AI-Driven Learning Analytics Capabilities and Learning Data Quality for Intelligent Academic Decision-Making in Jordanian Higher Education: A Pilot Study

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Abstract

Artificial intelligence (AI) and learning analytics have become key drivers of data-driven decision-making in higher education. However, limited research has examined how AI-Driven Learning Analytics Capabilities and Learning Data Quality influence Intelligent Academic Decision Support and Academic Decision Quality. Accordingly, this study aims to develop and preliminarily validate an integrated research model based on Decision Support Systems (DSS) Theory. A quantitative pilot study was conducted to assess the reliability and validity of the proposed measurement instrument before undertaking a full-scale empirical investigation.

The measurement model was evaluated using SmartPLS 4 by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The findings provide preliminary evidence supporting the suitability of the proposed measurement instrument for testing the hypothesized relationships among AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality.

Keywords: *Artificial Intelligence 1, Learning Analytic 2, Learning Data Quality 3, Intelligent Academic Decision Support 4, Academic Decision Quality 5, Decision Support Systems 6.*

ISSN 2991-9371

1. Introduction

The rapid advancement of digital technologies has fundamentally transformed higher education, significantly influencing teaching, assessment, and the management of academic operations [1], [2]. Over the last few years, higher education institutions have generated a significant amount of data through Learning Management Systems (LMSs), online learning platforms, digital assessments, student information systems, and other educational technologies [3]. Digital transformation has encouraged universities to move from traditional administrative processes toward data-driven approaches in which institutional success increasingly depends on their ability to transform large amounts of learning data into knowledge that supports effective planning and decision-making [3], [4]. As a result, higher education institutions are not only expected to collect educational data but also to use it effectively to improve the quality of education, promote student success, design curricula, and enhance institutional performance [5].

Artificial Intelligence (AI) has emerged as one of the most transformative technologies driving this digital revolution by enabling higher education institutions to move beyond conventional data analysis toward intelligent and adaptive analytical approaches [6]. In contrast to traditional analytical methods, AI technologies such as machine learning, deep learning, natural language processing, and predictive analytics enable institutions to process complex datasets, discover hidden patterns, predict future outcomes, and provide recommendations that support evidence-based decision-making [7]. Consequently, AI is no longer viewed merely as an emerging technology but rather as a strategic enabler that enhances institutional efficiency, supports personalized learning experiences, identifies at-risk students, optimizes resource allocation, and supports high-quality academic decision-making [8], [9].

2. Background of AI-Driven Learning Analytics in Higher Education

2.1 Digital Transformation and Artificial Intelligence in Higher Education

Rapid digitalization of the higher education sector has revolutionized the educational environment and created opportunities to utilize modern digital tools to improve teaching and learning processes, conduct research, and manage higher education institutions. The widespread adoption of LMSs, cloud computing, educational platforms, the Internet of Things (IoT), and artificial intelligence has generated substantial amounts of educational data that can be used to optimize academic activities and institutional performance [10], [1]. Consequently, educational data have become a strategic institutional asset, enabling universities to make evidence-based decisions across both academic and administrative domains.

One of the most disruptive technological trends in the field of higher education is the emergence of artificial intelligence that provides the opportunity to implement intelligent, adaptive, and predictive methods of decision making in place of traditional information processing. Using AI technologies such as machine learning, deep learning, natural language processing, and

intelligent recommendation systems, institutions are able to discover hidden data patterns, predict academic outcomes, and make recommendations that improve decision making in academic and managerial contexts [10].

2.2 Evolution of Learning Analytics

Over the past decade, learning analytics (LA) has emerged as one of the most important fields of educational technology research. Traditionally, the learning analytics process focused primarily on collecting and presenting descriptive data about learners' engagement and performance. These conventional methods relied mainly on historical educational data to track student behavior and evaluate learning outcomes. Although they provided useful descriptive insights, they were limited in their ability to predict outcomes or prescribe appropriate actions [11].

Advances in artificial intelligence have led to a paradigm shift from descriptive reporting toward intelligent analysis in the domain of learning analytics. AI-based learning analytics combines machine learning, predictive analytics, deep learning, and intelligent recommendation systems to predict learner performance, identify at-risk students, personalize educational experiences, and provide appropriate instructional interventions [12].

This paradigm shift implies that learning analytics is no longer merely an instrument for reporting but also a tool for intelligent decision-making, enabling universities to make informed decisions based on continuously generated educational data.

Additionally, recent systematic reviews indicate that universities are increasingly using artificial intelligence in learning analytics not only to support student success but also to redesign learning environments and instructional practices and improve institutional decision-making processes. At the same time, the integration of artificial intelligence into learning analytics remains at an early stage in many higher education institutions, indicating considerable opportunities for future theoretical and practical development [5], [4].

3. Literature Review

3.1 AI-Driven Learning Analytics Capabilities

AI-powered learning analytics has emerged as a powerful approach that enables higher education institutions to derive valuable insights from large educational datasets. In contrast to conventional learning analytics, which primarily focuses on describing past learning processes, AI-powered learning analytics applies technologies such as machine learning, deep learning, and predictive analytics to identify learning patterns, predict academic outcomes, and generate intelligent recommendations for academic decision-making [7], [5].

From a Management Information Systems (MIS) perspective, AI-driven learning analytics capabilities refer to an institution's ability to effectively utilize AI technologies and analytical resources to transform educational data into valuable knowledge. These capabilities enable universities to make more effective evidence-based decisions, improve learning processes, identify at-risk students, and enhance student and institutional performance through intelligent analytical techniques [1], [4].

Based on the existing literature, this study conceptualizes AI-Driven Learning Analytics Capabilities as a multidimensional construct comprising four main dimensions: Predictive Analytics Capability, Real-Time Feedback Capability, Personalized Recommendation Capability, and Adaptive Analytical Capability. Through the integration of these four capabilities, higher education institutions can transform learning data into meaningful insights that support intelligent academic decision-making.

3.2 Learning Data Quality

Learning Data Quality (LDQ) refers to the degree to which learning data are accurate, complete, consistent, timely, and relevant for supporting analysis and academic decision-making [13]. In the context of AI-based learning analytics, high-quality learning data provide the foundation for reliable analytics and effective academic decision-making. From a Management Information Systems (MIS) perspective, data quality is widely recognized as an important factor influencing information quality, system effectiveness, and decision support performance [14]. Recent literature emphasizes the importance of learning data quality and effective data management for the successful application of AI technologies in education [10], [15].

Recent studies indicate that the effectiveness of AI-generated learning analytics depends heavily on the quality of learning data. Higher-quality learning data can contribute to more accurate predictions, better personalized learning recommendations, and more reliable real-time analytical insights. Conversely, inconsistencies, inaccuracies, and other data-quality problems may reduce the effectiveness of AI-based tools and lead to biased predictions and academic decisions [5], [16].

Accordingly, Learning Data Quality can be considered a strategic organizational asset that enables higher education institutions to derive greater value from AI-driven learning analytics. Providing high-quality learning data is therefore essential for generating reliable analytics, supporting intelligent academic decision-making, and ultimately improving the quality of academic decisions.

3.3 Synthesis of the Literature

The existing literature indicates that AI-driven learning analytics has become an important tool for supporting data-driven decision-making in higher education institutions. Previous research has emphasized the importance of AI capabilities and learning data quality in improving educational outcomes; however, these factors have generally been examined separately. Limited attention has been given to examining the relationships among AI-driven learning analytics capabilities, learning data quality, intelligent academic decision support, and academic decision quality within an integrated framework from a Management Information Systems (MIS) perspective.

4. Research Model and Hypotheses Development

Based on DSS Theory, the existing literature, and the conceptual framework proposed in this study (see Figure 1), five hypotheses are proposed to examine the relationships among AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality in higher education institutions. The hypotheses are as follows:

- H1: AI-driven learning analytics capabilities positively influence intelligent academic decision support in higher education institutions.
- H2: Learning data quality positively influences intelligent academic decision support in higher education institutions.
- H3: Intelligent academic decision support positively influences academic decision quality in higher education institutions.
- H4: AI-driven learning analytics capabilities positively influence academic decision quality in higher education institutions.
- H5: Learning data quality positively influences academic decision quality in higher education institutions.

4.1 Research Model

Based on Decision Support Systems (DSS) Theory and the reviewed literature, the proposed research model illustrates the relationships among AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality. The model provides the theoretical foundation for the proposed hypotheses.

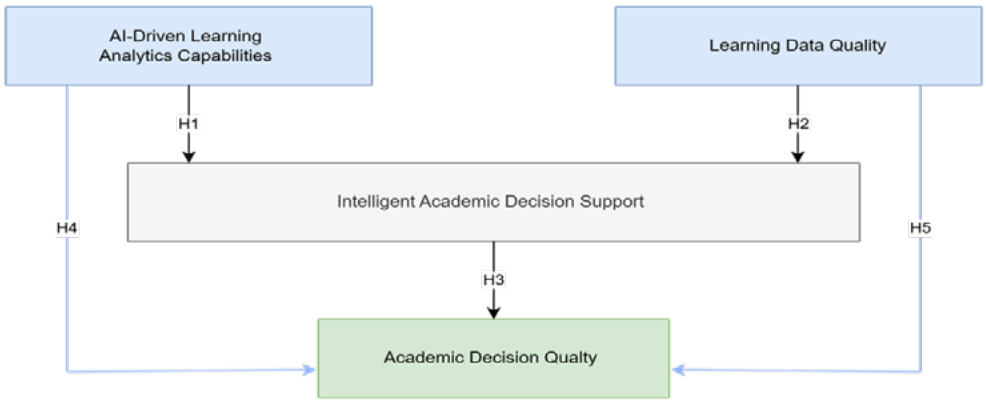


Figure 1. Proposed Conceptual framework.

- H1: AI-Driven Learning Analytics Capabilities → Intelligent Academic Decision Support
- H2: Learning Data Quality → Intelligent Academic Decision Support
- H3: Intelligent Academic Decision Support → Academic Decision Quality
- H4: AI-Driven Learning Analytics Capabilities → Academic Decision Quality
- H5: Learning Data Quality → Academic Decision Quality

4.2 Decision Support Systems (DSS) Theory

Decision Support Systems (DSS) Theory provides a theoretical framework for understanding how information systems support the analysis of complex data and enhance decision-making quality. A DSS is defined as a computerized system that facilitates the collection, processing, and analysis of data to support semi-structured and unstructured decision-making processes [19]. In line with developments in artificial intelligence, contemporary DSSs incorporate intelligent analytical tools, predictive models, and advanced data-processing capabilities to facilitate timely and accurate decision-making [5].

AI-driven learning analytics can be considered an advanced form of decision support system that transforms learning data into actionable insights for academic planning, curriculum development, assessment of learning performance, and institutional decision-making in higher education. Accordingly, DSS Theory is employed in this study to explain the relationships between AI-Driven Learning Analytics Capabilities and Learning Data Quality, and their influence on Intelligent Academic Decision Support and Academic Decision Quality in higher education institutions.

5. Research Methodology

5.1 Pilot study Design

The research design follows a quantitative pilot study approach to provide an initial assessment of the proposed research model and measurement instrument. A pilot study was conducted to evaluate the psychometric properties of the research measurement instrument before undertaking a large-scale empirical investigation. In this study, the reliability and validity of the scales used to measure AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality were examined. Conducting a pilot study before the main study is recommended to improve the quality of the measurement instrument and minimize measurement error [10], [29].

5.2 Pilot Study

The pilot study was conducted to assess the clarity, consistency, and validity of the questionnaire items and to determine the initial psychometric characteristics of the measurement instrument. Pilot studies are important for identifying potential weaknesses in survey instruments before large-scale data collection and for improving the quality of both measurement and research. The results of the pilot study provide preliminary evidence regarding the suitability of the proposed measurement model for future hypothesis testing [29], [10].

5.3 Population and Sample

The target population of the study includes faculty members and academic administrative staff at Jordanian higher education institutions, as they participate directly in academic planning and decision-making and may be involved in the implementation of artificial intelligence and learning analytics initiatives. The pilot sample is expected to comprise approximately 30–50 respondents, which is considered appropriate for the preliminary assessment of the measurement instrument before the main study. Such sample sizes are commonly considered acceptable for pilot studies focused on instrument assessment rather than hypothesis testing [14], [13], [10].

5.4 Measurement Instrument

The research instrument was developed through a thorough review of the literature related to artificial intelligence, learning analytics, educational data quality, intelligent decision support systems, and academic decision quality. All measurement items were adapted from previously validated scales and tailored to the context of higher education. The questionnaire consists of five sections: demographic information, AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality. Responses are measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), which is commonly used in information systems and educational technology research [10], [6].

Table 1 presents the measurement constructs used in this pilot study, including their definitions, number of questionnaire items, measurement sources, alternative measurement approaches reviewed, and the rationale for selecting the final measurement approach. All measurement items were derived from previously validated instruments and adapted to the context of AI-driven learning analytics and intelligent academic decision-making in higher education.

Construct	Definition	Number of Items	Selected measurement Approach / Source	Alternative Measurement Approach Reviewed	Rational for selecting the final Approach
AI-Driven Learning Analytics Capabilities (AILAC)	The institution's capability to utilize AI technologies and learning analytics to collect, analyze, and interpret educational data for supporting academic decision-making.	XX	Adapted from AI and Learning Analytics Literature (2023–2025) Webber&Zheng (2024); Drugovaet al. (2024)	General learning analytics capability measures	General LA measures do not sufficiently capture the AI-enabled predictive, real time personalized and adaptive capabilities emphathasized in the study
Learning Data Quality (LDQ)	The extent to which learning data are accurate, complete, timely, consistent, and relevant for supporting intelligent academic decisions.	XX	Adapted from Information Quality and Learning Analytics literature Delone & McLean (2003) Webber&Zheng (2024)	General information and data quality measures	Broader data-quality measures may not sufficiently reflect the specific characteristics of learning data used for AI-driven academic decision-making.
Intelligent Academic Decision Support (IADS)	The capability of AI-enabled decision support systems to provide timely, reliable, and evidence-based recommendations for academic decision-making.	XX	Adapted from Decision Support Systems literature Power (2002), Arnott &Pervan (2014), Webber&Zheng (2024)	Traditional Decision Support System measures	Traditional DSS measures may not fully capture AI-enabled analytical recommendations and intelligent academic decision support.
Academic Decision Quality (ADQ)	The effectiveness, accuracy, and timeliness of academic decisions made using AI-supported information and analytical insights	XX	adapted from decision quality and higher education research Spetzler, Winter, &Meyer (2016) Schwartz &Sachs (2022)	General organizational decision-quality	General decision-quality measures are not sufficiently specific to academic decision-making in higher education.

Table 1. Measurement Construct and Sources
Source: adapted from the author from a previous validated study.

5.5 Data Analysis

The pilot data were analyzed using SmartPLS 4 to evaluate the measurement model. Specifically, indicator reliability, internal consistency reliability, convergent validity, and discriminant validity were assessed. Factor loadings were used to assess indicator reliability, while Cronbach's Alpha and Composite Reliability (CR) were used to examine internal consistency reliability. Average Variance Extracted (AVE) was used to assess convergent validity, while the Heterotrait–Monotrait ratio (HTMT) was used to assess discriminant validity. As the primary purpose of the pilot study is to validate the measurement instrument, hypothesis testing and structural model analysis will be conducted in the subsequent full-scale empirical study [10], [12].

6. Pilot Study Results

6.1 Respondents' Profile

The pilot test comprised faculty members and academic administrative staff from Jordanian higher education institutions. The primary purpose of the pilot test was to evaluate the research instrument rather than to obtain a representative sample of the target population. Therefore, the relatively small sample size was considered appropriate for assessing the preliminary psychometric properties of the measurement instrument. Respondents' demographic characteristics, including gender, academic rank, years of teaching experience, and university type, were examined using descriptive statistics [10], [29].

Table 2 presents the demographic characteristics of the pilot study participants. The frequencies and percentages shown in this table will be updated after completing the pilot data collection.

Variable	Category	Frequency	Percentage
Gender	Male	xx	xx
	female	xx	xx
Age	Less than 30	xx	xx
	30-39	xx	xx
	40-49	xx	xx
	50 and above	xx	xx

Academic Rank	Lecturer	xx	xx
	Assistant professor	xx	xx
	Associate professor	xx	xx
	Professor	xx	xx
Years of experience	Less than 5 years	xx	xx
	5-10 years	xx	xx
	11-15 years	xx	xx
	More than 15 years	xx	xx
University type	Public	xx	xx
	Private	xx	xx

Table 2. Demographic Characteristics of the Pilot Study Participants.

6.2 Measurement Model Evaluation

The measurement model was evaluated before examining the relationships among the study constructs. The evaluation considered indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. This assessment helps determine whether the measurement instrument appropriately measures the intended constructs and provides reliable results for subsequent empirical research [10], [12]

6.3 Indicator Reliability and Internal Consistency Reliability

Indicator reliability was assessed based on the standardized factor loadings of the measurement items. According to Hair et al. [10], standardized loadings above 0.70 indicate adequate indicator reliability, whereas loadings above 0.60 may be acceptable in pilot studies. Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). Values above 0.70 generally indicate acceptable reliability, whereas values above 0.90 may indicate potential item redundancy [10].

6.4 Convergent Validity

Convergent validity was assessed using the Average Variance Extracted (AVE). An AVE value of 0.50 or higher indicates that a construct explains at least 50% of the variance in its indicators and therefore provides evidence of adequate convergent validity [10], [9]. The AVE values for all constructs were examined against this threshold to assess the quality of the measurement model.

6.5 Discriminant Validity

Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT), a widely recommended criterion for assessing discriminant validity in variance-based structural equation modeling. An HTMT value below 0.85, or below 0.90 under certain conditions, indicates adequate discriminant validity between constructs. The results provide preliminary evidence regarding the distinctiveness of the study constructs and the appropriateness of the proposed measurement model [12], [10].

6.6 Summary of the Pilot Study

In general, the pilot study was conducted in order to assess the quality of the measurement instrument before conducting the actual empirical study. Reliability and validity assessments are the first steps towards obtaining evidence on whether the questionnaire is appropriate for the assessment of AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality. If the psychometric properties of the questionnaire are satisfactory, the instrument may be used for further empirical testing of the research hypotheses through Structural Equation Modelling (PLS-SEM) [10], [29].

7. Conclusion and Future Research

This study developed a conceptual research framework comprising AI-Driven Learning Analytics Capabilities, Learning Data Quality, Intelligent Academic Decision Support, and Academic Decision Quality in the context of higher education in Jordan. Grounded in Decision Support Systems (DSS) Theory, the study presents a conceptual model for understanding the role of artificial intelligence and learning data quality in supporting academic decision-making [19], [5].

The study was designed as a pilot study to assess the reliability and validity of the research instrument before conducting a full-scale empirical investigation. The pilot study provides preliminary evidence regarding the clarity, relevance, and psychometric properties of the measurement items [29], [10].

The study makes both theoretical and practical contributions. Theoretically, it extends the application of Decision Support Systems Theory by incorporating AI-driven learning analytics capabilities into the context of academic decision-making. Practically, the proposed framework may assist university administrators and academic decision-makers in using learning data and artificial intelligence to support more informed academic decisions.

Future research should conduct a full-scale empirical study using a larger sample and Structural Equation Modeling (PLS-SEM) to test the proposed hypotheses and examine the relationships among the study constructs. Future studies could also compare different types of higher education institutions and extend the investigation to other countries to assess the generalizability of the proposed model.

Limitations of the Study

This study has several limitations. First, the research is based on a pilot study and therefore does not provide empirical testing of the proposed hypotheses. The primary purpose of the pilot study was to assess the reliability and validity of the measurement instrument before conducting the full-scale study.

Second, the scope of the study is limited to the higher education context in Jordan, which may limit the generalizability of the findings to other educational contexts and countries. Future research should therefore use larger samples and Structural Equation Modeling (PLS-SEM) to empirically test the proposed hypotheses. Comparative studies involving different types of universities and higher education systems in other countries would also provide valuable insights into the applicability and generalizability of the proposed research model

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