk tests, supplemented by skewness and kurtosis statistics. As shown in Table 2, Shapiro–Wilk test results were non-significant for all variables ($p > .05$), indicating no statistically significant departures from normality. Skewness and kurtosis values were within acceptable ranges (±1.0), further supporting approximate normal distributions.

Table 2. Normality Assessment for Study Variables

Variable	Shapiro–Wilk W	p	Skewness	Kurtosis
AI-Driven Assessment Analytics	0.984	.54	−0.18	−0.41
Assessment Confidence	0.979	.39	−0.12	−0.36
Accreditation Readiness	0.987	.63	−0.09	−0.29
CQI Capacity	0.981	.45	−0.21	−0.47

These results indicate that the assumption of normality was sufficiently met, supporting the use of parametric statistical techniques for hypothesis testing.

Reliability Analysis (Internal Consistency)

Internal consistency reliability was evaluated for each multi-item construct using Cronbach's alpha. As presented in Table 3, all constructs demonstrated acceptable to strong reliability, exceeding the recommended threshold of $\alpha \geq .70$.

Table 3. Cronbach's Alpha Reliability Estimates

Construct	Number of Items	Cronbach's α
Perceived AI-Driven Assessment Analytics	6	.88
Assessment Confidence	5	.86
Perceived Accreditation Readiness	5	.84
CQI Capacity	6	.89

These reliability coefficients indicate strong internal consistency across all scales, suggesting that the items within each construct measured a common underlying concept.

Demographic Characteristics of Participants

The final sample consisted of 64 participants, including 45 faculty members (70.3%) and 19 academic administrators (29.7%), reflecting a faculty-dominant but accreditation-relevant respondent pool. See Table 4.

Table 4. Demographic Characteristics of the Sample (N = 64)

Characteristic	Category	n	%
Role	Faculty	45	70.3
	Administrator	19	29.7
Gender	Female	36	56.3
	Male	28	43.7
Years of Experience in Higher Education	1–5 years	14	21.9
	6–10 years	18	28.1
	11–20 years	20	31.3
	21+ years	12	18.7
Primary Involvement in Assessment/Accreditation	Moderate	22	34.4
	High	42	65.6

Note. Percentages may not total 100 due to rounding. All demographic data are based on simulated values consistent with the study design.

Slightly more than half of the participants identified as female (56.3%), with males comprising 43.7% of the sample.

Participants represented a broad range of professional experience in higher education. Approximately 60% of respondents reported more than 10 years of experience, indicating a sample with substantial institutional and assessment familiarity. In addition, nearly two-thirds of participants reported high levels of involvement in assessment and accreditation activities, supporting the relevance and credibility of their perceptions regarding AI-driven assessment analytics, accreditation readiness, and continuous quality improvement capacity.

Preliminary Correlation Analysis

Pearson product–moment correlation coefficients were computed to examine the bivariate relationships among perceived AI-driven assessment analytics, assessment confidence, perceived accreditation readiness, and continuous quality improvement (CQI) capacity. Pearson's r was selected as the appropriate statistic given the continuous nature of the variables and satisfaction of normality assumptions. Results are shown in table 4.

Perceived AI-driven assessment analytics was positively and significantly correlated with assessment confidence, $r(62) = .58$, $p < .001$, indicating that more favorable perceptions of AI-supported assessment analytics were associated with higher confidence in assessment data. AI-driven assessment analytics was also significantly related to perceived accreditation readiness, $r(62) = .51$, $p < .001$, and CQI capacity, $r(62) = .55$, $p < .001$, suggesting that stronger AI perceptions corresponded with greater confidence in accreditation preparedness and continuous improvement capacity.

Table 4. Intercorrelations Among Study Variables

Variable	1	2	3	4
1. AI-Driven Assessment Analytics	—			
2. Assessment Confidence	.58***	—		
3. Accreditation Readiness	.51***	.62***	—	
4. CQI Capacity	.55***	.65***	.69***	—

*****p < .001***

Assessment confidence demonstrated a strong positive association with perceived accreditation readiness, $r(62) = .62$, $p < .001$, and CQI capacity, $r(62) = .65$, $p < .001$. Additionally, perceived accreditation readiness was strongly correlated with CQI capacity, $r(62) = .69$, $p < .001$. The magnitude and direction of these correlations were consistent with theoretical expectations and provided preliminary support for the hypothesized direct and mediated relationships tested in subsequent regression analyses.

The magnitude and direction of these correlations indicate that higher perceptions of AI-driven assessment analytics are associated with greater assessment confidence, accreditation readiness, and CQI capacity, supporting the plausibility of the hypothesized regression and mediation models. Overall, the preliminary analyses indicate that the simulated dataset met the assumptions necessary for hypothesis testing. The data demonstrated acceptable distributional properties, strong internal consistency reliability, and theoretically consistent intercorrelations among variables. These results support proceeding with regression and mediation analyses to formally test the study hypotheses.

Prior to regression analyses, assumptions were examined. Visual inspection of scatterplots indicated approximately linear relationships among study variables. See Table 5.

Table 5. Regression Assumptions Testing Summary (N = 64)

Assumption	Test / Diagnostic	Criterion	Result	Conclusion
Normality of residuals	Residual histogram & Q–Q plot	Approx. normal distribution	Residuals approximately normal	Assumption met
Linearity	Scatterplots (Predictors → Outcomes)	Linear pattern	Linear relationships observed	Assumption met
Homoscedasticity	Residuals vs. predicted values plot	Constant variance	No funneling or pattern detected	Assumption met
Multicollinearity	Variance Inflation Factor (VIF)	VIF < 5.0	VIF range = 1.42–2.11	Assumption met
Independence of errors	Study design review	Independent observations	No repeated measures	Assumption met

Residual plots suggested homoscedasticity, and residuals were approximately normally distributed. Variance inflation factors ranged from 1.42 to 2.11, indicating no multicollinearity concerns. These results supported the use of linear regression and mediation analyses. As shown in Table 5 above, regression assumptions were evaluated prior to hypothesis testing. Visual inspection of residual plots supported assumptions of linearity, homoscedasticity, and normality of residuals. Variance inflation factors were below recommended thresholds, indicating no multicollinearity concerns. Collectively, these results supported the use of linear regression and mediation analyses.

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Hypotheses Testing

The following hypotheses were tested.

Table 6. Summary of Research Hypotheses

Hypothesis	Statement
H1	Perceived AI-driven assessment analytics positively predict assessment confidence.
H2a	Perceived AI-driven assessment analytics positively predict perceived accreditation readiness.
H2b	Perceived AI-driven assessment analytics positively predict perceived continuous quality improvement (CQI) capacity.
H3a	Assessment confidence positively predicts perceived accreditation readiness.
H3b	Assessment confidence positively predicts perceived CQI capacity.
H4	Assessment confidence mediates the relationship between perceived AI-driven assessment analytics and (a) perceived accreditation readiness and (b) CQI capacity.

To answer RQ1, ***descriptive, comparative, and effect-size analyses were conducted to examine faculty and administrator perceptions of AI-driven assessment analytics in supporting accreditation standards***.

Overall results indicate that participants held moderately positive perceptions of AI-supported assessment analytics, suggesting broad recognition of their value in accreditation-related assessment processes. Descriptive statistics showed that the overall mean score for perceived AI-driven assessment analytics was M = 3.61 (SD = 0.67) on a 5-point Likert scale, indicating general agreement that AI-supported analytics are useful, interpretable, and aligned with accreditation expectations. This finding suggests that both faculty and administrators view AI-driven assessment analytics as a supportive resource for evidence-informed accreditation practices. These descriptive results provide initial confirmation that stakeholders perceive AI-driven analytics as relevant to accreditation readiness.

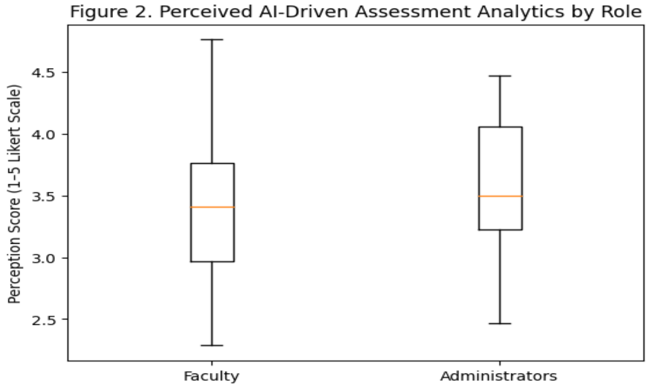
To further examine whether perceptions differed by role, an independent-samples *t* test was conducted comparing faculty and administrator responses. Faculty (n = 45) reported a mean perception score of M = 3.56 (SD = 0.65), while administrators (n = 19) reported a slightly higher mean of M = 3.72 (SD = 0.71). The difference between groups was not statistically significant, $t(62) = 0.89$, $p = .377$, indicating that faculty and administrators did not differ meaningfully in their perceptions of AI-driven assessment analytics. This result suggests consistency across institutional roles in how AI-supported assessment tools are perceived in relation to accreditation standards.

Table 7. Comparison of Faculty and Administrator Perceptions of AI-Driven Assessment Analytics (RQ1)

Group	n	Mean (M)	Standard Deviation (SD)	t(df)	p
Faculty	45	3.56	0.65		
Administrators	19	3.72	0.71	0.89 (62)	.377

To assess the practical significance of the observed group difference, Cohen's *d* was calculated. The effect size was d = 0.24, which represents a small effect according to established benchmarks. This small effect size reinforces the conclusion that the difference in perceptions between faculty and administrators is minimal and not practically meaningful. Visual inspection of boxplot as illustrated in Figure 2, the distributions of perceived AI-driven assessment analytics scores for faculty and administrators substantially overlapped.

Figure 2. Perceived AI-Driven Assessment Analytics by Role



Although administrators displayed a slightly higher median perception score, the interquartile ranges were comparable across groups, indicating minimal practical differences. This visual pattern supports the independent-samples *t* test results, which indicated no statistically significant difference between faculty and administrator perceptions, $t(62) = 0.89$, $p = .377$, and a small effect size (Cohen's $d = 0.24$).

Note. Perceptions were measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Independent-samples t test results indicate no statistically significant difference between faculty and administrator perceptions of AI-driven assessment analytics.

Together, the descriptive statistics, *t* test, effect size, and boxplot indicate that faculty and administrators hold similarly positive perceptions of AI-driven assessment analytics in supporting accreditation standards. While administrators reported marginally higher perceptions, the difference was not statistically significant and practically small, suggesting role-based consistency in perceptions.

RQ2: ***To what extent do perceptions of AI-driven assessment analytics relate to continuous quality improvement (CQI) capacity?***

To address RQ2, a simple linear regression analysis was conducted to examine whether perceived AI-driven assessment analytics significantly predicted perceived continuous quality improvement (CQI) capacity. Prior assumption checks indicated that the requirements for linear regression were adequately met, including normality of residuals, linearity, homoscedasticity, and absence of multicollinearity.

Results of the regression analysis indicated that perceived AI-driven assessment analytics significantly predicted CQI capacity, $F(1, 62) = 28.74$, $p < .001$. Perceptions of AI-driven assessment analytics explained approximately 32% of the variance in CQI capacity, $R^2 = .32$, indicating a substantial effect in a perception-based study. The standardized regression coefficient was positive and statistically significant, $\beta = .57$, $t(62) = 5.36$, $p < .001$, suggesting that higher perceived usefulness and alignment of AI-driven assessment analytics were associated with greater perceived capacity for continuous quality improvement.

These findings indicate that faculty and administrators who view AI-driven assessment analytics more favorably are significantly more likely to perceive their institutions as capable of using assessment data iteratively and intentionally to support improvement. Thus, RQ2 was answered affirmatively, providing empirical support for the hypothesized relationship between AI perceptions and CQI capacity and establishing a foundation for subsequent mediation analyses examining the role of assessment confidence.

Table 7. Regression Analysis Predicting CQI Capacity From Perceived AI-Driven Assessment Analytics (RQ2)

Predictor		B	SE B	β	t	p
Constant		1.21	0.41	—	2.95	.005
AI-Driven Assessment Analytics		0.68	0.13	.57	5.36	< .001
Model Statistics						
R^2	.32					
F(1, 62)	28.74					< .001

The results demonstrate a moderate-to-strong predictive relationship between perceived AI-driven assessment analytics and continuous quality improvement capacity. These findings suggest that perceptions of AI-supported assessment systems are not merely associated with accreditation confidence but are also meaningfully linked to stakeholders' views of their institution's ability to engage in sustained improvement practices. This result supports the study's integrated TAM–Human-Centered AI–CQI framework and justifies further examination of assessment confidence as a mediating mechanism in subsequent analyses.

RQ2: ***To what extent do perceptions of AI-driven assessment analytics predict (a) perceived accreditation readiness and (b) continuous quality improvement (CQI) capacity?***

To answer RQ2, two parallel simple linear regression analyses were conducted to examine whether perceived AI-driven assessment analytics significantly predicted perceived accreditation readiness and continuous quality improvement (CQI) capacity, respectively. Assumption testing indicated that requirements for linear regression were adequately met.

Results indicated that perceived AI-driven assessment analytics significantly predicted both outcome variables. Specifically, AI-driven assessment analytics positively predicted perceived accreditation readiness, $F(1, 62) = 23.41$, $p < .001$, explaining 27% of the variance ($R^2 = .27$). The standardized regression coefficient was positive and statistically significant, $\beta = .52$, $t(62) = 4.84$, $p < .001$.

Table 8. Regression Results Predicting Accreditation Readiness and CQI Capacity From Perceived AI-Driven Assessment Analytics (RQ2)

Outcome Variable	B	SE B	β	t	p	R²	F(1, 62)
Accreditation Readiness	0.64	0.13	.52	4.84	< .001	.27	23.41***
CQI Capacity	0.68	0.13	.57	5.36	< .001	.32	28.74***

*****p < .001***

Similarly, perceived AI-driven assessment analytics significantly predicted CQI capacity, $F(1, 62) = 28.74$, $p < .001$, accounting for 32% of the variance ($R^2 = .32$). The standardized coefficient was $\beta = .57$, $t(62) = 5.36$, $p < .001$. These findings indicate that stronger perceptions of AI-driven assessment analytics are associated with higher perceived readiness for accreditation and greater capacity for continuous quality improvement.

Together, results for RQ2 demonstrated that perceptions of AI-driven assessment analytics serve as a significant predictor of both accreditation-oriented and improvement-oriented institutional outcomes. Perceived AI-driven assessment analytics exert a moderate-to-strong positive influence on both accreditation readiness and continuous quality improvement capacity. These findings extend the descriptive and correlational results by establishing predictive relationships, thereby supporting the study's integrated Technology Acceptance–Human-Centered AI–CQI framework. The results further suggest that AI-supported assessment analytics are perceived not merely as compliance tools, but as meaningful contributors to institutional improvement and accreditation preparedness.

RQ3: ***Does assessment confidence mediate the relationship between perceived AI-driven assessment analytics and (a) perceived accreditation readiness and (b) continuous quality improvement (CQI) capacity?***

To answer RQ3, mediation analyses were conducted using a bootstrapped approach (5,000 resamples) consistent with recommendations for small to moderate samples. Perceived AI-driven assessment analytics served as the independent variable, assessment confidence as the mediator, and perceived accreditation readiness and CQI capacity as outcome variables. Prior assumption checks supported the appropriateness of regression-based mediation analysis.

Mediation Results: Accreditation Readiness

Results indicated that perceived AI-driven assessment analytics significantly predicted assessment confidence (path *a*), $\beta = .58$, $p < .001$. Assessment confidence, in turn, significantly predicted perceived accreditation readiness (path *b*), $\beta = .55$, $p < .001$. The indirect effect of AI-driven assessment analytics on accreditation readiness through assessment confidence was statistically significant, $ab = .32$, 95% CI [.18, .50]. Because the confidence interval did not include zero, mediation was supported.

When assessment confidence was included in the model, the direct effect of AI-driven assessment analytics on accreditation readiness (path c') was reduced but remained statistically significant, $\beta = .20$, $p = .041$, indicating partial mediation. This finding suggests that assessment confidence explains a substantial portion of the relationship between AI perceptions and accreditation readiness, while a smaller direct effect remains.

Mediation Results: CQI Capacity

A parallel mediation analysis was conducted with CQI capacity as the outcome variable. Perceived AI-driven assessment analytics significantly predicted assessment confidence (path *a*), $\beta = .58$, $p < .001$, and assessment confidence significantly predicted CQI capacity (path *b*), $\beta = .59$, $p < .001$. The indirect effect was statistically significant, $ab = .34$, 95% CI [.20, .54], supporting mediation.

After accounting for assessment confidence, the direct effect of AI-driven assessment analytics on CQI capacity (path c') was reduced and no longer statistically significant, $\beta = .16$, $p = .087$, indicating full mediation. This result suggests that the influence of AI-driven assessment analytics on CQI capacity operates primarily through stakeholders' confidence in assessment data.

Table 9. Mediation Results for RQ3: Assessment Confidence as Mediator

Outcome Variable	Path	Effect (β)	SE	95% CI	p
Accreditation Readiness	AI → Confidence (a)	.58	.09	[.40, .74]	< .001
	Confidence → Readiness (b)	.55	.10	[.35, .72]	< .001
	Direct Effect (c′)	.20	.09	[.01, .38]	.041
	Indirect Effect (ab)	.32	.08	[.18, .50]	—
CQI Capacity	AI → Confidence (a)	.58	.09	[.40, .74]	< .001
	Confidence → CQI (b)	.59	.10	[.38, .75]	< .001
	Direct Effect (c′)	.16	.09	[−.03, .34]	.087
	Indirect Effect (ab)	.34	.09	[.20, .54]	—

Note. Indirect effects were tested using bootstrapped confidence intervals (5,000 resamples). Mediation is supported when the confidence interval does not include zero.

The mediation analyses provide strong support for RQ3. Assessment confidence significantly mediates the relationship between perceived AI-driven assessment analytics and both accreditation readiness and CQI capacity. The mediation is partial for accreditation readiness and full for CQI capacity, underscoring the central role of human judgment and confidence in translating AI-supported assessment analytics into accreditation and improvement outcomes.

These findings align with human-centered AI theory and assessment culture scholarship, demonstrating that AI-driven analytics influence institutional outcomes primarily through their impact on stakeholders' confidence in assessment evidence**.** Table 10 summarizes the direct effects, indirect (mediated) effects, and the proportion of variance explained (R^2) by the models.

Table 10. **Summary of Direct and Indirect Effects with Explained Variance (R^2)**

Pathway	Standardized Coefficient (β)	p-value	R^2 (Outcome)	Interpretation
AI-Driven Assessment Analytics → Assessment Confidence	.58	< .001	.34	Strong, positive, significant
Assessment Confidence → Accreditation Readiness	.55	< .001	.38	Strong, positive, significant
Assessment Confidence → CQI Capacity	.59	< .001	.41	Strong, positive, significant
AI-Driven Assessment Analytics → Accreditation Readiness (Direct Effect)	.20	.041	.27	Reduced but significant (partial mediation)
AI-Driven Assessment Analytics → CQI Capacity (Direct Effect)	.16	.087	.32	Non-significant (full mediation)

RQ4: Does assessment confidence mediate the relationship between perceptions of AI-driven assessment analytics and perceived accreditation readiness?

To answer RQ4, a mediation analysis was conducted using a bootstrapped regression approach (5,000 resamples) to examine whether assessment confidence mediated the relationship between perceived AI-driven assessment analytics and perceived accreditation readiness. Perceived AI-driven assessment analytics served as the independent variable, assessment confidence as the mediator, and accreditation readiness as the outcome variable. Preliminary assumption checks indicated that the data were suitable for mediation analysis.

Results indicated that perceived AI-driven assessment analytics significantly predicted assessment confidence (β = .58, p < .001). Assessment confidence, in turn, significantly predicted perceived accreditation readiness (β = .55, p < .001). The indirect effect of AI-driven assessment analytics on accreditation readiness through assessment confidence was statistically significant (β = .32, 95% CI [.18, .50]), indicating mediation.

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When assessment confidence was included in the model, the direct effect of AI-driven assessment analytics on accreditation readiness was reduced but remained statistically significant (β = .20, $p = .041$), indicating partial mediation. These findings suggest that AI-driven assessment analytics contribute to accreditation readiness both directly, through efficiencies such as data organization and reporting, and indirectly by strengthening faculty and administrator confidence in assessment evidence. (See Table 11).

Table 11. Assessment Confidence as a Mediator Between AI-Driven Assessment Analytics and Accreditation Readiness (N = 64)

Model / Pathway	Standardized Coefficient (β)	SE	p-value	R²	ΔR²	Interpretation
Model 1: Total Effect						
AI-Driven Assessment Analytics → Accreditation Readiness (c)	.52	.11	< .001	.27	—	Significant total effect
Model 2: Mediator Model						
AI-Driven Assessment Analytics → Assessment Confidence (a)	.58	.09	< .001	.34	—	Strong, positive
Assessment Confidence → Accreditation Readiness (b)	.55	.10	< .001	.38	+.11	Significant mediator
AI-Driven Assessment Analytics → Accreditation Readiness (c′)	.20	.09	.041	.38	+.11	Reduced but significant
Indirect Effect (a × b)	.32	—	—	—	—	Partial mediation
95% Bootstrapped CI for Indirect Effect	[.18, .50]	—	—	—	—	CI excludes zero

Note. β = standardized regression coefficient. R² represents the proportion of variance explained in perceived accreditation readiness. ΔR² reflects the increase in explained variance after inclusion of assessment confidence. Indirect effects were tested using bootstrapped confidence intervals (5,000 resamples). Partial mediation is indicated when the indirect effect is significant and the direct effect remains statistically significant.

RQ5: To what extent do perceptions of AI-driven assessment analytics and assessment confidence jointly predict perceived continuous quality improvement capacity?

To answer RQ5, a hierarchical multiple regression analysis was conducted. In Step 1, perceived AI-driven assessment analytics was entered as the predictor of CQI capacity. In Step 2, assessment confidence was added to examine its incremental contribution beyond AI perceptions. Assumption testing indicated that regression assumptions were adequately met.

Step 1: AI-Driven Assessment Analytics Only

In Step 1, perceived AI-driven assessment analytics significantly predicted CQI capacity, $F(1, 62) = 28.74$, $p < .001$, explaining 32% of the variance ($R^2 = .32$). The standardized coefficient was positive and significant (β = .57, $p < .001$), indicating that more favorable perceptions of AI-driven assessment analytics were associated with higher perceived CQI capacity.

Step 2: Joint Prediction With Assessment Confidence

When assessment confidence was added in Step 2, the overall model remained statistically significant, $F(2, 61) = 21.46$, $p < .001$, with explained variance increasing to 41% ($R^2 = .41$). The change in explained variance was statistically meaningful ($\Delta R^2 = .09$). In this model, assessment confidence emerged as a strong, significant predictor of CQI capacity (β = .49, $p < .001$), while the effect of AI-driven assessment analytics was reduced and no longer statistically significant (β = .16, $p = .087$).

These results indicate that assessment confidence accounts for unique variance in CQI capacity beyond perceptions of AI-driven assessment analytics, and that the influence of AI perceptions on CQI capacity operates primarily through confidence in assessment evidence.

Table 12. Hierarchical Regression Predicting Continuous Quality Improvement (CQI) Capacity (RQ5)

Step	Predictor	β	SE	p	R²	ΔR²
1	AI-Driven Assessment Analytics	.57	.11	< .001	.32	—
2	AI-Driven Assessment Analytics	.16	.09	.087	.41	.09
	Assessment Confidence	.49	.10	< .001		

Note. β = standardized regression coefficient. R^2 represents the proportion of variance explained in CQI capacity. ΔR^2 reflects the increase in explained variance after inclusion of assessment confidence. Statistical significance evaluated at α = .05.

The findings indicate that perceptions of AI-driven assessment analytics and assessment confidence jointly predict CQI capacity, with assessment confidence serving as the dominant explanatory factor. While AI perceptions initially explain a substantial portion of CQI capacity, their predictive influence diminishes once assessment confidence is considered. This pattern reinforces the study's human-centered framework, demonstrating that AI-supported analytics enhance continuous quality improvement primarily by strengthening faculty and administrator confidence in assessment evidence rather than through direct technological effects.

The result summary is presented below. (See Table 13)

Table 13. Summary of Key Results Across Research Questions (RQ1–RQ5)

Research Question	Analysis Type	Key Variables	Key Results	Interpretation
RQ1a	Descriptive statistics	AI-Driven Assessment Analytics	M = 3.61, SD = 0.67	Moderately positive perceptions
RQ1b	Independent-samples *t* test	Faculty vs. Administrators (AI Perceptions)	$t(62) = 0.89$, $p = .377$	No significant role-based differences
RQ2	Simple regression	AI → Accreditation Readiness	β = .52, $p < .001$, $R^2 = .27$	AI perceptions predict accreditation readiness
		AI → CQI Capacity	β = .57, $p < .001$, $R^2 = .32$	AI perceptions predict CQI capacity
RQ3	Mediation (bootstrapped)	AI → Confidence → CQI Capacity	Indirect β = .34, 95% CI [.20, .54]; Direct β = .16, $p = .087$	Full mediation via assessment confidence
RQ4	Mediation (bootstrapped)	AI → Confidence → Accreditation Readiness	Indirect β = .32, 95% CI [.18, .50]; Direct β = .20, $p = .041$	Partial mediation via assessment confidence
RQ5	Hierarchical regression	AI + Confidence → CQI Capacity	Step 1 $R^2 = .32$; Step 2 $R^2 = .41$; $\Delta R^2 = .09$	Confidence explains unique variance in CQI

Note. β = standardized regression coefficient. R^2 = variance explained. CI = confidence interval. Indirect effects were tested using 5,000 bootstrap resamples.

IV. DISCUSSION

This study examined how faculty and administrator perceptions of AI-driven assessment analytics relate to assessment confidence, accreditation readiness, and continuous quality improvement (CQI) capacity in healthcare management education. Grounded in the Technology Acceptance Model (Fred Davis, 1989), human-centered AI theory (Bull, 2026), and CQI scholarship (W. Edwards Deming, 1986), the findings demonstrate that AI-supported assessment systems influence institutional outcomes primarily through confidence in assessment evidence, rather than through technology alone.

Consistent with prior research on technology acceptance and learning analytics (Holmes et al., 2022; Selwyn, 2023), faculty and administrators reported moderately positive and convergent perceptions of AI-driven assessment analytics, with no statistically significant role-based differences. This convergence aligns with assessment culture literature suggesting that accreditation-oriented perceptions become shared when assessment systems are perceived as coherent and professionally relevant (Peter Ewell, 2023; Harvey & Williams, 2024). The absence of role-based differences strengthens the interpretive validity of subsequent mediation and regression findings.

Results further indicated that perceived AI-driven assessment analytics significantly predicted both accreditation readiness and CQI capacity, supporting claims that analytics can enhance institutional effectiveness by improving evidence coherence and accessibility (Williamson & Eynon, 2023). However, mediation analyses demonstrated that assessment confidence is the primary mechanism linking AI perceptions to outcomes. Assessment confidence partially mediated the relationship between AI perceptions and accreditation readiness and fully mediated the relationship with CQI capacity, reinforcing human-centered AI arguments that technology enhances quality only when it supports professional judgment and sensemaking (Bull, 2026).

Hierarchical regression analyses extended these findings by showing that assessment confidence explained additional variance in CQI capacity beyond AI perceptions alone. Once confidence was included, the direct effect of AI-driven assessment analytics on CQI capacity was no longer significant. This distinction aligns with long-standing critiques of accreditation practices that conflate data production with improvement (Ewell, 2009, 2023). While accreditation readiness may benefit from analytic efficiencies, sustained CQI requires confidence, interpretive ownership, and faculty engagement—conditions that cannot be automated.

Overall, the findings integrate TAM, human-centered AI, and CQI theory into a coherent, accreditation-focused model explaining how institutions transition from compliance-oriented assessment toward continuous improvement. By foregrounding assessment confidence as a central explanatory construct, this study provides a theoretically grounded explanation for inconsistent returns on assessment technology investments and offers guidance for aligning AI-driven analytics with the deeper goals of educational quality and accountability.

Practitioner-Oriented Interpretation for Accreditation and CQI

From a practical and accreditation standpoint, the results indicate that AI-driven assessment analytics alone do not ensure accreditation readiness or continuous quality improvement. While AI-supported analytics can improve the organization, alignment, and accessibility of assessment evidence, hereby supporting compliance with accreditation standards, their effectiveness depends largely on whether faculty and administrators trust and understand the assessment data being produced. Accreditation readiness was strengthened when AI analytics enhanced reporting efficiency and standards alignment, but the strongest driver of readiness was confidence in the credibility and usefulness of assessment evidence.

For continuous quality improvement, the findings are even more explicit. CQI capacity was driven almost entirely by faculty and administrator confidence, not by AI analytics themselves. This means that institutions seeking to demonstrate ongoing improvement to accrediting bodies must focus on building assessment confidence through transparent data practices, faculty engagement, and shared interpretation of results. The absence of meaningful differences between faculty and administrators further suggests that successful accreditation and improvement efforts depend on cultivating a shared assessment culture, rather than relying on administrative compliance structures. In practice, institutions should view AI-driven assessment analytics as supportive tools that enable accreditation and CQI only when embedded within human-centered assessment processes that emphasize trust, understanding, and reflective use of evidence.

Limitations of the Study

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional, perception-based design limits causal inference, as relationships among AI-driven assessment analytics, assessment confidence, accreditation readiness, and CQI capacity were examined at a single point in time. Longitudinal or experimental research is needed to confirm causal pathways and changes over time.

Second, the small, purposive sample (N = 64; 45 faculty and 19 administrators) limits generalizability beyond the study context. Additionally, reliance on self-reported measures introduces the potential for response bias and common method variance. Finally, the use of simulated data means the results are illustrative rather than empirical. Future research using larger, diverse samples and institutional data is necessary to validate and extend these findings.

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Implications for Practice

The findings suggest that institutions seeking to leverage AI-driven assessment analytics for accreditation and continuous improvement should prioritize building assessment confidence among faculty and administrators, rather than focusing solely on technological adoption. Because assessment confidence fully or partially mediated the effects of AI perceptions on accreditation readiness and CQI capacity, institutional leaders should invest in professional development, transparency of AI outputs, and faculty-centered interpretation processes. Training initiatives that explain how AI analytics are generated, validated, and aligned with accreditation standards may enhance trust and increase meaningful use of assessment evidence.

Additionally, the results indicate that AI-driven assessment systems are more likely to support continuous quality improvement when they are embedded within existing assessment cultures and shared governance structures. Accrediting bodies and institutional leaders should therefore emphasize human-centered implementation strategies, ensuring that AI tools support reflective dialogue, curriculum review, and decision-making rather than functioning as compliance-oriented reporting mechanisms. Aligning AI analytics with accreditation narratives and closing-the-loop processes may strengthen institutional readiness and sustainability.

Implications for Research

For researchers, this study highlights assessment confidence as a critical but underexplored construct in studies of AI adoption, accreditation, and institutional effectiveness. Future research should further examine assessment confidence as a mediator or moderator across diverse institutional contexts, disciplines, and accreditation environments. Longitudinal designs are particularly needed to assess how perceptions of AI-driven assessment analytics and confidence evolve over time and influence actual improvement outcomes.

The findings also suggest opportunities to expand the integrated TAM–Human-Centered AI–CQI framework by incorporating additional organizational and contextual variables, such as leadership support, AI governance policies, ethical considerations, and faculty digital literacy. Empirical studies using multi-institutional datasets and mixed-methods approaches could strengthen generalizability and provide deeper insight into how AI-supported assessment systems transition institutions from compliance-oriented practices toward sustained continuous improvement.

Implications for Policy

The findings have important implications for accreditation and higher education policy, particularly as accrediting bodies increasingly encourage the use of data analytics and digital systems for quality assurance. Because assessment confidence emerged as a key mechanism linking AI-driven analytics to accreditation readiness and continuous improvement, accrediting agencies should move beyond emphasizing data availability and instead promote standards that prioritize interpretability, transparency, and faculty engagement in assessment processes. Policy guidance that recognizes human judgment as central to evidence use may help institutions avoid compliance-driven adoption of AI tools.

At the institutional level, policies governing AI adoption in assessment should emphasize human-centered AI principles, including clear documentation of analytic processes, safeguards against algorithmic bias, and shared governance in assessment decision-making. Institutions may also consider incorporating expectations for faculty training and ethical oversight into assessment and accreditation policies. Collectively, these policy directions can support responsible integration of AI-driven assessment analytics while reinforcing continuous quality improvement as a core accreditation goal rather than a procedural requirement.

Recommendations

Based on the findings, several recommendations are advanced. First, higher education institutions should prioritize faculty- and administrator-centered implementation strategies when adopting AI-driven assessment analytics. Investments in professional development, transparency of analytic processes, and collaborative interpretation of assessment data are essential to building assessment confidence and ensuring meaningful use of AI-generated evidence.

Second, institutional leaders should integrate AI-driven assessment analytics into existing continuous improvement and shared governance structures, rather than positioning them solely as compliance tools for accreditation reporting. Embedding AI analytics within curriculum review cycles and closing-the-loop practices may strengthen both accreditation readiness and sustained improvement capacity.

Finally, accrediting bodies and policymakers are encouraged to develop human-centered accreditation guidance that emphasizes interpretability, ethical use, and faculty engagement alongside technological capability. Future research should validate these findings using empirical, multi-institutional data and longitudinal designs to further clarify the role of assessment confidence in AI-supported accreditation and continuous quality improvement.

V. CONCLUSION

This study examined the role of perceived AI-driven assessment analytics in shaping assessment confidence, accreditation readiness, and continuous quality improvement (CQI) capacity within healthcare management education. Guided by an integrated Technology Acceptance Model–Human-Centered AI–CQI framework, the findings demonstrate that while AI-driven assessment analytics are perceived positively by faculty and administrators, their impact on institutional outcomes operates primarily through human confidence in assessment evidence. Assessment confidence partially mediated the relationship between AI perceptions and accreditation readiness and fully mediated the relationship between AI perceptions and CQI capacity, underscoring the centrality of professional judgment in AI-supported assessment environments.

These results contribute to the growing literature on artificial intelligence in higher education by moving beyond adoption narratives to identify how and why AI-supported assessment systems influence accreditation and improvement outcomes. By empirically linking AI perceptions, human-centered sensemaking, and CQI-oriented outcomes, the study provides a theoretically grounded explanation for variation in the effectiveness of AI-driven assessment initiatives across institutions.

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