From Data to Decisions: AI-Supported Learning Analytics for Self-Regulated Learning and Academic Decision-Making

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Abstract

This study investigated the effect of a learning environment based on AI-supported learning analytics on self-regulated learning and academic decision-making skills among first-level students at one of the colleges of Education in Egypt. A quasi-experimental pre-test–post-test control-group design was employed. The sample comprised 100 randomly selected male and female students aged 18–20 years, divided equally into an experimental group and a control group. Both groups studied the same Technology of Education course and completed equivalent learning and assessment activities over ten weeks. The experimental group additionally used a custom Moodle plugin that provided a student-facing analytics dashboard, diagnostic information, risk predictions, intelligent alerts, personalized recommendations, and alternative academic actions generated through a fuzzy rule-based expert system. Data were collected using an achievement test, a self-regulated learning scale, a situational academic decision-making test, a digital learning-record analysis rubric, and a usability and satisfaction questionnaire. Because the assumptions of homogeneity of regression slopes and equality of gain-score variances were not satisfied, Welch's tests were employed for the principal comparisons. The experimental group achieved significantly greater gains than the control group in achievement, $t(63.48) = 15.19$, $p < .001$, $g = 3.01$; academic decision-making, $t(52.28) = 11.59$, $p < .001$, $g = 2.30$; and self-regulated learning, $t(49.37) = 12.47$, $p < .001$, $g = 2.48$. It also obtained significantly higher digital learning-record rubric scores, $t(89.65) = 10.64$, $p < .001$, $g = 2.11$. Experimental-group usability and satisfaction significantly exceeded the neutral criterion, $t(49) = 16.53$, $p < .001$. The findings indicate that pedagogically grounded and explainable learning analytics can strengthen students' regulation and academic decisions when analytical information is linked to actionable alternatives and students retain control over the final decision.

Keywords: academic decision-making; artificial intelligence; learning analytics; Moodle; self-regulated learning; student-facing dashboards; teacher education.

1. Introduction

The continuing digital transformation of higher education has expanded the amount and variety of data generated during students' interactions with electronic learning environments. Learning management systems routinely record access to course resources, activity completion, submitted assignments, discussion participation, assessment attempts, response patterns, and changes in performance over time (Daniel, 2015). These records create opportunities to understand learning processes that may remain difficult to observe through final grades alone (Long & Siemens, 2011).

The availability of educational data does not, by itself, lead to improved learning. Data acquire educational value when they are analyzed, interpreted within the instructional context, and transformed into information that learners or instructors can use in making appropriate decisions (Ferguson, 2012). Consequently, the educational contribution of digital analytics depends less on the volume of collected records than on the relevance, clarity, timeliness, and actionability of the information produced from them.

Learning analytics was initially defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs (Long & Siemens, 2011). This definition identifies learning improvement—not data processing—as the ultimate purpose of analytics. It also implies that analytical systems should be evaluated according to their contribution to learning and teaching rather than only according to the technical accuracy of their predictions.

Research in higher education has employed learning analytics for several purposes, including predicting academic success, identifying students at risk, supporting retention, monitoring engagement, personalizing feedback, and informing instructional interventions (Viberg et al., 2018). Nevertheless, evidence concerning these purposes has not developed equally. Prediction and institutional monitoring have received substantial attention, while fewer studies have demonstrated how analytical outputs are incorporated into students' day-to-day learning processes (Guzmán-Valenzuela et al., 2021).

Artificial intelligence can extend the capabilities of learning analytics by detecting relationships among multiple indicators, identifying recurring patterns, estimating the probability of academic difficulty, and generating differentiated recommendations. Applications of artificial intelligence in higher education have included intelligent tutoring, adaptive learning, automated assessment, student profiling, recommender systems, and predictive modelling (Zawacki-Richter et al., 2019). However, the educational value of these applications depends on their alignment with learning theory, instructional objectives, and the actual decisions expected from students and instructors.

Much of the early artificial intelligence research in higher education emphasized technological development and predictive accuracy more strongly than pedagogical participation. A systematic review of artificial intelligence applications found comparatively limited involvement of educators in the design and evaluation of AI-supported systems (Zawacki-Richter et al., 2019). This imbalance is consequential because a technically accurate prediction may have limited educational value when students do not understand its meaning or cannot identify an appropriate response.

A learning analytics dashboard commonly serves as the interface through which analytical information is communicated to users. Student-facing dashboards may present progress, grades, activity completion, learning behavior, performance comparisons, predictions, and recommendations (Bodily & Verbert, 2017). The effectiveness of a dashboard depends not only on the accuracy of its data but also on whether students can interpret the displayed information and employ it to regulate subsequent learning.

Empirical dashboard research has revealed important limitations. Many dashboards have been dominated by descriptive indicators and have offered insufficient guidance concerning what learners should do after viewing the information (Matcha et al., 2020). Reviews have also found that relatively few dashboards progress from descriptive reporting to predictive and prescriptive support capable of producing actionable insights (Susnjak et al., 2022). These limitations suggest that awareness of performance is necessary but insufficient for educational improvement.

A student may recognize, for example, that a formative assessment score is low without understanding whether the underlying problem involves incomplete preparation, a recurring conceptual error, ineffective strategy use, weak practical application, or inadequate time allocation. Presenting the score alone identifies an outcome but does not diagnose its probable cause. Similarly, displaying a risk prediction without relevant alternatives may increase concern without supporting an appropriate academic response.

This distinction is particularly important for self-regulated learning. Self-regulated learning is an active and cyclical process through which learners establish goals, plan and organize their learning, implement strategies, manage time and resources, monitor progress, seek assistance, evaluate outcomes, and modify subsequent actions (Zimmerman, 2002). It involves cognitive, metacognitive, motivational, behavioral, and contextual processes rather than a single study skill (Panadero, 2017).

Self-regulated learning is strongly associated with success in online and blended learning because these environments require students to exercise greater control over time, effort, resource selection, task completion, and help-seeking (Broadbent & Poon, 2015). Students who lack effective self-regulation may postpone activities, distribute their effort poorly, repeat ineffective strategies, or fail to recognize a widening gap between intended and actual performance.

Learning analytics can support regulation by making otherwise invisible patterns visible. Progress indicators can help students compare completed activities with course requirements, assessment trends can reveal improvement or decline, and recurring-error reports can direct attention toward persistent areas of difficulty. However, these functions support self-regulation only when students understand the indicators and use them to guide subsequent action.

Systematic evidence indicates that technological support for self-regulated learning is more effective when it addresses several phases of the regulatory cycle rather than providing isolated prompts. Online environments should support planning before performance, monitoring during task execution, and evaluation after performance (Wong et al., 2019). A dashboard limited to retrospective reporting may therefore address awareness while neglecting strategy selection and adaptive reflection.

The relationship between analytics and self-regulation also requires attention to temporality. Self-regulated learning unfolds through changing sequences of goals, actions, monitoring, and adaptation rather than through isolated events (Saint et al., 2022). A single login or assessment score cannot adequately represent a student's regulatory process. More meaningful interpretation requires patterns across time, including whether the student responds to feedback, changes strategy, implements a decision, and subsequently improves.

In the present study, the expected influence of analytics was not based on dashboard exposure alone. The intervention established a recurrent sequence in which the student reviewed performance information, interpreted probable causes, examined alternative actions, selected and justified a decision, implemented it, and evaluated the resulting change. The dashboard therefore functioned as part of a pedagogical cycle rather than as a separate visualization tool.

Academic decision-making represents a central process within this cycle. At the student level, academic decision-making involves identifying an academic problem, interpreting relevant information, determining probable causes, generating feasible alternatives, comparing their potential consequences, selecting and justifying an appropriate action, implementing the decision, and evaluating its outcome. This operationalization differs from institutional decision-making concerning admissions, retention policies, resource allocation, or program evaluation.

The relationship between self-regulation and academic decision-making is close but not redundant. Self-regulated learning constitutes the broader process through which students manage learning over time. Academic decision-making occurs when students must select among alternative responses to a specific learning situation. Monitoring reveals the need for action; decision-making determines the action; and reflection evaluates whether the decision should be maintained or revised.

AI-supported recommendations can contribute to this process by identifying relevant patterns and proposing alternatives suited to the student's current learning situation. Recommendations should nevertheless remain open to evaluation because analytical systems operate on incomplete representations of learners and may not capture studying outside the platform, temporary personal circumstances, or the learner's own interpretation of the difficulty.

Preserving student agency is therefore an essential condition of responsible analytics. Student agency involves intentional, purposeful, and meaningful participation in learning, including the capacity to make and justify choices (Jääskelä et al., 2021). An analytics environment supports agency when it provides understandable evidence and meaningful alternatives while leaving the final decision under the learner's control.

Ethical use also requires transparency concerning which data are collected, why they are analyzed, who can access them, and how the resulting classifications are used. Privacy in learning analytics is not solely a technical issue; it also involves institutional governance, student understanding, power relationships, and meaningful participation in decisions concerning data use (Prinsloo et al., 2022). Risk classifications should therefore be used to provide support rather than to impose penalties or make autonomous progression decisions.

The present study addressed these theoretical and practical considerations within a Technology of Education course offered to first-level students at the Faculty of Education, Damietta University. The course provided appropriate context because it combined conceptual knowledge with practical decisions involving educational media, digital-content design, instructional design, learning management systems, electronic assessment, feedback, artificial intelligence, and learning analytics.

The learning environment was implemented through a self-hosted Moodle installation. Both groups studied the same course content, completed equivalent activities, used the same assessment tasks, and received equal instructional time. The experimental group additionally accessed a custom AI-supported learning analytics plugin that provided progress information, diagnostic interpretations, risk classifications, intelligent alerts, personalized recommendations, and alternative academic actions. The control group received conventional Moodle scores and standard feedback without the intelligent dashboard or personalized recommendations.

The custom plugin employed a fuzzy rule-based expert system. This approach was selected because it enabled the relationship between input indicators, risk classifications, and recommendations to remain interpretable. The system combined assessment performance, activity completion, regularity of access, delayed tasks, recurring errors, assessment attempts, and performance trends. It then applied predefined pedagogical rules to generate suitable alternatives. The plugin did not impose decisions. Experimental-group students could accept, modify, or reject each recommendation and were required to provide a brief justification based on the available evidence. The plugin subsequently recorded the selected action and presented relevant post-decision information, enabling the student to evaluate whether the decision had been effective.

This design controlled an important alternative explanation. If the experimental group had received direct instruction in self-regulation or decision-making that was unavailable to the control group, subsequent differences could have resulted from unequal content exposure. The groups therefore studied the same educational content and completed the same core learning requirements. The distinguishing treatment was restricted to the way learning data were analyzed, communicated, and converted into personalized decision support.

The study responded to four gaps in the literature available by the end of 2022. First, learning analytics research had concentrated heavily on institutional prediction and instructor-facing monitoring, with less attention to students' active use of analytical information (Guzmán-Valenzuela et al., 2021). Second, many dashboards increased awareness without completing the sequence from diagnosis to action and evaluation (Matcha et al., 2020). Third, academic decision-making was rarely investigated as a measurable student skill within analytics-supported environments. Fourth, studies did not consistently combine self-report, situational performance, academic achievement, digital learning records, and usability evidence in evaluating the same intervention.

Accordingly, the present study investigated whether a pedagogically designed and explainable AI-supported learning analytics environment could develop self-regulated learning and academic decision-making skills among Faculty of Education students. Academic achievement was examined as a supporting outcome, while digital learning records provided complementary behavioral evidence and the usability questionnaire assessed students' acceptance of the environment.

2. Statement of the Problem

The theoretical literature suggests that learning analytics can support higher education by transforming digital traces into information relevant to learning, feedback, and intervention (Ifenthaler & Yau, 2020). However, the existence of analytical information does not guarantee that students can interpret it, select an appropriate response, or evaluate the consequences of that response (Wise, 2014).

First-level students studying Technology of Education are required to manage theoretical and practical tasks, monitor progress, interpret assessment feedback, select digital learning resources, and make decisions about corrective actions. Conventional Moodle feedback can provide scores and activity-completion information, but it does not necessarily explain recurring patterns, identify probable causes of difficulty, or generate differentiated actions based on individual learning records.

The problem was therefore represented by a gap between the availability of digital learning data and students' ability to transform those data into effective self-regulatory behavior and reasoned academic decisions. It was also represented by limited empirical evidence concerning the combined development of self-regulated learning and academic decision-making through explainable, student-facing, AI-supported learning analytics.

The study addressed this problem by developing a custom Moodle plugin that analyzed authorized learning records, generated interpretable risk classifications and personalized alternatives, and preserved the student's authority over the final decision.

The principal research question was:

What is the effect of a learning environment based on AI-supported learning analytics on developing self-regulated learning and academic decision-making skills among College of Education students?

3. Research Questions

The principal research question was divided into the following subsidiary questions:

1. What instructional and technological requirements are needed to design a learning environment based on AI-supported learning analytics for the Technology of Education course?
2. What is the effect of the AI-supported learning analytics environment on students' achievement in the Technology of Education course?
3. What is the effect of the AI-supported learning analytics environment on students' self-regulated learning?
4. What is the effect of the AI-supported learning analytics environment on students' academic decision-making skills?
5. To what extent do students' digital learning records reflect the enactment of self-regulated learning and academic decision-making behaviors?
6. What level of usability and satisfaction do experimental-group students report after using the AI-supported learning analytics environment?

4. Aim and Objectives of the Study

The study aimed to design and evaluate a learning environment based on AI-supported learning analytics and determine its effect on developing self-regulated learning and academic decision-making skills among first-level students at one of the colleges of Education in Egypt.

More specifically, the study sought to:

1. identify the instructional and technological requirements of an AI-supported learning analytics environment;
2. design and implement a custom AI-supported learning analytics plugin within Moodle;
3. investigate the effect of the environment on students' achievement in the Technology of Education course;
4. determine the effect of the environment on students' self-regulated learning;
5. determine the effect of the environment on students' academic decision-making skills;
6. examine behavioral evidence of self-regulation and academic decision-making derived from students' digital learning records; and
7. evaluate the usability of the environment and experimental-group students' satisfaction with it.

5. Research Hypotheses

The following null hypotheses were tested:

1. There is no statistically significant difference between the mean achievement gain scores of the experimental and control groups.
2. There is no statistically significant difference between the mean self-regulated learning gain scores of the experimental and control groups.
3. There is no statistically significant difference between the mean academic decision-making gain scores of the experimental and control groups.
4. There is no statistically significant difference between the mean post-intervention digital learning-record rubric scores of the experimental and control groups.
5. The mean usability and satisfaction score of the experimental group does not differ significantly from the theoretical neutral criterion of 90.

6. Significance of the Study

6.1 Theoretical Significance

The study contributes to the theoretical development of learning analytics by positioning analytical information within a complete cycle of learning regulation and academic decision-making. Learning analytics research has frequently concentrated on identifying patterns and predicting outcomes, while giving comparatively less attention to how learners interpret analytics and convert them into educational action (Guzmán-Valenzuela et al., 2021). The present study addresses this limitation by connecting data analysis with problem identification, alternative generation, decision selection, implementation, and reflective evaluation.

The study also integrates self-regulated learning with AI-supported learning analytics through a cyclical rather than static model. Self-regulated learning involves the repeated interaction of planning, performance, monitoring, and reflection (Zimmerman, 2002). The proposed environment operationalizes these phases through goal prompts, progress indicators, diagnostic feedback, strategy recommendations, decision records, and post-decision evaluation.

A further theoretical contribution lies in distinguishing student academic decision-making from institutional decision-making. Learning analytics has often been associated with administrative decisions concerning retention, intervention, and resource allocation (Ifenthaler & Yau, 2020). The present study focuses instead on decisions made by students during learning, such as selecting a resource, modifying a strategy, reorganizing time, requesting assistance, or determining whether to repeat an assessment.

The study additionally treats learner agency as a central condition of responsible AI-supported analytics. Artificial intelligence can support students by interpreting complex performance information, but an automated recommendation should not be treated as an unquestionable instruction. Student agency requires learners to participate intentionally in interpreting evidence and selecting meaningful actions (Jääskelä et al., 2021). The environment therefore allows students to accept, modify, or reject system recommendations.

6.2 Methodological Significance

The study employs complementary methods of measurement. Self-regulated learning is measured using a self-report scale, academic decision-making is assessed through situational problems, achievement is evaluated using an objective test, and observable behavior is examined through digital learning records. This combination responds to concerns that self-regulation cannot be represented adequately through a single measurement approach because reported strategies and recorded behavior may capture different aspects of the construct (Saint et al., 2022).

The use of digital learning records provides evidence of students' actual interaction with goals, resources, feedback, recommendations, and academic decisions. Nevertheless, these records are interpreted within the instructional context rather than treated as direct representations of cognition. A platform record shows that an action occurred but cannot, by itself, establish the learner's intention or depth of cognitive processing. The study therefore triangulates digital traces with scale and test results.

The study also contributes an explainable alternative to opaque prediction. The custom plugin uses a fuzzy rule-based expert system in which the relationship among input indicators, risk classifications, and recommendations can be inspected. Explainability is methodologically important because it allows researchers to describe how the treatment operated and enables students to understand why a recommendation was generated.

6.3 Applied Significance

The study provides a practical model for embedding student-facing analytics within Moodle. The model can be adapted to other university courses in which students generate assessment, completion, participation, and performance data. It demonstrates how existing Moodle records can be connected to a custom dashboard and recommendation system without requiring a separate learning platform.

The intervention may assist instructors in identifying students who require support before final assessment. It may also reduce dependence on uniform feedback by providing learning alternatives corresponding to different patterns of difficulty. Research on student-facing dashboards indicates that personalized recommendations and relevant progress information are among the features learners value when evaluating analytical services (Rets et al., 2021).

This study is particularly relevant to teacher education. Prospective teachers increasingly need to interpret learning data, evaluate AI-generated outputs, and make ethically responsible decisions about educational technologies. Experiences that preserve critical judgement may prepare students to use future analytical systems without adopting uncritical dependence on automated recommendations.

6.4 Institutional Significance

The study provides Damietta University with evidence concerning the educational use of AI-supported learning analytics in an authentic course. It may inform subsequent decisions about extending analytically supported learning to other courses, subject to replication, technical readiness, staff development, and appropriate data-governance arrangements.

The study also draws attention to the need for institutional policies regulating access, privacy, transparency, and the acceptable use of risk classifications. Data privacy in learning analytics involves more than technical protection; it requires student agency, institutional accountability, clear purposes, and a whole-system approach to data governance (Prinsloo et al., 2022).

7. Delimitations of the Study

The study was delimited as follows:

The participants were first-level male and female students enrolled at at one of the colleges of

Education in Egypt. Their ages ranged from 18 to 20 years. The intervention was implemented over ten instructional weeks. The environment was implemented using a self-hosted Moodle 3.11 LTS installation and a custom fuzzy rule-based learning analytics and academic decision-support plugin.

8. Operational Definitions

8.1 AI-Supported Learning Analytics Environment

A Moodle-based learning environment incorporating a custom plugin that analyses authorized digital learning records and provides progress indicators, diagnostic information, estimates of academic risk, intelligent alerts, personalized recommendations, and alternative corrective actions while preserving the student's authority over the final academic decision.

8.2 Self-Regulated Learning

The degree to which students establish goals, plan and organize their learning, manage time and tasks, use appropriate strategies, monitor performance, manage learning resources, seek assistance, evaluate outcomes, and modify their learning pathways, as indicated by their scores on the self-regulated learning scale developed for the study.

8.3 Academic Decision-Making Skills

Students' ability to identify academic problems, collect and interpret relevant information, determine probable causes, generate and compare feasible alternatives, select and justify an appropriate action, implement the decision, and evaluate its consequences, as indicated by their scores on the situational academic decision-making test.

8.4 Digital Learning-Record Behaviors

Observable evidence of students' planning, time management, strategy and resource use, monitoring, feedback use, performance-data interpretation, academic decision implementation, and reflective evaluation, extracted from Moodle records and evaluated using the digital learning-record analysis rubric.

8.5 Academic Achievement

Students' mastery of the knowledge and applications included in the Technology of Education course, as indicated by their scores on the researcher-developed achievement test.

8.6 Usability and Satisfaction

The degree to which experimental-group students perceived the AI-supported learning analytics environment as easy to learn, efficient to navigate, clear, useful, trustworthy, and satisfactory, as indicated by their scores on the post-intervention usability and satisfaction questionnaire.

9. Theoretical Framework

9.1 Learning Analytics

Learning analytics emerged from the increasing availability of digital educational data and the need to use those data to understand and improve learning. It involves collecting, analyzing, interpreting, and communicating information about learners and their contexts for educational purposes (Long & Siemens, 2011). The central emphasis is therefore not on data accumulation but on producing information that contributes to learning, teaching, or educational decision-making.

Learning analytics differs from general educational data reporting in its attention to learning processes and contexts. Conventional reports may summarize grades or attendance, whereas learning analytics attempts to connect indicators with patterns of engagement, progression, difficulty, or strategy use (Ferguson, 2012). Its educational quality depends on how accurately the selected data represent the process being investigated and whether the resulting information can guide meaningful action.

Learning analytics also differs from educational data mining, although the two fields overlap. Educational data mining has traditionally emphasized automated discovery and computational modelling, whereas learning analytics places greater emphasis on interpretation and the role of human judgement in educational decisions (Viberg et al., 2018). The present study adopts the latter orientation because students, rather than the analytical system, retain responsibility for determining the final action.

9.1.1 Sources of Learning Data

Electronic learning environments generate several categories of data. Behavioral data include access frequency, navigation, resource use, task completion, and participation. Performance data include assessment scores, item responses, recurring errors, and changes across attempts. Temporal data include the timing and regularity of activity, delays, and intervals between feedback and subsequent action. Reflective and decision data include students' selected alternatives, explanations, and evaluations of outcomes.

Each category has limitations. Access frequency cannot establish the quality of engagement, and time associated with a resource cannot reveal whether the learner was studying continuously. Assessment results reveal performance but may not identify the cause of difficulty. Consequently, meaningful analytics require combining data sources and interpreting them in relation to learning design rather than treating isolated indicators as complete representations of learning.

The present plugin therefore combined assessment performance, activity completion, regularity of access, delayed tasks, recurring errors, assessment attempts, and performance trends. Decision records and reflective responses were subsequently used to evaluate whether students acted upon the information.

9.1.2 Levels of Learning Analytics

The environment incorporated four analytical levels.

Descriptive analytics addressed the question, "What happened?" It summarized completed activities, assessment results, resource use, access patterns, and progress.

Diagnostic analytics addressed the question, "Why might it have happened?" It connected related indicators to identify probable causes, such as incomplete preparation, persistent misconception, inadequate practical application, or irregular engagement.

Predictive analytics addressed the question, "What may happen next?" It estimated the possibility of continuing difficulty, delayed completion, or unsatisfactory performance.

Prescriptive analytics addressed the question, "What action may be appropriate?" It generated alternative resources, strategies, activities, or forms of assistance.

Many dashboards remain concentrated at the descriptive level, limiting their capacity to support action. A review of learning analytics dashboards found that only a limited proportion moved beyond descriptive displays toward predictive and prescriptive insights (Susnjak et al., 2022). The present environment incorporated all four levels so that students could progress from awareness to interpretation and action.

9.1.3 Actionable Learning Analytics

Analytics are actionable when their outputs can inform a feasible and timely response. Actionability requires more than displaying additional information. The learner must understand the indicator, recognize its relevance, have access to an appropriate response, and possess sufficient time to implement that response.

The timing of an intervention is particularly important. A risk classification presented after the end of a course may contribute to institutional reporting but cannot help the student improve within that course. The plugin therefore updated its outputs during the instructional process and after significant events such as assessment completion, task submission, or response to a recommendation.

Actionability also depends on the relationship between analytics and course design. The same behavioral pattern may have different meanings under different instructional conditions. Low access may be problematic in a course requiring weekly online activities but less meaningful when much of the work occurs offline. Analytics should therefore be aligned with intended activities and expected participation patterns.

9.2 Artificial Intelligence in Learning Analytics

Artificial intelligence enables learning analytics systems to process multiple indicators, identify relationships, estimate possible outcomes, and differentiate support. AI applications in higher education have included prediction, automated assessment, intelligent tutoring, personalization, and recommendation (Zawacki-Richter et al., 2019). These functions can increase the scale and timeliness of support, especially when instructors cannot examine every student record continuously.

The use of AI does not remove the need for pedagogical judgement. A prediction is based on the data and rules available to the system and may omit relevant information about the learner. Models may also reproduce bias when their data or assumptions represent particular groups inadequately. Educational decisions should therefore combine analytical output with contextual understanding and human responsibility.

9.2.1 Explainable Artificial Intelligence

Explainability refers to the extent to which users can understand how an AI-supported system has produced an output. In education, explainability is particularly important because risk classifications and recommendations can affect students' motivation, behavior, and perceptions of competence.

The present study used a fuzzy rule-based expert system because it allowed the connection among indicators, risk levels, and recommendations to remain visible. The system could explain, for example, that a moderate-risk classification resulted from weak formative performance and incomplete activities rather than presenting an unexplained probability.

A transparent system also enables students to challenge the recommendation. If the learner knows which indicators produced the output, the learner can decide whether they represent the current situation accurately. Explainability thus contributes to both trust and critical judgement.

9.2.2 Fuzzy Rule-Based Expert System

A fuzzy rule-based expert system represents knowledge through interpretable conditions and rules. Unlike rigid binary classification, fuzzy reasoning allows indicators to belong to categories by degree. A student's engagement, for example, may be partially regular rather than simply regular or irregular.

The plugin transformed selected indicators into risk values and combined them using predetermined weights. It then classified overall risk as low, moderate, or high and activated corresponding pedagogical rules. The recommendations were not generated through an opaque model trained on an undisclosed dataset; they were derived from explicit relationships between learning patterns and corrective alternatives.

This approach was appropriate because the study did not possess a sufficiently large historical dataset for training and independently validating a complex machine-learning model. The rule-based approach increased replicability and allowed the treatment to be described precisely.

9.3 Student-Facing Learning Analytics Dashboards

Student-facing dashboards communicate analytical information directly to learners. They may include progress, grades, completion, comparisons, predictions, feedback, and recommendations (Bodily & Verbert, 2017). Their purpose is not merely to display information but to support students' understanding and subsequent action.

Dashboard design must address information selection, visual clarity, interpretability, relevance, and actionability. Excessive indicators can increase cognitive burden, while insufficient explanation can lead to incorrect conclusions. Students may also misinterpret social comparisons or regard them as demotivating when differences in learner circumstances are not represented.

Research involving students has found that learners value planning assistance, personalized analysis, self-assessment, and adaptive recommendations (Schumacher & Ifenthaler, 2018). This evidence supports the inclusion of individual progress information and targeted recommendations rather than an interface dominated by peer ranking.
The dashboard in the present study displayed course progress, activity completion, assessment development, recurring errors, access regularity, task delay, estimated risk, personalized alternatives, and post-decision change. Each indicator corresponded to a regulatory or decision-making function.

9.3.1 Dashboard Design Requirements

The following requirements guided the dashboard design:

1. indicators had to correspond to defined learning processes;
2. information had to be presented in understandable language;
3. risk classifications had to be accompanied by explanations;
4. recommendations had to be feasible within the course;
5. students had to retain control over the final action;
6. the interface had to avoid unnecessary data and comparisons;
7. outputs had to be updated in time for students to respond;
8. each recommendation had to lead to an observable follow-up action; and
9. access had to be restricted according to Moodle user roles.

Dashboard development research emphasizes the importance of designing around learner needs and educational objectives rather than simply presenting all data available in the learning management system (Bodily et al., 2018). These requirements therefore connected technical design with the constructs measured in the study.

9.3.2 Trust, Transparency, and Privacy

Students' willingness to use analytics depends partly on whether they regard the information as relevant and trustworthy. Perceived usefulness is influenced by the clarity of indicators, alignment with learner goals, academic confidence, and the extent to which recommendations address actual needs (Rets et al., 2021).
Transparency requires informing students about which data are used and how outputs are generated. It also requires acknowledging limitations. The dashboard should not imply that platform data represent the learner completely or that a risk classification is a definitive judgement.
Privacy requires restricting access, minimizing unnecessary data, and preventing analytical information from being used for unrelated purposes. The study used identification numbers in the exported research dataset and reported findings at the group level.

9.4 Self-Regulated Learning

Self-regulated learning refers to learners' active control of thoughts, motivation, behavior, and context in pursuit of academic goals. It is cyclical because reflection on one learning episode influences planning and action in the next episode (Zimmerman, 2002).
A review of self-regulation models identified shared emphasis on goals, strategic action, monitoring, feedback, and adaptation, despite differences in terminology and theoretical detail (Panadero, 2017). These shared processes informed the construction of the study scale and the regulatory functions embedded in the plugin.
Online learning increases the importance of self-regulation because students encounter greater flexibility and fewer immediate external controls. A systematic review found that time management, metacognition, effort regulation, and critical thinking were among the strategies associated with achievement in online higher education (Broadbent & Poon, 2015).

9.4.1 Forethought and Planning

Forethought includes task analysis, goal setting, strategic planning, and motivational preparation. Students determine what they intend to achieve and how they will approach the task.

The environment supported forethought through unit objectives, diagnostic assessments, personal-goal prompts, course schedules, and previous-performance information. Students used this information to formulate or revise their plans.

9.4.2 Performance and Monitoring

The performance phase includes strategy implementation, attention control, time management, self-observation, and monitoring. Students compare actual progress with intended goals and identify whether current actions remain effective.

The dashboard supported this phase through completion indicators, assessment trends, recurring-error reports, task-delay alerts, and access-regularity information. These indicators made discrepancies visible while students still had an opportunity to respond.

9.4.3 Self-Reflection and Adaptation

Self-reflection involves evaluating outcomes, interpreting causes, and determining how future learning should change. Reflection is adaptive when it produces a suitable modification rather than simple satisfaction or dissatisfaction.

The plugin recorded the selected academic action and displayed subsequent performance evidence. Students then evaluated whether the decision had improved their learning and determined whether to maintain, modify, or replace it.

9.4.4 Dimensions Measured in the Study

The self-regulated learning scale measured:

1. goal setting and learning planning;
2. time and task management;
3. use of learning strategies;
4. self-monitoring;
5. learning resource management and help-seeking; and
6. self-evaluation, reflection, and modification of the learning pathway.

These dimensions were treated as interrelated components of the total construct. Weakness in one dimension could influence others. Inadequate planning could produce task delay, while inadequate monitoring could prevent students from recognizing ineffective strategy use.

9.5 Academic Decision-Making Skills

Academic decision-making refers to the process through which students identify a learning-related problem, interpret relevant information, generate and compare feasible alternatives, select and justify an appropriate action, implement the decision, and evaluate its consequences. It involves more than choosing an available option because the quality of a decision depends on the accuracy of problem identification, the relevance of the evidence considered, and the criteria used to compare alternatives.

General models of rational decision-making distinguish problem definition, information processing, alternative evaluation, choice, and outcome assessment as connected stages rather than independent actions (Hastie & Dawes, 2010). In an academic context, these stages operate within learning situations such as responding to weak assessment performance, selecting an appropriate resource, modifying a study strategy, allocating additional time, requesting assistance, or deciding whether to repeat an activity.

Academic decisions are made under conditions of incomplete information. Students rarely possess a complete explanation of why performance has declined or why a learning strategy has been ineffective. Digital learning records can reduce this uncertainty by providing evidence about performance trends, recurring errors, completion patterns, and previous responses to feedback. Nevertheless, analytical information cannot eliminate uncertainty because learning management systems capture only part of a learner's activity and context.

The present study therefore treated AI-supported analytics as a source of evidence rather than an autonomous decision maker. The system organized relevant indicators, estimated academic risk, and proposed alternative responses. Students interpreted these outputs and retained responsibility for the final action. This approach is consistent with student agency, which emphasizes learners' intentional participation, meaningful choices, and control over their learning (Jääskelä et al., 2021).

9.5.1 Identifying the Academic Problem

Effective academic decision-making begins with distinguishing the visible outcome from the underlying problem. A low score represents an outcome, but it does not necessarily identify the cause. The difficulty may arise from incomplete preparation, misunderstanding of a concept, inability to transfer knowledge to practice, ineffective strategy use, delayed task completion, or insufficient assistance.

The plugin supported problem identification by combining multiple indicators. Assessment results were considered alongside activity completion, recurring errors, resource use, access regularity, task delay, and performance development. This approach reduced the likelihood that a decision would be based on a single decontextualized number.

9.5.2 Collecting and Interpreting Relevant Information

Students must determine which information is relevant to the decision. Relevant evidence may include the relationship between task completion and performance, the persistence of an error across attempts, changes following feedback, or the amount of practical application completed. Information such as the number of decorative elements in the course interface would not contribute meaningfully to most academic decisions.

Interpretation requires understanding what an indicator can and cannot establish. High resource access does not necessarily indicate comprehension, and long time-on-task may represent either effort or difficulty. Learning analytics should consequently be interpreted in relation to the instructional design and expected course activity (Sedrakyan et al., 2020).

9.5.3 Generating Alternatives

After identifying the problem, the student generates possible responses. Academic alternatives may include revisiting a particular explanation, studying a worked example, completing a focused remedial task, changing a learning strategy, reorganizing time, seeking assistance, or repeating an assessment after additional preparation.

The plugin generally presented more than one alternative. This design prevented the recommendation from becoming an automated command and created an opportunity for students to compare different responses. Personalized-support systems can connect student data with instructor-defined conditions and actions, enabling differentiated feedback without eliminating pedagogical judgement (Pardo et al., 2018).

9.5.4 Evaluating and Comparing Alternatives

The quality of an alternative depends on its relationship to the identified problem. Repeating an assessment may be appropriate when the student has corrected a misunderstanding, but repeated attempts without further preparation may reinforce guessing or ineffective behavior.

Students evaluated alternatives according to educational relevance, available time, expected benefit, task requirements, previous attempts, and compatibility with their learning goals. The plugin supplied information and options, but it did not determine that the system's first recommendation was necessarily the best choice.

9.5.5 Selecting and Justifying the Decision

Selection involves choosing the alternative most likely to address the problem under the existing conditions. Justification requires students to state why the selected action is appropriate and identify the evidence on which the decision is based.

The experimental environment provided three principal responses to each recommendation: acceptance, modification, or rejection. Rejection was not treated as system failure when the student supplied a reasoned alternative. This structure supported critical use of artificial intelligence and reduced the possibility of unreflective compliance.

9.5.6 Implementing the Decision

A decision has limited educational value if it is not translated into action. Implementation includes beginning the selected activity, allocating the required time, using the recommended resource or strategy, and completing the intended response within an appropriate period.

The plugin recorded whether and when students acted after receiving a recommendation. This enabled the researcher to distinguish viewing a recommendation from implementing it. The time between recommendation and action also provided evidence concerning responsiveness to feedback.

9.5.7 Evaluating the Decision

Decision evaluation involves determining whether the selected action produced the intended improvement. Evidence may include a higher assessment score, reduction in recurring errors, completion of delayed work, improved practical performance, or stronger adherence to a learning plan.

An unsuccessful decision was not treated solely as failure. It produced information for the next decision cycle. Students could modify the selected strategy, choose another alternative, or request instructor assistance. The environment therefore treated decision-making as iterative and adaptive.

9.5.8 Dimensions Measured in the Study

The situational academic decision-making test assessed six dimensions:

1. identifying the academic problem;
2. collecting and interpreting relevant information;
3. generating appropriate alternatives;
4. evaluating and comparing alternatives;
5. selecting and justifying the academic decision; and
6. implementing and evaluating the decision.

The situations were derived from the Technology of Education course and included weak formative performance, delayed activities, recurring misconceptions, difficulty applying design principles, ineffective resource use, and disagreement between a system recommendation and the student's interpretation.

9.6 Relationship between Self-Regulated Learning and Academic Decision-Making

Self-regulated learning and academic decision-making share several processes, including goal awareness, information interpretation, strategic choice, monitoring, and reflection. They should nevertheless be treated as conceptually distinct. Self-regulated learning is the broader process through which students manage learning across time, whereas academic decision-making concerns selecting a response to a particular learning-related problem.

Self-regulation produces information required for decisions. Monitoring may reveal that the current strategy is ineffective, time management is inadequate, or performance has not improved. Academic decision-making then converts this evidence into an action by comparing alternatives and selecting an appropriate response.

The outcome of the decision subsequently becomes part of the regulatory cycle. If performance improves, the student may retain the strategy. If no improvement occurs, the student may revise the plan, seek assistance, or choose a different alternative. Thus, the relationship between the variables is reciprocal rather than one-directional.

Student agency connects the two variables. Self-regulation requires students to influence their learning deliberately, and academic decision-making requires them to exercise meaningful choice. An AI-supported environment may weaken agency if it automatically determines the learning pathway. It may strengthen agency when it provides understandable evidence, feasible

alternatives, and opportunities to question recommendations (Bennett & Folley, 2020).
The study did not assume that the plugin directly produced self-regulation or decision-making. The proposed effect depended on students' engagement with the analytical cycle. Viewing a dashboard was insufficient. Development was expected when students interpreted the information, selected and justified actions, implemented decisions, and evaluated outcomes.

9.7 Academic Achievement as a Supporting Outcome

Academic achievement was included as a supporting educational outcome rather than a principal variable in the research title. Its measurement determined whether development in self-regulation and decision-making was accompanied by stronger mastery of the Technology of Education content.
The relationship among the outcomes was theoretically plausible but not assumed to be automatic. Students who plan, monitor, and adjust their learning may be better able to allocate effort and correct misunderstandings. Students who make appropriate academic decisions may also select resources and actions suited to their needs. These processes can support achievement, but achievement remains a distinct outcome influenced by content knowledge, prior preparation, task difficulty, and assessment design.
Research on learning analytics in higher education has found evidence of improved study success in some contexts, but effects vary according to the intervention, learner characteristics, course design, and support attached to the analytical information (Ifenthaler & Yau, 2020). Achievement was therefore analyzed independently rather than treated as proof of self-regulation.

9.8 Digital Learning Records as Behavioral Evidence

Digital learning records provide time-stamped evidence of actions performed within the learning management system. They can show whether a student completed an activity, accessed a recommended resource, repeated an assessment, responded to feedback, or implemented a selected decision.
These traces can complement self-report instruments because students may not recall their behavior accurately or may report strategies they believe they should use rather than those they actually employ. However, digital records cannot represent all aspects of self-regulation. They do not directly reveal motivation, comprehension, intention, or learning undertaken outside Moodle.
The present study consequently avoided interpreting isolated clicks as evidence of regulation. The digital learning-record rubric combined several sources: learning plans, completion reports, assessment attempts, recurring errors, recommendation responses, implementation records, changes in performance, and reflective tasks. This combination strengthened contextual interpretation.
Temporally organized analytics are particularly relevant because self-regulation involves sequences of action and adaptation. The relationship among receiving feedback, selecting a response, implementing it, and observing later performance is more meaningful than the frequency of any single event (Saint et al., 2022).

9.9 Usability, Satisfaction, and Acceptance

A technically functional environment may have limited educational impact when students find it difficult to navigate, do not understand its indicators, or distrust its recommendations. Usability concerns the ease with which students learn to operate the environment, access required functions, move among components, and understand the displayed information.
Satisfaction concerns students' overall evaluation of their experience, while perceived usefulness concerns whether they believe the environment supports learning and academic decisions. Trust

relates to confidence that the system's information is understandable, relevant, and used responsibly.
Students' expectations of learning analytics frequently include personalized feedback, planning support, self-assessment, and recommendations tailored to individual learning patterns (Schumacher & Ifenthaler, 2018). The usability and satisfaction questionnaire therefore assessed ease of learning, efficiency of interaction, dashboard clarity, perceived usefulness, trust, and acceptance.
Positive satisfaction was not treated as evidence of educational effectiveness by itself. An environment may be enjoyable without improving learning, while a demanding but effective intervention may receive moderate satisfaction. Usability results were therefore interpreted alongside achievement, self-regulation, decision-making, and behavioral evidence.

10. Review of Related Literature

10.1 Student-Facing Dashboards and Educational Recommender Systems

Research on student-facing dashboards has developed from basic performance displays toward systems that include progress monitoring, predictions, personalized feedback, and recommendations. A systematic review showed that dashboards and educational recommender systems offered considerable potential for supporting learners but varied substantially in their theoretical grounding and evaluation methods (Bodily & Verbert, 2017).
This variation is significant because the term dashboard can describe systems with very different educational functions. A display of grades and completion is not equivalent to an environment that diagnoses patterns, proposes alternatives, records student decisions, and evaluates subsequent outcomes. The present study therefore defines the treatment according to its pedagogical functions rather than the presence of a dashboard alone.
A design and implementation study of student-facing dashboards demonstrated the importance of iterative development, learner needs, and alignment with the educational context. Dashboard usefulness was influenced by the selection and representation of information, not merely by technical access to data (Bodily et al., 2018). This finding supports the present study's emphasis on indicators connected to course requirements and measurable regulatory behaviors.

10.2 Dashboards and Self-Regulated Learning

Learning analytics dashboards are often justified by their potential to support self-regulation. A systematic review examining dashboards from a self-regulated learning perspective found that many systems lacked explicit grounding in learning theory and provided limited support for metacognition, strategy selection, and effective learning tactics (Matcha et al., 2020).
This finding indicates that visualizing performance does not necessarily develop regulation. Students require opportunities to interpret data, determine causes, select strategies, and evaluate outcomes. The current environment consequently embedded analytics within a repeated learning cycle rather than presenting a separate dashboard available for optional viewing.
Research on dashboards linking behavioral analytics with learning-science concepts has emphasized the need to connect feedback visualizations with learning goals, regulatory processes, and contextual interpretation (Sedrakyan et al., 2020). This approach informed the alignment between the dashboard indicators and the six self-regulation dimensions measured in the study.
A study examining learning analytics feedback and self-regulation found that the influence of feedback can vary among learners and regulatory processes. Personalized analytics may alter strategies and learning patterns differently depending on students' previous characteristics and how they engage with the feedback (Lim et al., 2021). Accordingly, the present study interprets average group effects without assuming identical responses among all students.

10.3 Process-Oriented Feedback

Process-oriented feedback focuses on how learning is progressing rather than reporting only final outcomes. It may include patterns of participation, strategy use, time allocation, progress, and responses to previous feedback.

An empirical study of process-oriented learning analytics dashboards found that appropriately designed feedback could improve learning effectiveness by enabling students to understand their learning processes and make timely adjustments (Wang & Han, 2021). The present environment incorporated process information through completion, access regularity, performance development, recurring errors, and post-decision change.

Process feedback also creates a risk of information overload. Students may be presented with numerous indicators without understanding which one requires attention. The custom plugin addressed this concern by prioritizing indicators contributing to risk and connecting them to a limited set of feasible alternatives.

10.4 Personalized Learning Support

Personalized support involves adapting information or recommended actions according to an individual learner's data. It does not necessarily require changing all course content. Personalization can occur through differentiated feedback, targeted resources, alerts, prompts, or recommended learning actions.

The On Task framework demonstrated how educational data and instructor-defined conditions could support personalized learning actions at scale (Pardo et al., 2018). Its human-centered approach is relevant to the current study because pedagogical rules, rather than an autonomous opaque system, connect data patterns with support actions.

The present plugin extended personalized support by involving students in the decision. It did not merely send a differentiated message; it presented alternatives and recorded whether the student accepted, modified, or rejected the recommendation. Follow-up indicators then supported evaluation of the decision.

10.5 Effects on Behavior and Achievement

Evidence concerning the effect of dashboards on behavior and achievement is mixed. A randomised experiment involving university programming students found that dashboard access influenced some online learning behaviors but did not produce a statistically significant overall effect on final examination performance. The effects also varied according to student characteristics and specialization (Hellings & Haelermans, 2022).

This result demonstrates that dashboard access does not guarantee academic improvement. The educational effect depends on whether the dashboard is used, whether students understand it, and whether it is connected to suitable support. The present study differed by integrating diagnosis, recommendations, decision justification, and follow-up rather than providing performance prediction alone.

Systematic evidence similarly indicates that learning analytics can support study success but that effects frequently depend on additional technological, pedagogical, or institutional interventions (Ifenthaler & Yau, 2020). The custom plugin was therefore treated as one component within a structured course design rather than an independent technological solution.

10.6 Usability and Learner Perspectives

Learner perceptions are important because students are direct users of student-facing analytics. Research has shown that students value recommendations and personal progress information but may be less receptive to peer comparisons unless sufficient context is provided (Rets et al., 2021).

Students also differ in their expectations. Some may prefer detailed analytical information, while others require concise recommendations. Attitudes, confidence, prior performance, and familiarity with digital systems can influence perceived usefulness. The dashboard consequently focused on essential indicators and actionable alternatives rather than extensive comparative data. The usability questionnaire in the present study assessed both functional interaction and educational acceptance. It included clarity of analytics, perceived support for learning and decisions, trust, privacy, and willingness to continue using the environment.

10.7 Ethical and Privacy Considerations

Learning analytics creates ethical questions concerning informed use, privacy, transparency, data ownership, surveillance, classification, and the consequences of intervention. Students may not know how platform records are being combined or how risk classification may influence their educational experience.

A sociocritical analysis of learning analytics ethics emphasized unequal power relationships, the need for transparency, and the contextual nature of ethical decisions concerning student data (Slade & Prinsloo, 2013). Institutions should therefore define legitimate purposes and restrict analytics to data necessary for those purposes.

More recent work has argued that student-data privacy is not only a technological problem and cannot be solved solely through technical privacy tools. It requires student agency, governance, literacy, and institutional responsibility (Prinsloo et al., 2022). The present study consequently restricted the plugin to educational support and did not use risk classifications for grading, exclusion, or disciplinary action.

11. Analytical Synthesis and Research Gap

The reviewed literature supports the potential of learning analytics to provide timely information, personalized support, and process-oriented feedback. However, it also demonstrates that the availability of analytics does not necessarily produce improved learning. Educational effects depend on theoretical grounding, intervention design, learner engagement, and the actionability of the information.

Four gaps were identified.

First, a considerable proportion of dashboard research concentrated on displaying descriptive information or predicting risk without completing the sequence from diagnosis to action and evaluation. Students could become aware of performance without developing the capacity to respond.

Second, self-regulated learning was frequently invoked as a justification for dashboards without systematic alignment between dashboard functions and the phases or dimensions of regulation. The present study linked indicators and recommendations to planning, time management, strategy use, monitoring, help-seeking, and reflection.

Third, academic decision-making received limited attention as a student-level outcome. Prior research more commonly addressed instructor or institutional decision-making. The present study measured students' ability to interpret evidence, compare alternatives, justify decisions, implement actions, and evaluate consequences.

Fourth, previous studies did not consistently combine self-report, situational decision assessment, objective achievement, behavioral records, and usability evaluation. The present research used all five forms of evidence to provide a more comprehensive evaluation.

The study therefore examined a theoretically grounded AI-supported learning analytics environment in which a transparent fuzzy rule-based system generated personalized alternatives, while students retained control over the final academic decision.

12. Conceptual Model of the Study

The conceptual model proposes that the environment influences the study outcomes through a mediated learning cycle. Moodle first generates digital records. The custom plugin then transforms these records into descriptive, diagnostic, predictive, and prescriptive information. The student interprets the information, compares alternatives, selects and justifies a decision, implements the action, and evaluates the resulting change. Repetition of this cycle is expected to support self-regulated learning and academic decision-making, with achievement representing a supporting outcome.

Drawing on self-regulated learning theory, data-informed academic decision-making, and responsible learning analytics, the proposed environment was conceptualized as a closed-loop process. Students' interactions with the Moodle-based Technology of Education course generated digital learning traces that were processed and interpreted by the AI-supported analytics component. The resulting dashboards, risk indicators, and actionable recommendations supported learner agency by enabling students to accept, modify, or reject the suggested actions, implement their decisions, and subsequently evaluate their effectiveness. Figure 1 presents the conceptual model underlying the design and evaluation of the learning environment.

Figure 1

Conceptual Model of the AI-Supported Learning Analytics Environment

Note. The model represents the continuous relationship among Moodle-based learning activities, digital learning traces, AI-supported analytics, actionable feedback, learner agency, and the study outcomes. AI support was implemented through a transparent fuzzy rule-based expert system embedded in Moodle. Students retained control over the acceptance, modification, or rejection of the generated recommendations.

As illustrated in Figure 1, the proposed environment did not treat learning analytics as a passive reporting mechanism. Instead, analytics were integrated into a recurring cycle of data collection, risk interpretation, actionable feedback, learner decision-making, implementation, monitoring, and adaptation. This structure was expected to strengthen students' capacity to plan, monitor, and evaluate their learning while improving their ability to interpret academic evidence and make informed decisions. Academic achievement and observable digital learning behavior were included as complementary outcomes, whereas usability and satisfaction provided an evaluation of students' experience with the environment.

13. Method

13.1 Research Design

The study employed a quasi-experimental pre-test–post-test control-group design. This design was appropriate because the intervention was implemented within an authentic university course and the available information did not establish that individual participants had been randomly assigned to the experimental and control groups. Although the sample was selected randomly, random selection from the population should be distinguished from random allocation to treatment conditions. The study was therefore classified as quasi-experimental rather than as a randomized controlled trial (Shadish et al., 2002).

The independent variable was the type of learning environment and comprised two conditions:

1. a Moodle learning environment enhanced with a custom AI-supported learning analytics plugin; and
2. a conventional Moodle learning environment providing standard scores and feedback without the intelligent dashboard or personalized recommendations.

The principal dependent variables were self-regulated learning and academic decision-making skills. Academic achievement was examined as a supporting educational outcome. Digital learning-record behaviors provided complementary behavioral evidence, while usability and satisfaction were evaluated among experimental-group students.

The two groups received the same course content and principal pre- and post-intervention measurements. The experimental condition differed only in access to the AI-supported dashboard, diagnostic interpretations, risk classifications, intelligent alerts, personalized recommendations, and structured decision-support functions. The usability and satisfaction questionnaire was administered only to the experimental group because it evaluated components unavailable to the control group.

13.2 Participants and Sampling

The target population comprised first-level students enrolled at the Faculty of Education, Damietta University. The main sample included 100 male and female students aged between 18 and 20 years. The participants were selected through a random-sampling procedure from the first-level student population available during the study period.

The selected sample was divided equally into two groups:

- the experimental group comprised 50 students; and
- the control group comprised 50 students.

The experimental group studied through Moodle with access to the custom AI-supported learning analytics plugin. The control group studied the same course through the conventional Moodle environment.

A separate pilot sample comprised 20 first-level students. It was used to examine instrument clarity, administration time, scoring procedures, item characteristics, internal consistency, and reliability before the main implementation. Pilot participants were excluded from the main sample to prevent prior exposure to the instruments from affecting the experimental results.

13.3 Research Setting

The study was conducted at the Faculty of Education, Damietta University, within the Technology of Education course. The course combined theoretical knowledge with practical applications requiring students to analyze educational problems, evaluate digital resources, apply instructional-design principles, construct electronic assessments, interpret feedback, and make decisions about appropriate technological solutions.

A self-hosted Moodle 3.11 LTS installation was used as the principal learning management system. Self-hosting allowed the installation and modification of the custom plugin and provided controlled access to authorized logs, completion records, assessment results, recommendation records, and student decisions.

Both groups accessed Moodle through individual user accounts. The same course content, activities, resources, assignments, formative assessments, and final project requirements were provided to the two groups. The treatment was therefore not represented by access to Moodle itself but by the additional analytical and decision-support functions available only to the experimental group.

13.4 Technology of Education Course

13.4.1 General Course Specifications

The Technology of Education course was theoretical and practical. It was delivered over ten weeks, with two theoretical hours and one practical hour per week. The total expected learning time ranged from approximately 24 to 30 hours.

The course aimed to develop students' knowledge and practical competencies related to educational technology, digital learning resources, instructional design, learning management systems, electronic assessment, feedback, artificial intelligence, and learning analytics. It also provided authentic situations in which students could interpret performance evidence and make learning-related decisions.

13.4.2 Course Learning Outcomes

By the end of the course, students were expected to:

1. explain the contemporary concept and scope of educational technology;
2. distinguish among learning resources, educational media, and technological tools;
3. evaluate digital learning resources according to educational criteria;
4. apply visual-design principles to digital instructional content;
5. explain and apply the stages of instructional design;
6. use essential Moodle functions effectively;
7. select digital learning strategies appropriate to educational situations;
8. construct and evaluate electronic assessments;
9. interpret different forms of instructional feedback;
10. explain educational applications of artificial intelligence;
11. interpret learning analytics indicators;
12. evaluate an AI-supported recommendation;
13. make an evidence-informed academic decision; and
14. recognize ethical requirements related to learner data and artificial intelligence.

13.4.3 Course Organization

Table 2 presents the temporal Organization of the course. It shows the relationship between the content of each instructional week and the principal practical application through which students produced learning and performance data.

Table 1

Temporal Organization of the Technology of Education Course

Stage/week	Course unit	Principal practical application
Introductory stage	Orientation to the environment and administration of pre-intervention instruments	Moodle orientation and preparation of the student profile
Week 1	Introduction to educational technology	Analyzing an educational problem through the systems approach
Week 2	Learning resources and digital media	Evaluating digital resources and selecting the most appropriate resource
Week 3	Digital instructional-content design	Redesigning an instructional screen according to visual-design principles
Week 4	Instructional design	Preparing an instructional-unit plan based on the ADDIE model
Week 5	E-learning and learning management systems	Completing integrated learning tasks through Moodle
Week 6	Digital learning strategies	Selecting a strategy appropriate to a specified educational situation
Week 7	Electronic assessment and feedback	Constructing an electronic assessment and

		interpreting its results
Week 8	Artificial intelligence and learning analytics	Interpreting a learning analytics dashboard and making an academic decision
Week 9	Applied course project	Producing a short digital instructional unit
Week 10	Final assessment	Administering the post-intervention instruments

Table 1 demonstrates that learning analytics was integrated across the course rather than confined to the eighth unit. Although the eighth unit explicitly addressed artificial intelligence and analytics as course content, the experimental-group plugin analyzed learning behavior and provided support throughout the intervention. This distinction prevented the treatment from being reduced to a single lesson about analytics.

13.4.4 Recurring Structure of the Learning Units

Each unit followed a recurring sequence:

1. presentation of the intended learning outcomes;
2. administration of a short diagnostic assessment;
3. formulation of a personal learning goal;
4. presentation of content in manageable sections;
5. provision of more than one learning resource;
6. completion of an applied activity;
7. administration of a formative assessment;
8. presentation of an individual performance report;
9. generation of an alert or personalized recommendation for the experimental group;
10. presentation of alternative learning actions;
11. selection and justification of an academic decision;
12. implementation of the selected action;
13. evaluation of the effect of the action;
14. completion of a brief reflective response; and
15. updating of the student's progress information.

This recurring structure connected analytical information with authentic learning activity. It also provided repeated opportunities for students to plan, monitor, decide, act, and reflect.

13.5 Development of the AI-Supported Learning Analytics Environment

13.5.1 Analysis Phase

The analysis phase addressed learner characteristics, course requirements, intended outcomes, learning difficulties, Moodle functions, data sources, and the dependent variables. First-level students were expected to possess basic digital skills but varied in their ability to organize independent learning, interpret performance information, and select appropriate corrective actions.

The Technology of Education content was analyzed to identify tasks capable of producing meaningful evidence of achievement, regulation, and academic decision-making. The research instruments were also analyzed to ensure that the environment provided authentic opportunities for the behaviors represented in the scale, situational test, and digital learning-record rubric.

13.5.2 Design Phase

The environment was designed according to the following principles:

1. both groups would receive identical content and core activities;
2. analytical indicators would correspond to defined learning processes;
3. no single behavioral indicator would be interpreted as complete evidence of learning;
4. risk classifications would be explainable;
5. recommendations would lead to feasible course actions;

6. students would retain control over the final decision;
7. each decision would be followed by implementation and evaluation;
8. access would be restricted according to Moodle roles; and
9. the plugin would not make autonomous grading, progression, or disciplinary decisions.

The design phase also specified the dashboard structure, analytical rules, risk categories, recommendation library, decision interface, reflection prompts, data fields, and follow-up procedures.

13.5.3 Development Phase

The instructional and analytical specifications were prepared by the researcher. A Moodle developer implemented the custom plugin under the researcher's academic supervision. The researcher reviewed successive versions to ensure alignment with the course outcomes, instructional activities, analytical indicators, and research instruments.
The plugin was named the Intelligent Learning Analytics and Academic Decision Support Plugin (ILA-ADSP). The interface used the shorter label Smart Learning Support.

13.5.4 Evaluation Phase

The environment underwent:

- functional testing;
- scenario-based rule testing;
- educational review;
- interface and navigation review; and
- pilot implementation with 20 students.

Functional testing examined whether the plugin retrieved the intended data, calculated the appropriate indicators, displayed the corresponding risk classification, generated the expected recommendation, recorded the student's decision, and updated the dashboard following subsequent activity.
Scenario-based testing used simulated low-, moderate-, and high-risk profiles. The expected classifications and recommendations were specified before each scenario was run. Inconsistent rules or displays were revised before pilot implementation.

13.6 Applications, Programs, Systems, and Tools

The technological environment comprised Moodle functions and the custom plugin. Table 3 identifies each component and its role in the intervention.

Table 2
Applications, Programs, Systems, and Tools Used in the Learning Environment

Technological component	**Program, system, or tool**	**Function within the environment**
Learning management system	Self-hosted Moodle 3.11 LTS	Hosting and managing users, course units, resources, activities, and assessments
AI-supported analytical component	Custom ILA-ADSP Moodle plugin	Analyzing digital learning records and generating diagnostic, predictive, and prescriptive outputs
Content presentation	Moodle pages and resource modules	Presenting outcomes, explanations, examples, learning resources, and activity instructions
Diagnostic and formative assessment	Moodle Quiz	Recording responses, scores, attempts, recurring errors, and performance changes
Practical-task management	Moodle Assignment	Receiving practical activities and the final course project
Electronic interaction	Moodle Forum	Supporting academic discussion, questions, and help-seeking

Completion monitoring	Moodle activity completion	Recording completed and incomplete resources, activities, and assessments
Performance management	Moodle Gradebook	Organizing and displaying assessment and activity results
Digital trace collection	Moodle event logs and reports	Recording access, participation, completion, attempts, and timing
Data retrieval	Moodle Events, Completion, Gradebook, and Task APIs	Transferring authorized learning indicators to the custom plugin
Server-side programming	PHP 7.4	Processing data, applying rules, and integrating the plugin with Moodle
Interactive interface	JavaScript, HTML5, and CSS3	Managing dashboard interaction, navigation, and information presentation
Data visualization	Chart.js	Displaying progress, performance trends, completion, and risk indicators
Database	MariaDB 10.5	Storing analytical indicators, recommendations, decisions, and follow-up records
Student-facing dashboard	Dashboard embedded in the plugin	Presenting progress, difficulty, risk, recommendations, and subsequent change
Decision interface	Decision-support module	Recording acceptance, modification, or rejection of recommendations
Reflection tool	Structured Moodle prompts	Recording students' evaluation of decisions and outcomes
Behavioral evaluation	Digital learning-record analysis rubric	Converting recorded actions into structured behavioral evidence

Table 2 shows that Moodle functioned as the central platform rather than merely as a content repository. Its assessment, completion, gradebook, interaction, and event-recording functions provided the data required by the custom plugin. The plugin added the intelligent analytical and decision-support functions constituting the experimental treatment.

13.7 Technical Architecture of the Custom Plugin

13.7.1 Data Layer

The data layer retrieved authorized indicators from Moodle:

- diagnostic and formative assessment scores;
- correct and incorrect responses;
- recurring errors;
- number of assessment attempts;
- change across attempts;
- completed and incomplete activities;
- delayed tasks;
- regularity of access;
- use of specified course resources;
- responses to recommendations;
- selected academic decisions; and
- post-decision performance.

The plugin did not interpret a single indicator as definitive evidence. It combined related indicators within the relevant learning unit and task.

13.7.2 Processing Layer

The processing layer normalized selected indicators to a common scale. Higher risk values represented a greater need for support. The layer organized the indicators for subsequent diagnostic and predictive processing.

13.7.3 Diagnostic Layer

The diagnostic layer applied explicit rules to identify probable learning problems. For example:

- weak performance combined with low resource access suggested insufficient preparation;
- weak performance despite extensive resource access suggested misunderstanding or ineffective strategy use;
- repeated attempts without improvement suggested the need to stop retesting and review feedback;
- strong theoretical performance with weak practical work suggested difficulty applying knowledge; and
- delayed activities combined with irregular access suggested a time- and task-management problem.

These interpretations were presented as probable explanations rather than definitive judgements.

13.7.4 Predictive Layer

The predictive layer calculated an overall academic-risk score:

$$R = 0.30P + 0.25C + 0.15A + 0.10I$$

where:

- (R) represented the overall risk score;
- (P) represented performance risk;
- (C) represented incomplete-activity risk;
- (A) represented irregular-access risk;
- (D) represented delayed-task risk;
- (E) represented recurring-error and unsuccessful-attempt risk; and
- (T) represented negative performance-trend risk.

The weights reflected the relative importance assigned to the indicators within the course. Assessment performance and activity completion received the greatest weights because they were most directly connected to required learning outcomes and task progression.

13.7.5 Risk Classification

The overall score was interpreted as follows:

Table 3

Score Interpretation

Overall risk score	Risk classification	General system response
Less than 35	Low risk	Continue the current pathway and provide optional enrichment
35–59	Moderate risk	Present a targeted alert and corrective alternatives
60 or higher	High risk	Present immediate remedial alternatives and recommend academic assistance

These classifications determined the intensity of support. They did not alter grades, restrict content access, or determine academic progression.

13.7.6 Recommendation Layer

The recommendation layer connected detected patterns to educational alternatives. Examples included:

- reviewing a focused explanation;
- studying a worked example;
- completing a short remedial activity;
- revising a learning schedule;
- prioritizing delayed tasks;
- changing a strategy;
- analyzing previous errors;
- repeating an assessment after preparation; and
- requesting assistance from the instructor.

The plugin generally presented two or three alternatives. Students could accept the recommended action, choose another alternative, modify the recommendation, reject it with justification, or request assistance.

13.7.7 Decision and Follow-Up Layer

The decision layer recorded:

- the displayed recommendation;
- the alternative selected by the student;
- whether the recommendation was accepted, modified, or rejected;
- the student's justification;
- the time between recommendation and implementation;
- the action performed; and
- the change in performance following the action.

This layer enabled the environment to connect decision-making with subsequent evidence rather than recording choice alone.

To operationalize the conceptual model, the AI-supported learning analytics environment was implemented through a custom plugin embedded within the institutional Moodle 3.11 LTS platform. The plugin integrated data acquisition, indicator construction, fuzzy risk classification, rule-based recommendation generation, learner decision logging, and user-facing dashboards within a continuous analytics–action cycle. Figure 2 illustrates the technical architecture of the plugin and the flow of data from Moodle learning records to actionable student and instructor support.

Figure 2

Technical Architecture and Data Flow of the Custom Moodle Plugin

Note. ILA-ADSP = Intelligent Learning Analytics and Academic Decision Support Plugin; P = performance risk; C = incompletion risk; A = access irregularity; D = delay; E = repeated errors or failed attempts; T = negative performance trend. The student-facing interface was labeled "Smart Learning Support." The fuzzy rule-based engine classified composite risk scores as low ($R < 35$), moderate ($R = 35–59$), or high ($R \geq 60$).

As shown in Figure 2, the plugin retrieved authorized learning records through Moodle's Events, Completion, Task, and Gradebook application programming interfaces. These records were aggregated and transformed into interpretable indicators before the fuzzy rule-based engine calculated a composite risk score. Risk classification subsequently activated transparent recommendation rules that produced context-sensitive actions for students and evidence-based alerts for the instructor. Students retained authority to accept, modify, or reject each recommendation, while their justifications, implemented actions, and subsequent performance were recorded as new learning evidence. This feedback loop enabled continuous monitoring without delegating grading, academic progression, or disciplinary decisions to the automated component.

13.8 Experimental and Control Conditions

13.8.1 Experimental Condition

Experimental-group students received:

- the Technology of Education course through Moodle;
- diagnostic and formative assessment results;
- progress and completion indicators;
- recurring-error information;
- analysis of engagement and task-delay patterns;
- explainable risk classifications;
- intelligent alerts;
- personalized recommendations;
- alternative corrective actions;
- opportunities to accept, modify, or reject recommendations;

- prompts requiring justification of decisions; and
- follow-up information concerning the effects of implemented actions.

13.8.2 Control Condition

Control-group students received:

- the same Technology of Education content;
- the same learning resources;
- the same practical activities and assignments;
- the same diagnostic and formative assessments;
- the same instructional duration;
- conventional Moodle scores; and
- standard feedback.

They did not receive the custom dashboard, risk classifications, intelligent alerts, personalized recommendations, or structured decision alternatives.

13.9 Implementation Procedures

The study was implemented through the following steps:

1. The course content and intended outcomes were analyzed.
2. The eight instructional units and practical activities were prepared.
3. The conventional Moodle course was constructed.
4. Moodle quizzes, assignments, forums, completion tracking, gradebook records, and event reports were configured.
5. The custom plugin was programmed and integrated with Moodle.
6. The analytical rules, risk classifications, and recommendation library were tested.
7. The research instruments were piloted with 20 students.
8. The main participants completed the pre-intervention measures.
9. Both groups studied the same course content over ten weeks.
10. The experimental group received AI-supported analytics and decision support throughout the intervention.
11. The control group received conventional scores and standard feedback.
12. Digital learning evidence was collected during the instructional period.
13. The principal post-intervention measures were administered to both groups.
14. The usability and satisfaction questionnaire was administered to the experimental group.
15. The data were scored, screened, and prepared for statistical analysis.

13.10 Ethical and Data-Protection Considerations

Formal approval from a separate research ethics committee was not required under the institutional procedures applicable to this course-based educational study at the time of implementation. The researcher was a faculty member conducting the intervention within the regular academic context of the Technology of Education course.

The absence of separate committee approval did not remove the responsibility to protect student data. Access to analytical information was restricted through Moodle user roles. Students could access only their own dashboards and recommendations. The researcher accessed information required for instructional monitoring and research analysis.

Numerical identification codes replaced student names in the exported analytical dataset. Findings were reported at the group level, and the plugin's risk classifications were not used to impose grades, deny access, determine progression, or apply disciplinary action.

The plugin collected only course-related indicators required for the analytical and research purposes of the study. Its outputs were presented as support rather than definitive judgements, and students retained control over their final academic decisions.

14. Research Instruments

Five instruments were used to evaluate the intervention:

1. an achievement test in the Technology of Education course;
2. a self-regulated learning scale;
3. a situational academic decision-making test;
4. a digital learning-record analysis rubric; and
5. a usability and satisfaction questionnaire.

The instruments were developed in alignment with the study objectives, course content, theoretical framework, and expected learning behaviors. Evidence concerning validity was based on alignment with the intended construct and course-content domains, specialist review, and internal-consistency relationships observed in the pilot sample. Reliability and item characteristics were calculated from the scores of the 20 pilot participants.

Validity and reliability were treated as related but distinct properties. Validity concerns the interpretation and use of scores, whereas reliability concerns their consistency. A high reliability coefficient does not by itself establish that an instrument measures the intended construct (American Educational Research Association et al., 2014). Instrument development therefore combined content alignment, specialist judgement, item analysis, and reliability estimation.

Table 4 summarizes the instruments, administration conditions, number of items or indicators, scoring ranges, and participants to whom each instrument was administered.

Table 4
Summary of the Research Instruments

Instrument	Structure	Score range	Administration	Participants
Achievement test	40 four-option multiple-choice items	0–40	Pre- and post-intervention	Experimental and control groups
Self-regulated learning scale	36 statements across six dimensions	36–180	Pre- and post-intervention	Experimental and control groups
Academic decision-making test	24 four-option situational items across six skills	0–24	Pre- and post-intervention	Experimental and control groups
Digital learning-record analysis rubric	24 indicators across eight dimensions	0–72	During the intervention, with a final composite score	Experimental and control groups
Usability and satisfaction questionnaire	30 statements across five dimensions	30–150	Post-intervention	Experimental group only

Table 4 demonstrates that the study used different measurement formats appropriate to the nature of each outcome. Achievement and decision-making were assessed through objectively scored responses, self-regulated learning and satisfaction were measured through Likert-type responses, and recorded behavior was evaluated using performance indicators derived from digital evidence.

14.1 Achievement Test

14.1.1 Purpose

The achievement test measured students' mastery of the knowledge and applications included in the eight units of the Technology of Education course. It was administered before and after the intervention to determine the amount of academic development achieved by each group.

14.1.2 Test Construction

Construction proceeded through the following stages:

1. analyzing the course content;
2. identifying the intended learning outcomes;
3. specifying the cognitive levels to be measured;
4. preparing a test blueprint;
5. writing four-option multiple-choice items;
6. reviewing item relevance, clarity, and technical quality;
7. preparing the scoring key;
8. piloting the test; and
9. calculating item characteristics and reliability.

The test contained 40 items. Each item had one correct or best answer and three distractors. One point was awarded for a correct response and zero for an incorrect response. No marks were deducted for incorrect answers. Total scores could range from 0 to 40, with higher scores indicating stronger achievement.

The allotted administration time was 45 minutes. The same scoring procedure and maximum score were used in the pre- and post-intervention administrations.

14.1.3 Test Blueprint

The blueprint ensured balanced representation of the eight course units and three cognitive levels: recall, comprehension, and application. Table 5 presents the distribution of items.

Table 5

Blueprint of the Achievement Test

Course unit	**Recall**	**Comprehension**	**Application**	**Total items**	**Weight**
Introduction to educational technology	1	2	2	5	12.5 %
Learning resources and digital media	1	2	2	5	12.5 %
Digital instructional-content design	1	2	2	5	12.5 %
Instructional design	1	2	2	5	12.5 %
E-learning and learning management systems	1	2	2	5	12.5 %
Digital learning strategies	1	2	2	5	12.5 %
Electronic assessment and feedback	1	2	2	5	12.5 %
Artificial intelligence and learning analytics	1	2	2	5	12.5 %
Total	**8**	**16**	**16**	**40**	**100 %**
Cognitive-level weight	**20 %**	**40%**	**40%**	**100 %**	—

As shown in Table 5, every unit contributed five items, preventing any course topic from dominating the total score. The test assigned 80% of its items to comprehension and application, which was appropriate for a course combining conceptual understanding with educational application.

14.1.4 Content Validity

The initial test was examined for:

- alignment with course outcomes;
- representation of the eight units;
- appropriateness of cognitive levels;
- clarity of item stems;
- plausibility of distractors;
- absence of unintended clues;
- accuracy of the scoring key; and
- suitability for first-level Faculty of Education students.

Necessary wording and content revisions were completed before pilot administration. The blueprint provided additional evidence that the final items represented the intended course-content domains.

14.1.5 Pilot Item Analysis and Reliability

The test was administered to the 20 pilot participants. Item difficulty was calculated as the proportion of students answering each item correctly. Item discrimination was calculated by comparing performance in the upper and lower pilot-score groups. Corrected item-total correlations were used to examine the relationship between individual items and the remaining test score.

Because the items were scored dichotomously, KR-20 was used to estimate total-score reliability. KR-20 evaluates the internal consistency of a test composed of items scored as correct or incorrect (Kuder & Richardson, 1937).

Table 6 presents the pilot results.

Table 6

Pilot Characteristics of the Achievement Test

Indicator	Result
Pilot sample	20
Number of items	40
Possible score range	0–40
Pilot mean	28.60
Pilot standard deviation	9.05
Item-difficulty range	.55–.90
Item-discrimination range	.17–.83
Corrected item-total correlation range	.135–.873
KR-20 reliability	.921

The KR-20 coefficient indicated excellent consistency for the total test score. All items produced positive discrimination values, although the lowest corrected item-total correlation was comparatively weak. This value was considered when evaluating the instrument, but the total test retained strong reliability and balanced blueprint coverage. The test was therefore considered suitable for comparing achievement development at the total-score level.

14.2 Self-Regulated Learning Scale

14.2.1 Purpose and Dimensions

The scale measured students' self-regulated learning within the Technology of Education course. It contained 36 statements distributed equally across six dimensions:

1. goal setting and planning;
2. time and task management;
3. use of learning strategies;
4. self-monitoring;
5. resource management and help-seeking; and
6. self-evaluation, reflection, and modification of the learning pathway.

The dimensions were derived from the cyclical conceptualization of self-regulation and aligned with the regulatory opportunities embedded in the Moodle environment.

14.2.2 Response and Scoring System

Students responded using a five-point Likert scale:

- strongly agree = 5;
- agree = 4;
- neutral = 3;
- disagree = 2; and
- strongly disagree = 1.

Items 6, 12, 18, 24, 30, and 36 were negatively worded and reverse-scored. For these items, strongly agree received one point and strongly disagree received five points.
Each dimension contained six statements and produced a score between 6 and 30. The total scale score ranged from 36 to 180. Higher scores represented stronger self-regulated learning.

14.2.3 Content and Construct Alignment

The statements were examined for:

- relevance to the intended dimension;
- clarity and linguistic suitability;
- applicability to the Technology of Education course;
- absence of unnecessary overlap;
- balance between positive and negative wording; and
- representation of planning, performance, and reflective processes.

The dimensions were specified theoretically before analyzing the pilot data. Because the pilot sample included only 20 students, no exploratory or confirmatory factor analysis was claimed. A sample of this size would not provide stable evidence for a six-factor structure. Internal-consistency relationships were used as preliminary evidence, while the interpretation of the dimensions remained grounded in their theoretical and content alignment.

14.2.4 Pilot Reliability and Internal Consistency

Cronbach's alpha was calculated for each dimension and for the total scale. Alpha estimates the consistency of a composite score by examining the relationships among its items, although its interpretation should consider the number of items and the breadth of the construct (Cronbach, 1951).
Corrected item-dimension correlations were calculated by correlating each statement with the score of its dimension after excluding that statement. Table 7 presents the results.

Table 7

Pilot Internal Consistency and Reliability of the Self-Regulated Learning Scale

Dimension	Items	Corrected item–dimension correlations	Cronbach's alpha
Goal setting and planning	6	.545–.879	.893
Time and task management	6	.543–.805	.879
Use of learning strategies	6	.623–.766	.878
Self-monitoring	6	.488–.826	.878
Resource management and help-seeking	6	.522–.763	.879
Self-evaluation and pathway modification	6	.551–.888	.894
Total scale	**36**	**.630–.888**	**.983**

Table 7 shows that the six dimensions produced alpha coefficients ranging from .878 to .894. Corrected item-dimension correlations were positive and exceeded .48. The total-scale alpha was .983, indicating very high internal consistency. The result supported use of the total score and the theoretically specified dimensional scores, while recognizing that the small pilot sample limited the precision of the coefficient estimates.
The pilot mean for the total scale was 128.45, with a standard deviation of 24.25. The scores were calculated after reversing all negatively worded items.

14.3 Situational Academic Decision-Making Test

14.3.1 Purpose

The test measured students' ability to make reasoned academic decisions in situations derived from the Technology of Education course and the AI-supported learning environment. It assessed applied judgement rather than students' agreement with general statements about decision-making.

14.3.2 Test Structure

The test consisted of 24 situations. Each situation was followed by four alternatives representing different responses. One point was awarded for the most educationally appropriate response and zero for each other response. Total scores ranged from 0 to 24.

The situations addressed weak assessment performance, recurring conceptual errors, delayed tasks, inappropriate resource selection, ineffective strategy use, disagreement with system recommendations, implementation of corrective actions, and evaluation of decision outcomes.

The six skill domains are presented in Table 8.

Table 8

Blueprint of the Situational Academic Decision-Making Test

Skill domain	Item numbers	Number of situations	Weight	Score
Identifying the academic problem	1–4	4	16.67%	4
Collecting information and evidence	5–8	4	16.67%	4
Interpreting learning data	9–12	4	16.67%	4
Generating alternatives	13–16	4	16.67%	4
Evaluating alternatives and selecting the decision	17–20	4	16.67%	4
Implementing, monitoring, and evaluating the decision	21–24	4	16.67%	4
Total	**1–24**	**24**	**100%**	**24**

Table 8 shows that each skill domain contributed equally to the total score. This balance prevented the test from measuring decision selection alone and ensured representation of the stages preceding and following the decision.

14.3.3 Development and Content Validity

The situations were prepared according to the following requirements:

- relevance to first-level university students;
- connection to authentic Technology of Education tasks;
- availability of sufficient evidence within each situation;
- plausibility of the four alternatives;
- presence of one clearly superior educational response;
- absence of linguistic cues revealing the answer;
- representation of all six skill domains; and
- consistency between each situation and its scoring key.

The alternatives were designed to distinguish evidence-informed decisions from responses based on irrelevant information, immediate convenience, uncritical acceptance of the system, or action without evaluation.

14.3.4 Pilot Item Analysis and Reliability

The test was administered to the pilot sample. Difficulty, discrimination, corrected item-total correlations, and KR-20 were calculated. The results are shown in Table 9.

Table 9

Pilot Characteristics of the Academic Decision-Making Test

Indicator	Result
Pilot sample	20
Number of situations	24
Possible score range	0–24
Pilot mean	17.75
Pilot standard deviation	6.14
Item-difficulty range	.65–.80
Item-discrimination range	.33–.83
Corrected item-total correlation range	.358–.780

KR-20 reliability	.910

Table 9 indicates that the decision-making test demonstrated strong reliability and positive item discrimination. The corrected item-total relationships were also consistently positive. These results supported use of the total test score in the principal analysis.

Separate reliability estimates for the six skill domains were not used as principal evidence because each domain contained only four items and the pilot sample was small. Under these conditions, subscale reliability coefficients would be unstable and could underestimate consistency because of the limited number of items. The total score was therefore the primary outcome.

14.4 Digital Learning-Record Analysis Rubric

14.4.1 Purpose

The rubric evaluated behavioral evidence of self-regulation and academic decision-making derived from Moodle records and related student tasks. It was included to complement the self-report and situational instruments with evidence of behavior occurring during the course.

14.4.2 Data Sources

Evidence was extracted from:

- personal learning goals and plans;
- activity-completion reports;
- assessment results and attempts;
- recurring-error patterns;
- resource-access records;
- timing and task-delay information;
- recommendation records;
- acceptance, modification, or rejection of recommendations;
- decision justifications;
- implementation records;
- changes in performance after action; and
- reflective responses.

The rubric did not treat login counts or time indicators as sufficient evidence independently. Each indicator was evaluated using the most relevant source or combination of sources.

14.4.3 Dimensions and Scoring

The rubric contained 24 indicators across eight dimensions. Each dimension included three indicators. Table 10 presents the structure.

Table 10

Dimensions of the Digital Learning-Record Analysis Rubric

Dimension	Indicator numbers	Number of indicators	Score range
Planning and goal setting	1–3	3	0–9
Time and task management	4–6	3	0–9
Learning strategies and resources	7–9	3	0–9
Monitoring progress and performance	10–12	3	0–9
Using feedback and seeking assistance	13–15	3	0–9
Interpreting data and identifying the problem	16–18	3	0–9
Selecting and implementing the decision	19–21	3	0–9
Evaluating the decision and modifying the pathway	22–24	3	0–9
Total	**1–24**	**24**	**0–72**

Table 10 shows that the rubric represented both principal dependent variables. The first five dimensions primarily reflected self-regulated learning, while the final three captured the interpretation, implementation, and evaluation of academic decisions.

Each indicator was scored from 0 to 3:

- **3:** the behavior was fully and consistently demonstrated;

- **2:** the behavior was demonstrated to a moderate extent;
- **1:** the behavior was demonstrated to a limited extent; and
- **0:** the behavior was not demonstrated or no supporting evidence was available.

Where a behavior did not have an equal opportunity to occur every week, the weekly score was expressed relative to the maximum score of the indicators observable during that period. This prevented students from being penalized for behaviors not elicited by a particular unit.

14.4.4 Validity and Pilot Reliability

The rubric indicators were examined for:

- relevance to their intended dimensions;
- observability within Moodle or associated tasks;
- clarity of performance anchors;
- availability of supporting evidence;
- distinction among score levels; and
- consistency with the theoretical definitions of self-regulation and academic decision-making.

Pilot analysis produced an alpha coefficient of .950 for the total rubric score. Corrected indicator-total correlations ranged from .412 to .840. These results indicated strong consistency at the total-score level.

Internal consistency does not replace inter-rater reliability because rubric scoring also depends on the consistency of judgement between evaluators. The supplied pilot dataset contained only one final score for each participant and did not include separate ratings from two independent evaluators. An intraclass correlation coefficient could therefore not be estimated from the available data. This limitation is reported explicitly rather than substituting alpha for inter-rater agreement.

14.5 Usability and Satisfaction Questionnaire

14.5.1 Purpose and Structure

The questionnaire evaluated experimental-group students' perceptions after using the AI-supported learning analytics environment. It contained 30 statements distributed equally across five dimensions:

1. ease of learning to use the environment;
2. efficiency of interaction, navigation, and access;
3. clarity of analytics and recommendations;
4. perceived usefulness; and
5. satisfaction, trust, and acceptance.

14.5.2 Response and Scoring System

A five-point Likert response format was used:

- strongly agree = 5;
- agree = 4;
- neutral = 3;
- disagree = 2; and
- strongly disagree = 1.

Items 6, 12, 18, 24, and 30 were negatively worded and reverse-scored. Each dimension produced a score from 6 to 30, while the total score ranged from 30 to 150. Higher scores indicated stronger usability and satisfaction.

A total score of 90 represented the theoretical neutral criterion because it corresponded to an average response of three across the 30 statements.

14.5.3 Pilot Internal Consistency and Reliability

Table 11 presents the pilot results.

Table 11

Pilot Internal Consistency and Reliability of the Usability and Satisfaction Questionnaire

Dimension	Items	Corrected item–dimension correlations	Cronbach's alpha
Ease of learning to use the environment	6	.516–.958	.899
Efficiency of interaction, navigation, and access	6	.499–.863	.867
Clarity of analytics and recommendations	6	.485–.925	.870

Perceived usefulness	6	.470–.895	.892
Satisfaction, trust, and acceptance	6	.497–.914	.878
Total questionnaire	**30**	**.573–.954**	**.978**

Table 11 indicates strong internal consistency across the five dimensions. Alpha coefficients ranged from .867 to .899, and all corrected item-dimension relationships were positive. The total-questionnaire alpha of .978 supported use of the overall score.

The pilot mean was 105.75, with a standard deviation of 20.94. These values were used only to describe the pilot administration and not as evidence of the main intervention's effectiveness.

14.6 Overall Evaluation of Pilot Instrument Quality

Table 12 summarizes the reliability coefficients for the five instruments.

Table 12

Summary of Pilot Reliability Evidence

Instrument	Number of items or indicators	Reliability coefficient
Achievement test	40	KR-20 = .921
Self-regulated learning scale	36	Cronbach's α = .983
Academic decision-making test	24	KR-20 = .910
Digital learning-record rubric	24	Cronbach's α = .950
Usability and satisfaction questionnaire	30	Cronbach's α = .978

Table 12 demonstrates that the total scores of all five instruments produced high internal-consistency estimates in the pilot sample. These coefficients supported their use in the main study. Nevertheless, the estimates were interpreted in conjunction with instrument content, item characteristics, theoretical alignment, and the small pilot-sample size.

15. Statistical Analysis

15.1 Data Preparation and Screening

The main dataset was examined for:

- participant and group coding;
- missing values;
- scores outside the permitted ranges;
- accuracy of reverse-scored items;
- consistency of total scores;
- extreme values;
- distribution shape; and
- suitability of statistical assumptions.

No missing values were found for the pre- or post-intervention achievement, self-regulated learning, academic decision-making, or digital learning-record scores. Usability and satisfaction scores were structurally absent for the control group because the questionnaire evaluated the experimental environment.

15.2 Descriptive Statistics

The following descriptive statistics were calculated:

- frequency and sample size;
- arithmetic mean;
- standard deviation;
- minimum and maximum;
- skewness; and
- kurtosis.

Descriptive statistics were reported before inferential tests to show the direction and magnitude of observed differences.

15.3 Baseline Equivalence

Independent-samples t-tests were used to compare experimental and control pre-intervention scores. Levene's test was examined to evaluate equality of variances. Standardized differences were also calculated because a nonsignificant probability value alone does not demonstrate practical equivalence.

15.4 Selection of the Principal Comparative Test

Analysis of covariance was initially considered because pre- and post-intervention scores were available. However, ANCOVA assumes that the relationship between the pre-intervention covariate and the post-intervention outcome is equivalent across the study groups.

The group-by-pre-test interaction was statistically significant for achievement, academic decision-making, and self-regulated learning. The homogeneity-of-regression-slopes assumption was therefore not satisfied, making conventional ANCOVA inappropriate as the primary analysis.

Individual gain scores were calculated as:

Gain score=Post-intervention score−Pre-intervention score

Because the groups were equivalent at baseline but the gain-score variances were unequal, Welch's independent-samples t-test was used. Welch's test adjusts the standard error and degrees of freedom and is more appropriate than the equal-variance t-test when group variances differ.

15.5 Supporting Analyses

The Mann–Whitney test was calculated as a sensitivity analysis for the principal comparisons. It does not require normally distributed scores or equal variances. Agreement between Welch's test and Mann–Whitney results was used to assess whether the substantive decisions were robust to the choice of analytical method.

The digital learning-record rubric was compared using Welch's test because its group variances differed. Experimental-group usability and satisfaction were evaluated using a one-sample t-test against the theoretical neutral criterion of 90.

15.6 Effect Sizes and Confidence Intervals

Hedges' g was reported for independent-group comparisons. It was selected because it applies a small-sample correction to the standardized mean difference. Cohen's d was reported for the one-sample usability and satisfaction comparison.

Effect sizes were interpreted alongside raw mean differences and 95% confidence intervals. Statistical significance alone does not indicate the educational magnitude or precision of an intervention effect (Lakens, 2013).

All tests used a two-sided significance level of .05. Exact probability values were reported except when p was smaller than .001.

16. Results

16.1 Preliminary Data Screening

The main dataset contained records for 100 students: 50 in the experimental group and 50 in the control group. No missing values were identified in the achievement, self-regulated learning, academic decision-making, or digital learning-record rubric scores. Usability and satisfaction scores were available for the 50 experimental-group students only because the questionnaire evaluated components exclusive to the AI-supported learning analytics environment.

All recorded scores fell within the permissible ranges of their respective instruments. Across the principal pre- and post-intervention variables, skewness values ranged from −0.11 to 0.48, while kurtosis values ranged from −1.14 to −0.78. These results indicated no substantial univariate distributional irregularity in the principal scores.

The following group codes were used in the analytical dataset:

- **Group 1:** experimental group;
- **Group 2:** control group.

16.2 Pre-Intervention Equivalence

Before testing the research hypotheses, experimental- and control-group pre-intervention scores were compared to determine whether the groups began the study at comparable levels. Independent-samples t-tests were conducted for achievement, self-regulated learning, and academic decision-making.

Levene's tests were nonsignificant for the three pre-intervention variables:

- achievement: $p = .617$;
- self-regulated learning: $p = .190$; and

- academic decision-making: $p = .284$.

The equality-of-variance assumption was therefore considered acceptable for the baseline comparisons. Table 13 presents the results.

Table 13
Pre-Intervention Equivalence of the Experimental and Control Groups

Variable	Experimental group M (SD)	Control group M (SD)	t(98)	p	Hedges' g
Achievement	14.60 (2.61)	14.50 (2.76)	0.19	.853	0.04
Self-regulated learning	96.58 (13.39)	97.06 (15.76)	−0.16	.870	−0.03
Academic decision-making	8.86 (2.18)	8.94 (2.49)	−0.17	.864	−0.03

As shown in Table 13, none of the baseline differences was statistically significant. The corresponding Hedges' g values ranged from −0.03 to 0.04, indicating negligible standardized differences. The groups therefore demonstrated close pre-intervention comparability on the principal outcome measures.

The absence of statistically and practically meaningful baseline differences supported comparison of the groups' subsequent development. It did not, however, justify treating the design as randomized because baseline equivalence does not substitute for random treatment allocation.

16.3 Descriptive Development across the Intervention

Pre-intervention means, post-intervention means, and gain scores were calculated for the three repeatedly measured outcomes. Gain scores represented the difference between each student's post- and pre-intervention scores.

Table 14 presents the descriptive results. The percentage in the final column represents the post-intervention mean as a proportion of the maximum possible score for the relevant instrument.

Table 14
Descriptive Statistics for the Repeatedly Measured Outcomes

Outcome	Group	Pre-intervention M (SD)	Post-intervention M (SD)	Gain M (SD)	Post-intervention percentage of maximum
Achievement	Experimental	14.60 (2.61)	30.56 (4.00)	15.96 (4.13)	76.40%
	Control	14.50 (2.76)	20.94 (4.25)	6.44 (1.61)	52.35%
Self-regulated learning	Experimental	96.58 (13.39)	137.96 (12.89)	41.38 (15.82)	76.64%
	Control	97.06 (15.76)	110.48 (16.17)	13.42 (0.97)	61.38%
Academic decision-making	Experimental	8.86 (2.18)	17.72 (3.02)	8.86 (3.29)	73.83%
	Control	8.94 (2.49)	12.32 (2.77)	3.38 (0.60)	51.33%

Table 14 shows that both groups improved between the pre- and post-intervention administrations. This pattern was expected because the two groups studied the same Technology of Education content, completed the same core activities, and received regular instruction and assessment.

The magnitude of development was nevertheless greater in the experimental group for all three outcomes. Its mean gain exceeded the control-group gain by 9.52 points in achievement, 27.96 points in self-regulated learning, and 5.48 points in academic decision-making. Inferential tests were required to determine whether these observed differences were statistically reliable.

16.4 Examination of the ANCOVA Assumption

ANCOVA was initially considered because pre- and post-intervention scores were available. Before using it, the homogeneity-of-regression-slopes assumption was tested through the interaction between group membership and the relevant pre-intervention score.

Table 15 presents the interaction tests.

Table 15

Tests of the Homogeneity-of-Regression-Slopes Assumption

Outcome	Group × pre-intervention interaction F	df	p	Decision
Achievement	27.20	1, 96	< .001	Assumption not satisfied
Self-regulated learning	37.28	1, 96	< .001	Assumption not satisfied
Academic decision-making	16.86	1, 96	< .001	Assumption not satisfied

As Table 15 demonstrates, the group-by-pre-intervention interaction was statistically significant for each outcome. The relationship between baseline and post-intervention performance therefore differed across the experimental and control groups.

A conventional ANCOVA omitting these interactions would violate a central analytical assumption. ANCOVA was consequently not used as the principal hypothesis test. Because the groups demonstrated close baseline equivalence, gain scores were compared instead.

Levene's tests indicated unequal gain-score variances:

- achievement: $p < .001$;
- self-regulated learning: $p < .001$; and
- academic decision-making: $p < .001$.

Welch's independent-samples t-test was therefore used because it does not assume equal population variances.

16.5 Effect on Achievement

The first hypothesis stated that there would be no statistically significant difference between the mean achievement gain scores of the experimental and control groups.

The experimental group obtained a mean achievement gain of 15.96 points (SD = 4.13), compared with 6.44 points (SD = 1.61) for the control group. The raw difference between the group gains was 9.52 points.

Welch's test indicated that this difference was statistically significant, $t(63.48) = 15.19$, $p < .001$, 95% CI [8.27, 10.77]. The confidence interval excluded zero and indicated that the experimental-group advantage was unlikely to be attributable to sampling variation alone.

Hedges' g was 3.01, representing a very large standardized difference in achievement development. A Mann–Whitney sensitivity analysis produced the same substantive decision, $U = 2487.00$, $p < .001$.

Accordingly, the first null hypothesis was rejected. Students using the AI-supported learning analytics environment achieved significantly greater development in Technology of Education achievement than students receiving conventional Moodle feedback.

The result should be interpreted as the observed effect within the study context. The large standardized difference does not establish that an effect of identical magnitude would occur in other courses, institutions, or student populations.

16.6 Effect on Self-Regulated Learning

The second hypothesis stated that there would be no statistically significant difference between the mean self-regulated learning gain scores of the experimental and control groups.

The experimental group obtained a mean gain of 41.38 points (SD = 15.82), compared with 13.42 points (SD = 0.97) for the control group. The mean gain difference was 27.96 points.

Welch's test demonstrated that the difference was statistically significant, $t(49.37) = 12.47$, $p < .001$, 95% CI [23.46, 32.46]. Hedges' g was 2.48, indicating a very large standardized difference in favor of the experimental group.

The Mann–Whitney sensitivity analysis supported the same conclusion, $U = 2437.00$, $p < .001$. Agreement between the parametric and

nonparametric results indicated that the substantive decision was not dependent on the equal-variance assumption or a single analytical procedure.
The second null hypothesis was therefore rejected. The experimental group demonstrated significantly greater development in self-regulated learning.
The experimental group's post-intervention mean of 137.96 represented 76.64% of the maximum scale score, compared with 61.38% for the control group. The result indicates stronger overall regulation but should not be interpreted as evidence that every self-regulation dimension changed by the same amount because the main dataset contained total scale scores rather than separate dimensional totals.

16.7 Effect on Academic Decision-Making Skills

The third hypothesis stated that there would be no statistically significant difference between the mean academic decision-making gain scores of the experimental and control groups.
The experimental group achieved a mean gain of 8.86 points (SD = 3.29), compared with 3.38 points (SD = 0.60) for the control group. The difference between the gains was 5.48 points.
Welch's test indicated a statistically significant difference, $t(52.28) = 11.59$, $p < .001$, 95% CI [4.53, 6.43]. Hedges' g was 2.30, indicating a very large standardized difference.
The Mann–Whitney sensitivity analysis produced a consistent result, $U = 2387.00$, $p < .001$. The third null hypothesis was consequently rejected.
The experimental group's post-intervention mean represented 73.83% of the maximum test score, compared with 51.33% for the control group. These results indicate that students who accessed explainable analytics, personalized alternatives, and structured decision follow-up demonstrated greater development in academic decision-making than students receiving conventional feedback.

16.8 Comparative Summary of Gain-Score Results

Table 16 consolidates the principal inferential results. Presenting the outcomes together facilitates comparison of raw differences, statistical precision, and standardized magnitude.

Table 16
Welch Comparisons of Experimental- and Control-Group Gain Scores

Outcome	Experimental gain M (SD)	Control gain M (SD)	Mean difference	Welch's t	df	p	95% CI for difference	Hedges' g
Achievement	15.96 (4.13)	6.44 (1.61)	9.52	15.19	63.48	< .001	[8.27, 10.77]	3.01
Self-regulated learning	41.38 (15.82)	13.42 (0.97)	27.96	12.47	49.37	< .001	[23.46, 32.46]	2.48
Academic decision-making	8.86 (3.29)	3.38 (0.60)	5.48	11.59	52.28	< .001	[4.53, 6.43]	2.30

Note. Gain scores were calculated as post-intervention score minus pre-intervention score. Positive mean differences favor the experimental group.
Table 16 shows a consistent experimental advantage across the three outcomes. Each confidence interval was entirely above zero, and each effect size exceeded 2.00. The greatest standardized difference was observed for achievement, followed by self-regulated learning and academic decision-making.
The large effect sizes require cautious interpretation. They describe separation between the groups within the present dataset and should not be treated as universal estimates of AI-supported learning analytics effects.

16.9 Digital Learning-Record Behaviors

The fourth hypothesis stated that there would be no statistically significant difference between the mean post-intervention digital learning-record rubric scores of the experimental and control groups.

The rubric assessed planning, time and task management, strategy and resource use, progress monitoring, feedback use, performance-data interpretation, decision implementation, and decision evaluation. Table 17 presents the descriptive and inferential results.

Table 17

Comparison of Digital Learning-Record Rubric Scores

Group	n	M	SD	Percentage of maximum
Experimental	50	54.96	9.50	76.33%
Control	50	37.28	6.93	51.78%

Mean difference	Welch's t	df	p	95% CI	Hedges' g
17.68	10.64	89.65	< .001	[14.38, 20.98]	2.11

Levene's test indicated unequal variances, $F(1, 98) = 7.84$, $p = .006$; Welch's test was therefore retained. As shown in Table 17, the experimental group exceeded the control group by 17.68 points. The difference was statistically significant and associated with a very large effect size.

The Mann–Whitney sensitivity analysis reached the same decision, $U = 2320.00$, $p < .001$. The fourth null hypothesis was therefore rejected.

The behavioral result provides evidence convergent with the self-regulated learning scale and academic decision-making test. Experimental-group students not only reported stronger regulation and selected more appropriate situational responses; they also demonstrated stronger planning, monitoring, feedback use, decision implementation, and reflective evaluation in their recorded course behavior.

Digital traces remain partial representations of learning. The result therefore indicates stronger behavior recorded within the Moodle environment and associated course tasks, not a complete measurement of all learning undertaken by students.

16.10 Usability and Satisfaction

The fifth hypothesis stated that the mean usability and satisfaction score of the experimental group would not differ significantly from the theoretical neutral criterion of 90.

The questionnaire contained 30 five-point statements. A total score of 90 corresponded to a mean response of three and therefore represented the neutral criterion. Table 18 presents the result.

Table 18

Experimental-Group Usability and Satisfaction

n	Observed M	SD	Neutral criterion	Mean difference	t(49)	p	95% CI for observed mean	Cohen's d
50	121.86	13.63	90	31.86	16.53	< .001	[117.99, 125.73]	2.34

Table 18 shows that the experimental-group mean was 31.86 points above the neutral criterion. The observed mean represented 81.24% of the maximum questionnaire score and corresponded to an average item response of approximately 4.06 out of 5.

The difference was statistically significant, and Cohen's d indicated a very large standardized difference from neutrality. The fifth null hypothesis was therefore rejected.

The result indicates strong overall acceptance of the environment. However, the main dataset contained only total questionnaire scores. Separate numerical claims concerning ease of use, dashboard clarity, perceived usefulness, or trust were therefore not made.

16.11 Decisions Concerning Research Hypotheses

Table 19 summarizes the statistical decisions.

Table 19
Summary of Hypothesis Decisions

Hypothesis	Principal statistical evidence	Decision
No difference between the groups in achievement gain	t(63.48) = 15.19, p < .001, g = 3.01	Rejected
No difference between the groups in self-regulated learning gain	t(49.37) = 12.47, p < .001, g = 2.48	Rejected
No difference between the groups in academic decision-making gain	t(52.28) = 11.59, p < .001, g = 2.30	Rejected
No difference in digital learning-record rubric scores	t(89.65) = 10.64, p < .001, g = 2.11	Rejected
Experimental-group usability and satisfaction do not differ from neutrality	t(49) = 16.53, p < .001, d = 2.34	Rejected

As shown in Table 19, all five null hypotheses were rejected. The experimental group achieved greater development in achievement, self-regulated learning, and academic decision-making. It also obtained stronger digital learning-record rubric scores, and its usability and satisfaction exceeded the neutral criterion.

The consistency of the findings across objective tests, self-report, behavioral records, and user evaluation provides a coherent pattern of evidence. Interpretation of the mechanisms and educational implications is presented in the discussion.

17. Discussion

17.1 Overview of the Findings

The study examined whether a Moodle learning environment enhanced with AI-supported learning analytics could develop self-regulated learning and academic decision-making skills among first-level students at the Faculty of Education, Damietta University. Academic achievement, digital learning-record behaviors, usability, and satisfaction were examined as supporting outcomes.

The results produced a consistent pattern. The experimental and control groups began the study at comparable levels, and both improved after studying the Technology of Education course. The experimental group nevertheless demonstrated substantially greater development in achievement, self-regulated learning, and academic decision-making. It also achieved higher digital learning-record rubric scores and reported usability and satisfaction significantly above the neutral criterion.

Because the design was quasi-experimental, the findings should not be interpreted as possessing the same causal certainty as a fully randomized experiment. However, the close baseline equivalence, identical course content, equal instructional duration, common assessment procedures, and consistent differences across multiple outcomes strengthen the interpretation that the AI-supported learning analytics environment contributed to the observed experimental-group advantage.

The treatment should not be reduced to the presence of artificial intelligence or a dashboard. The environment combined learning data, explainable risk classifications, personalized alternatives, student-controlled decisions, implementation, and reflective follow-up. The discussion therefore interprets the results in relation to this complete pedagogical cycle.

17.2 Achievement in the Technology of Education Course

The experimental group achieved a mean gain of 15.96 points in achievement, compared with 6.44 points for the control group. The difference was statistically significant and associated with a very large standardized effect. This result indicates that the experimental environment was associated with stronger mastery of the Technology of Education content.

One plausible explanation is that the plugin reduced the distance between assessment information and corrective action. Conventional feedback informed control-group students of their results, whereas experimental-group students received additional information concerning recurring errors, completion patterns, probable causes of difficulty, and suitable learning alternatives. The analytical information therefore helped direct attention toward the content or activity most relevant to the student's immediate need.

The diagnostic function was particularly important. A low assessment score does not identify whether the learner requires additional explanation, practical application, time reorganization, or assistance. The plugin combined assessment results with activity completion, error patterns, resource use, and performance trends. This combination may have enabled students to select more precise corrective actions than would have been possible through the score alone.

The result is consistent with systematic evidence indicating that learning analytics can support study success when analytical information is connected to appropriate interventions and educational support (Ifenthaler & Yau, 2020). The finding also aligns with process-oriented dashboard research showing that feedback focused on learning processes can improve learning effectiveness by enabling students to make timely adjustments (Wang & Han, 2021).

Nevertheless, the wider literature does not support the assumption that dashboard access automatically improves achievement. A randomised study involving university programming students found changes in some online behaviors but no overall improvement in final examination performance (Hellings & Haelermans, 2022). The difference between that finding and the present result reinforces the importance of intervention design. The current environment did not merely display predicted grades or progress; it connected diagnosis to personalized alternatives, required a student decision, and followed the result of that decision.

The practical nature of the Technology of Education course may also have contributed. Many course outcomes required students to apply principles to authentic tasks, such as evaluating resources, redesigning instructional screens, preparing an instructional plan, and constructing an electronic assessment. The recommendation engine could therefore connect a detected weakness with a specific practical response rather than offering generic encouragement.

The control group's achievement gain remains educationally meaningful. Both groups received organized course content, electronic activities, formative assessments, and standard feedback. The experimental difference should consequently be interpreted as the added value of AI-supported analytics and structured decision support over a functioning Moodle course rather than as a comparison between instruction and no instruction.

17.3 Self-Regulated Learning

The experimental group demonstrated significantly greater development in self-regulated learning. Its mean gain was 41.38 points, compared with 13.42 points for the control group. The magnitude and consistency of this difference suggest that the environment influenced how students managed their learning rather than affecting content achievement alone.

The result can be interpreted through the cyclical structure embedded in each unit. Students established a goal, studied content, completed an activity, reviewed performance evidence, selected a response, implemented it, and evaluated the outcome. This structure corresponded to the forethought, performance, and self-reflection phases of self-regulated learning (Zimmerman, 2002).

The dashboard contributed by making relevant aspects of learning visible. Completion indicators supported comparison between planned and completed work. Performance trends allowed students to identify improvement or decline. Error reports directed attention toward persistent difficulties. Task-delay and access-regularity indicators highlighted possible weaknesses in time and task management.

Learning-science-informed dashboards are more likely to support regulation when their indicators are connected to meaningful learning processes and goals (Sedrakyan et al., 2020). The current dashboard was designed around the scale dimensions rather than around all data technically available in Moodle. This alignment may explain why the effect extended across the total self-regulated learning score.

The personalized recommendations also provided strategic scaffolding. Students may recognize that they are not progressing without knowing which strategy to adopt. The plugin presented feasible alternatives associated with the detected pattern, such as reviewing a focused explanation, examining a worked example, completing a remedial task, reorganizing time, or requesting assistance.

The recommendations did not remove student responsibility. Students had to determine whether the system's interpretation was appropriate and could accept, modify, or reject the recommendation. This choice was important because direct automation of the next learning action could increase short-term compliance without developing independent regulation.

The finding is consistent with evidence that online environments support self-regulation more effectively when they address multiple phases of the learning cycle instead of providing isolated prompts (Wong et al., 2019). It also responds to the limitation identified in dashboard research that many systems increase awareness but provide insufficient support for metacognition, strategy use, and regulatory action (Matcha et al., 2020).

The effect of analytics-based feedback may vary among learners according to previous achievement, initial self-regulation, engagement with the feedback, and the extent to which recommendations are acted upon (Lim et al., 2021). The present mean difference therefore represents an overall group pattern and should not be interpreted as evidence that every experimental-group student benefited equally.

The control group's smaller improvement can be attributed to participation in the same structured course and exposure to formative assessment and standard feedback. Completing repeated course activities may itself support some planning and monitoring. The additional experimental gain is plausibly associated with the individualized analytical cycle that was unavailable to the control group.

17.4 Academic Decision-Making Skills

The experimental group achieved significantly greater development in academic decision-making, with a mean gain of 8.86 points compared with 3.38 points in the control group. The result indicates that the environment supported students' ability to identify academic problems, interpret evidence, generate and evaluate alternatives, select decisions, and consider their consequences.

A primary explanation lies in the alignment between the plugin and the decision process measured by the situational test. Students repeatedly encountered situations requiring them to examine performance evidence, interpret probable causes, compare suggested actions, and justify a final choice. Academic decision-making was therefore practiced within authentic course activity rather than presented only as theoretical information.

Explainability contributed to the quality of this practice. The fuzzy rule-based system connected risk classifications with identifiable indicators. Students could understand, for example, that a recommendation resulted from weak assessment performance combined with incomplete activities, or that repeated attempts without improvement indicated the need to review feedback before retesting.

An unexplained prediction may inform students that they are at risk while giving them little basis for evaluating the classification. By contrast, an explainable recommendation allows learners to compare the system's interpretation with their own knowledge of the situation. This comparison is central to reasoned decision-making.

The opportunity to reject a recommendation was equally important. If the system had automatically determined the next activity, students might have completed suitable resources without developing the ability to choose among alternatives. Allowing acceptance, modification, and rejection preserved meaningful participation and aligned the intervention with the concept of student agency (Jääskelä et al., 2021).

Learner dashboards can support agency when they provide intelligible information and meaningful opportunities for action, but they can weaken agency when students are positioned as passive recipients of automated direction (Bennett & Folley, 2020). The present environment attempted to avoid this risk by requiring the student to justify the final decision.

The recommendation architecture was also consistent with human-centered personalized-support models in which educational data are connected to instructor-defined conditions and actions (Pardo et al., 2018). The present study added a student decision layer by requiring learners to respond explicitly to the recommendation and evaluate its later effect.

The relationship between self-regulation and decision-making may have strengthened both outcomes. Monitoring provided evidence that a change was needed, while decision-making converted that evidence into a specific response. Evaluation of the decision subsequently informed the next regulatory cycle. The variables therefore operated as mutually reinforcing processes while remaining conceptually distinct.

17.5 Digital Learning-Record Behaviors

The experimental group obtained significantly higher digital learning-record rubric scores. Its mean represented 76.33% of the maximum score, compared with 51.78% for the control group. The result provides behavioral evidence supporting self-report and situational-test findings.

The rubric assessed whether students established goals, managed tasks, used resources, monitored progress, responded to feedback, interpreted data, implemented decisions, and evaluated subsequent outcomes. Higher experimental-group scores indicate that differences were visible in recorded course behavior, not only in students' reported perceptions.

This convergence strengthens interpretation because self-report measures can be affected by memory limitations and socially desirable responding. Digital traces can show whether an action occurred and when it occurred. However, platform traces cannot directly reveal cognitive processing, motivation, or intention. They also omit learning undertaken outside Moodle.

For this reason, the study did not interpret frequency of access or number of clicks as self-regulation in isolation. The rubric connected several data sources with the instructional context. A recommendation response, for example, was examined in relation to implementation and subsequent performance rather than being scored solely because a student opened the dashboard.

The temporal sequence of events was especially important. Self-regulation unfolds through cycles of action and adaptation, making relationships among feedback, decision, implementation, and subsequent performance more informative than individual events considered separately (Saint et al., 2022).

The digital-record result also provides evidence that the intervention's theoretical mechanism operated as intended. Experimental-group students had access to structured opportunities for goal setting, decision justification, and follow-up, and their records showed stronger enactment of these behaviors. Nevertheless, alignment between the intervention and rubric should be considered when interpreting the magnitude of the difference.

17.6 Usability and Satisfaction

The experimental group's usability and satisfaction mean was significantly higher than the neutral criterion. The mean represented 81.24% of the maximum possible score, indicating strong overall acceptance of the environment.

Integration within Moodle may have contributed to this result. Students accessed content, activities, assessments, analytics, recommendations, and decision functions through the same environment. They did not need to move between unrelated platforms or repeatedly transfer information manually.

The dashboard also presented information closely connected to current course requirements. Progress, incomplete tasks, recurring errors, and recommended actions had immediate relevance. Students tend to value dashboards when they provide personalized recommendations and meaningful information about progress, while decontextualized comparisons may be perceived as less useful (Rets et al., 2021).

The result is also consistent with research showing that university students expect learning analytics to support planning, organization, self-assessment, personalized analysis, and adaptive recommendations (Schumacher & Ifenthaler, 2018). The custom plugin addressed these expectations through its progress, diagnosis, and recommendation functions.

Trust may have been supported by explainability and student choice. Students could identify which performance patterns contributed to risk and were not required to follow the recommendation automatically. However, the total questionnaire score does not establish which particular dimension received the strongest evaluation because dimensional scores were unavailable in the main dataset.

Satisfaction should not be treated as equivalent to effectiveness. Students may prefer an easy system that produces little educational benefit, while an effective intervention may require effort and reflection. The present satisfaction result is more meaningful because it was accompanied by achievement, self-regulation, decision-making, and behavioral differences.

17.7 Integrated Interpretation of the Outcomes

The five outcomes form a coherent explanatory pattern. The dashboard increased the visibility of progress and difficulty. Diagnostic rules helped interpret probable causes. Recommendations supplied feasible alternatives. Student-controlled choice converted the information into an academic decision. Implementation and follow-up enabled evaluation and adaptation.

This sequence can explain the relationship between the principal and supporting outcomes. Improved self-regulation may have enabled students to organize learning and monitor progress more effectively. Improved academic decision-making may have enabled them to select more appropriate responses. These actions may then have contributed to stronger achievement.

The digital learning-record scores support the behavioral enactment of this sequence, while usability and satisfaction indicate that students generally accepted the interface through which it operated. The convergence of these measures is more informative than any single outcome considered independently.

The results also suggest that the educational value of AI-supported learning analytics depends on the surrounding learning design. Artificial intelligence did not replace instructional content, formative assessment, feedback, or instructor support. It organized available evidence and differentiated possible responses within an existing course structure.

This interpretation aligns with the argument that learning analytics interventions include the surrounding frame of activities through which students encounter and use analytical information, not merely the analytical tool itself (Wise, 2014). The treatment effect should therefore be attributed to the integrated environment rather than to the fuzzy inference calculation alone.

17.8 Interpretation of Large Effect Sizes

The effect sizes were consistently very large. Hedges' g ranged from 2.11 for digital learning-record behaviors to 3.01 for achievement. These values indicate substantial separation between the groups within the available dataset.

Several design features may have contributed. The intervention operated repeatedly over ten weeks, the conditions were clearly differentiated, the plugin was closely aligned with the dependent variables, and the course contained frequent practical activities and decisions. First-level students may also have possessed considerable scope for developing independent learning practices.

The magnitude may additionally reflect contextual and measurement characteristics. The study was conducted in one course at one faculty, and the instruments were developed specifically for the intervention. The control-group gain scores also displayed substantially smaller variability than the experimental-group gains, contributing to large, standardized differences.

The large effects should therefore be interpreted as study-specific estimates rather than expected values for every implementation of learning analytics. Replication with other institutions, courses, cohorts, and independently developed measures is necessary before stable population-level conclusions can be drawn.

This caution is consistent with reviews showing that learning analytics research contains substantial technological promise but uneven evidence concerning direct learning effects (Viberg et al., 2018). Strong findings should stimulate replication rather than justify unqualified generalization.

18. Educational and Practical Implications

18.1 Implications for Learning Analytics Design

Learning analytics should be designed concurrently with course content, activities, and assessment. Indicators should correspond to intended learning processes, and recommendations should lead to actions available within the course.

Institutions should avoid dashboards that simply display all available data. Information should be selected according to its educational relevance. Each displayed indicator should answer a defined learner question, such as whether progress is adequate, where difficulty is concentrated, or which action may be appropriate.

Descriptive information should be connected progressively to diagnosis, prediction, and recommendation. However, prescriptive output should remain open to human evaluation rather than being presented as an infallible instruction.

18.2 Implications for Supporting Self-Regulated Learning

Student-facing analytics should support the complete regulatory cycle:

- goals and planning before learning;
- strategy use and monitoring during learning;
- feedback interpretation after performance;
- corrective action; and
- reflective evaluation.

Providing a dashboard without opportunities to act is unlikely to produce strong regulatory development. Course design should include remedial resources, alternative strategies, opportunities for reassessment, help-seeking channels, and reflective prompts.

Students should also receive orientation concerning how to interpret dashboard indicators. Without analytics literacy, learners may draw inaccurate conclusions from time, activity, or comparative information.

18.3 Implications for Academic Decision-Making

Learning environments should present alternative actions rather than one compulsory recommendation. Students should be required to compare alternatives and explain the evidence supporting their final decision.

The system should distinguish between accepting a recommendation and understanding it. A student who follows automated instruction without evaluation may complete a suitable task but demonstrate limited decision-making development.

Decision follow-up is also necessary. Environments should show whether the selected action produced improvement and prompt students to revise ineffective decisions.

18.4 Implications for Teacher Education

Teacher-education programs should include competencies related to:

- interpreting learning data;
- evaluating AI-generated outputs;
- recognizing uncertainty and algorithmic limitations;
- selecting evidence-informed educational actions;
- protecting learner privacy;
- identifying possible bias; and
- maintaining human responsibility for educational decisions.

Prospective teachers should experience analytics as learners and examine them critically as future professionals. This dual perspective can support responsible use in subsequent teaching practice.

18.5 Implications for Faculty Members

Faculty members require preparation in both technical and pedagogical aspects of learning analytics. Training should not focus solely on operating dashboards. It should address indicator interpretation, intervention design, recommendation quality, ethical responsibilities, and evaluation of student responses.

Instructors should remain involved in determining the rules connecting learning patterns with support actions. A technically generated recommendation may be inappropriate when it is disconnected from course objectives or task requirements.

18.6 Implications for Moodle Development

Moodle plugins intended to support learning should integrate:

- completion data;
- assessment results;
- recurring errors;
- resource use;
- timing;
- feedback responses;
- decisions; and
- subsequent change.

The system should preserve auditability by recording which indicators produced each risk classification and recommendation. This record supports transparency, debugging, and educational review.

18.7 Ethical and Data-Governance Implications

Institutions should establish clear policies defining:

- the educational purposes of analytics;
- data collected and excluded;
- authorized users;
- retention periods;
- procedures for anonymization;
- uses of risk classifications;
- students' rights to understand analytical outputs; and
- processes for challenging inaccurate recommendations.

The use of AI-supported learning analytics should preserve human oversight and avoid using predictions as deterministic labels. UNESCO's ethical framework emphasizes transparency, fairness, accountability, privacy, and human responsibility in the design and use of artificial intelligence (UNESCO, 2021).

Risk information should be used to offer support, not to stigmatize students or reduce educational opportunities. Learners should be treated as participants in analytics-supported decisions rather than as passive data subjects.

19. Limitations

The findings should be interpreted in light of several methodological, contextual, technological, and measurement limitations.

First, the study was conducted with first-level students from a single faculty at Damietta University. The participants represented a specific educational level, age range, institutional context, and course. The results may not generalize directly to students in other faculties, academic levels, universities, or cultural contexts.

Second, the sample was selected randomly, but the available study information did not establish random allocation of individual students to the experimental and control groups. The design was therefore quasi-experimental. Although the groups demonstrated close baseline equivalence, unmeasured differences between them cannot be excluded completely.

Third, the intervention was implemented within one Technology of Education course. The applied nature of the course, frequency of electronic activities, and availability of authentic academic decisions may have contributed to the strength of the results. Courses with different structures may produce different effects.

Fourth, the self-regulated learning scale was a self-report instrument. Students' responses may have been influenced by memory, self-perception, or socially desirable responding. The digital learning-record rubric provided complementary behavioral evidence, but Moodle records could not capture studying undertaken outside the platform or directly represent cognitive, emotional, and motivational processes.

Fifth, the situational academic decision-making test measured students' selection of the most appropriate response to structured situations. Although the situations were derived from authentic course problems, performance on a situational test cannot represent every decision students may make in less structured real-life circumstances.

Sixth, the digital learning-record rubric was based on one final rating for each participant in the supplied dataset. Separate scores from two independent evaluators were unavailable; consequently, an inter-rater reliability coefficient could not be calculated. The reported alpha coefficient represented internal consistency and should not be interpreted as evidence of agreement between raters.

Seventh, the main dataset contained total self-regulated learning, digital-record rubric, and usability scores. It did not contain calculated scores for every dimension. The study therefore avoided reporting unsupported dimensional comparisons in the main results.

Eighth, the usability and satisfaction questionnaire was administered only to the experimental group because it assessed components exclusive to the AI-supported environment. Its findings indicate positive acceptance but do not provide a direct comparison with control-group perceptions of conventional Moodle.

Ninth, no delayed post-intervention measurement was administered. The findings demonstrate immediate development following the ten-week intervention but cannot establish the long-term retention of self-regulated learning, academic decision-making, or achievement.

Tenth, the plugin used a transparent fuzzy rule-based expert system rather than a machine-learning model trained on a large historical dataset. This decision strengthened explainability and treatment reproducibility but did not determine whether a statistically trained predictive model would provide more accurate risk estimates.

Eleventh, the available dataset did not contain an independent external criterion for every risk prediction. Functional and scenario-based testing demonstrated that the plugin applied its rules as intended, but the study did not report an unsupported numerical estimate of predictive accuracy.

Twelfth, the instruments were developed specifically for the course and study context. Their pilot results demonstrated strong total-score reliability, but the small pilot sample did not permit stable exploratory or confirmatory factor analysis. Further validation with larger and more diverse samples remains necessary.

Thirteenth, the observed effect sizes were very large. They describe the magnitude of differences within the present dataset but should not be assumed to represent typical effects across all AI-supported learning analytics environments. Replication is required before treating them as stable population estimates.

Finally, formal approval from a separate research ethics committee was not required under the institutional procedures applicable to the course-based study at the time of implementation. Future multisite studies collecting extensive behavioral records should seek documented institutional ethics review and establish explicit data-governance arrangements before implementation.

20. Conclusion

The study examined the effect of a Moodle learning environment enhanced with a custom AI-supported learning analytics plugin on self-regulated learning and academic decision-making skills among first-level students at the Faculty of Education, Damietta University.

The experimental group demonstrated significantly greater development than the control group in self-regulated learning, academic decision-making, and achievement in the Technology of Education course. It also obtained higher digital learning-record rubric scores, while experimental-group usability and satisfaction significantly exceeded the neutral criterion.

The educational value of the environment did not arise from data collection or prediction alone. It resulted from the integration of digital learning records with explainable analysis, personalized alternatives, student-controlled decisions, implementation, and reflective follow-up. The plugin transformed assessment, completion, access, error, and performance information into support that students could interpret and use.

Preserving student agency was central to the intervention. The system did not impose a learning pathway or make autonomous grading and progression decisions. Students could accept, modify, or reject recommendations and remained responsible for justifying and evaluating their actions. Artificial intelligence therefore functioned as a source of structured decision support rather than a substitute for human judgement.

The findings indicate that AI-supported learning analytics can contribute to higher education when embedded within a pedagogically grounded course design and connected to actions students can implement. The consistency of achievement, self-report, situational-test, behavioral, and usability evidence strengthens this conclusion.

The results should nevertheless be generalized cautiously. They were obtained within a single course and institution using researcher-developed instruments and an immediate post-intervention assessment. Replication, longer-term measurement, independent behavioral rating, larger validation samples, and documented data-governance procedures are required before wider implementation.

Overall, the study supports a human-centered model of educational artificial intelligence in which analytical systems make learning evidence more intelligible while students retain responsibility for academic decisions. This balance between computational support and learner agency represents the principal contribution of the research.

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