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# THE EFFECT OF EARLY-WARNING ALERT TIMING (PROACTIVE VS. REMEDIAL ALERTS) IN A LEARNING ANALYTICS-BASED PERSONALIZED LEARNING ENVIRONMENT ON EDUCATIONAL TECHNOLOGY STUDENTS' SELF-REGULATED LEARNING AND ACADEMIC DECISION-MAKING

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## ABSTRACT

***This study examined the effect of early-warning alert timing, represented by proactive versus remedial alerts, within a learning analytics-based personalized learning environment, on educational technology students' self-regulated learning and academic decision-making. The study adopted a quasi-experimental design with two experimental groups and pre- and post-measurements. The first experimental group studied the e-learning course through a personalized learning environment based on proactive alerts, whereas the second experimental group studied the same course through the same environment, with the alert pattern modified to provide remedial alerts. The sample consisted of 100 male and female fourth-year students from the Department of Educational Technology, Faculty of Specific Education, Alexandria University. The participants were equally assigned to two experimental groups, with 50 students in each group. Six main measurement instruments were used: the Self-Regulated Learning Skills Scale, the Self-Regulated Learning Performance Rubric within the environment, the Learning Analytics and Alert Response Log, the Academic Decision-Making Scale, the Academic Decision-Making Situational Test, and the Academic Decision Quality Rubric. In addition, four instruments were used for control and interpretive purposes: the Design Standards Checklist for the Personalized Learning Environment, the Alert Scenario Validation Rubric, the Environment Usability and Alert Clarity Questionnaire, and the Semi-Structured Interview Guide. The data were analyzed using the independent-samples t-test to verify pre-measurement equivalence, and analysis of covariance (ANCOVA) to compare the two groups in the post-measurement after controlling for the effect of the pre-measurement. Partial eta squared, Cohen's d, Moodle log analysis, and thematic analysis of the interviews were also used. The results revealed statistically significant differences in favor of the proactive-alerts group across all main***

***measurement instruments, with effect sizes ranging from moderate to large. These findings indicate that providing alerts before actual academic difficulty occurs gives students a better opportunity to plan, manage their time, use support resources, review their performance, and make preventive academic decisions based on learning data, compared with remedial alerts that are provided after difficulty has already appeared. The study recommends that personalized learning environments should incorporate interpretable proactive alert mechanisms linked to clear learning indicators, in ways that support self-regulated learning and academic decision-making without replacing students' responsibility for their own learning.***

**KEYWORDS:** Early Warning of Academic Difficulty; Proactive Alerts; Remedial Alerts; Personalized Learning Environment; Learning Analytics; Self-Regulated Learning; Academic Decision-Making; Moodle; Educational Technology Students.

## 1. INTRODUCTION

In recent years, university education has become increasingly data-driven, not merely because data emerge as a by-product of using digital platforms, but because they have become an essential entry point for understanding, guiding, and improving learning. Digital learning environments are no longer limited to content repositories or tools for managing assignments; rather, they have evolved into environments capable of recording students' interactions, tracking their learning progress, monitoring patterns of participation, and converting these indicators into information that can help both instructors and students make more accurate decisions.

Learning analytics has therefore emerged as one of the influential directions in educational technology, as it enables learning behavior to be interpreted in light of actual data, such as login regularity, interaction time, activity completion, access to support resources, and responses to feedback. However, the educational value of such data is not achieved simply by collecting or displaying it. Rather, this value is realized when data are translated into clear instructional support that helps students understand their current situation and adjust their learning path at the appropriate time (Kleimola et al., 2023; Matcha et al., 2019; Tzimas & Demetriadis, 2022).

This shift has contributed to reconsidering the nature of support provided to students in digital learning environments. Traditional support is often offered after an activity has been completed or after a result has appeared, whereas learning analytics makes it possible to provide more timely and personalized support based on early indicators that reveal potential academic difficulty before it develops into actual failure. This has led to growing interest in early-warning systems, which rely on learning data and performance indicators to identify students at risk and guide them toward appropriate actions. Nevertheless, prediction accuracy alone is not sufficient to ensure improved learning. A student may receive an alert without understanding its cause, or without knowing what action should be taken afterward. For this reason, recent literature emphasizes that the effectiveness of early-warning alerts is closely related to the clarity of the alert, its timing, its interpretability, and its connection to a specific learning action that the student can carry out (Arnold & Pistilli, 2012; Chang et al., 2022; Kubsch et al., 2022).

In the present study, early warning of academic difficulty refers to the use of early digital learning indicators within Moodle, such as login regularity, content access, activity completion, use of support resources, and performance in formative tests. These indicators are not treated as an independent algorithmic model for automated prediction, but as educational rules used to issue alerts that help students understand their learning situation and take appropriate action. Accordingly, the study focuses primarily on the instructional design and pedagogical dimensions of early alerts, rather than on constructing a statistical or machine-learning prediction model.

A personalized learning environment provides an appropriate context for examining the effect of this type of support, as it gives students a higher degree of control over their learning, enables them to monitor their progress, select resources, organize their effort, and respond to alerts according to their actual needs. In this study, the personalized learning environment is not understood merely as a digital platform, but as a flexible learning system built within Moodle. It includes structured content, interactive activities, formative tests, applied tasks, support resources, a learning analytics log, and instructional alerts generated in light of students' behavior and performance within the environment. In this way, the personalized environment becomes a space in which self-directed learning, feedback, learning analytics, and academic decision-making intersect (Awad Elgendy & Aly Khalil, 2021; Alserhan et al., 2023).

This context is particularly important for educational technology students, as the nature of their specialization requires them to engage in complex tasks that go beyond receiving information to include design, analysis, production, and evaluation. In an e-learning course, students in this specialization engage in tasks such as designing learning pathways, developing digital activities, reading progress indicators, interpreting feedback, and evaluating the quality of a learning environment. Such tasks require clear abilities to plan, manage time, use support resources, review performance, and make sequential academic decisions (Haleem et al., 2022). Therefore, academic difficulty in this context does not appear only through low grades; it may emerge early in delayed access to content, failure to complete a preliminary activity, neglecting task instructions, or not using a support resource before completing an activity that requires guidance (Zamiri & Esmaeili, 2022).

Self-regulated learning is one of the central concepts for explaining students' success in personalized learning environments. A self-regulated student does not wait until the final result to discover areas of weakness. Instead, the student sets goals, plans learning, manages time, monitors progress, seeks support when needed, and adjusts strategies in light of feedback. Zimmerman's model emphasizes that self-regulated learning is a cyclical process that includes forethought, performance, and self-reflection, all of which may be strongly affected by the timing of feedback and the nature of the alert provided to the student (Zimmerman, 2002). If the alert arrives early, it may support planning, initiative, and adjustment before weaknesses accumulate. If it arrives after difficulty has occurred, it may play a remedial role in correcting errors and reviewing performance.

Similarly, academic decision-making is closely connected to data-informed learning environments. Students do not need only to know that they are late or that their performance is low; they also need to understand why this has happened, identify the alternatives available to them, anticipate the consequences of each alternative, choose an appropriate action, and then monitor the effect of that decision (Solé-Beteta et al., 2022). Instructional alerts, when designed clearly and without punitive language, can therefore function as a mediator between learning data and student behavior. They do not merely inform the student of a problem, but direct attention to the meaning of the indicator and the possible action that can be taken. Studying the effect of alerts on academic decision-making thus represents an important extension of learning analytics literature, as it shifts attention from merely predicting academic difficulty to developing students' ability to respond to it (Alfredo et al., 2022).

Despite the growing interest in learning analytics and early-warning systems, there remains a need for experimental studies that distinguish between the alert patterns themselves. The question is no longer limited to whether alerts are useful or not; rather, it has become more specific: Is an alert more effective when it is provided before academic difficulty occurs, or when it is provided after difficulty has already appeared? Does this difference in the timing and function of the alert contribute to developing self-regulated learning and academic decision-making? The present study is grounded in this gap. It compares proactive and remedial alerts within a learning analytics-based personalized learning environment, using multiple measurement instruments that combine self-report, actual performance, learning analytics logs, academic decision-making situations, and the quality of academic justification.

## 2. RESEARCH PROBLEM

Although digital learning environments are capable of recording detailed data on students' performance and interactions, these data do not produce a direct educational effect unless they are transformed into guided instructional support that helps students understand their situation and act accordingly. A learning environment may indicate that a student has not accessed the unit content, has not completed a preliminary activity, has not used a support resource, or has obtained a low score on a formative test. Yet these indicators remain of limited value if they remain silent data or reports that students cannot use to adjust their behavior. This creates the need for instructional alerts that connect indicators of academic difficulty with appropriate actions, enabling students to become more aware of their learning path and more capable of making decisions at the right time.

This problem becomes more evident in the e-learning course studied by educational technology students, as the course requires a sequence of applied and analytical tasks. Students need to read instructions, review models, complete activities, use support resources, analyze progress data, and adjust their performance in light of feedback. If support is delayed until the final result appears, the student may have already lost an important opportunity for early adjustment. By contrast, if the student receives a clear indicator before academic difficulty occurs, the student may be able to change the learning plan or use an appropriate support resource before the problem becomes more serious.

The literature indicates that learning analytics can support self-regulated learning when students are provided with feedback that is understandable and usable, and when such feedback helps them plan, monitor, reflect, and take appropriate action (Kleimola et al., 2023; Matcha et al., 2019; Tzimas & Demetriadis, 2022). Studies on early-warning systems also emphasize that personalized and guided intervention may be more effective when it is linked to clear performance indicators, provided at the appropriate time, and expressed in language that avoids punishment or labeling (Chang et al., 2023; Kubsch et al., 2023). Nevertheless, there remains a need to examine the effect of alert timing itself: Are proactive alerts more supportive of self-regulation and decision-making because they precede academic difficulty, or are remedial alerts sufficient because they are provided after students encounter a visible problem?

Accordingly, the research problem of the present study is defined as the need to examine the effect of early-warning alert timing—proactive alerts versus remedial alerts—within a learning analytics-based personalized learning environment on educational technology students' self-regulated learning and academic decision-making.

## 3. RESEARCH OBJECTIVES

The present study aimed to examine the effect of early-warning alert timing—proactive alerts versus remedial alerts—within a learning analytics-based personalized learning environment on educational technology students' self-regulated learning and academic decision-making. This main objective was translated into the following procedural objectives:

1. To measure the effect of early-warning alert timing on the development of self-regulated learning as reflected in the Self-Regulated Learning Skills Scale.
2. To examine the effect of early-warning alert timing on students' actual performance of self-regulated learning skills within the personalized learning environment.
3. To analyze the effect of early-warning alert timing on students' actual learning behavior and responses to alerts, as reflected in the Moodle Learning Analytics Log.
4. To measure the effect of early-warning alert timing on the development of academic decision-making, as reflected in the Academic Decision-Making Scale.
5. To examine the effect of early-warning alert timing on students' performance in academic decision-making situations.
6. To measure the effect of early-warning alert timing on the quality of academic decision-making in terms of understanding the situation, using data, selecting an appropriate decision, providing logical justification, anticipating consequences, and following up and adjusting the decision.
7. To interpret the quantitative results in light of students' experiences, as revealed through semi-structured interviews conducted after the experimental treatment.

## 4. SIGNIFICANCE OF THE STUDY

The theoretical significance of this study lies in its treatment of a precise gap in the literature on learning analytics and personalized learning environments: the effect of alert timing and function in supporting self-regulated learning and academic decision-making. The study does not merely examine the effect of the presence of alerts within the environment. Rather, it compares two different alert patterns: a proactive pattern provided before actual academic difficulty occurs, and a remedial pattern provided after difficulty has appeared. This distinction allows for a deeper understanding of the relationship among learning data, feedback, and students' self-regulatory and decision-making behaviors.

The study also contributes to broadening the view of early-warning systems from tools used to identify students at risk to tools that help students develop the ability to read their own data, understand their learning situation, and take appropriate action. In doing so, the study connects three important lines of inquiry in educational technology: learning analytics, self-regulated learning, and academic decision-making.

The practical significance of the study is reflected in the presentation of an applicable model within Moodle for designing a personalized learning environment that includes instructional alerts linked to specific learning indicators. The findings may benefit e-course designers, faculty members, and learning management system developers by emphasizing that an effective alert should not be a generic message. Rather, it should be linked to student behavior, clearly explain the reason for the alert, specify the action to be taken, and be designed in a way that supports student autonomy without increasing anxiety or stigmatization.

The significance of the study is further strengthened in the context of preparing educational technology students. These students do not use digital learning environments only as learners; they are also expected to become future designers, developers, and evaluators of such environments. Therefore, their exposure to a personalized learning environment based on learning analytics and instructional alerts may not only improve their current learning, but also deepen their professional understanding of how to design data-informed digital support.

## 5. RESEARCH QUESTIONS

The present study sought to answer the following main question:

**What is the effect of early-warning alert timing—proactive alerts versus remedial alerts—within a learning analytics-based personalized learning environment on educational technology students' self-regulated learning and academic decision-making?**

This main question was further divided into the following sub-questions:

1. What is the effect of early-warning alert timing on the development of self-regulated learning among educational technology students, as measured by the Self-Regulated Learning Skills Scale?
2. What is the effect of early-warning alert timing on educational technology students' actual performance of self-regulated learning skills, as measured by the Self-Regulated Learning Performance Rubric within the environment?
3. What is the effect of early-warning alert timing on students' actual learning behavior and responses to alerts, as reflected in the Moodle Learning Analytics Log?
4. What is the effect of early-warning alert timing on the development of academic decision-making among educational technology students, as measured by the Academic Decision-Making Scale?
5. What is the effect of early-warning alert timing on educational technology students' performance in academic decision-making situations?
6. What is the effect of early-warning alert timing on the quality of academic decision-making among educational technology students, as measured by the Academic Decision Quality Rubric?
7. How do students' experiences, as revealed through semi-structured interviews, explain the effect of proactive and remedial alerts on self-regulated learning and academic decision-making?

## 6. RESEARCH HYPOTHESES

In light of the research problem and questions, the following hypotheses were formulated:

1. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Self-Regulated Learning Skills Scale, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.
2. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Self-Regulated Learning Performance Rubric within the personalized learning environment, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.
3. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the Learning Analytics and Alert Response Log within Moodle, in favor of the proactive-alerts group.
4. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision-Making Scale, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.
5. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision-Making Situational Test, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.
6. There are statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision Quality Rubric, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.
7. The results of the semi-structured interviews contribute to explaining the quantitative differences between the two research groups by revealing differences in students' experiences in understanding alerts, responding to them, and using them to regulate learning and make academic decisions.

## 7. DELIMITATIONS OF THE STUDY

The present study was delimited to fourth-year students in the Department of Educational Technology, Faculty of Specific Education, Alexandria University, during the first semester of the academic year 2022/2023. The application was also delimited to the e-learning course and to a personalized learning environment based on Moodle and learning analytics.

The independent variable was early-warning alert timing, represented by two patterns: proactive alerts and remedial alerts. The dependent variables were self-regulated learning and academic decision-making, as measured by the main research instruments. The generalizability of the findings is therefore related to the extent to which other educational contexts are similar to the context of the present study in terms of the nature of the sample, the course, the platform, and the mechanism used to design alerts.

Technically, the study was delimited to the use of learning indicators and alert rules within Moodle. It did not aim to build an independent machine-learning model for predicting academic difficulty or to test its classification accuracy. Accordingly, the findings should be interpreted in light of the educational effect of alert timing and function, rather than in light of the efficiency of an algorithmic prediction model.

## 8. OPERATIONAL DEFINITIONS

### *Early-Warning Alert Timing*

Early-warning alert timing is operationally defined in the present study as the way in which the personalized learning environment uses students' learning data and performance indicators within Moodle to generate guided instructional alerts. In this study, it does not refer to the construction of an independent automated prediction model. Rather, it refers to the use of educational rules based on early or actual indicators of academic difficulty, whereby alerts appear either before actual difficulty occurs in the form of proactive alerts, or after difficulty has occurred in the form of remedial alerts.

### *Proactive Alerts*

Proactive alerts are operationally defined in the present study as instructional messages that appear to students before actual academic difficulty occurs, based on early risk indicators, such as not accessing the unit content, not completing a preliminary activity, or not reviewing the task model before implementation. These alerts aim to help students prevent academic difficulty by taking early action.

### *Remedial Alerts*

Remedial alerts are operationally defined in the present study as instructional messages that appear to students after actual academic difficulty has occurred, such as obtaining a low score on a formative test, failing to submit an assignment, showing weak performance in an applied activity, or misinterpreting progress data. These alerts aim to help students address the difficulty and correct their learning path.

### *Learning Analytics-Based Personalized Learning Environment*

A learning analytics-based personalized learning environment is operationally defined in the present study as a digital learning environment designed within Moodle for studying the e-learning course. It includes structured learning units, interactive activities, formative tests, applied tasks, support resources, progress indicators, a learning analytics log, and instructional alerts generated in light of students' behavior and performance within the environment.

### *Self-Regulated Learning*

Self-regulated learning is operationally defined in the present study as the student's ability to set learning goals, plan tasks, manage time, organize the digital learning environment, use appropriate learning strategies, monitor progress, seek support, persist when facing difficulty, evaluate performance, and adjust the learning path within the personalized learning environment.

### *Academic Decision-Making*

Academic decision-making is operationally defined in the present study as the student's ability to diagnose an academic situation, gather relevant information, analyze available alternatives, anticipate the consequences of a decision, choose the most appropriate academic action, justify that action, and monitor its effect within the personalized learning environment.

### *Learning Analytics and Alert Response Log*

The Learning Analytics and Alert Response Log is operationally defined in the present study as a digital record based on Moodle data, used to measure students' actual learning behavior. This includes login regularity, task completion, interaction with content, opening alerts, response speed, use of support resources, and improvement after receiving an alert.

## 9. THEORETICAL FRAMEWORK AND PREVIOUS STUDIES

The present study is grounded in the intersection of three major lines of inquiry in educational technology: learning analytics-based personalized learning environments, early-warning systems and instructional alerts, and the development of self-regulated learning and academic decision-making. This intersection is significant because contemporary digital learning environments no longer merely deliver content or measure achievement at the end of learning. They are increasingly capable of tracking performance indicators while learning is taking place and transforming these indicators into feedback or alerts that may influence students' behavior either before academic difficulty escalates or after it has appeared.

Accordingly, the theoretical framework of this study does not treat alerts as technical messages. Rather, it views them as a pedagogical mechanism that can reshape students' relationship with their own learning data and support their capacity for planning, monitoring, self-intervention, and appropriate academic decision-making.

### *9.1 Learning Analytics-Based Personalized Learning Environments*

The personalized learning environment is one of the concepts that has redefined the learner's role within digital environments. Students are no longer passive recipients of a fixed instructional pathway; they have become active participants in constructing their learning paths, selecting resources, organizing activities, and monitoring progress. Such environments are based on enabling learners to exercise relative control over the elements of their learning, while providing tools that help them access content, interact with activities, seek support, and review their performance.

However, this degree of control does not mean leaving students without guidance. An effective personalized learning environment requires a careful balance between autonomy and support. It should give students space to make decisions while also providing clear indicators that help them understand the consequences of their learning decisions (Dabbagh & Kitsantas, 2012; Tur et al., 2022).

A personalized learning environment becomes more powerful when learning analytics is integrated into it. Learning analytics makes students' behavior within the environment observable and interpretable by tracking data such as access to the environment, content views, activity completion, assignment submission, performance in formative tests, use of support resources, and responses to alerts. These data make it possible to build a more accurate picture of students' learning than relying solely on final grades. Recent reviews have shown that personalized learning supported by learning analytics can contribute to improving learning pathways, providing more appropriate feedback, and supporting instructional interventions connected to learners' actual needs (Ning et al., 2023; Tzimas & Demetriadis, 2022).

In the context of the present study, the personalized learning environment is not used merely as a platform for delivering the e-learning course. Rather, it is used as a data-informed learning structure. It includes organized units, interactive activities, formative tests, applied tasks, support resources, a learning analytics log, and instructional alerts generated on the basis of actual indicators of students' behavior within Moodle. This is consistent with the procedural design of the study, which indicates that the environment was built within Moodle to enable the tracking of logins, activity completion, test performance, assignment submission, alert opening, and use of support resources. The experimental difference between the two groups was limited to the alert pattern, while content, activities, time, and support resources were held constant.

This design is particularly important for educational technology students, as their specialization is closely related to digital, design-based, and analytical tasks. In the e-learning course, students do not only need to understand concepts; they must also deal with instructions, models, tools, resources, and progress indicators. Thus, the personalized learning environment becomes a practical space for developing both professional and cognitive skills. Students learn within a digital environment while simultaneously gaining direct experience of how digital learning environments can be designed on the basis of support, feedback, and analytics.

### *9.2 Learning Analytics and Early Warning of Academic Difficulty*

Early warning of academic difficulty refers to the use of students' learning indicators to identify the likelihood that they may encounter academic difficulty before it develops into visible failure or severe delay in achievement. This direction emerged from the need to move beyond delayed intervention, which occurs only after performance has declined, toward more timely intervention that benefits from the data generated by digital environments during learning. Early-warning systems are among the most prominent applications of learning analytics because they attempt to connect educational data with a pedagogical action, such as alerting students, directing them to a support resource, or informing the instructor that a risk requires follow-up (Arnold & Pistilli, 2012; Chang et al., 2023).

Nevertheless, early warning should not be understood as a purely technical or automated process. A system may succeed in identifying risk indicators but fail to produce an educational effect if these indicators are not translated into meaningful information for students. Therefore, recent literature distinguishes between prediction accuracy on the one hand and the effectiveness of prediction-based intervention on the other. A predictive model may be statistically accurate but pedagogically limited if it provides a general, vague, delayed, or non-actionable alert. In this sense, the quality of the alert constitutes a critical link between data analysis and learning improvement (Kubsch et al., 2023; Matcha et al., 2019).

Chang et al. indicated that early-warning systems in higher education are more effective when they are associated with personalized interventions. In other words, the system should not simply identify students who are at risk; it should also provide support that is appropriate to the nature and source of that risk. This aligns with the contemporary view that learning analytics should not be confined to predicting performance, but should be used to build learning environments that are more responsive to students' needs and better able to support them at the right time (Chang et al., 2023; Ning et al., 2023).

In the present study, early warning of academic difficulty was operationalized through practical indicators within Moodle, such as not accessing the unit content, not completing a preliminary activity, not opening a support resource, obtaining a low score on a formative test, or failing to submit an assignment. These indicators were not used to classify or judge students. Rather, they were used to guide students toward a specific learning action. In this sense, early warning in the present study is inseparable from instructional design, as it does not merely identify risk but connects it with an alert message, a support resource, and a follow-up indicator.

### *9.3 Proactive Alerts and Remedial Alerts*

Alert pattern represents the independent variable in the present study and consists of two forms: proactive alerts and remedial alerts. Proactive alerts refer to messages that appear to students before actual academic difficulty occurs, based on early risk indicators. They do not wait for a low score or task failure; rather, they intervene when learning data suggest that difficulty is likely to occur soon. Examples include not opening instructions before an assignment deadline or not reviewing an applied example before completing an activity. In this way, proactive alerts serve a preventive function, as they give students an opportunity to adjust their behavior before a potential problem turns into a negative outcome (Bañeres et al., 2020; Embarak & Hawarna, 2022).

Remedial alerts, by contrast, appear after actual academic difficulty has occurred, such as obtaining a low test score, failing to submit an assignment, or demonstrating weak performance in an applied activity. They serve a corrective function by helping students understand the problem after it becomes visible and directing them toward an action that addresses the area of weakness. This does not mean that remedial alerts are inherently less important. They may be appropriate when students need clear evidence that a problem exists. However, their timing makes them pedagogically different because they arrive after the student has already lost part of the available time, made an error, or received a low result (Hassan, 2023).

This difference in timing leads to a difference in instructional function. A proactive alert supports preventive decision-making because it directs students to adjust their learning path before academic difficulty occurs. A remedial alert, on the other hand, supports corrective decision-making after the problem has appeared. Accordingly, proactive alerts may be more strongly associated with planning, time management, and early help-seeking, whereas remedial alerts may be more closely associated with self-evaluation, error analysis, and strategy adjustment after difficulty becomes visible. For this reason, it is not sufficient to study alerts as a single broad category. The timing of the alert may change the way students respond, the type of decision they make, and the self-regulatory skill that is activated (Akçapınar et al., 2019; Cleland et al., 2010; Skittou et al., 2023).

### *9.4 Self-Regulated Learning in Digital Environments*

Self-regulated learning is a central concept for explaining students' learning in digital environments, as these environments provide students with greater freedom while simultaneously requiring a higher capacity to control and manage their own learning. Self-regulated learning includes a set of processes that students practice before, during, and after learning, such as goal setting, planning, time management, strategy use, comprehension monitoring, help-seeking, persistence, and self-evaluation. According to Zimmerman, self-regulated students do not approach learning as a series of imposed tasks; rather, they treat it as a process that they plan, monitor, and adjust in light of their performance and the outcomes of their actions (Zimmerman, 2002).

The importance of self-regulated learning increases in personalized learning environments because these environments transfer part of the responsibility for managing learning to students. When students are able to choose the time, resources, sequence of activities, and ways of responding to feedback, their success becomes closely linked to their ability to regulate learning internally and externally. Studies on e-learning and recent reviews have indicated that students with higher levels of self-regulation are better able to benefit from digital environments because they use performance indicators and feedback actively, rather than treating them as information detached from their learning behavior (Barnard et al., 2009; Luo & Zhou, 2022).

Learning analytics offers an important opportunity to support self-regulated learning because it makes some learning processes visible to students. A student may not realize that their login pattern is irregular, that their interaction time is lower than expected, or that they have not reviewed a support resource before completing a task. However, when the environment displays progress indicators or sends a clear alert, the student becomes more able to compare their behavior with the requirements of the learning situation. Matcha et al. showed that learning analytics dashboards can support self-regulated learning when they are explicitly connected to its phases and strategies, but their impact may remain limited if they merely display data without guidance or interpretation (Matcha et al., 2019).

Tzimas and Demetriadis further emphasized that learning analytics-based guidance can improve self-regulated learning skills when it provides students with clear support on how to interpret data and use it to enhance performance. Similarly, Kleimola et al. indicated that students in higher education value learning analytics when it helps them monitor their progress, identify areas requiring improvement, and reflect on their learning behavior through clear indicators (Kleimola et al., 2023; Tzimas & Demetriadis, 2022).

In the present study, self-regulated learning was not measured through self-report alone. It was measured through the Self-Regulated Learning Skills Scale, the Performance Rubric within the environment, and the Learning Analytics and Alert Response Log. This integration is important because self-regulated learning may appear in students' perceptions of their abilities, in their actual behavior within the environment, and in the digital traces recorded in Moodle.

### *9.5 Academic Decision-Making in Personalized Learning Environments*

Academic decision-making represents a natural extension of self-regulated learning. Self-regulated students do not merely monitor their performance; they use that monitoring to decide what should be done next. Academic decision-making refers to students' ability to diagnose a learning situation, gather relevant information, analyze alternatives, anticipate possible consequences, select the most appropriate academic action, and then monitor and adjust the decision when necessary. This ability becomes especially important in personalized learning environments, where students encounter multiple situations that require decisions: Should they review the content? Should they access a support resource? Should they try again? Should they seek help? Should they change their learning strategy? Should they begin the task now or postpone it? (Caputo et al., 2022; Farber, 2023).

The literature suggests that the quality of academic decision-making is closely related to the quality of information available to students and their ability to interpret it. A student who sees a clear indicator of delay or low performance is in a better position to make an appropriate decision than a student who only discovers the problem after the task has ended. Yet data alone are not sufficient. Students need to understand what the indicator means, connect it to a possible cause, and then select an action that matches that cause. Instructional alerts can therefore play a mediating role between data and decision-making, as they transform abstract data into a meaningful message and a proposed action (Vietze et al., 2022).

In the context of the present study, academic decision-making is not understood as a general ability separated from the learning environment. Rather, it is viewed as a practice connected to the situations students encounter within the e-learning course. A student may receive an alert indicating that they have not opened the activity instructions, that their score on a short quiz is low, or that their interpretation of progress indicators is inaccurate. In each situation, the student needs to read the data, diagnose the problem, analyze the available alternatives, and choose an appropriate action. For this reason, the instruments used to measure academic decision-making in this study were designed to combine a self-report scale, a situational test, and a decision quality rubric. This ensured that measurement was not limited to what students believed they could do, but extended to what they actually chose and how they justified their choices.

### *9.6 Related Previous Studies*

Several studies have examined the relationship between learning analytics and self-regulated learning in higher education. Matcha et al. conducted an analysis of empirical studies on learning analytics dashboards from the perspective of self-regulated learning. Their review indicated that many dashboards aim to support students' awareness of progress, but they are not always clearly connected to self-regulated learning strategies or theoretical phases. This finding confirms that displaying data is not sufficient, and that the design of guidance accompanying the data is a key condition for transforming analytics into actual learning support (Matcha et al., 2019).

In a more recent study, Tzimas and Demetriadis examined the effect of learning analytics-based guidance on students' self-regulated learning skills, performance, and satisfaction. They concluded that stronger and clearer guidance can contribute to improving some dimensions of self-regulated learning, such as time management, metacognitive activities, and help-seeking. This study supports the premise of the present research: learning analytics need to be offered in the form of guided support, rather than as abstract indicators or general reports (Tzimas & Demetriadis, 2022).

Kleimola et al. also examined the role of learning analytics in enhancing self-regulated learning among higher education students through a qualitative study. They showed that students value analytics when it helps them understand their progress and identify clear steps for improvement. This finding intersects with the present study, which does not focus on the analytics dashboard itself, but on the alert generated from learning indicators and on the ability of that alert to prompt students toward a specific self-regulatory or decision-making action (Kleimola et al., 2023).

In the field of early-warning systems, the study by Arnold and Pistilli is considered one of the foundational studies that demonstrated the possibility of using learning analytics to provide early signals to students and instructors regarding potential academic risk. Despite the importance of this study, subsequent literature has moved beyond the idea of a general signal toward the need to design interventions that are more personalized and more closely connected to students' learning contexts. Chang et al. reinforced this direction by developing an early-warning system with personalized interventions to improve the outcomes of at-risk students in higher education, based on the idea that personalized support is more useful than a general warning (Arnold & Pistilli, 2012; Chang et al., 2023).

Kubsch et al. suggested that building early-warning systems that support self-regulated learning requires a precise understanding of the relationship between digital learning indicators and the regulatory processes students perform. Not every digital indicator necessarily reflects academic difficulty, and not every alert necessarily leads to better learning. Therefore, early-warning systems should be built on a pedagogical logic that connects data, the potential problem, the type of intervention, and the expected student response (Kubsch et al., 2023).

With regard to personalized learning environments, recent reviews have shown that these environments provide an appropriate context for developing self-regulated learning, but they require careful design that supports learners in planning, monitoring, and evaluation. Cenka et al. indicated that personalized learning environments can support self-regulated learning strategies when they provide clear tools for organizing resources, tracking progress, and receiving feedback. Tur et al. also emphasized the close relationship between personalized learning environments and self-regulated learning, while noting that this relationship does not occur automatically; rather, it depends on the quality of environmental design and the level of support provided to students (Cenka et al., 2022; Tur et al., 2022).

Despite the importance of these studies, they leave a clear research gap. Some focused on learning analytics dashboards, others addressed early-warning systems in general, and others examined personalized learning environments and self-regulated learning. However, few studies have experimentally compared proactive and remedial alerts within a personalized learning environment and connected this comparison to two complementary variables: self-regulated learning and academic decision-making. Moreover, many studies measure outcomes through self-report scales or general academic performance, whereas the present study uses a more diverse set of instruments, including self-report, actual performance, digital behavior within Moodle, academic decision-making situations, decision quality, and semi-structured interviews.

### *9.7 Research Gap and Position of the Current Study*

The preceding review shows that recent literature agrees on the importance of learning analytics in supporting personalized learning and self-regulated learning, as well as on the value of early-warning systems in identifying indicators of academic difficulty and intervening at the appropriate time. However, it does not yet provide a sufficient answer to a more specific question: Which has a stronger effect on developing self-regulated learning and academic decision-making—the alert that reaches students before academic difficulty occurs, or the alert that reaches them after difficulty has already appeared? This question is not merely about the presence of support; rather, it concerns its timing, function, and the type of decision it prompts students to make.

The present study is therefore distinctive in that it examines early-warning alert timing as a design variable within a learning analytics-based personalized learning environment. It does not compare a digital environment with a traditional one, nor does it compare one platform with another. Instead, it compares two alert patterns within the same environment, while controlling for content, activities, support resources, time, and measurement instruments. This control makes it more possible to attribute differences to the alert pattern itself, rather than to differences in content or teaching method.

The study is also distinctive in its examination of the effect of alerts on two interrelated variables: self-regulated learning and academic decision-making. Self-regulated learning represents students' ability to manage their own learning, whereas academic decision-making represents their ability to translate that management into practical choices in specific situations. Thus, the study does not merely ask whether students improved. It asks how the alert pattern was reflected in their perceptions, performance, digital behavior, decisions, and the quality of their justifications for those decisions.

Based on the theoretical review and the identified research gap, the current study proposes a conceptual model that explains how early-warning alert timing may influence students' learning behavior. The model assumes that alerts do not affect learning automatically; rather, their effect is mediated by students' interpretation of Moodle learning indicators and their subsequent engagement in self-regulated learning and academic decision-making processes.

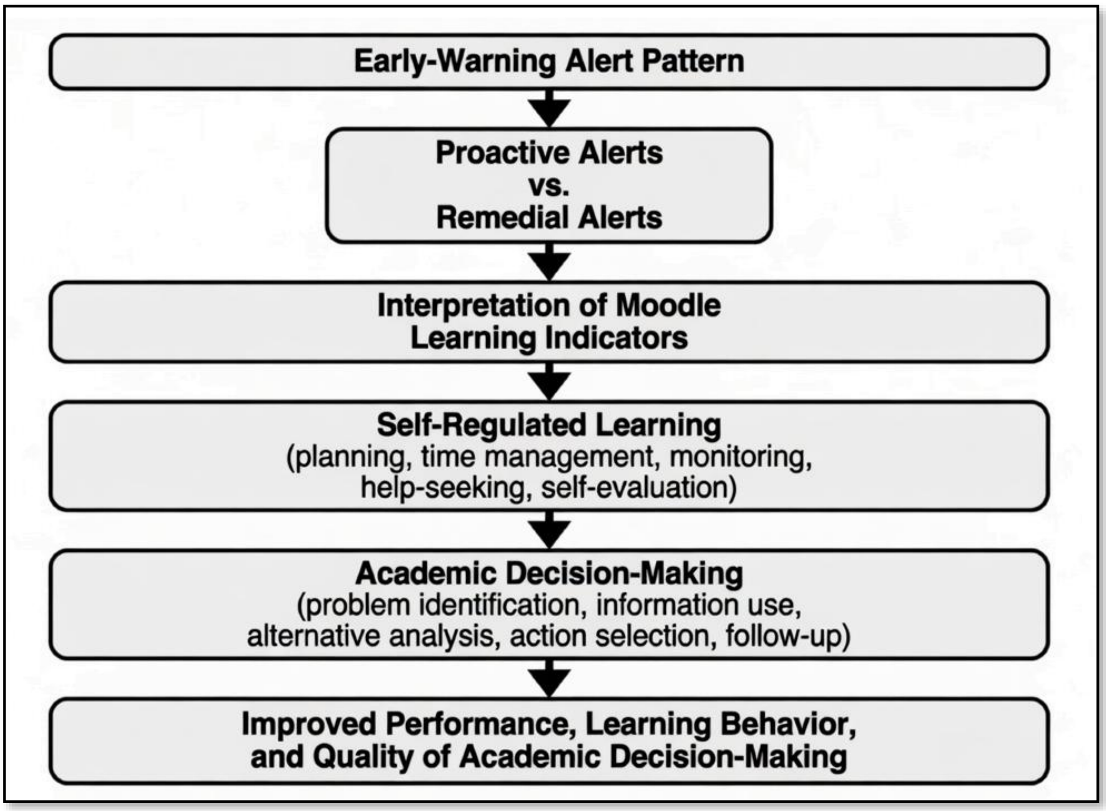


*Figure 1. Conceptual Model of the Study.*

As shown in Figure 1, alert timing is positioned as a design variable within the learning analytics-based personalized learning environment. Proactive and remedial alerts are expected to influence students' interpretation of learning indicators, which in turn supports self-regulated learning processes, such as planning, time management, monitoring, help-seeking, and self-evaluation. These processes are then expected to enhance academic decision-making and improve students' performance, learning behavior, and quality of academic decisions.

This model does not assume that alerts operate automatically. Rather, it assumes that their effect passes through students' understanding of the meaning of the indicator and their response to it. A proactive alert may expand the student's decision space because it arrives before academic difficulty occurs, whereas a remedial alert may narrow that space because it arrives after the problem has already appeared. This is the basis for the experimental test adopted in the present study.

## 10. RESEARCH METHODOLOGY AND PROCEDURES

The present study adopted the quasi-experimental method, as it was the most appropriate approach for the nature of the research problem. The study did not merely describe the current use of digital learning environments; rather, it sought to examine the effect of a specific instructional treatment within a learning analytics-based personalized learning environment. This treatment was represented by the difference in early-warning alert timing: proactive alerts versus remedial alerts. This choice was appropriate because the study compared two experimental groups exposed to the same learning environment, the same content, the same activities, and the same support resources, with the only difference being the independent variable represented by alert timing.

The use of a quasi-experimental design was consistent with the nature of educational technology research, which often examines the effect of a design variable within an authentic educational environment where full control over all variables, as in laboratory experiments, is difficult. To control this design, the platform, e-learning course, instructional units, duration, activities, formative tests, performance tasks, support resources, and measurement instruments were unified. Thus, the essential difference between the two groups was attributable to the timing of the alert and its educational function. The research methodology and procedures confirmed that the experiment was designed so that both groups studied the e-learning course within a Moodle-based personalized learning environment, with all learning elements held constant and the difference limited to the alert pattern.

### *10.1 Experimental Design*

The study used a quasi-experimental design based on two equivalent experimental groups with pre- and post-measurements. The first experimental group studied through a personalized learning environment based on proactive alerts, whereas the second experimental group studied through a personalized learning environment based on remedial alerts. The measurement instruments were administered before the treatment to verify the equivalence of the two groups in the research variables. The experimental treatment was then implemented, after which the instruments were administered again to measure the effect of alert timing.

***Table 1. Experimental Design of the Study.***

| Group | Pre-Measurement | Experimental Treatment | Post-Measurement |
|---|---|---|---|
| First experimental group | Administration of the measurement instruments before the treatment | Personalized learning environment based on proactive alerts | Administration of the measurement instruments after the treatment |
| Second experimental group | Administration of the measurement instruments before the treatment | Personalized learning environment based on remedial alerts | Administration of the measurement instruments after the treatment |

This design allowed for a comparison between two forms of support within the same environment, rather than comparing two different environments in which other factors, such as content, activities, or assessment methods, might overlap. Therefore, controlling the environmental elements across the two groups was an essential condition in the present study. The aim was not to examine the effect of Moodle itself or the e-learning course as such, but to examine the effect of alert timing and function on the development of self-regulated learning and academic decision-making.

### *10.2 Research Population and Sample*

The research population consisted of fourth-year students in the Department of Educational Technology, Faculty of Specific Education, Alexandria University, during the first semester of the academic year 2022/2023. The sample consisted of 100 male and female students who were assigned to two equivalent experimental groups: 50 students in the proactive-alerts group and 50 students in the remedial-alerts group. After identifying the members of the sample, students were assigned to the two experimental groups using simple random assignment, while ensuring the pre-treatment equivalence of the two groups in self-regulated learning and academic decision-making.

***Table 2. Distribution of the Research Sample Across the Two Experimental Groups.***

| Group | Treatment Pattern | Number of Students |
|---|---|---|
| First experimental group | Proactive alerts | 50 |
| Second experimental group | Remedial alerts | 50 |
| Total | – | 100 |

To provide a more controlled description of the research sample, the general characteristics of the participants were recorded in terms of gender, age, and prior experience using Moodle and e-learning. This was done to ensure that the participants had the minimum level of technical experience required to interact with the learning analytics-based personalized learning environment, and to reduce the possibility that the results would be affected by difficulty using the platform or by limited prior experience with e-learning. Table 3 presents the characteristics of the study participants.

***Table 3. Characteristics of the Study Participants (N = 100).***

| Variable | Proactive-Alerts Group | Remedial-Alerts Group | Total |
|---|---|---|---|
| Number of participants | 50 | 50 | 100 |
| Males | 22 | 24 | 46 |
| Females | 28 | 26 | 54 |
| Mean age | 21.4 | 21.6 | 21.5 |
| Standard deviation of age | 0.85 | 0.92 | 0.88 |
| Had previously used Moodle | 50 | 50 | 100 |
| Had not previously used Moodle | 0 | 0 | 0 |
| Had prior experience with e-learning | 50 | 50 | 100 |
| Had no prior experience with e-learning | 0 | 0 | 0 |

Table 3 shows that the research sample consisted of 100 male and female fourth-year students from the Department of Educational Technology, with 50 students in the proactive-alerts group and 50 students in the remedial-alerts group. The table also indicates that gender distribution was relatively similar across the two groups. The proactive-alerts group included 22 male and 28 female students, whereas the remedial-alerts group included 24 male and 26 female students, for a total of 46 male and 54 female students in the overall sample.

The table also shows clear similarity in the participants' mean ages. The mean age in the proactive-alerts group was 21.4 years, with a standard deviation of 0.85, while the mean age in the remedial-alerts group was 21.6 years, with a standard deviation of 0.92. The overall mean age of the sample was 21.5 years, with a standard deviation of 0.88. This descriptive similarity in age indicates appropriate homogeneity between the two groups in terms of age stage.

The data on prior experience indicate that all participants in both groups had previously used Moodle and had prior experience with e-learning. This was appropriate for the nature of the present study, as it helps ensure that any differences that appear between the two groups after the experimental treatment are more likely to be attributable to the alert pattern used within the personalized learning environment, whether proactive or remedial, rather than to substantial differences in students' ability to use the platform or interact with e-learning environments.

Thus, the sample characteristics helped control extraneous variables related to gender, age, prior Moodle use, and previous e-learning experience. They also reinforced the suitability of the sample for the experimental treatment, which required an initial ability to interact with a digital learning environment based on learning analytics and instructional alerts.

Before the experiment began, the equivalence of the two groups was verified in the pre-treatment variables related to self-regulated learning and academic decision-making. The results of the t-test for pre-measurement differences showed no statistically significant differences between the two groups in the main measurement instruments. This supported the validity of the post-treatment comparison and reduced the possibility that subsequent differences were due to prior differences between the two groups.

### *10.3 Learning Analytics-Based Personalized Learning Environment*

The personalized learning environment was designed within Moodle to deliver the e-learning course through organized instructional units that combined digital content, interactive activities, formative tests, performance tasks, support resources, progress indicators, and instructional alerts. In this study, Moodle was not used merely as a platform for providing access to content; rather, it was used as a personalized learning environment capable of tracking students' behavior, identifying indicators of academic difficulty or risk of difficulty, and providing guided instructional alerts in light of students' learning data.

The environment included a main course page presenting the general objectives, usage instructions, unit map, and activity schedule. Each instructional unit included clear objectives, focused content, an applied example, an interactive activity, a formative test, an applied task, a support resource, and feedback. Moodle features were used to track activity completion, login records, content access, test performance, assignment submission, alert opening, and responses to alerts. The methodology file confirmed that the environment was built so that Moodle logs could be used to construct the Learning Analytics and Alert Response Log, thereby allowing students' actual behavior within the environment to be measured, rather than relying solely on their self-reported responses.

The experimental treatment was built around six instructional units in the e-learning course: Introduction to e-Learning and Its System, Designing an E-Course and Learning Pathway, Developing Digital Content and Interaction, E-Assessment and Learning Analytics, Quality of the Learning Environment and Operational Management, and Support, Feedback, and Continuous Improvement. These units were selected because they provide appropriate opportunities for identifying indicators of academic difficulty and issuing alerts. They are also aligned with the nature of educational technology as a specialization that integrates design, analysis, production, and evaluation.

### 10.4 Stages of Environment Design

The personalized learning environment was designed according to a systematic instructional design logic and passed through five interconnected stages: analysis, design, development, implementation, and evaluation.

During the analysis stage, the characteristics of fourth-year students in the Department of Educational Technology were identified, along with the nature of the e-learning course and the targeted self-regulated learning and academic decision-making skills. Potential points of academic difficulty within the course were also identified, such as delayed access to content, failure to complete the preliminary activity, low scores on short quizzes, failure to submit assignments, and limited use of support resources.

During the design stage, the learning outcomes for each unit were specified, the learning pathway was built within Moodle, and the activities, tests, applied tasks, and support resources were designed. The rules for issuing proactive and remedial alerts were also developed so that each alert would be linked to a specific learning indicator and a suggested action. The structure of each unit was kept relatively consistent, including the unit objective, focused content, applied example, interactive activity, formative test, applied task, support resource, and feedback.

During the development stage, the units were built within Moodle, the digital content was uploaded, the interactive activities were designed, the formative tests were prepared, the applied tasks were developed, and tracking features such as Activity Completion, Gradebook, Logs, and Reports were activated. The alert messages were also prepared and linked to the appropriate indicators within the environment.

During the implementation stage, the two groups studied the same content and completed the same activities during the application period, with the only difference being the alert pattern. During implementation, data were collected on login, interaction, task completion, alert opening, response speed, and use of support resources.

During the evaluation stage, the post-measurement instruments were administered, the Learning Analytics Log was extracted, the Environment Usability and Alert Clarity Questionnaire was applied, and semi-structured interviews were conducted with a purposive sample of students to interpret the quantitative results.

### 10.5 The First Experimental Treatment: Proactive Alerts

Students in the first experimental group were exposed to a personalized learning environment based on proactive alerts. In the present study, a proactive alert refers to an instructional message that appears to students before actual academic difficulty occurs, based on an early risk indicator within Moodle. Examples of these indicators included not accessing the unit content before the formative test, not opening the task model before implementation, spending less time than expected interacting with the content, or not accessing a support resource before completing an important activity.

Proactive alerts were based on a preventive logic. They did not inform students that they had failed or already encountered difficulty; rather, they drew students' attention to the possibility that their current learning behavior might lead to difficulty if no appropriate action was taken. Therefore, the alert messages were written in supportive, non-punitive language and were connected to specific actions, such as opening the unit summary, watching a short video, reviewing the task model, using a checklist, or accessing a support resource before submission.

***Table 4. Examples of Proactive Alerts Used in the Personalized Learning Environment.***

| Early Risk Indicator | Proactive Alert Message | Suggested Action |
|---|---|---|
| The student did not access the unit content before the test. | You have not yet started reviewing the unit content. Accessing it now may help you perform better on the short quiz. | Open the unit summary and watch the introductory video. |
| The student did not open the task model before implementation. | Before completing the task, it is recommended that you review the attached model so that the completion steps are | Open the task model and checklist. |

| Early Risk Indicator | Proactive Alert Message | Suggested Action |
|---|---|---|
| | clear. | |
| The student spent less time than expected interacting with the content. | Your interaction time with the unit content is lower than expected. Review the applied example before completing the activity. | Open the applied example. |
| The student did not access the support resource before the activity. | There is a short support resource that can help you avoid common errors in the upcoming activity. | Open the support resource before submission. |

This treatment was based on the assumption that an early alert expands the student's decision space because it provides an opportunity to plan or adjust before a negative outcome appears. In this sense, the proactive alert becomes a tool for supporting self-regulated learning, particularly the skills of planning, time management, self-monitoring, and help-seeking.

### *10.6 The Second Experimental Treatment: Remedial Alerts*

Students in the second experimental group were exposed to a personalized learning environment based on remedial alerts. In the present study, a remedial alert refers to an instructional message that appears after actual academic difficulty has occurred, such as obtaining a low score on a formative test, failing to submit an assignment on time, showing clear weakness in an applied activity, or making an error in interpreting progress data.

Remedial alerts were based on a corrective logic. They helped students understand the problem after it had appeared and guided them toward an appropriate action to address the weakness. Therefore, these alerts were linked to feedback, retrying, reviewing instructions, correcting the task, and using a support resource appropriate to the nature of the error.

***Table 5. Examples of Remedial Alerts Used in the Personalized Learning Environment.***

| Actual Difficulty Indicator | Remedial Alert Message | Suggested Action |
|---|---|---|
| Low score on the short quiz. | Your result indicates that you need to review the basic concepts in this unit. | Read the feedback and then try again. |
| Failure to submit the assignment. | The assignment was not submitted on time. Review the task instructions and identify the steps needed to complete it. | Open the task instructions and submit the assignment after revision. |
| Weakness in a learning pathway design task. | The task needs improvement in linking the objective, activity, and assessment. | Review the applied example and then revise the task. |
| Error in interpreting progress data. | Your analysis of the performance indicators shows inaccuracy in identifying the cause of difficulty. | Read the feedback and analyze the report again. |

Thus, the experimental difference between the two groups became clear and specific: the first group received preventive support before academic difficulty occurred, whereas the second group received remedial support after actual difficulty had appeared. All other elements of the environment were held constant to avoid confounding variables.

### *10.7 Controlling the Difference Between the Two Treatments*

The study carefully controlled the similarities and differences between the two treatments to ensure a fair comparison. Both groups studied the same content, used the same Moodle platform, completed the same activities, followed the same duration, accessed the same support resources, and were assessed using the same measurement instruments. The only difference lay in the timing of the alert and its instructional function.

***Table 6. Differences Between Proactive Alerts and Remedial Alerts.***

| Comparison Aspect | Proactive Alerts | Remedial Alerts |
|---|---|---|
| Alert timing | Before academic difficulty occurs | After academic difficulty occurs |
| Nature of the indicator | Potential risk of academic difficulty | Actual academic difficulty |
| Alert function | Preventing academic difficulty | Treating academic difficulty |
| Type of support | Preventive support before the task | Remedial support after an error or delay |
| Student role | Adjusting the learning path before the problem occurs | Correcting the learning path after the problem appears |
| Example | Review the example before completing the task. | Review the feedback after receiving a low score. |

This control was one of the most important strengths of the design, as it made the interpretation of later results more strongly connected to the alert pattern itself, rather than to accompanying factors such as differences in the instructor, content, activity, or duration of implementation.

### 10.8 Research Instruments

The study used ten instruments: six main measurement instruments and four instruments for control and interpretation. These instruments were designed to cover the dependent variables from several angles: self-perception, actual performance, digital behavior, situational decision-making, and quality of justification. The final research instruments file indicated that the main instruments included the Self-Regulated Learning Skills Scale, the Self-Regulated Learning Performance Rubric within the environment, the Learning Analytics and Alert Response Log, the Academic Decision-Making Scale, the Academic Decision-Making Situational Test, and the Academic Decision Quality Rubric.

To further control the experimental treatment and define the operational difference between the two research groups, clear rules were formulated for issuing alerts within Moodle. Each alert was linked to a specific learning indicator, a particular timing of issuance, a suggested instructional action, and a later indicator for tracking the student's response. Both groups were kept similar in terms of content, activities, tasks, formative tests, and support resources. The difference was limited to the timing and function of the alert: the proactive alert appeared before actual academic difficulty occurred, based on an early risk indicator, whereas the remedial alert appeared after difficulty had occurred or after a decline in performance had become visible.

***Table 7. Rules for Issuing Alerts Within Moodle According to the Experimental Treatment Pattern.***

| Alert Type | Issuing Indicator Within Moodle | Alert Timing | Alert Message Used | Suggested Instructional Action | Response Follow-Up Indicator |
|---|---|---|---|---|---|
| Proactive | Failure to access the unit content before the formative test date. | Before taking the formative test. | You have not yet started reviewing the unit content. Accessing it now may help you perform better on the short quiz. | Open the unit summary and review the video or introductory material. | Accessing the content before the test and increasing interaction time with the unit. |
| Proactive | Failure to open the task model or checklist before completing the activity. | Before the applied task date. | Before completing the task, it is recommended that you review the attached model and checklist so that the completion steps are clear. | Open the task model and checklist before starting the task. | Opening the model and then submitting the task on time. |
| Proactive | Lower interaction time with the content compared with the expected time. | During the study of the unit and before completing the activity. | Your interaction time with the unit content is lower than expected. Review the applied example before completing the activity. | Review the applied example and return to the section related to the activity. | Increased interaction time, opening the applied example, and improved activity performance. |
| Proactive | Failure to open the support resource linked to the activity before submission. | Before submitting the activity or task. | There is a short support resource that can help you avoid common errors in the upcoming activity. | Open the support resource before submission. | Opening the support resource and then completing the activity or submitting the task. |
| Proactive | Delay in starting the task despite the approaching submission deadline. | An appropriate period before the submission deadline. | You have not yet started the task. Starting now will help you review it before final submission. | Begin completing the task and review the instructions. | Starting the task and submitting an initial or final version before the deadline. |
| Proactive | Failure to review previous feedback before a new activity. | Before the next activity. | Reviewing previous feedback may help you improve your performance in the current activity. | Read the previous feedback and identify points for improvement. | Opening the feedback and improving the quality of the next activity. |
| Remedial | Formative test score below the acceptable level. | After the test result appears. | Your result indicates that you need to review the basic concepts in this unit. | Read the feedback, review the content, and retry if available. | Opening the feedback and improving the score in the next attempt. |
| Remedial | Failure to submit the assignment on time. | After the submission deadline has passed. | The assignment was not submitted on time. Review the task instructions and identify the steps needed to complete it. | Open the task instructions, complete the task, and submit it after revision. | Uploading the assignment after the alert and reducing the delay time. |
| Remedial | Weak performance in a learning | After the task has been assessed or | The task needs improvement in linking | Review the applied example and revise | Uploading an improved version |

| Alert Type | Issuing Indicator Within Moodle | Alert Timing | Alert Message Used | Suggested Instructional Action | Response Follow-Up Indicator |
|---|---|---|---|---|---|
| | pathway design task. | reviewed. | the objective, activity, and assessment. | the task according to the comments. | and improving the rubric score. |
| Remedial | Error in interpreting progress data or performance indicators. | After reviewing the analysis activity. | Your analysis of the performance indicators shows inaccuracy in identifying the cause of difficulty. | Read the feedback and reanalyze the report. | Resubmitting the analysis more accurately. |
| Remedial | Weak use of support resources after a performance problem appears. | After performance declines or the error is repeated. | The activity result indicates that you need to use the support resource linked to this section. | Open the support resource and then revise the activity or retry. | Opening the support resource and improving performance after the alert. |
| Remedial | Continued low completion after more than one activity. | After repeated low performance. | Your completion log indicates that you need to review your learning plan and organize your time within the environment. | Review the learning plan, identify compensatory activities, and seek support when needed. | Increased login regularity and completion of delayed activities. |

Table 7 shows that the rules for issuing alerts were designed to link each alert to a specific learning behavior within Moodle, rather than to a general or random message. In the proactive-alerts group, alerts were issued when early risk indicators appeared that could lead to academic difficulty, such as not accessing the content, not reviewing the task model, or showing weak interaction with learning resources before completing the activity. In the remedial-alerts group, alerts were issued after actual difficulty had appeared, such as obtaining a low formative test score, failing to submit a task, or showing weak quality of performance in an applied activity.

To further clarify the experimental manipulation, Figure 2 illustrates the procedural difference between the two treatment conditions within Moodle. Both groups studied the same content, completed the same activities, used the same support resources, and were assessed using the same instruments. The only systematic difference between the two groups was the timing and function of the alerts.

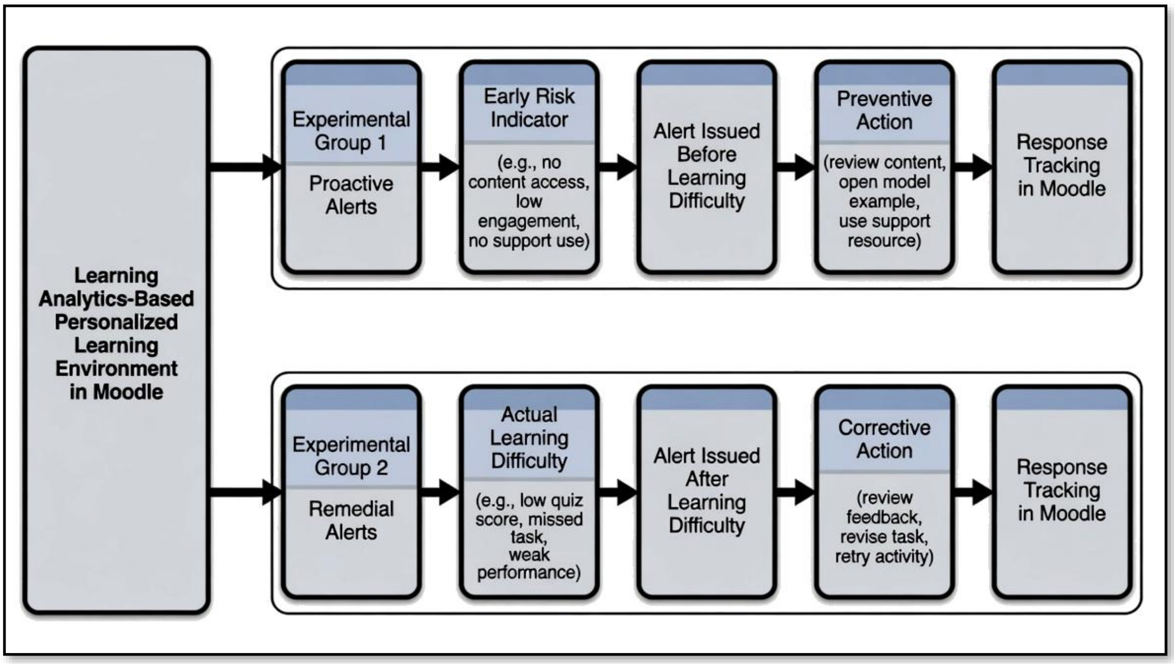


***Figure 2. Experimental Treatment Design in Moodle.***

Figure 2 shows that the proactive-alerts group received alerts before actual learning difficulty occurred, based on early risk indicators such as lack of content access, low engagement, or non-use of support resources. In contrast, the remedial-alerts group received alerts after actual learning difficulty had appeared, such as a low quiz score, a missed task, or weak task performance. This design helped isolate the effect of alert timing and function as the independent variable of the study.

Accordingly, the experimental treatment design maintained the stability of the instructional environment across the two groups in terms of content, activities, tests, tasks, and support resources. The difference was limited to the timing of the alert and its instructional function. This control made it possible to attribute post-treatment differences between the two groups to the alert pattern itself, as the independent variable of the study, rather than to differences in content, teaching method, or support resources.

These rules also made it possible to digitally track students' responses to alerts through Moodle logs. The tracked indicators included opening the alert, response speed, opening the support resource linked to the alert, completing the activity after the alert, and improvement in performance in the subsequent attempt. Accordingly, the function of the alert in the present study was not limited to informing students of a problem or a potential risk; it extended to guiding them toward a specific instructional action that could be observed and analyzed within the environment.

***Table 8. Main Measurement Instruments Used in the Study.***

| Instrument | Purpose | Number of Items/Indicators | Minimum Score | Maximum Score |
|---|---|---|---|---|
| Self-Regulated Learning Skills Scale | Measuring students' perceived self-regulated learning | 48 items | 48 | 240 |
| Self-Regulated Learning Performance Rubric | Measuring actual performance of self-regulated learning skills within the environment | 32 indicators | 0 | 96 |
| Learning Analytics and Alert Response Log | Measuring digital learning behavior and response to alerts | 6 digital dimensions | 0 | 100 |
| Academic Decision-Making Scale | Measuring perceived ability to make academic decisions | 36 items | 36 | 180 |
| Academic Decision-Making Situational Test | Measuring academic decision selection in specific situations | 12 situations | 0 | 60 |
| Academic Decision Quality Rubric | Measuring the quality of justification and analysis accompanying the decision | 6 criteria × 12 situations | 0 | 216 |

The control and interpretive instruments included the Design Standards Checklist for the Personalized Learning Environment, the Validation Rubric for Proactive and Remedial Alert Scenarios, the Usability and Alert Clarity Questionnaire for the Personalized Learning Environment, and the Semi-Structured Interview Guide. These instruments were used to control the quality of the environment, verify the validity of alert scenarios, and understand students' experiences after implementation. They were not used to test the main quantitative hypotheses directly.

### *10.9 Validity and Reliability of the Research Instruments*

The validity of the research instruments was verified through face validity and content validity. The instruments, in their initial form, were submitted to a panel of specialists in educational technology, e-learning environment design, learning analytics, measurement and evaluation, and educational psychology. The reviewers were asked to judge the clarity of the items, their relevance to the dimensions to which they belonged, the appropriateness of their wording for the research sample, the absence of overlap among items, and their suitability for pre- and post-application.

The validation matrix showed that the main measurement instruments were reviewed by 11 experts. The agreement percentages ranged from 91% to 100%, with an overall mean agreement of approximately 97%. This high percentage supports the content validity and suitability of the instruments after the necessary revisions had been made.

***Table 9. Expert Agreement Percentages on the Suitability of the Main Measurement Instruments.***

| Instrument | Number of Reviewers | Agreement Percentage |
|---|---|---|
| Self-Regulated Learning Skills Scale | 11 | 100% |
| Self-Regulated Learning Performance Rubric | 11 | 91% |
| Academic Decision-Making Scale | 11 | 100% |
| Academic Decision-Making Situational Test | 11 | 91% |
| Academic Decision Quality Rubric | 11 | 100% |
| Learning Analytics Log | 11 | 100% |
| Mean agreement percentage | 11 | 97% |

The reliability of the research instruments was calculated using the statistical or procedural method appropriate to the nature of each instrument. For the self-report scales, Cronbach's alpha was used to estimate internal consistency. For the performance rubrics, inter-rater agreement was calculated after training the raters on the scoring criteria. For the Learning Analytics and Alert Response Log, reliability was verified through expert agreement on the suitability of the digital indicators, in addition to reviewing the consistency of the indicators extracted from Moodle logs.

A pilot study was also conducted to test the clarity of the instruments, the appropriateness of the instructions, the time required for application, and the suitability of the items for the research sample. The pilot study helped refine some item wordings and improve internal consistency without altering students' raw scores.

The results showed that the reliability and internal consistency coefficients fell within educationally acceptable limits, supporting the suitability of the instruments for the main experiment. Table 10 presents a summary of the reliability coefficients for the main research instruments.

***Table 10. Reliability Coefficients of the Research Instruments.***

| Instrument | Reliability Calculation Method | Reliability/Consistency Coefficient | Judgment |
|---|---|---|---|
| Self-Regulated Learning Skills Scale | Cronbach's alpha | 0.768 | Acceptable and suitable for application |
| Academic Decision-Making Scale | Cronbach's alpha | 0.720 | Acceptable and suitable for application |
| Academic Decision-Making Situational Test | Cronbach's alpha after revising weak situations | 0.740 | Acceptable and suitable for application |
| Self-Regulated Learning Performance Rubric within the environment | Inter-rater agreement coefficient | 0.860 | Good and suitable for application |
| Academic Decision Quality Rubric | Inter-rater agreement coefficient | 0.880 | Good and suitable for application |
| Learning Analytics and Alert Response Log | Expert agreement and review of digital indicator consistency | 0.900 | Good and suitable for application |

Table 10 shows that the reliability coefficients ranged from 0.720 to 0.900. These coefficients are acceptable in light of the nature and diversity of the research instruments, which included self-report scales, a situational test, performance rubrics, and a digital learning analytics log. The reliability coefficient of the Self-Regulated Learning Skills Scale was 0.768, while the reliability coefficient of the Academic Decision-Making Scale was 0.720, indicating acceptable internal consistency for both scales. The reliability coefficient of the Academic Decision-Making Situational Test, after revising the weak situations, was 0.740, which supports its suitability for measuring students' performance in academic decision-making situations.

The inter-rater agreement coefficient for the Self-Regulated Learning Performance Rubric within the environment reached 0.860, and the coefficient for the Academic Decision Quality Rubric reached 0.880. These values indicate a good level of consistency among raters in assessing students' actual performance and the quality of their academic decisions. The reliability coefficient of the Learning Analytics and Alert Response Log reached 0.900 after the digital indicators had been reviewed and validated. This supports the use of the log in measuring actual learning behavior within Moodle, including login regularity, activity completion, alert opening, response speed, use of support resources, and improvement after receiving an alert.

Accordingly, it was possible to conclude that the research instruments had an appropriate level of reliability. This justified their use in the main experiment and supported the trustworthiness of the results derived from them when comparing the proactive-alerts group with the remedial-alerts group.

## 10.10 Application Procedures

The application procedures began with analyzing the e-learning course and identifying the instructional units suitable for the experimental treatment. The personalized learning environment was then built within Moodle, and the activities, tasks, tests, and support resources were designed. After that, the proactive and remedial alert scenarios were prepared, and the environment, scenarios, and research instruments were submitted to reviewers for feedback and the necessary revisions.

The actual implementation of the experimental treatment lasted 10 weeks during the first semester of the academic year 2022/2023, with approximately one instructional unit covered in each application period. The implementation was organized so that the experiment began with the pre-measurement, followed by studying the e-learning course units within Moodle. The post-measurement was then administered, the learning analytics logs were extracted, and the semi-structured interviews were conducted after the end of the application.

To ensure that the experimental treatment was implemented systematically, a timetable was developed for the research experiment from October 2022 to December 2022. It included orientation, pre-measurement, implementation of the instructional units, activation of alert rules, tracking of students' responses, extraction of Moodle logs, and finally the administration of the post-measurement and qualitative interpretation instruments. The timetable allowed sufficient time for studying the e-learning course units, monitoring progress and difficulty indicators, and observing the effect of alerts on students' behavior within the environment.

***Table 11. Timetable for Implementing the Research Experiment During the First Semester of the Academic Year 2022/2023.***

| Week | Week Start Date | Main Procedures and Tasks Implemented |
|---|---|---|
| First | October 13, 2022 | Orienting students, explaining how to use the Moodle environment, clarifying the instructions for dealing with alerts, administering the pre-measurement instruments, and verifying that all students had access to the environment. |
| Second | October 20, 2022 | Beginning the first unit, Introduction to e-Learning, tracking access to the environment, monitoring interaction with content, and activating the rules for issuing alerts according to the pattern assigned to each group. |
| Third | October 27, 2022 | Implementing the activities of the second unit, Designing an E-Course and Learning Pathway, monitoring progress and difficulty indicators, and sending proactive or remedial alerts according to the experimental treatment rules. |
| Fourth | November 03, 2022 | Implementing applied tasks related to designing learning pathways, following up students' responses to alerts, and monitoring the use of support resources within the environment. |
| Fifth | November 10, 2022 | Implementing activities from the third and fourth units related to developing digital content, e-assessment, and learning analytics; administering short formative tests; and analyzing interaction and achievement indicators. |
| Sixth | November 17, 2022 | Implementing an extended applied task on designing an electronic activity, and following up the effect of alerts on improving performance, adjusting the learning path, and using support resources. |
| Seventh | November 24, 2022 | Completing the activities of the fifth unit, Quality of the Learning Environment and Operational Management, documenting learning logs, and monitoring patterns of response to alerts within Moodle. |
| Eighth | December 01, 2022 | Studying the sixth unit, Support, Feedback, and Continuous Improvement, implementing a final academic decision-making situation, and documenting performance and response indicators. |
| Ninth | December 08, 2022 | Conducting a general review within the environment, completing delayed tasks, reviewing support resources, and ensuring the completeness and suitability of Moodle logs for final analysis. |
| Tenth | December 15, 2022 | Administering the post-measurement instruments, extracting Moodle logs, administering the Environment Usability and Alert Clarity Questionnaire, and conducting semi-structured interviews with a sample of students. |

Table 11 shows that the research experiment extended over ten weeks, which was appropriate for the nature of the experimental treatment. The implementation was not limited to delivering content or issuing alerts; rather, it included monitoring students' responses to alerts, tracking behavioral improvement after alerts, analyzing the use of support resources, and reviewing interaction and completion indicators within Moodle. The extended duration of implementation helped provide more stable quantitative, digital, and qualitative data on the effect of alert timing in both the proactive-alerts group and the remedial-alerts group.

The experimental implementation was conducted over ten weeks during the first semester of the 2022/2023 academic year. Figure 3 summarizes the main implementation stages, including orientation, pretesting, instructional unit delivery, alert activation, response tracking, posttesting, Moodle log extraction, and the semi-structured interviews.

Figure 3 summarizes the main implementation stages, including orientation, pretesting, instructional unit delivery, alert activation, response tracking, posttesting, Moodle log extraction, usability evaluation, and semi-structured interviews.

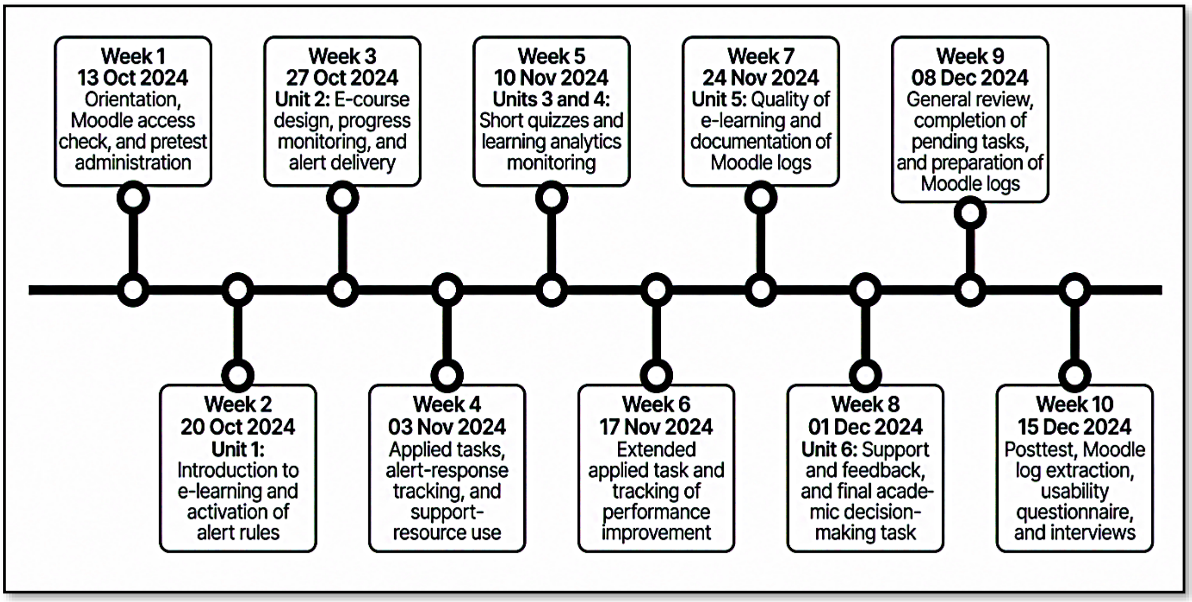


*Figure 3. Research Implementation Timeline.*

As shown in Figure 3, the implementation extended over ten weeks, allowing students sufficient time to engage with the instructional units, receive alerts according to their assigned treatment condition, respond to those alerts, use the support resources, and demonstrate behavioral improvement within Moodle before the post-measurement and qualitative interpretation procedures were completed.

During the implementation, Moodle data were collected regarding login activity, activity completion, test performance, alert opening, response speed, use of support resources, and improvement after receiving alerts. After the experiment ended, the post-measurement instruments were administered, the Learning Analytics Log was extracted, the Environment Usability Questionnaire was applied, and semi-structured interviews were conducted with 10 students: five from the proactive-alerts group and five from the remedial-alerts group. These students were purposively selected to represent different levels of response to alerts. The interviews were used to interpret the quantitative findings, not to test the statistical hypotheses directly.

### 10.11 Statistical Methods

The study used a set of statistical methods appropriate to the nature of the design and instruments. The independent-samples t-test was used to verify the pre-treatment equivalence of the two groups in the main measurement instruments. Analysis of covariance (ANCOVA) was also used to compare the two groups in the post-measurement after controlling for the effect of the pre-measurement. This was appropriate because the design included both pre- and post-measurements, and controlling for the pre-measurement allowed for a more accurate estimation of the effect of the experimental treatment.

#### *Testing the Assumptions of Statistical Analysis*

Before interpreting the ANCOVA results, the basic statistical assumptions required for using ANCOVA were reviewed to ensure the suitability of this method for the nature of the study data. This included verifying that there were no statistically significant pre-treatment differences between the two research groups in the main measurement instruments, examining the homogeneity of regression slopes between the covariate and the post-measurement, reviewing the similarity of variances between the two groups, and ensuring that there were no influential outliers that could affect the accuracy of the results.

The results of the pre-treatment equivalence tests showed no statistically significant differences between the two research groups in the pre-measurements, which supports the homogeneity of the two groups before implementing the experimental treatment. The examination of the homogeneity of regression slopes also showed that the relationship between the pre-measurement and the post-measurement did not differ significantly between the two groups. This supported the validity of using ANCOVA to compare the two groups after controlling for the effect of the pre-measurement.

Accordingly, ANCOVA could be used as an

appropriate method for examining the effect of alert timing, proactive versus remedial, on the dependent variables, while reducing the influence of possible pre-treatment differences among students. This procedure also enhanced the accuracy of interpreting the results and helped link post-treatment differences to the experimental treatment pattern rather than to factors that existed before the application.

Before conducting ANCOVA, the homogeneity of regression slopes assumption was tested through the group × pre-measurement interaction, which was non-significant across all instruments. This supported the suitability of ANCOVA. Effect size was also calculated using partial eta squared (Partial $\eta^2$) in the ANCOVA results, and Cohen's d was used to estimate the strength of the differences between the two groups. Because the Learning Analytics and Alert Response Log did not have a directly equivalent pre-measurement form, it was analyzed post-treatment using the independent-samples t-test, with Cohen's d calculated. Thematic analysis was used to analyze the semi-structured interview data.

For greater accuracy in interpreting the magnitude of differences between the two research groups, the study used Cohen's d as an effect size indicator complementary to statistical significance, alongside partial eta squared (Partial $\eta^2$) derived from ANCOVA. Cohen's d was calculated based on the difference between the post-measurement means of the two groups divided by the pooled standard deviation, according to the following equation:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

In this equation, $\mathbf{M_1}$ refers to the mean of the proactive-alerts group, $\mathbf{M_2}$ refers to the mean of the remedial-alerts group, and $SD_{pooled}$ refers to the pooled standard deviation of the two groups. This indicator was used to estimate the practical strength of the differences between the two groups, not merely to judge their statistical significance.

Partial eta squared (Partial $\eta^2$) was used to interpret the effect size in the ANCOVA results after controlling for the effect of the pre-measurement. Thus, the results were interpreted in light of three integrated indicators: the level of statistical significance, the effect size derived from ANCOVA, and the practical magnitude of the difference between the means of the two groups.

Cohen's d was considered small when its value was close to 0.20, moderate when it was close to 0.50, and large when it reached 0.80 or above, while interpreting the effect size in light of the nature of the educational field and the context of application.

***Table 12. Statistical Methods Used in the Study.***

| Analytical Purpose | Statistical Method |
|---|---|
| Verifying pre-treatment equivalence between the two groups | Independent-samples t-test |
| Testing the homogeneity of regression slopes assumption | Group × pre-measurement interaction test |
| Comparing post-measurements after controlling for the pre-measurement | Analysis of covariance (ANCOVA) |
| Estimating effect size in ANCOVA | Partial eta squared (Partial $\eta^2$) |
| Estimating the strength of the difference between the two groups | Cohen's d |
| Analyzing the Moodle log post-treatment | Independent-samples t-test |
| Interpreting the semi-structured interviews | Thematic analysis |

### *10.12 Ethical Considerations*

The study adhered to the ethical principles of educational research. Students were informed that their participation in the research instruments was for scientific purposes only, that their data would be treated confidentially, and that their participation or responses would not affect their academic grades. Numerical codes were used instead of students' names during data analysis. Participants' consent was obtained before conducting the semi-structured interviews or audio-recording them. With regard to Moodle logs, students were informed that their interaction data within the environment would be used in aggregate form for research purposes, without disclosing their individual identities or using their data in any way that could affect their academic assessment.

### *10.13 Data Availability*

The study used quantitative and qualitative data related to students' performance within the Moodle environment and their responses to the measurement instruments and interviews. Because these data are connected to individual learning records and student information, making the full dataset publicly available is not possible in order to preserve confidentiality. Aggregated statistical tables, descriptions of the instruments, analysis indicators, and examples of alerts may be made available upon request for purposes of scholarly review, after removing any data that could reveal participants' identities.

## 11. RESULTS

The data were analyzed using the independent-samples t-test to verify pre-treatment equivalence, analysis of covariance (ANCOVA) to compare the two groups in the post-measurements after controlling for the effect of the pre-measurements, and partial eta squared to estimate effect size in the ANCOVA models. Cohen's d was also used to estimate the strength of the differences between the two groups. The Learning Analytics Log was analyzed post-treatment using the independent-samples t-test because it did not have a directly equivalent pre-measurement form. The semi-structured interviews were interpreted using thematic analysis.

In presenting the results, the tables were kept concise and direct, and the accompanying comments were limited to the immediate statistical and educational meanings. The broader discussion and connection of the findings to previous literature are presented in the following section.

### *11.1 Verification of Pre-Treatment Equivalence Between the Two Groups*

Before testing the research hypotheses, the equivalence of the two research groups was verified in the pre-measurements of the main instruments. This was done to ensure that any differences appearing after the experimental treatment could be attributed more directly to the alert pattern used within the personalized learning environment, rather than to prior differences between the two groups. The t-test results showed no statistically significant differences between the two groups in any of the pre-measurement instruments, as all p-values were greater than .05.

***Table 13. Results of the t-Test for Pre-Treatment Differences Between the Two Research Groups.***

| Instrument | Proactive-Alerts Mean | Remedial-Alerts Mean | t | df | p | Judgment |
|---|---|---|---|---|---|---|
| Self-Regulated Learning Scale | 148.52 | 153.52 | -0.94 | 98 | .351 | Non-significant |
| Self-Regulated Learning Performance Rubric | 58.34 | 56.74 | 0.54 | 98 | .591 | Non-significant |
| Academic Decision-Making Scale | 108.18 | 113.80 | -1.33 | 98 | .188 | Non-significant |
| Academic Decision-Making Situational Test | 36.32 | 38.28 | -1.25 | 98 | .213 | Non-significant |
| Academic Decision Quality Rubric | 138.36 | 135.40 | 0.55 | 98 | .586 | Non-significant |

The table shows that the two groups began the experiment from comparable levels in self-regulated learning and academic decision-making. Accordingly, the post-treatment differences could be interpreted with greater confidence as being related to the experimental treatment pattern, while recognizing the usual limits of quasi-experimental designs.

### *11.2 Testing the Homogeneity of Regression Slopes Assumption*

Before using ANCOVA, the homogeneity of regression slopes assumption was examined through the group × pre-measurement interaction. The interaction values were not statistically significant for any of the measurement instruments. This indicated that the assumption was met and justified the use of ANCOVA to compare the two groups in the post-measurements after controlling for the effect of the pre-measurements.

***Table 14. Results of Testing the Homogeneity of Regression Slopes Before Conducting ANCOVA.***

| Instrument | Interaction F | df | p | Judgment |
|---|---|---|---|---|
| Self-Regulated Learning Scale | 0.14 | 1, 96 | .705 | Assumption met |
| Self-Regulated Learning Performance Rubric | 0.00 | 1, 96 | .944 | Assumption met |
| Academic Decision-Making Scale | 1.57 | 1, 96 | .213 | Assumption met |
| Academic Decision-Making Situational Test | 2.29 | 1, 96 | .133 | Assumption met |
| Academic Decision Quality Rubric | 0.59 | 1, 96 | .446 | Assumption met |

These results show that the relationship between the pre-measurement and the post-measurement did not differ significantly between the two groups. This allowed the post-treatment comparisons to be conducted using ANCOVA with appropriate statistical confidence.

### *11.3 General Descriptive Results of the Measurement Instruments*

The following table presents the means and standard deviations of the research instruments according to group and measurement type. The descriptive values show a general trend in favor of the proactive-alerts group across all post-measurements, whether in self-regulated learning, academic decision-making, or the Learning Analytics Log.

***Table 15. Means and Standard Deviations of the Research Instruments According to Group and Measurement Type.***

| Instrument | Group | Pre-Mean | Pre-SD | Post-Mean | Post-SD |
|---|---|---|---|---|---|
| Self-Regulated Learning Scale | Proactive alerts | 148.52 | 27.08 | 196.82 | 20.71 |
| Self-Regulated Learning Scale | Remedial alerts | 153.52 | 26.25 | 173.14 | 23.80 |
| Self-Regulated Learning Performance Rubric | Proactive alerts | 58.34 | 15.63 | 79.72 | 9.47 |
| Self-Regulated Learning Performance Rubric | Remedial alerts | 56.74 | 14.01 | 70.80 | 14.07 |
| Academic Decision-Making Scale | Proactive alerts | 108.18 | 20.36 | 152.88 | 18.93 |
| Academic Decision-Making Scale | Remedial alerts | 113.80 | 21.98 | 129.34 | 22.84 |
| Academic Decision-Making Situational Test | Proactive alerts | 36.32 | 7.46 | 51.36 | 5.22 |
| Academic Decision-Making Situational Test | Remedial alerts | 38.28 | 8.16 | 46.10 | 7.50 |
| Academic Decision Quality Rubric | Proactive alerts | 138.36 | 26.06 | 187.44 | 19.28 |
| Academic Decision Quality Rubric | Remedial alerts | 135.40 | 28.04 | 154.18 | 24.08 |
| Learning Analytics and Alert Response Log | Proactive alerts | — | — | 80.95 | 13.55 |
| Learning Analytics and Alert Response Log | Remedial alerts | — | — | 61.99 | 17.62 |

The descriptive values indicate that the proactive-alerts group achieved greater improvement across all measurement instruments. The lower dispersion in some post-measurements among the proactive-alerts group may also reflect a higher degree of performance regularity after the treatment, rather than merely higher mean scores.

When presenting the hypothesis results, the study used the expression "the results support the hypothesis" rather than "the hypothesis is accepted." This wording was used because the aim was not to prove the hypothesis in an absolute sense, but to indicate that the analyzed data provide statistical and educational support for the hypothesis within the limits of the sample, design, and procedures of the study.

### *11.4 Results of the First Hypothesis: The Effect of Alert Timing on the Self-Regulated Learning Scale*

The first hypothesis stated that there would be statistically significant differences at the level of **$p \leq .05$** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Self-Regulated Learning Skills Scale, after controlling for the effect of the pre-application, in favor of the proactive-alerts group

***Table 16. Results of the Self-Regulated Learning Scale.***

| Group | Pre-Mean | Post-Mean | Improvement |
|---|---|---|---|
| Proactive alerts | 148.52 | 196.82 | 48.30 |
| Remedial alerts | 153.52 | 173.14 | 19.62 |

***Table 17. ANCOVA Results for the Self-Regulated Learning Scale.***

| Adjusted Mean for Proactive Alerts | Adjusted Mean for Remedial Alerts | F | df | p | Partial $\eta^2$ | Cohen's d |
|---|---|---|---|---|---|---|
| 196.52 | 173.44 | 26.81 | 1, 97 | < .001 | .217 | 1.06 |

The results show a statistically significant difference between the two groups in the post-measurement of the Self-Regulated Learning Scale after controlling for the effect of the pre-measurement, in favor of the proactive-alerts group. The adjusted mean for the proactive-alerts group was 196.52, compared with 173.44 for the remedial-alerts group, and the F value was 26.81 at a significance level of less than .001. The partial eta squared value of .217 indicates a clear effect of alert timing on self-regulated learning, while Cohen's d of 1.06 reflects a large difference between the two groups.

Accordingly, the results support the first hypothesis and indicate that the proactive-alerts pattern was more effective than the remedial-alerts pattern in developing self-regulated learning skills among educational technology students after controlling for the effect of the pre-measurement.

### *11.5 Results of the Second Hypothesis: The Effect of Alert Timing on the Actual Performance of Self-Regulated Learning Skills*

The second hypothesis stated that there would be statistically significant differences at the level of **$p \leq .05$** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Self-

Regulated Learning Performance Rubric within the personalized learning environment, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.

***Table 18. Results of the Self-Regulated Learning Performance Rubric.***

| Group | Pre-Mean | Post-Mean | Improvement |
|---|---|---|---|
| Proactive alerts | 58.34 | 79.72 | 21.38 |
| Remedial alerts | 56.74 | 70.80 | 14.06 |

***Table 19. ANCOVA Results for the Self-Regulated Learning Performance Rubric.***

| Adjusted Mean for Proactive Alerts | Adjusted Mean for Remedial Alerts | F | df | p | Partial $\eta^2$ | Cohen's d |
|---|---|---|---|---|---|---|
| 79.70 | 70.82 | 13.52 | 1, 97 | < .001 | .122 | 0.74 |

The results showed a statistically significant difference in favor of the proactive-alerts group in the Self-Regulated Learning Performance Rubric. The adjusted mean for the proactive-alerts group was 79.70, compared with 70.82 for the remedial-alerts group. The F value was 13.52 at a significance level of less than .001. The partial eta squared value of .122 indicates a moderate effect tending toward strength, while Cohen's d of 0.74 indicates a clear educational difference between the two groups.

Accordingly, the results support the second hypothesis and indicate that students in the proactive-alerts group achieved higher performance in self-regulated learning skills within the personalized learning environment than students in the remedial-alerts group, after controlling for the effect of the pre-measurement.

## *11.6 Results of the Third Hypothesis: The Effect of Alert Timing on the Learning Analytics and Alert Response Log*

The third hypothesis stated that there would be statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the Learning Analytics and Alert Response Log within Moodle, in favor of the proactive-alerts group.

Because the Learning Analytics Log was based on students' actual behavior throughout the experiment and did not have a directly equivalent pre-measurement form, the post-treatment difference between the two groups was analyzed using the independent-samples t-test, with effect size calculated.

***Table 20. Results of the Difference Between the Two Groups in the Learning Analytics and Alert Response Log.***

| Group | Mean | Standard Deviation | t | df | p | Cohen's d |
|---|---|---|---|---|---|---|
| Proactive alerts | 80.95 | 13.55 | 6.03 | 98 | < .001 | 1.21 |
| Remedial alerts | 61.99 | 17.62 | – | – | – | – |

The results reveal a statistically significant superiority of the proactive-alerts group in the Learning Analytics and Alert Response Log. The mean score of the proactive-alerts group was 80.95, compared with 61.99 for the remedial-alerts group. The t value was 6.03 at a significance level of less than .001. Cohen's d was 1.21, indicating a large effect.

This result suggests that proactive alerts were reflected in students' actual digital behavior within Moodle, including login regularity, task completion, opening alerts, response speed, use of support resources, and improvement after receiving alerts. Accordingly, the results support the third hypothesis and indicate that the proactive-alerts pattern contributed more strongly to improving actual learning behavior and responses to alerts within Moodle than the remedial-alerts pattern.

## *11.7 Results of the Fourth Hypothesis: The Effect of Alert Timing on the Academic Decision-Making Scale*

The fourth hypothesis stated that there would be statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision-Making Scale, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.

***Table 21. Results of the Academic Decision-Making Scale.***

| Group | Pre-Mean | Post-Mean | Improvement |
|---|---|---|---|
| Proactive alerts | 108.18 | 152.88 | 44.70 |
| Remedial alerts | 113.80 | 129.34 | 15.54 |

***Table 2.2 ANCOVA Results for the Academic Decision-Making Scale.***

| Adjusted Mean for Proactive Alerts | Adjusted Mean for Remedial Alerts | F | df | p | Partial $\eta^2$ | Cohen's d |
|---|---|---|---|---|---|---|
| 152.68 | 129.54 | 29.72 | 1, 97 | < .001 | .235 | 1.12 |

The results showed a statistically significant difference between the two groups in the post-measurement of the Academic Decision-Making Scale after controlling for the effect of the pre-measurement, in favor of the proactive-alerts group. The adjusted mean for the proactive-alerts group was 152.68, compared with 129.54 for the remedial-alerts group. The F value was 29.72 at a significance level of less than .001. Partial eta squared was .235, and Cohen's d was 1.12.

These values indicate a large effect of alert timing on students' perceived ability to make academic decisions. Accordingly, the results support the fourth hypothesis and indicate that proactive alerts were more effective than remedial alerts in developing academic decision-making among educational technology students after controlling for the effect of the pre-measurement.

### *11.8 Results of the Fifth Hypothesis: The Effect of Alert Timing on the Academic Decision-Making Situational Test*

The fifth hypothesis stated that there would be statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision-Making Situational Test, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.

***Table 23. Results of the Academic Decision-Making Situational Test.***

| Group | Pre-Mean | Post-Mean | Improvement |
|---|---|---|---|
| Proactive alerts | 36.32 | 51.36 | 15.04 |
| Remedial alerts | 38.28 | 46.10 | 7.82 |

***Table 24. ANCOVA Results for the Academic Decision-Making Situational Test.***

| Adjusted Mean for Proactive Alerts | Adjusted Mean for Remedial Alerts | F | df | p | Partial η² | Cohen's d |
|---|---|---|---|---|---|---|
| 51.33 | 46.13 | 15.78 | 1, 97 | < .001 | .140 | 0.81 |

The results show a statistically significant difference in favor of the proactive-alerts group in the Academic Decision-Making Situational Test. The adjusted mean for the proactive-alerts group was 51.33, compared with 46.13 for the remedial-alerts group. The F value was 15.78 at a significance level of less than .001. The partial eta squared value of .140 indicates a moderate effect tending toward strength, while Cohen's d of 0.81 indicates a relatively large effect.

This result indicates that the effect of proactive alerts was not limited to students' self-perceived ability to make academic decisions. It also appeared in their performance in specific academic situations requiring them to read the situation, analyze alternatives, and select the most appropriate decision. Accordingly, the results support the fifth hypothesis and indicate that students in the proactive-alerts group performed better in academic decision-making situations than students in the remedial-alerts group, after controlling for the effect of the pre-measurement.

### *11.9 Results of the Sixth Hypothesis: The Effect of Alert Timing on the Quality of Academic Decision-Making*

The sixth hypothesis stated that there would be statistically significant differences at the level of **p ≤ .05** between the mean scores of students in the proactive-alerts group and those in the remedial-alerts group in the post-application of the Academic Decision Quality Rubric, after controlling for the effect of the pre-application, in favor of the proactive-alerts group.

***Table 25. Results of the Academic Decision Quality Rubric.***

| Group | Pre-Mean | Post-Mean | Improvement |
|---|---|---|---|
| Proactive alerts | 138.36 | 187.44 | 49.08 |
| Remedial alerts | 135.40 | 154.18 | 18.78 |

***Table 26. ANCOVA Results for the Academic Decision Quality Rubric.***

| Adjusted Mean for Proactive Alerts | Adjusted Mean for Remedial Alerts | F | df | p | Partial η² | Cohen's d |
|---|---|---|---|---|---|---|
| 187.61 | 154.01 | 59.75 | 1, 97 | < .001 | .381 | 1.52 |

The results reveal a statistically significant difference in favor of the proactive-alerts group in the Academic Decision Quality Rubric. The adjusted mean for the proactive-alerts group was 187.61, compared with 154.01 for the remedial-alerts group. The F value was 59.75 at a significance level of less than .001. Partial eta squared was .381, the highest value among the main measurement instruments, while Cohen's d was 1.52, indicating a large effect.

This result suggests that proactive alerts had a strong effect on the quality of students' thinking accompanying academic decision-making, particularly in terms of understanding the situation, using data, selecting an appropriate decision, providing logical justification, anticipating consequences, and following up and adjusting the decision. Accordingly, the results support the sixth hypothesis and indicate that the proactive-alerts pattern was more effective than the remedial-alerts pattern in improving the quality of academic decision-making among educational technology students.

Because the main instruments had different maximum scores, the posttest means were converted to a standardized scale ranging from 0 to 5 to allow visual comparison across instruments. Figure 4 presents the standardized posttest mean scores of the proactive-alerts and remedial-alerts groups across the six main instruments.

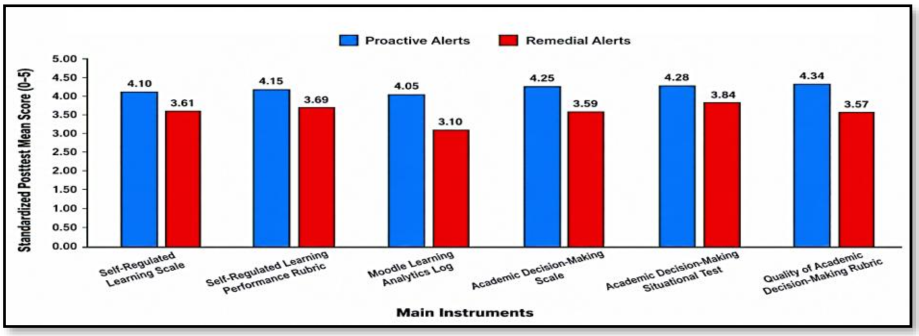


***Figure 4. Standardized Posttest Mean Scores of the Two Groups Across the Main Instruments.***

Figure 4 shows that the proactive-alerts group achieved higher standardized posttest mean scores than the remedial-alerts group across all main instruments. This pattern indicates that the advantage of proactive alerts was not limited to a single outcome, but appeared consistently across self-regulated learning, actual learning behavior in Moodle, academic decision-making, and the quality of academic decision-making.

### *11.10 Summary of the Quantitative Hypothesis Results*

The following table presents a summary of the quantitative hypothesis results, making it possible to identify the general direction of the findings across the different measurement instruments.

***Table 27. Summary of the Quantitative Hypothesis Results.***

| Hypothesis | Measurement Instrument | Direction of the Result | Significance | Effect Size | Decision |
|---|---|---|---|---|---|
| First | Self-Regulated Learning Scale | In favor of proactive alerts | $p < .001$ | $d = 1.06$ | Supported |
| Second | Self-Regulated Learning Performance Rubric | In favor of proactive alerts | $p < .001$ | $d = 0.74$ | Supported |
| Third | Learning Analytics Log | In favor of proactive alerts | $p < .001$ | $d = 1.21$ | Supported |
| Fourth | Academic Decision-Making Scale | In favor of proactive alerts | $p < .001$ | $d = 1.12$ | Supported |
| Fifth | Academic Decision-Making Situational Test | In favor of proactive alerts | $p < .001$ | $d = 0.81$ | Supported |
| Sixth | Academic Decision Quality Rubric | In favor of proactive alerts | $p < .001$ | $d = 1.52$ | Supported |

This summary shows that all quantitative results were in favor of the proactive-alerts group. The effect sizes ranged from moderate to large, with the strongest effect appearing in the Academic Decision Quality Rubric, followed by the Learning Analytics Log, the Academic Decision-Making Scale, and the Self-Regulated Learning Scale.

To complement the statistical significance results, Cohen's d was used to interpret the practical magnitude of the differences between the two groups. Figure 5 displays Cohen's d effect sizes across the six main instruments, with reference lines indicating conventional benchmarks for small, medium, and large effects.

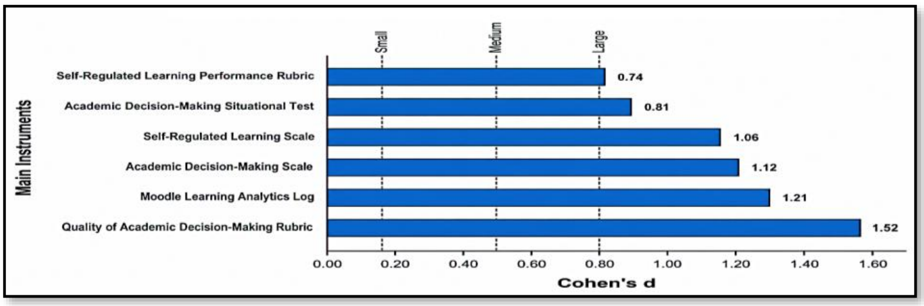


***Figure 5. Cohen's d Effect Sizes Across the Main Instruments.***

Figure 5 shows that all Cohen's d effect sizes supported the practical superiority of the proactive-alerts group over the remedial-alerts group across the main measurement instruments. The effect size values ranged from 0.74 to 1.52, extending from a moderate-to-large effect to a very large effect. The highest effect size appeared in the Academic Decision Quality Rubric, where Cohen's d reached 1.52, followed by the Moodle Learning Analytics Log with d = 1.21, the Academic Decision-Making Scale with d = 1.12, and the Self-Regulated Learning Skills Scale with d = 1.06. A relatively large effect also appeared in the Academic Decision-Making Situational Test, with d = 0.81, while the effect size for the Self-Regulated Learning Performance Rubric within the environment reached d = 0.74, which represents a moderate effect tending toward large. These results indicate that the effect of proactive alerts was not only statistically significant, but also practically meaningful, particularly in improving the quality of academic decision-making and actual learning behavior within Moodle.

### *11.11 Results of the Semi-Structured Interviews*

Semi-structured interviews were used to interpret the quantitative findings and to understand students' experiences in dealing with alerts within the personalized learning environment. The interviews were conducted with 10 students: five from the proactive-alerts group and five from the remedial-alerts group. Participants were purposively selected to represent different levels of response to alerts: high, moderate, and low. The interview data were analyzed using thematic analysis. The main areas of focus were students' experience of using the environment, their understanding of alerts, their responses to alerts, the perceived effect of alerts on self-regulated learning, the perceived effect of alerts on academic decision-making, and the difficulties and developmental suggestions they reported.

***Table 28. Summary of the Semi-Structured Interview Data.***

| Item | Description |
|---|---|
| Number of interviews | 10 interviews |
| Distribution of participants | 5 from the proactive-alerts group and 5 from the remedial-alerts group |
| Selection method | Strategic purposive sampling |
| Selection criterion | Representing different levels of response to alerts |
| Timing of interviews | After the main experiment and the administration of the post-measurement instruments |
| Analysis method | Thematic analysis |
| Function of interviews | Interpreting the quantitative findings, not measuring students' performance |

The thematic analysis of the interviews revealed four main themes. The first theme was the sense of control over learning. Students in the proactive-alerts group described the environment as giving them "a sense of control over learning," because the alert arrived before the problem occurred, making them more able to act early. By contrast, some students in the remedial-alerts group described the alerts as "useful, but sometimes arriving late," which suggests that remedial alerts helped them correct their learning, but did not prevent academic difficulty from occurring.

The second theme concerned the clarity of the relationship between the alert and the student's learning situation. Students in the proactive-alerts group indicated that the alerts were "personalized and directly connected to my situation," whereas some students in the remedial-alerts group described the alerts as "relatively general" or as being connected to the problem only after it had appeared. This finding suggests that alert timing shaped students' perceptions of message relevance. An alert that precedes the problem may make students feel that the message is directed toward avoiding a specific risk, whereas an alert that comes after the problem may sometimes be understood as delayed correction.

The third theme was related to students' responses to alerts. Interviews with the proactive-alerts group showed a stronger tendency toward "immediate response in most cases," because the alert appeared before the activity or before the submission deadline, making the suggested action feasible at an appropriate time. By contrast, some students in the remedial-alerts group reported "postponement or partial neglect" of some alerts, particularly when they appeared after a low score had already been obtained or after the task deadline had passed.

The fourth theme concerned the relationship between alerts, self-regulated learning, and academic decision-making. Students in the proactive-alerts group explained that the alerts "transformed learning from a reaction into prior planning" and helped them "make informed, data-based decisions." Students in the remedial-alerts group, however, described the alerts as helping them "correct the path after deviation" or as "helping to get out of the crisis, but not preventing it from happening." These qualitative findings help explain the direction of the quantitative results, particularly the superiority of the proactive-alerts group in the Academic Decision Quality Rubric and the Learning Analytics Log.

*Table 29. Qualitative Themes Derived from the Semi-Structured Interviews.*

| Main Theme | What Appeared in the Proactive-Alerts Group | What Appeared in the Remedial-Alerts Group |
|---|---|---|
| Sense of control over learning | Greater sense of control and early action | Clear benefit, but often after the problem had occurred |
| Understanding of alerts | Higher awareness of the connection between the alert and the actual learning situation | Relatively lower awareness because the alert was linked to a problem that had already occurred |
| Response to alerts | Faster and more direct response | Postponement or partial neglect in some cases |
| Self-regulated learning | Prior planning, time management, and early help-seeking | Path correction and review after error |
| Academic decision-making | Preventive, data-based decisions | Remedial decisions to address existing difficulty |

The interview findings provided qualitative explanations for the quantitative differences between the two groups. Figure 6 summarizes how students' interview responses helped interpret the stronger outcomes observed in the proactive-alerts group compared with the remedial-alerts group.

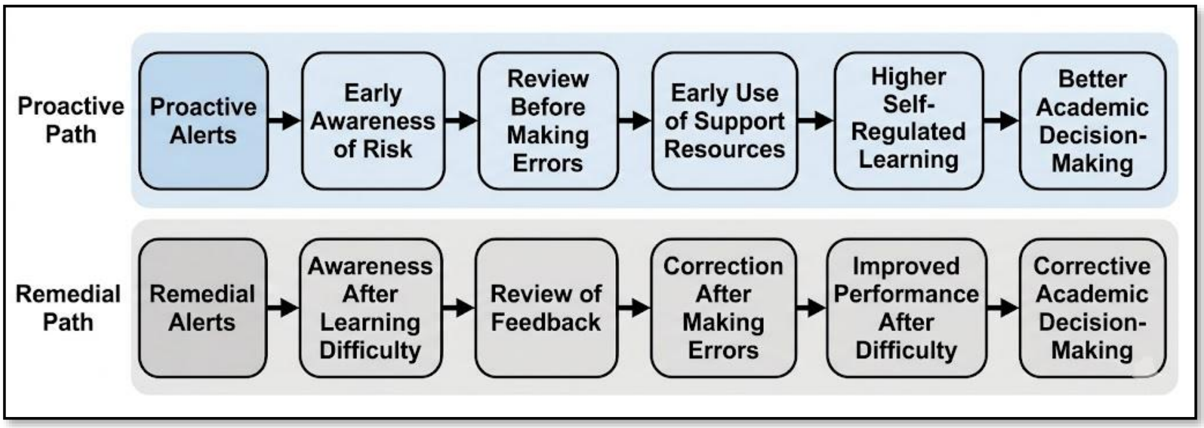


*Figure 6. Interview-Based Explanation of the Quantitative Results.*

Figure 6 indicates that proactive alerts were associated with early awareness of risk, review before making errors, and early use of support resources. These experiences helped students regulate their learning and make more preventive academic decisions. In contrast, remedial alerts were associated with awareness after difficulty, review of feedback, and correction after errors. Thus, the interview results support the quantitative findings by showing that proactive alerts expanded students' opportunity to act before learning difficulty occurred, whereas remedial alerts mainly supported correction after the problem had already appeared.

The interview results support the seventh hypothesis, as they provided a qualitative explanation for the quantitative differences between the two groups. They showed that proactive alerts were not merely early messages; rather, they helped students build a more active relationship with their learning data. Remedial alerts, although useful for correction, were less able to prevent the accumulation of academic difficulty.

The results of the semi-structured interviews were not limited to identifying the main themes associated with students' experiences of dealing with alerts. Students' statements also supported and explained these themes in greater depth. One student in the proactive-alerts group stated that the alert helped him to "recognize that I was moving slowly in reading the content before the short quiz date, which made me study faster to avoid receiving the message again" (Student 3, Proactive Group). This statement reflects early awareness of the risk before actual academic difficulty occurred. It also shows that the proactive alert did not function merely as an informational message, but as a regulatory trigger that prompted the student to adjust his learning behavior before a negative result appeared.

Another student from the same group stated that the alert made him "review the applied example that the system directed me to as soon as the notification arrived, because I realized that I would face difficulty completing the task without it" (Student 1, Proactive Group). This response shows that the proactive alert contributed to activating early help-seeking and helped the student connect the risk indicator with the appropriate action. This is consistent with the nature of self-regulated learning in terms of monitoring performance, managing time, and using support resources before completing the task.

By contrast, one student in the remedial-alerts group explained that the alert was useful, but that it came "somewhat late; if I had known that my solution method was wrong before submitting the activity, my result would have been better" (Student 7, Remedial Group). This statement reflects the student's recognition of the value of the alert, while also revealing the effect of its timing. The alert came after the problem had already appeared, making its function closer to correcting the learning path after the error had occurred, rather than preventing the error before it happened.

Another student from the remedial-alerts group indicated that he used the alert to "return to the detailed feedback to fix the error I had made and try again to improve the low grade" (Student 9, Remedial Group). This statement shows that remedial alerts performed an important corrective role, helping the student review feedback and improve performance after a low score or academic difficulty had appeared. However, this role remained connected to the post-problem stage, unlike proactive alerts, which gave students a wider opportunity to plan, review, and seek support before difficulty occurred.

Taken together, these qualitative accounts indicate that the difference between the two alert patterns was not the presence or absence of support, but the timing of that support and its instructional function. Proactive alerts were associated with a preventive learning experience based on early awareness, review before error, and use of support resources before task completion. Remedial alerts, by contrast, were associated with a corrective learning experience based on reviewing feedback, fixing errors, and improving performance after weakness had appeared. In this way, the interview results help explain the quantitative findings, which showed the superiority of the proactive-alerts group in self-regulated learning and academic decision-making, while still acknowledging the remedial value of alerts provided after academic difficulty had occurred.

### *11.12 Summary of the Research Results*

The results of the study can be summarized by stating that the proactive-alerts pattern outperformed the remedial-alerts pattern across all main measurement instruments. This superiority appeared in the Self-Regulated Learning Scale, the Self-Regulated Learning Performance Rubric, the Learning Analytics Log, the Academic Decision-Making Scale, the Academic Decision-Making Situational Test, and the Academic Decision Quality Rubric. The semi-structured interviews were also consistent with the quantitative results, as they showed that proactive alerts helped students plan early, adjust behavior before academic difficulty occurred, use support resources at an appropriate time, and make academic decisions more strongly grounded in learning data.

Accordingly, the difference between proactive and remedial alerts was not merely a difference in message wording, but a difference in the timing of support and its pedagogical function. A proactive alert gave students an opportunity to act before the problem occurred, whereas a remedial alert played a corrective role after the problem had appeared. This explains the superiority of the proactive pattern in variables that require planning, monitoring, early response, and quality academic decision-making.

## 12. DISCUSSION OF THE RESULTS

The results of the study clearly revealed the superiority of proactive alerts over remedial alerts in developing self-regulated learning and academic decision-making among educational technology students across all measurement instruments used. This superiority was not limited to self-report scales; it also appeared in students' actual performance within the environment, the Learning Analytics Log, the Academic Decision-Making Situational Test, and the Academic Decision Quality Rubric. This consistency strengthens the interpretation of the findings, as they do not rely on a single source of data but are supported by a coherent pattern of quantitative and qualitative evidence.

The results indicate that the difference between proactive and remedial alerts is not a superficial difference in message wording. Rather, it is a fundamental difference in the timing and function of support. A proactive alert reaches the student before actual academic difficulty occurs, giving the student sufficient time to understand the indicator, review their behavior, and choose a preventive action. A remedial alert, by contrast, reaches the student after the problem has appeared; therefore, its role is closer to correction or compensation. This does not mean that remedial alerts are not useful. The results of the remedial-alerts group showed improvement in most instruments, but their effect was weaker than that of proactive alerts because the intervention occurred after students had already lost part of the opportunity for early adjustment.

The findings should therefore not be interpreted as suggesting that remedial alerts lack educational value. Rather, they indicate that proactive alerts were more effective in the context of the present study because they expanded students' opportunity to act before actual academic difficulty occurred. These alerts provided students with an early opportunity to understand the risk indicator, review their learning behavior, use support resources, and adjust their learning path before a negative outcome appeared. Remedial alerts, on the other hand, performed an important corrective function after the problem had appeared, helping students review feedback, correct errors, and improve performance after a low score or delayed achievement.

Accordingly, the superiority shown by proactive alerts should not be understood as negating the value of remedial alerts. Instead, it should be interpreted as evidence that the timing of support is a decisive factor in the effectiveness of instructional alerts within learning analytics-based personalized learning environments. The earlier the alert is provided, the greater its potential to support planning, time management, self-monitoring, and preventive decision-making. Remedial alerts, however, remain more closely associated with correcting the learning path after academic difficulty has occurred.

### *12.1 Interpreting the Superiority of Proactive Alerts in Self-Regulated Learning*

The results of the Self-Regulated Learning Scale and the Self-Regulated Learning Performance Rubric showed a statistically significant advantage for the proactive-alerts group, with an effect size of **d = 1.06** for the scale and **d = 0.74** for the performance rubric. This result indicates that proactive alerts did not only influence students' perceptions of their ability to regulate their learning, but were also reflected in their actual behaviors within the environment, such as starting tasks earlier, monitoring progress, using support resources, and adjusting their learning plans.

This finding can be interpreted in light of Zimmerman's model of self-regulated learning, which emphasizes that self-regulated learning passes through the phases of forethought, performance, and self-reflection (Zimmerman, 2002). A proactive alert operates precisely near the forethought phase or during the early stage of performance. It alerts the student before academic difficulty occurs and prompts the student to reorganize time, access a support resource, review instructions, or adjust the path of task completion. In this way, the student does not wait until failure appears before acting, but responds to an early risk indicator. This explains why proactive alerts had a stronger effect on planning, monitoring, and help-seeking skills.

This result is consistent with the learning analytics literature, which emphasizes that data do not support self-regulated learning automatically. Data need to be presented to students in a form that is understandable and connected to a specific action. Matcha et al. indicated that learning analytics dashboards are more effective when designed in light of self-regulated learning processes, rather than merely presenting general indicators (Matcha et al., 2019). Tzimas and Demetriadis also showed that learning analytics-based guidance can enhance self-regulated learning skills when it provides students with clear guidance that helps them use their data to improve performance (Tzimas & Demetriadis, 2022). In the present study, proactive alerts served as a practical translation of this type of guidance because they linked the risk indicator to the proposed action.

The interview findings support this interpretation. Students in the proactive-alerts group described the alerts as transforming learning "from reaction into prior planning," a statement that captures the essence of self-regulated learning. Students no longer waited for the problem to occur; instead, they dealt with learning as a pathway that could be monitored and adjusted. Students in the remedial-alerts group, by contrast, described the alerts as helping them "correct the path after deviation," which shows that remedial alerts remained useful, but their effect occurred at a later stage of the self-regulation cycle.

### *12.2 Interpreting the Superiority of Proactive Alerts in the Learning Analytics Log*

The Learning Analytics and Alert Response Log showed a strong advantage for the proactive-alerts group, with an effect size of **d = 1.21**. This is one of the most important findings of the study because it is based on actual data extracted from Moodle, including login regularity, task completion, interaction with content, alert opening, response speed, use of support resources, and improvement after receiving alerts. Therefore, this result does not merely reflect students' perceptions or the researcher's judgment; it reflects documented digital behavior within the environment.

This finding can be explained by the fact that the proactive alert appeared at a moment when action was still possible and useful. When students received an alert indicating that they had not opened the task model before the submission date, or had not reviewed the unit content before the test, they were still able to take immediate action. When the alert appeared after a low score or a missed assignment, however, the opportunity for action became narrower, and the behavior often shifted from prevention to compensation. Therefore, the proactive-alerts group achieved higher scores in the log because early alerts prompted students to take observable actions within Moodle.

This result is consistent with recent literature emphasizing the importance of behavioral data in understanding self-regulated learning. Contemporary studies in learning analytics indicate that platform logs can reveal indicators that do not necessarily appear in self-report scales, such as regularity, interaction sequence, response timing, and return to support resources (Cabral, 2023; Heikkinen, 2023). In the present study, the superiority of the proactive-alerts group in the analytics log was evidence that early alerts changed students' learning behavior itself, not merely their perceptions.

This finding is also consistent with Kubsch et al., who argued that early-warning systems designed to support self-regulated learning should be connected to the actual processes students perform within the environment, rather than relying only on general indicators or broad predictions (Kubsch et al., 2023). This was achieved in the present study by linking each alert to a specific learning indicator, a support resource, an executable action, and a follow-up indicator after the alert.

### *12.3 Interpreting the Superiority of Proactive Alerts in Academic Decision-Making*

The results of the Academic Decision-Making Scale and the Academic Decision-Making Situational Test showed a statistically significant advantage for the proactive-alerts group, with an effect size of **d = 1.12** for the scale and **d = 0.81** for the situational test. This means that students who received proactive alerts did not only develop a stronger sense of their ability to make academic decisions, but also demonstrated better performance in practical situations requiring them to diagnose the situation, interpret data, analyze alternatives, and determine the most appropriate academic action.

This result can be explained by the fact that a proactive alert places the student in front of a decision before academic difficulty occurs. This is a type of preventive decision that requires reading the indicator and acting accordingly. When a student receives an alert indicating that they have not opened the support resource before the activity, the student faces a clear decision: whether to ignore the alert, open the resource, or postpone the task. Through repeated exposure to such situations, students are implicitly trained to make decisions based on their learning data. Thus, the proactive alert becomes a small instructional situation for decision-making, not merely a passing notification.

A remedial alert, on the other hand, usually places students in front of a decision after the problem has occurred. This decision is important, but it is constrained by an outcome that has already taken place, such as a low score or an unsubmitted assignment. As a result, the student may become more preoccupied with compensating for the error than with analyzing the learning path before the error occurred. This explains why the proactive-alerts group outperformed the remedial-alerts group in the situational test, as they became more capable of reading early indicators and making appropriate decisions before academic difficulty escalated.

This finding aligns with literature emphasizing that academic decision-making depends on the availability of clear and usable information, and that decision quality improves when students are able to connect information to the context of the situation and the available alternatives (Vietze et al., 2022). It also supports the view that learning analytics should move beyond displaying data toward enabling students to use that data in making informed educational decisions (Kleimola et al., 2023; Tzimas & Demetriadis, 2022).

### *12.4 Interpreting the Superiority of Proactive Alerts in Academic Decision Quality*

The strongest result in the study appeared in the Academic Decision Quality Rubric, where the effect size reached **d = 1.52** and partial eta squared reached **Partial $\eta^2$ = .381**, the highest value among the main measurement instruments. This result is notable because the rubric does not only measure whether students select the correct answer in a given situation. It measures the quality of the thinking that accompanies the decision: understanding the situation, using data, selecting an appropriate decision, providing logical justification, anticipating consequences, and following up and adjusting the decision.

This result suggests that proactive alerts helped students develop a deeper pattern of academic thinking. Students did not simply receive a message and perform a mechanical action; rather, they became more able to interpret the reason behind the alert, connect it to a performance indicator, and justify their choice of the appropriate action. This explains the higher quality of academic decisions in the proactive-alerts group compared with the remedial-alerts group.

This is related to the nature of the proactive alert itself. It invites students to think about the possibility of academic difficulty before it occurs. This preventive moment requires anticipation, comparison among alternatives, and a degree of responsibility. In the case of the remedial alert, the cause of the problem may be clearer, but it appears after the outcome has already emerged, making the decision closer to direct correction. Therefore, the effect of proactive alerts was greater in decision quality because they encouraged students to think about cause, consequence, and alternatives before academic difficulty became a reality.

This result is consistent with recent literature emphasizing the importance of learning analytics in supporting self-reflection and future-oriented recommendations, rather than merely describing current performance. Kleimola et al. noted that students expect learning analytics to help them reflect on their performance and identify what should be done next (Kleimola et al., 2023). In the present study, proactive alerts appear to have fulfilled this role more strongly because they prompted students to think about what should be done before the problem occurred.

### *12.5 Interpreting the Semi-Structured Interview Results*

The semi-structured interviews were consistent with the quantitative findings and provided an important explanation of the differences between the two groups. Students in the proactive-alerts group described their experience as giving them a greater sense of control over learning, whereas students in the remedial-alerts group described the alerts as useful but sometimes late. This difference in subjective experience reflects the difference in alert function: the proactive alert gives students a sense that they can prevent the problem, whereas the remedial alert gives them an opportunity to address the problem after it has occurred.

The interviews also showed that proactive alerts were more closely associated with immediate response. This seems logical because when students receive an alert before the submission deadline or before the test, the suggested action has direct value. However, when they receive the alert after a low score or after the deadline has passed, they may feel that the alert is less urgent or that its effect is limited, even if it remains useful for improving later performance.

The interviews further showed that students in the proactive-alerts group felt that the alerts were "personalized and directly connected to my situation." This suggests that alert timing affects students' perceptions of relevance. An early alert appears to students as if it is reading their current situation and giving them an opportunity to act, whereas a remedial alert may sometimes appear as a report about a problem that has already occurred. This finding highlights the importance of feedback timing in data-informed learning environments.

### *12.6 Significance of the Findings in Light of Previous Literature*

The findings of the present study are consistent with the general direction of learning analytics literature, which emphasizes that the effectiveness of analytics is not achieved merely by collecting data, but by transforming it into feedback or actionable guidance. Matcha et al. showed that learning analytics dashboards need to be built in light of theories of self-regulated learning; otherwise, they may become merely tools for displaying data (Matcha et al., 2019). The findings of the present study support this view. The Moodle log alone was not sufficient; the stronger effect appeared when data were transformed into proactive alerts connected to clear actions.

The findings are also consistent with the study by Tzimas and Demetriadis, which emphasized that learning analytics-based guidance can improve self-regulated learning and performance when it is clear and strong (Tzimas & Demetriadis, 2022). However, the present study adds a more precise distinction to this direction: the timing of guidance itself may be a decisive factor. Proactive guidance was more effective than remedial guidance, although both were based on the same environment and the same support resources.

The findings also align with Chang et al.'s study on the importance of personalized interventions in early-warning systems, but they add an experimental dimension that distinguishes between intervention before academic difficulty and intervention after it (Chang et al., 2023). They also support Kubsch et al.'s argument that early-warning systems should be based on an understanding of self-regulated learning processes, rather than on superficial behavioral indicators alone (Kubsch et al., 2023). In the present study, alerts were not used merely to inform students of risk; they were designed to support specific skills such as planning, monitoring, help-seeking, and decision analysis.

The findings also align with the literature on personalized learning environments, which suggests that such environments are more effective when they combine learner freedom with guided support. Excessive freedom without alerts or guidance may lead to distraction, whereas proactive support gives students responsible autonomy. It does not impose a decision on them; instead, it provides an indicator and a suggested action that help them make their own decision. This point represents an important contribution of the present study, as proactive alerts were not used to control students, but to enable them to read their learning data and act accordingly.

### 12.7 Scientific Contribution of the Present Study

The first scientific contribution of the study is that it moves the study of early-warning systems from the level of predicting at-risk students to the level of designing the alert intervention itself. The question is not only: Which student is at risk? Rather, it becomes: When should the alert be provided? How should it be worded? What action should it be linked to? What is its effect on self-regulated learning and academic decision-making? This shift is important because many early-warning systems may achieve predictive accuracy without producing a clear pedagogical effect.

The second contribution is that the study compares proactive and remedial alerts within the same environment, while controlling for content, activities, support resources, and time. This design allows for a clearer understanding of the effect of alert timing because it reduces the overlap of accompanying variables.

The third contribution lies in the use of multiple measurement instruments. The study combined a self-report scale, a performance rubric, a learning analytics log, a decision-making scale, a situational test, a decision quality rubric, and semi-structured interviews. This integration gives the findings greater explanatory strength, as the superiority of proactive alerts did not appear in one instrument only, but across multiple streams of data. The results files confirmed that all quantitative hypotheses favored proactive alerts, with effect sizes ranging from moderate to large, and that the qualitative interviews supported this direction.

The fourth contribution lies in linking self-regulated learning with academic decision-making within a learning analytics-based personalized learning environment. Many studies focus on self-regulated learning or achievement, whereas the present study highlights academic decision-making as an important outcome of self-regulation, especially in learning environments that require students to read data and choose appropriate actions.

### 12.8 A Critical Reading of the Findings

Although proactive alerts outperformed remedial alerts, the findings should be interpreted with scientific caution. Remedial alerts were not ineffective; they helped students address errors and correct their learning path after the problem had occurred. Therefore, the findings do not recommend eliminating remedial alerts. Rather, they suggest that remedial alerts should not be the only form of support. They may be necessary when academic difficulty has already occurred, but they become more effective when preceded by proactive alerts that reduce the likelihood of reaching that stage.

The strength of proactive alerts may also be related to the quality of their design in the present study. The alerts were designed to be clear, non-punitive, linked to a specific indicator, and connected to an executable action. Therefore, the finding should not be generalized to every proactive alert regardless of its wording. A vague, repetitive, or irritating proactive alert may be ignored or may increase students' burden. Thus, early timing alone is not sufficient; it must be accompanied by careful pedagogical design.

The findings also indicate that the effect of alerts cannot be separated from the nature of the environment. The personalized learning environment was built within Moodle in an organized way, with clear units, support resources, progress indicators, and a Learning Analytics Log. If the environment were disorganized or the support resources were inappropriate, the alerts might not have produced the same effect. Therefore, the findings should be understood as the result of integration among the environment, analytics, instructional design, and alert pattern.

## 13. CONCLUSIONS

The study concluded that the proactive-alerts pattern was more effective than the remedial-alerts pattern in developing self-regulated learning and academic decision-making among educational technology students within a learning analytics-based personalized learning environment. This conclusion was supported by the results of all main measurement instruments, including the self-report scales, performance rubrics, Moodle Learning Analytics Log, situational test, academic decision quality rubric, and semi-structured interviews.

The findings indicate that the educational value of early-warning alerts does not lie merely in notifying students of a risk or difficulty. Rather, it lies in the ability of the alert to appear at a pedagogically meaningful moment and to direct the student toward a clear, feasible action. In this sense, proactive alerts were more influential because they reached students before academic difficulty occurred, allowing them to plan, review, seek support, and adjust their learning behavior before a negative outcome appeared.

The study also concluded that remedial alerts remain educationally valuable, particularly when students have already encountered a problem and need support to correct errors, review feedback, and improve performance. However, their effect was more limited than that of proactive alerts because they were delivered after the problem had already appeared. Thus, the distinction between proactive and remedial alerts should not be understood as a distinction between useful and useless support, but as a distinction between preventive support and corrective support.

The findings further suggest that learning analytics become more educationally effective when they are transformed into interpretable alerts linked to specific actions. Data alone do not regulate students' learning. They support regulation only when they help students understand their situation, consider the available alternatives, and choose an appropriate course of action. For this reason, proactive alerts in the present study functioned as a bridge between learning data, self-regulated learning, and academic decision-making.

## 14. RECOMMENDATIONS

In light of the study findings, it is recommended that learning analytics-based personalized learning environments should include proactive alerts based on early risk indicators, such as delayed access to content, failure to complete a preliminary activity, or failure to review instructions before completing a task. These alerts should be designed in clear, non-punitive language and should be linked to a specific action and an appropriate support resource.

It is also recommended that early-warning systems in digital learning environments should not be limited to remedial alerts that appear after academic difficulty has occurred. Instead, they should combine proactive and remedial alerts within a graduated support structure. Proactive alerts help prevent academic difficulty, while remedial alerts remain necessary for addressing difficulty when it actually occurs.

E-course designers and faculty members are encouraged to use learning analytics not only to monitor students, but also to enable students to monitor themselves. This requires presenting indicators in a way that students can understand and use, rather than keeping them as technical reports available only to the instructor or system administrator.

The study also recommends that instructional alerts should be connected to actual learning behavior within the environment. An effective alert should not be a general message sent to all students in the same way. Rather, it should be based on a specific indicator, such as not opening the content, not submitting a task, weak interaction, or not using a support resource.

Programs preparing educational technology students should include practical experiences in designing data-informed instructional alerts. Such experiences would help students develop a professional understanding of how to build digital learning environments that support self-regulated learning and academic decision-making.

It is further recommended that students be trained to read progress indicators within learning environments, interpret alerts, and use the support resources linked to them. The effectiveness of an alert does not depend solely on its appearance; it also depends on students' ability to understand and respond to it.

## 15. LIMITATIONS

Despite the strength of the experimental design and the use of multiple measurement instruments, the study has several limitations that should be considered when interpreting the findings. First, the study was limited to fourth-year students in the Department of Educational Technology, Faculty of Specific Education, Alexandria University. Therefore, generalizing the findings to other specializations or universities depends on the similarity of the educational context and student characteristics.

Second, the study was applied in the e-learning course, which is closely related to the nature of the research topic and to the specialization of the sample. The findings may differ if the model is applied in other theoretical or practical courses with different task structures and different indicators of academic difficulty.

Third, the environment was designed within Moodle, a platform that provides appropriate features for tracking and analytics. The results may vary if the same treatment is implemented in another learning management system with different tracking capabilities, interface design, or support-resource structure.

Fourth, early warning of academic difficulty in the present study was based on learning indicators and alert-issuing rules within Moodle, such as accessing content, completing activities, performing in formative tests, submitting assignments, and using support resources. The study did not rely on an independent machine-learning model whose predictive accuracy could be tested in terms of sensitivity, specificity, or classification indicators. Therefore, the results should be interpreted in relation to the effect of alert timing and educational function, not in relation to the efficiency of an algorithmic prediction model.

Fifth, some measurement instruments relied on self-report, such as the Self-Regulated Learning Skills Scale and the Academic Decision-Making Scale. Although the study attempted to reduce this limitation by using performance instruments, Moodle digital logs, a situational test, and an Academic Decision Quality Rubric, self-report data still remain subject to students' perceptions and response tendencies.

Finally, the study measured the effect of the treatment immediately after implementation and did not include a long-term follow-up measurement to examine whether the effect of proactive or remedial alerts on self-regulated learning and academic decision-making continued after the end of the experiment.

Accordingly, the findings should be viewed as connected to the specific methodological and applied context of the study. They may be used to guide future studies that examine the same alert patterns in other courses, different specializations, longer application periods, and with more advanced predictive models.

## 16. FUTURE RESEARCH SUGGESTIONS

Future research may examine the effect of proactive and remedial alerts across different university specializations to determine whether the superiority of proactive alerts appears to the same extent in theoretical, practical, or design-based courses. The model may also be reapplied to larger samples from multiple universities, allowing researchers to examine the influence of institutional context and students' digital culture.

The study also suggests examining the effect of adaptive alerts that combine alert timing with students' preferences and prior level of self-regulated learning. Not all students may need the same type of alert, the same frequency, or the same degree of detail. Therefore, adaptive alerts may be more appropriate than uniform alerts.

Future studies may also investigate the effect of integrating artificial intelligence into the wording of instructional alerts, provided that transparency, privacy, and the avoidance of generic automated messages are carefully considered. It may be useful to test automatically generated alerts that remain reviewable by the instructor, thereby combining the speed of analytics with the accuracy of pedagogical judgment.

Longitudinal studies are also recommended to examine the long-term effect of proactive alerts on self-regulated learning and academic decision-making, particularly to determine whether students continue to use planning, monitoring, and decision-making skills after the experimental treatment has ended.

More in-depth qualitative studies may also be conducted to understand how students interpret alerts, what factors lead them to respond to some alerts while ignoring others, and how the wording, tone, and frequency of alerts influence students' motivation and sense of autonomy.

The study further suggests conducting future research comparing alerts based on educational rules within learning management systems, such as Moodle, with alerts generated by predictive machine-learning models. Such studies may examine the accuracy of predictive models in the early identification of students at risk of academic difficulty, the interpretability of the alerts generated by the system, students' trust in these alerts, and their effect on self-regulated learning and academic decision-making.

Future studies may also examine the effect of combining intelligent predictive models with interpretable instructional interventions. In such a model, the system would not merely identify students at risk; it would also provide the reason for the alert, the risk indicator, the suggested action, and the appropriate support resource. This direction is expected to contribute to the development of personalized learning environments that are more capable of providing early, fair, interpretable support while preserving students' responsibility for their own learning.

## 17. PRACTICAL IMPLICATIONS FOR DESIGNING PERSONALIZED LEARNING ENVIRONMENTS

The findings of the study offer several practical implications for designers of personalized learning environments. First, alerts should be based on interpretable learning indicators, rather than on general rules that are not connected to students' actual behavior. The more clearly students understand why an alert has appeared, the more likely they are to respond to it.

Second, an alert should include a clear and actionable step. It is not enough for an alert to tell students that their performance is low unless it also clarifies what they should do next: Should they review an example? Open a support resource? Try again? Ask for help? The findings of the present study show that the suggested action was an important element in the effectiveness of alerts.

Third, alerts should be written in supportive and non-stigmatizing language. The purpose of an alert is not to label students as struggling, but to help them understand their learning situation. Therefore, statements that may provoke anxiety or frustration should be avoided, and calm, practical language should be used, focusing on what can be done.

Fourth, alerts should be part of an integrated support cycle that includes detecting the indicator, sending the alert, providing a support resource, monitoring the student’s response, and then adjusting the support when needed. An alert that is disconnected from the environment and its support resources may become a passing message with little effect.

Fifth, a balance should be maintained between proactivity and overuse. Early alerts are useful, but they may lose their effect if they become too frequent or repetitive without justification. Therefore, the rules for issuing alerts should be carefully designed so that alerts appear only in situations with clear educational value.

## 18. CONCLUSION

The present study examined the effect of early-warning alert timing, represented by proactive versus remedial alerts, within a learning analytics-based personalized learning environment on educational technology students’ self-regulated learning and academic decision-making. The results showed a clear superiority of proactive alerts across all measurement instruments, including self-report scales, performance rubrics, the Learning Analytics Log, situational tests, and the Academic Decision Quality Rubric. The semi-structured interviews also supported this direction.

These findings confirm that the real value of learning analytics does not lie merely in collecting data or producing digital indicators, but in transforming these data into pedagogical support that reaches students at the right moment. When the alert arrives before academic difficulty occurs, students have the time and space to make better decisions and regulate their learning more consciously. When the alert arrives after difficulty has occurred, it remains useful for correction, but it does not necessarily give students the opportunity to prevent the problem.

The findings also confirm that the effectiveness of learning analytics is not determined only by the amount of data available within the learning environment. It depends more fundamentally on how these data are transformed into clear, interpretable instructional messages connected to actions that students can perform. Digital data alone are not sufficient to improve learning unless they are converted into pedagogical support that helps students understand their situation, identify the point of risk, and choose the appropriate action at the appropriate time.

Accordingly, the educational value of proactive alerts does not lie merely in their being early messages. Rather, it lies in their ability to enable students to read their learning data, regulate their behavior, use support resources, and make appropriate academic decisions before risk develops into actual academic difficulty. Remedial alerts also remain valuable when they are designed as corrective support that helps students review their performance, analyze their errors, and improve their decisions after the problem has appeared.

Thus, the study highlights the importance of viewing instructional alerts as a design element within personalized learning environments, rather than as merely informational or technical tools. An effective alert is one that connects the learning indicator, its meaning, the required action, and the opportunity for improvement. In doing so, it supports students’ autonomy and responsibility for their own learning, while enhancing the capacity of learning analytics-based environments to provide more humane and effective pedagogical support.

The present study therefore provides experimental evidence that alert timing should be viewed as a core design element in learning analytics-based personalized learning environments. Proactive alerts are not merely early messages; they are a mechanism for developing learners who are more aware of their data, more capable of regulating their learning, and more prepared to make evidence-based academic decisions.

## Declarations

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**Conflict of Interest:** The authors declare no conflict of interest.
**Ethical Considerations:** Informed consent was obtained from the participants, and all data were analyzed anonymously and in aggregate form.

**Data Availability:** Aggregated statistical outputs and instrument descriptions may be made available upon reasonable request after removing identifying information.

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