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INVESTIGATING THE INTERACTION BETWEEN E-TEST TYPE (ADAPTIVE VS. NON- ADAPTIVE) AND LEARNING STYLE (HOLISTIC VS. ANALYTICAL): IMPLICATIONS FOR SELF-EFFICACY AND STUDENTS' SATISFACTION WITH THE TEST AMONG EDUCATIONAL TECHNOLOGY STUDENTS

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ABSTRACT

This study is to examine how self-efficacy and test satisfaction among students studying educational technology are impacted by the type of electronic exam (adaptive vs. non-adaptive) and learning style (holistic vs. analytical). Recent trends toward the application of artificial intelligence in the development of intelligent assessment technologies that improve measurement accuracy and adjust assessments to the unique needs of each learner make the study significant. Using a 2x2 factorial experimental design, the study included a group of students studying educational technology who were categorized based on their learning preferences and exam types. When compared to non-adaptive exams, the results showed statistically significant differences in favor of adaptive exams, which raised students' academic satisfaction and sense of self-efficacy. In terms of efficiency and performance, analytical learners did better than holistic learners. Furthermore, when adaptive exams were combined with analytical learning styles, the interaction between exam type and learning style demonstrated a favorable combination effect that improved assessment effectiveness. These results are in line with current developments that highlight the value of implementing AI-based educational tools, including deep learning chatbots, which support individualized instruction and inspire exceptionally motivated pupils. In order to enhance educational quality and foster students' self-efficacy, the study suggests implementing

adaptive assessment models in online learning environments and combining them with AI-powered personalized learning tools.

KEYWORDS: Adaptive Exams, Non-Adaptive Exams, Learning Styles, Self-Efficacy, Academic Satisfaction, Educational Technology, Artificial Intelligence in Assessment, Personalized Learning, Smart E-Assessment

1. INTRODUCTION

Rapid advancements in educational technologies and the growing trend of using digital environments for teaching and evaluation have caused significant changes in the educational process in recent decades. One of the most notable examples of this change is electronic assessment, or "E-exams," which assist get around many of the drawbacks of traditional exams, including time, location, and logistical issues. However, the majority of e-exam systems in use today still offer the same information to all students without taking into account their unique learning preferences, which may lessen their ability to boost students' self-esteem and contentment with their education.

This emphasizes the necessity of creating new kinds of electronic tests that are flexible and adaptive to the individual traits and learning preferences of students. A more equitable and individualized experience can be had by using adaptive electronic tests, which are a creative solution based on examining students' learning patterns and tailoring exam items and pathways to students' aptitudes and chosen learning styles (Katsaris & Vidakis, 2021).

It is anticipated that by increasing students' confidence in their capacity to perform and overcome obstacles, these adaptive tests will improve their self-efficacy, which is a crucial component of successful learning. Additionally, they help people feel more satisfied with the process of learning and evaluation, which boosts their drive and perseverance (Stavropoulou, Daniilidou, & Nerantzaki, 2025).

When compared to traditional tests, a number of studies have demonstrated that the use of e-assessments enhances student happiness and boosts the efficacy of the educational process. According to other studies, using adaptive assessment technologies improves students' self-efficacy (confidence) and makes the exam process more adaptable and equitable (Baah, Konovalov, & Tenzin, 2024). Few research, nevertheless, have examined the effects of adaptive tests and learning type analysis on students' self-efficacy and satisfaction with educational technology. This disparity emphasizes how important the current study is to filling that gap and offering insightful theoretical and practical information (du Plooy, Casteleijn, & Franzsen, 2024).

Building on this basis, the current study aims to investigate how students studying educational technology build their sense of self-efficacy and pleasure in relation to adaptive versus non-adaptive electronic tests, which are based on differences in learning styles. The study intends to help the continuous digital change in education and enhance contemporary instructional practices.

1.1. Motivation

Because they offer flexibility, precision, and efficiency in evaluating learning outcomes, electronic exams have emerged as a promising instrument in the field of educational technology that has the potential to revolutionize assessment procedures. However, there are serious issues with educational institutions' capacity to accommodate students' individual variances, especially with regard to learning styles, as they use digital evaluation methods more and more. Understanding how individual learning styles—particularly holistic and analytical—interact with the multifaceted structure of adaptive e-exams, which can be created with different degrees of adaptation in question presentation, difficulty, and feedback types, is one of the main challenges.

While research on electronic and adaptive assessment has shown that such systems can boost students' motivation and confidence (Katona & Gyonyoru, 2025, Yan, Chiu, & Ko, 2020), prior studies have shown that learning styles have a significant impact on how students process information and interact with learning environments (Okafor, 2025, Wolniak & Stecuła, 2024). Nonetheless, there is still a significant lack of research on how learning styles and adaptive exam design affect students' self-efficacy and happiness with educational technology.

While pleasure is regarded as a key determinant of the caliber and efficacy of the learning process, self-efficacy is characterized as a student's confidence in their capacity to finish academic assignments (Prifti, 2020). Higher levels of success and academic performance have been linked to increased self-efficacy and contentment, according to research. However, further research is still needed to fully understand how learning style and adaptive exam design interact (Anthonysamy & Singh, 2023)

This study is motivated by the desire to answer the following important questions: What effects do the structure of adaptive versus non-adaptive electronic tests and learning styles (holistic vs. analytical) have on students' growth of self-efficacy and satisfaction with educational technology? Which e-exam design is best for boosting students' self-esteem and contentment with the evaluation process? This study aims to give educators, instructional designers, and policymakers useful information for creating more equitable and successful assessment practices in digital learning environments by using an experimental design based on independent and dependent variables.

1.2. Contributions

1. **Developing a factorial experimental framework**

This work makes a contribution by using a 2×2 factorial experimental design to investigate how the structure of adaptive versus non-adaptive electronic tests interacts with learning styles (holistic vs. analytical). This framework offers a methodical way to assess how these factors work together to affect students' pleasure and sense of self-efficacy.

2. **Measuring self-efficacy and satisfaction**

The study uses proven measuring measures to gauge students' satisfaction with their educational experience and self-efficacy, or their confidence in completing academic assignments. The impact of exam structure and learning styles on these dependent variables are objectively investigated using sophisticated statistical methods.

3. **Examining interaction effects**

This study's analysis of the interplay between learning style and exam design (adaptive vs. non-adaptive) is one of its main contributions. Compared to other combinations, it is expected that analytical learners who are subjected to highly adaptive tests will show higher levels of self-efficacy and pleasure.

4. **Integrating theoretical frameworks**

The study incorporates a number of theoretical viewpoints from the fields of e-assessment (Brink & Lautenbach, 2011, Jordan, 2016) and learning styles (Cassidy, 2004, El-Bishouty, Aldraiweesh, Alturki, & Kinshuk, 2018). The research offers a more thorough understanding of how technological design interacts with educational and psychological concepts to improve student results by combining these findings.

5. **Providing Practical Recommendations for Exam Design**

This study provides educators and system developers with useful guidelines on how to create adaptive and non-adaptive tests that take into account students' various learning preferences, guaranteeing a more equitable and fulfilling evaluation process. The goal of these designs is to improve students' performance, motivation, and self-esteem.

6. **Advancing Research in Assessment Design**

This study helps identify which adaptation elements—like difficulty level, feedback style, or question variation—best enhance self-efficacy and satisfaction by concentrating on the structure of adaptive and non-adaptive e-exams. Future research aimed at enhancing digital evaluation systems is made possible by this insight.

7. **Establishing a Foundation for Future Research**

The results of this study offer a fundamental framework for investigating how learning styles and adaptive versus non-adaptive e-assessment interact. By including other factors like exam anxiety or long-term academic success, future research can build on these findings and advance the field of educational technology and digital assessment.

1.3. Research Gap

There is still a glaring knowledge vacuum about the usefulness of multidimensional adaptive tests in the context of individual learning styles and their influence on students' self-efficacy and happiness, even with the increasing use of electronic and adaptable assessments in higher education.

The majority of earlier research has ignored the behavioral and psychological aspects of the learner's experience in favor of comparing the efficiency or correctness of traditional and electronic assessments. For example, studies have shown that students' happiness with e-learning is significantly impacted by their learning preferences and sense of self-efficacy (Avşar & Alkaya, 2017). According to other research, including learning style-based adaptive learning greatly improves interaction and participation in the educational process (Yaseen, Mohammad, Ashal, Abusaimeh, Ali, & Sharabati, 2025).

Similar to this, new research indicates that adaptable technologies enhance students' pleasure with their educational experiences in addition to their academic success (Contrino, Reyes-Millán, Vázquez-Villegas, & Membrillo-Hernández, 2024). Additionally, it has been discovered that adaptive assessment increases student motivation and decreases unhappiness (Lee & Jia, 2024).

Research directly linking learning styles, adaptive assessments, and their combined effects on students' self-efficacy and satisfaction with educational technology is still lacking, nevertheless. By putting forth an experimental framework that incorporates both psychological and pedagogical aspects, the current study aims to close this gap and create a more comprehensive and in-depth knowledge of the phenomenon.

1.4. Research Questions

The present study seeks to answer the following main question:

How do self-efficacy and test satisfaction among educational technology students change when the type of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical) interact?

The following follow-up questions are derived from this primary query:

1. What is the effect of the type of electronic test (adaptive vs. non-adaptive) on self-efficacy among educational technology students?
2. What is the effect of learning style (holistic vs. analytic) on self-efficacy among educational technology students?
3. What is the effect of the interaction between test type and learning style on self-efficacy among educational technology students?
4. What is the effect of the type of electronic test on students' satisfaction with the test?
5. What is the effect of learning style on students' satisfaction with the test?
6. What is the effect of the interaction between test type and learning style on students' satisfaction with the test?

1.5. Research Hypotheses

1. There is a statistically significant difference (at $\alpha = 0.05$) between the mean scores of students' self-efficacy due to the main effect of test type (adaptive vs. non-adaptive), favoring the adaptive test, regardless of learning style (holistic vs. analytic).
2. There is a statistically significant difference (at $\alpha = 0.05$) between the mean scores of students' self-efficacy due to the main effect of learning style (holistic vs. analytic), favoring the analytic learning style, regardless of test type.
3. There are statistically significant differences (at $\alpha = 0.05$) in self-efficacy scores due to the interaction effect between test type and learning style.
4. There is a statistically significant difference (at $\alpha = 0.05$) between the mean scores of students' test satisfaction due to the main effect of learning style, favoring the analytic learning style, regardless of test type.
5. There is a statistically significant difference (at $\alpha = 0.05$) between the mean scores of students' test satisfaction due to the main effect of test type, favoring the adaptive test, regardless of learning style.
6. There are statistically significant differences (at $\alpha = 0.05$) in test satisfaction due to the interaction effect between test type and learning style.

1.6. Research Objectives

The present study aims to:

1. Identify the effect of the type of electronic test (adaptive vs. non-adaptive) on self-efficacy among Educational Technology students.
2. Identify the effect of the type of electronic test (adaptive vs. non-adaptive) on students' satisfaction with the test.
3. Determine the effect of learning style (holistic vs. analytical) on self-efficacy among Educational Technology students.
4. Determine the effect of learning style (holistic vs. analytical) on students' satisfaction with the test.
5. Explore the effect of the interaction between the type of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical) on self-efficacy among Educational Technology students.
6. Explore the effect of the interaction between the type of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical) on students' satisfaction with the test.

1.7. Significance Of the Research

1. Theoretical Significance:

By examining the impact of adaptive and non-adaptive electronic assessments in the context of learning styles (holistic vs. analytical), this study adds to the body of knowledge in education. It supports contemporary theories in e-assessment and measurement by offering a scientific framework for comprehending the relationship between learning style and test type on the one hand, and self-efficacy and satisfaction on the other.

By combining learning style factors with adaptive assessment, the study opens up new avenues for future research in other fields and contributes a new dimension to educational research.

2. Practical Significance:

By taking into account the various learning styles (holistic/analytical) of Educational Technology students enrolled in the Fundamentals of Photographic Imaging course, the study aids in the improvement of the electronic exam design.

It allows teachers to select the best kind of electronic test (adaptive or non-adaptive) to boost student happiness, lower test anxiety, and raise self-efficacy.

The study offers useful metrics for creating dynamic online learning environments that enhance students' performance and the caliber of their education in both theoretical and applied facets of photography.

It helps instructional designers and decision-makers implement intelligent electronic assessment systems that foster creativity and increase students' self-assurance in applied learning settings.

1.8. Research Delimitations

1. Subject Delimitations:

Only two learning styles—holistic and analytical—are included in the study.

It focuses on electronic assessments that are both adaptive and non-adaptive.

It focuses on helping first-year Educational Technology students enrolled in the Fundamentals of Photographic Imaging course increase their sense of self-efficacy and pleasure.

2. Temporal Delimitations:

The trial ran for four weeks, from March 2 to March 28, 2024, during the second semester of the 2024–2025 school year.

3. Human Delimitations:

Sixty first-year male and female students from Kafrelsheikh University's Department of Educational Technology, Faculty of Specific Education, made up the study sample.

Because the researchers instructed this group, the sample was selected to enable efficient execution and close observation of the experiment.

1.9. Research Instruments

The current research relies on the following instruments:

1. Cognitive Style Scale (Holistic / Analytical).
2. Self-Efficacy Scale.
3. Student Satisfaction with Test Scale.
4. Electronic Testing Environment (Adaptive and Non-Adaptive).

1.10. Research Variables

1.10.1. Independent Variables

1. Cognitive Style (Holistic / Analytical).
2. Type of Electronic Test (Adaptive / Non-Adaptive).

1.11. Dependent Variables

1. Self-Efficacy.
2. Student Satisfaction with the Test.

1.12. Experimental Design

As can be seen below, the researchers employed a 2×2 factorial experimental design with four experimental groups that were tested both before and after the study:

E-Test Type / Learning Style	Adaptive	Non- Adaptive	
Holistic	Group (1)	Group (3)	
Analytical	Group (2)	Group (4)	

2. LITERATURE REVIEW

2.1. Adaptive And Non-Adaptive Electronic Exams

The presentation of test questions has changed significantly as a result of the move to electronic assessments, enabling a variety of formats that complement the assessment's goals and the content's characteristics. One important factor that has a direct impact on students' focus, motivation, and performance is the way questions are presented (Mate & Weidenhofer, 2021).

Presenting a single question at a time allows students to concentrate on their responses without interruptions, which lowers the likelihood of cheating and improves cognitive accuracy (Taşkın, 2024). However, when students encounter difficult problems that take more time, this method may provide difficulties and could have an impact on their ability to manage their time during tests (Csapai, Varga, & Berke, 2020).

Collaborative Question Presentation, on the other hand, permits the display of several questions at once, allowing students to move between them, investigate connections, and foster cooperation, dialogue, and problem-solving abilities (Fung, To, & Leung, 2016). However, because group members contribute differently, this approach can jeopardize the fairness of individual evaluations (Johnston & Miles, 2005).

According to educational research, the method of question presentation should be chosen to best support the desired learning outcomes. While collaborative presentations are better at fostering critical thinking and cooperative learning abilities, individual presentations are better at evaluating topic knowledge mastery (Tong, Uyen, & Ngan, 2022).

The navigation mechanism, which establishes whether students can freely move between questions or must adhere to a set sequence, is another crucial component of e-exam design. Students' experience, concentration, and performance results are significantly impacted by navigation (Du, Liu, &

Zhao, 2025).

By allowing students to begin with simpler questions before progressing to more challenging ones, Free Navigation promotes autonomy and self-regulation by letting them choose the sequence of questions based on their own techniques. However, this strategy could result in poor time management or unclear questions that are ignored (Sharma, 2018).

Conversely, Sequential Navigation offers a clear structure that reduces the possibility of students skipping questions by requiring them to follow a preset order. Nevertheless, it limits adaptability and could impede students' favored time-management techniques (Knage & Søndergaard, 2024).

Sequential navigation is more suited for students who require systematic direction, whereas free navigation is better for autonomous learners, according to research that suggests selecting navigation strategies based on the characteristics of learners and the assessment goal (Neil-Sztramko, Caldwell, & Dobbins, 2021).

2.2. Causes Of Deficiencies in Designing Electronic Tests

Even though electronic tests are widely used, their efficacy is mostly dependent on how well they are designed. The validity and dependability of their findings could be impacted by a number of flaws (Erlinawati & Muslim, 2021).

The first reason is the lack of specific learning objectives, which results in inquiries that are not in line with the desired learning results. Furthermore, poor quality management of test items frequently leads to biased or erroneous questions that are unable to accurately assess students' performance (Ajogbeje, 2023).

Furthermore, a significant obstacle is the lack of attention given to accessibility, since many assessments do not take individual characteristics or the requirements of students with disabilities into account. The usefulness of assessments may also be diminished by technological limitations, such as inadequate user interfaces and system failures (Khamaj & Ali, 2024).

Test developers' lack of training in educational design principles, the limited participation of stakeholders (students, teachers, and experts), time and resource constraints, and, lastly, the lack of pilot validation—a crucial step in ensuring test quality—are additional contributing factors (Ghaleb, 2024).

One of the most important recent advancements in electronic assessment is Multidimensional Adaptive Testing (MAT). It is a more sophisticated version of Computerized Adaptive Testing (CAT), which has historically only assessed one aspect of cognition. By evaluating students' performance across several interconnected cognitive or skill dimensions at once, MAT, on the other hand, seeks to diagnose student levels with more accuracy and thoroughness (Wang et al., 2022).

Multidimensional Item Response Theory (MIRT), the foundation of this kind of testing, postulates that a student's answer to any given question is impacted by a number of overlapping dimensions, including numerical aptitude, logical thinking, and problem-solving skills. Ackerman, Gierl, and Walker (2003) state that the exam is automatically created by choosing items based on the student's prior responses in each of these parameters, enabling a highly customized and adaptable assessment path.

Because these tests capitalize on correlations across several dimensions, research shows that they attain a better level of measurement accuracy than standard assessments. Additionally, they aid in shortening test durations and completion times without sacrificing accuracy (Mohajan, 2017).

Additionally, multidimensional adaptive assessments offer a comprehensive view of a student's aptitudes, making it possible to precisely pinpoint both strengths and limitations. This makes them especially useful in fields that are complex, including medicine, applied sciences, and languages (Tutunaru, 2023).

In practice, these assessments have been widely used in language proficiency evaluations, where a single adaptive test is used to assess speaking, listening, writing, and reading abilities. Additionally, they are employed in medical and engineering education to evaluate interrelated abilities like problem-solving, diagnosis, and decision-making (Burr et al., 2023).

But putting such testing into practice is still difficult. The need for large and dependable item banks that cover all targeted skills, the computational complexity of algorithms required to select items in a multidimensional environment, and a strong technical infrastructure that can process real-time data are some of the main challenges (van der Linden & Glas, 2010, p.98). Additionally, test developers and educators must have specific training in psychometrics and data analysis for successful deployment.

Notwithstanding these difficulties, researchers believe that Multidimensional Adaptive Electronic Testing has a bright future, particularly with the incorporation of machine learning and artificial intelligence algorithms, which can improve the accuracy of adaptive item selection and produce more individualized assessment pathways. As a result, these examinations mark a significant advancement toward more intelligent, equitable, and efficient computerized assessment systems.

The function of electronic testing and its effects on learning outcomes have been the subject of numerous research. For example, at Al-Adl University in Yemen, Balhareth & Al-kamzy (2025) compared adaptive and linear e-tests and discovered that adaptive exams were better at predicting student talents and enhanced academic accomplishment.

The impacts of multistage adaptive testing on eighth-grade students' experiences with arithmetic examinations were also examined by Lee & Jia (2024), who found that while adaptivity improved the experiences of low-performing students, it raised the time pressure for high performers.

Frey, Liu, Fink, and König (2024) examined adaptive testing research and came to the conclusion that, depending largely on how test items are presented and designed, adaptive testing does not necessarily have a beneficial effect on motivation and emotions.

2.3. Analytical Vs. Holistic Cognitive Style

Cognitive styles, which reflect the various ways people absorb, process, retain, and retrieve information, are basic ideas in educational psychology. According to Riding and Rayner (1998), they are permanent patterns of thinking and learning that affect how people approach different educational and cognitive settings rather than cognitive talents per se.

Consistent inclinations, preferences, and routine techniques that influence how a person sees, recalls, thinks, learns, and solves issues are referred to as cognitive style. As a vital connection between personality and cognition, it also includes how individuals engage with their surroundings. Cultural differences in perceptual and cognitive processes are reflected in two different ways of thinking: analytical and holistic (Kozhevnikov, Evans, & Kosslyn, 2014).

2.4. Analytical Cognitive Style

Information is typically processed by someone with an analytical cognitive style by dissecting it into smaller parts and looking at it sequentially and linearly, paying close attention to details. This approach is particularly useful in circumstances requiring systematic analysis or sophisticated problem-solving, notably in the scientific and mathematical realms, because it is intimately linked to logical and deductive reasoning (Zhang & Sternberg, 2005).

Analytical thinkers are adept at following procedures to arrive at conclusions and favor organized frameworks and categorized material. This is consistent with the sequential information processing that underpins analytical learning (Riding & Cheema, 1991).

Information is usually processed by analytical thinkers by breaking it up into digestible chunks (Lacko et al., 2023). Their emphasis is on specifics, logical progression, and methodical examination to comprehend the whole by dissecting its constituent parts. They often separate target things or people from their surroundings by focusing on particular components and their characteristics. Additionally, they avoid inconsistencies, categorize items in a hierarchical manner, and understand events using formal logic (Koo et al., 2018).

2.5. Holistic Cognitive Style

People with a holistic cognitive style, on the other hand, approach information by looking at the big picture before getting into the specifics. They concentrate on the connections and broad trends between concepts. These people are better at using intuitive thinking and making integrated connections between ideas, which improves their performance on activities that call for creativity or multifaceted problem-solving (Riding & Cheema, 1991).

Instead of processing information as discrete parts, holistic people process it as a whole (Lacko et al., 2023). Instead of emphasizing specific components, this style emphasizes the overall context and connections between various aspects. Holistic thinkers analyze events and occurrences by emphasizing the whole picture, attributing causality to surrounding elements, and drawing on experience-based knowledge. Additionally, they prefer to categorize items according to thematic linkages and predict cyclical changes (Koo et al., 2018).

According to Zhang and Sternberg (2000), this style is also linked to parallel information processing and nonlinear thinking, which makes its proponents more likely to employ mind maps and global concept visualizations.

2.6. Comparison Between the Two Styles

The processing methods of the two cognitive styles are different: holistic thinkers go from whole to part, whereas analytical thinkers go from part to whole. Analytical people place more emphasis on accuracy and detail, whereas holistic people pay more attention to relationships and patterns. As a result, each style has advantages and disadvantages. For example, analytical thinkers might ignore the larger picture, whereas holistic thinkers might overlook more specific details. Scholars have highlighted that incorporating both approaches into teaching practices improves the quality of learning and the variety of approaches used (Riding & Rayner, 1998).

2.7. Educational Applications

These variations emphasize how crucial it is to take into account both kinds when designing curricula. Both inclinations should be accommodated in the presentation of educational content; for example, mind maps and conceptual overviews can be used for holistic learners, while analytical learners can benefit from structured explanations with step-by-step instructions.

By enabling students to transition between linear information and hyperlinked materials, e-learning environments in particular can accommodate both learning styles. Fairness and inclusivity are promoted in assessment by using a combination of conceptually related items and analytical, sequential questions (Zhang & Sternberg, 2000).

Improving teaching methods requires an understanding of cognitive styles. Understanding these variations facilitates the creation of flexible learning settings that suit a range of cognitive preferences, improving learning outcomes and the development of higher-order thinking abilities (Lacko et al., 2023). Learning systems, for instance, can be tailored to display content in context-driven holistic formats or detail-oriented analytical formats, improving understanding and engagement for all students. To further detect these style variations and provide more individualized teaching practices, a number of cross-cultural cognitive evaluations, such as cognitive tasks and psychometric measures, have been established (Koo et al., 2018).

2.8. The Relationship Between Cognitive Style and Adaptive Testing

Because it enables test items to dynamically adjust based on a learner's performance level, adaptive testing is a significant advancement in psychometric and educational assessment. Given that learners' response patterns vary according to their preferred methods of information processing, it is anticipated that this type of testing will interact with cognitive styles (Wainer, 2000).

Analytical learners, for instance, typically concentrate on specific details of questions and use step-by-step techniques to solve problems. In order to enable analytical learners to gradually advance toward increasingly difficult tasks, an adaptive test can be created to include items that progressively increase in difficulty. Their inclination for sequential reasoning and linear processing is ideally suited to this progressive framework (Riding & Cheema, 1991).

2.9. Holistic Cognitive Style and Adaptive Testing

Prioritizing links between concepts over specifics, learners with a holistic cognitive style prefer to approach circumstances from a global perspective. Items that present complex, scenario-based circumstances that represent a larger picture or combine several concepts may be beneficial to these learners in the context of adaptive testing. This enables them to use holistic processing techniques to understand and successfully answer inquiries. The validity and efficacy of assessment are improved when test items for these students allow for conceptual linking and innovative solution production (Zhang & Sternberg, 2005).

Therefore, matching learners' cognitive processes with adaptive test design can enhance measurement validity and accuracy while boosting students' perceptions of assessment fairness. In line with current developments in tailored education, this alignment also enhances adaptive testing's capacity to foster personalized learning (Van der Linden & Glas, 2010).

Based on the individualization principle, adaptive testing is designed to modify the item difficulty in real time based on the learner's performance (Van der Linden & Glas, 2010). The aspects of cognitive styles (analytic vs. holistic) must be integrated into adaptive test design frameworks because, given individual differences, cognitive style is a critical variable impacting learners' response patterns (Riding & Rayner, 1998).

2.10. Analytic Cognitive Style and Adaptive Testing

Analytical learners are characterized by their attention to detail, linear processing, and reliance on methodical analytical reasoning (Riding & Cheema, 1991).

Adaptive testing application: In keeping with their progressive cognitive approach, test items can be presented gradually, starting with easy questions and working their way up to more difficult ones. Anticipated result: Because test format and analytical thinking are structurally compatible, there will be an increase in measurement accuracy and a decrease in cognitive worry.

2.11. Holistic Cognitive Style and Adaptive Testing

Holistic learners are characterized by their ability to see things holistically, integrate knowledge through linkages and patterns, and frequently rely on their intuition (Zhang & Sternberg, 2005).

Adaptive testing application: Test items that encourage conceptual linkages and holistic reasoning might be created as integrated or scenario-based tasks.

Anticipated results include enhanced motivation and engagement throughout testing as well as improved assessment validity for holistic learners.

2.12. Interaction Between Cognitive Styles and Adaptive Testing:

Both global (holistic) and linear (analytic) processing techniques can be combined with the adaptive testing framework.

In order to determine whether a student is more inclined toward analytical or holistic processing, adaptive systems can track response indicators like reaction time and selection patterns. Then, they can modify the test items' content accordingly (Wainer, 2000).

2.13. Relationship Between Cognitive Style and Item Difficulty:

A key component of educational assessment is figuring out how difficult test items are, as this has a direct impact on test validity and discrimination power (Haladyna & Rodriguez, 2013). Analytical and holistic learners react to test items differently, which reveals the association between this element and cognitive style.

1. Analytic Learners and Item Difficulty:

Analytical learners typically take a methodical and structured approach to problems, starting with data analysis and working their way up to conclusions. Since they prefer linear processing, they find it easier to answer questions with clear stages or comprehensive facts. On the other hand, because there is no sequential framework, queries that call for the integration of several concepts or holistic reasoning may be more challenging (Riding & Cheema, 1991).

2. Holistic Learners and Item Difficulty:

On the other side, complicated, contextualized, or integrated questions that call for understanding connections between ideas are simpler for holistic learners to handle. Their cognitive preferences are matched by problems that are presented as real-life scenarios or that involve several interacting factors. However, because they necessitate sequential, part-by-part processing, extremely detailed or computational issues could be more difficult (Zhang & Sternberg, 2005).

3. Integrating Both Styles in Test Construction:

Because each learner is presented with test items that are suitable with their preferred processing type, assessment fairness is improved when item difficulty is determined by taking into account both cognitive styles. This balance guarantees that the test gives a complete picture of students' performance in addition to measuring analytical or holistic skills (Riding & Rayner, 1998, Wainer, 2000).

3. RESEARCH METHODOLOGY

The current study adopts the following methodologies:

1. Descriptive-Analytical Method:

Reviewing previous studies related to the research topic.

Conducting content analysis, constructing the theoretical framework, and developing research instruments.

2. Experimental Method:

Investigating the effect of interaction between independent and dependent variables.

Testing hypotheses and answering the research questions.

3.1. Research Procedures

First: Preparation and Planning Stage

1. Reviewing Literature and Previous Studies

The researchers looked at Arabic and foreign literature on self-efficacy, satisfaction, learning styles (holistic and analytical), and adaptive and non-adaptive computerized testing.

The theoretical framework, the research challenge and objectives, and the research gap that the current study seeks to fill were all formulated with the assistance of this review.

2. Content Analysis of The Fundamentals of Photographic Imaging Course

To determine the desired learning outcomes (cognitive and skill-based), the researchers examined the targeted course's content.

To confirm its application and relevance, a team of educational technology specialists reviewed a list of critical abilities pertaining to the research issue.

Second: Research Instrument Development Stage

3. Cognitive Style Scale (Analytical/Holistic)

The researchers adopted the Felder & Silverman Learning Styles Model (1988) to identify students' cognitive learning styles.

4. Self-Efficacy Scale

A self-efficacy scale with 39 items spread over six dimensions—academic conduct, academic context, achievement, organization and time management, cognitive skills, and test-taking management—was created by the researchers.

A group of specialists examined the scale to make sure it was clear and had valid content.

5. Student Satisfaction with The Test Scale

To gauge how satisfied students were with the computerized testing process, a student satisfaction scale was created. It has 20 things spread over four dimensions: comfort, challenge level, fairness, and question clarity.

To ensure its authenticity and linguistic clarity, specialists also reviewed it.

Third: Experimental Environment Design Stage

6. Designing The Electronic Testing Environments

Two adaptive and non-adaptive digital testing environments were created and set up to store question banks and track student performance:

A system in which every student receives the same set of questions without any variation is known as a non-adaptive environment.

Adaptive Environment: The test dynamically modifies the questions and pathways based on each student's responses by modifying difficulty levels and offering feedback.

Steps For Creating a Non-Adaptive Test Using Moodle

Step 1: Creating The Question Bank

1. From the course page, select More → Question Bank.
2. Create Categories to organize questions by topic or unit.
3. Add questions (Multiple Choice, True/False, Short Answer, etc.).
4. Assign a score and estimated time for each question.

Step 2: Creating The Quiz Activity:

1. Go to the course page and click Turn editing on.
2. Select Add an activity or resource → Quiz.
3. Enter the quiz name (e.g., Educational Photographic Imaging Test).
4. Write instructions for students in the Description field.

Step 3: General Quiz Settings

1. Timing:

- Set the start and end date.
- Set the time limit (20 minutes).
- Enable When time expires → Submit automatically.

2. Grade:

Set the total grade (40 marks).

3. Layout:

Display questions across multiple pages.

4. Question Behaviour:

Choose Deferred feedback (show feedback after completion) or Immediate feedback depending on the purpose.

Enable Shuffle within questions to randomize answer options.

5. Review Options:

Display to students after completion (grade, feedback, correct answers).

Step 4: Adding Questions to the Quiz

- After saving settings, click Edit quiz.
- Add questions from the question bank or create new ones directly.
- Add individual questions (Add → from question bank) or random questions (Add → a random question) from specific categories.
- Set the grade weight for each question or for the whole section.

Step 5: Testing the Quiz

The test was piloted using a "test student" account to verify clarity, timing accuracy, and functionality.

Step 6: Implementation and Reporting

Detailed reports were generated for each student's responses, identifying the most difficult questions and average scores.

Summary of the Key Difference Between the Adaptive and Non-Adaptive Tests

1. Non-Adaptive Test: Fixed — all students take the same items.
2. Control Parameters: Limited to order of questions, number of attempts, feedback, and time.
3. No Algorithm: The test does not change the difficulty level dynamically during the

assessment.

Steps for Developing an Adaptive Test Using Moodle

Using a defined methodological approach as described below, the researchers created the adaptive exam by fusing the technical capabilities of the Moodle learning management system with the theoretical underpinnings of Item Response Theory (IRT):

1. Theoretical Planning Stage

Create a table in the test specification that lists the target domains, competencies, and levels of Bloom's taxonomy.

Specify the adaptive algorithm's halting criteria and test length restrictions.

2. Item Bank Development

- Write a large pool of test items that accurately cover all specified domains and skills.
- Have the items reviewed by experts to verify content and face validity.
- Enter the items into Moodle, classifying them into thematic categories and tagging each with its difficulty level.

3. Statistical Calibration of Items

- Administer the items to a pilot sample and collect response data.
- Use statistical packages (e.g., SPSS) to estimate item parameters and eliminate unsuitable items.
- Prepare an item parameter file for export and integration with the adaptive system.

4. Test Configuration within Moodle

- Install the Adaptive Quiz plugin.
- Configure test parameters such as:
- Starting difficulty level
- Minimum and maximum number of items
- Standard error threshold for stopping
- Add the tagged items to the test or import the parameter file if using an advanced plugin version.

5. Pilot Testing

- Conduct a small-scale pilot test to verify the algorithm's functionality and the correct progression of difficulty.
- Adjust item transition rules or stopping criteria based on pilot feedback.

6. Actual Implementation

- Administer the adaptive test to the research sample under controlled conditions.
- Extract ability estimates from Moodle and convert them into standardized scores suitable for analysis.

7. Test Trial and Validation

- Run the test using a dummy student account to confirm proper adaptive sequencing.
- Modify the settings until the desired balance and progression are achieved.

8. Data Collection and Reporting

Examine the ability estimates, the quantity of things offered, and the specifics of the students' performance from the Reports part of the activity.

3.2. Sample Selection and Experimental Design

3.2.1. Research Population and Sample

First-year students in the Department of Educational Technology at Kafrelsheikh University's Faculty of Specific Education made up the research population.

115 students were chosen as a purposive sample, and their cognitive styles were categorized.

3.3. Classification By Cognitive Style

Using a Cognitive Style Inventory, students were categorized as follows:

- Holistic learners: 64 students
- Analytical learners: 51 students

A total of 60 students were chosen from this group, 30 of whom were holistic and 30 of whom were analytical, in accordance with the independent variables of the study.

3.4. Division Into Experimental Groups (2×2 Factorial Design)

The participants were divided into four equal experimental groups as follows:

1. Holistic learners × Adaptive test
2. Holistic learners × non-adaptive test
3. Analytical learners × Adaptive test
4. Analytical learners × non-adaptive test

3.5. Implementation Phase

3.5.1. Pre-Measurement

To ascertain the baseline levels of each student, the researchers gave them pre-tests on self-efficacy and satisfaction measures.

3.6. Experimental Treatments

- The two types of tests (adaptive and non-adaptive) were applied across the four groups.
- All sessions were conducted under uniform conditions (time, location, and technological tools) to ensure fairness.
- The researchers' role during testing was limited to technical supervision without influencing student performance.

3.7. Post-Measurement

To assess the effects of the experimental treatments, the self-efficacy and satisfaction ratings were re-administered following the conclusion of the trial.

3.8. Research Results

3.9. First: Equivalence Of the Experimental Groups

Prior to the experiment, the degree of equivalency between the four experimental groups was ascertained by analyzing the findings of the self-efficacy scale pre-administration. This was accomplished by figuring out how the groups' pre-test self-efficacy scores varied from one another.

To check for statistically significant differences between the groups, a one-way analysis of variance (ANOVA) was employed.

The following table presents the results of the one-way ANOVA for the four experimental groups' pre-test self-efficacy scores.

Table:

Tool		Sum of Squares	df	Mean Square	F	Sig.
Self-efficacy scale	Between Groups	13.733	3	4.578	.279	.840
	Within Groups	919.200	56	16.414		
	Total	932.933	59			

Since the computed F-value was 0.279, which is not statistically significant at the (0.05) level, Table (2) makes it evident that there are no significant variations in the pre-test self-efficacy scores across the four experimental groups.

According to these findings, the groups' homogeneity suggests that the four experimental groups were equal prior to the trial, and any discrepancies that emerge following the experiment can be linked to variations in the study's independent variables.

4. RESULTS ANALYSIS AND INTERPRETATION

The study's primary goal was to assess how students' self-efficacy and test satisfaction among Educational Technology students were impacted by the interaction between the type of electronic test (adaptive vs. non-adaptive) and cognitive style (holistic vs. analytical). The findings pertaining to this goal are shown in the section that follows:

1. Responding To the Research Questions Related to Self-Efficacy Among Educational Technology Students

The levels of the first independent variable (electronic test type: adaptive vs. non-adaptive), the levels of the second independent variable (cognitive style: holistic vs. analytical), and the interaction effect between these two independent variables on students' self-efficacy were all compared using a two-way analysis of variance (Two-Way ANOVA) in order to test the research hypotheses pertaining to self-efficacy.

The findings of the Two-Way ANOVA examining the impact of the cognitive style and the type of electronic test, as well as their interaction, on students' self-efficacy in relation to educational technology are shown in the following table (Table 3).

Table:

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
test_type	1025.067	1	1025.067	40.505	.000
learning_style	1306.667	1	1306.667	51.632	.000
test_type learning_style	1815.000	1	1815.000	71.719	.000
Error	1417.200	56	25.307		
Total	1105012.000	60			
Corrected Total	5563.933	59			

1. First Research Question:

What impact does the type of electronic test (adaptive versus non-adaptive) have on students' self-efficacy in relation to educational technology?

The following hypothesis was examined in order to respond to this query:

First Hypothesis:

Regardless of the cognitive style (holistic/analytical), the main effect of the type of electronic test (adaptive vs. non-adaptive) favors the adaptive test, resulting in a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale.

Regardless of cognitive style, the major effect of the kind of electronic test results in a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale, according to the results shown in the preceding table. At the (0.05) level, the F-value of 40.505 indicates statistical significance.

This suggests that students' self-efficacy was significantly impacted by the kind of electronic test they took.

The adaptive test group's mean score was 139.500, while the non-adaptive test group's mean score was 131.233. This information was used to establish the direction of the discrepancy.

(Table 4):

test_type	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
adaptive	139.500	.918	137.660	141.340
non adaptive	131.233	.918	129.393	133.073

According to the preceding table, the adaptive electronic test had a higher mean score, indicating that it was significant.

The original hypothesis was approved in light of these findings and revised as follows: The major effect of the kind of electronic test (adaptive vs. non-adaptive) favors the adaptive test, regardless of the learning style (holistic/analytical), resulting in a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale.

Second Research Question:

What impact does a holistic versus analytical learning style have on students' self-efficacy in educational technology?

The following hypothesis was examined in order to respond to this query:

Regardless of the type of electronic test (adaptive vs. non-adaptive), the main effect of learning style (holistic vs. analytical) results in a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale in favor of the analytical learning style.

Regardless of the type of electronic test, Table (3) shows that the major influence of learning style causes a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale. At the (0.05) level, the F-value of 51.632 indicates statistical significance.

This suggests that students' self-efficacy was significantly impacted by their learning method.

In order to ascertain the direction of the difference, it was discovered that the analytical learning style group's mean score was 140.033, but the holistic learning style group's mean score was 130.700.

(Table 5):

learning_style	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
holistic	130.700	.918	128.860	132.540
analytical	140.033	.918	138.193	141.873

According to the preceding table, the analytical learning style had a higher mean score, indicating a significant advantage.

These findings led to the acceptance and rewording of the second hypothesis as follows: Regardless of the type of electronic test (adaptive vs. non-adaptive), the main effect of learning style (holistic vs. analytical) results in a statistically significant difference at the (0.05) level between the mean scores of students on the self-efficacy scale in favor of the analytical learning style.

Third Research Question:

What impact does the interplay between learning style (holistic vs. analytical) and electronic exam type (adaptive vs. non-adaptive) have on students' self-efficacy in educational technology? The following hypothesis was examined in order to respond to this query:

The interaction effect between the kind of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical) results in statistically significant variations between the mean scores of students on the self-efficacy scale at the (0.05) level.

According to Table (3), the interaction between the kind of electronic test and learning method resulted in statistically significant changes at the (0.05) level between the mean scores of students on the self-efficacy measure. At the (0.05) level, the F-value of 71.719 is statistically significant.

This suggests that students' self-efficacy is significantly impacted by the relationship between the type of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical).

A Tukey post hoc test was used to ascertain the direction of these changes, and Table (6) displays the findings.

Table (6):

VAR00001	N	Subset for alpha = 0.05	
		1	2
1.00	15	129.3333	
4.00	15	130.4000	
3.00	15	132.0667	
2.00	15		149.6667
Sig.		.451	1.000

The table makes it evident that Group 2, which consisted of students with an analytical learning style who took the adaptive test, had the highest mean score.

These results led to the acceptance of the third hypothesis, which was then rephrased as follows: The interaction effect between the kind of electronic test (adaptive vs. non-adaptive) and learning style (holistic vs. analytical) results in statistically significant variations between the mean scores of students on the self-efficacy scale at the (0.05) level.

2. *Answering The Research Questions Related to Students' Satisfaction with The Test*

The researchers employed a two-way analysis of variance (Two-Way ANOVA) to ascertain the differences between the following in order to assess the research hypotheses about students' satisfaction with the electronic test among Educational Technology students:

The first independent variable's levels are determined by the kind of electronic test (adaptive or non-adaptive).

The degrees of learning style (holistic vs. analytical), the second independent variable. The impact of the interaction between the two independent variables (learning style and test type) on students' test satisfaction was also investigated in this analysis.

Students' satisfaction with the test in the Educational Technology program is influenced by the type of electronic test (adaptive vs. non-adaptive), the learning style (holistic vs. analytical), and the interaction between these factors, as shown in the results of the two-way ANOVA in Table 7.

Table (7):

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
test_type	952.017	1	952.017	34.778	.000
learning_style	1206.017	1	1206.017	44.057	.000
test_type learning_style	1938.017	1	1938.017	70.798	.000
Error	1532.933	56	27.374		
Total	211081.000	60			
Corrected Total	5628.983	59			

Research Question Four:

What impact does an electronic test's kind (adaptive versus non-adaptive) have on students' satisfaction with educational technology courses?
The following hypothesis was examined in order to respond to this query:

Hypothesis (4):

There is a statistically significant difference at the (0.05) level between the mean scores of students on the Student Satisfaction with the Test Scale due to the main effect of the type of electronic test (adaptive/non-adaptive), in favor of the adaptive test, regardless of the learning style (holistic/analytical).

Regardless of cognitive style, it is clear from the preceding table that the type of electronic test (adaptive vs. non-adaptive) has a major impact on the mean scores of students on the satisfaction scale, resulting in a statistically significant difference at the (0.05) level. At the (0.05) level, the F value was 34.778, indicating statistical significance.

This suggests that regardless of a student's cognitive style, the type of electronic test has a major impact on their level of enjoyment.

The adaptive test group's mean score was 62.5000, whereas the non-adaptive test group's mean score was 54.5333. This information was used to establish the direction of the discrepancy.

Table (8):

Student satisfaction with the test	Mean	Std. Error	95% Confidence Interval for Mean	
			Lower Bound	Upper Bound
adaptive	62.5000	11.69365	58.1335	66.8665
non adaptive	54.5333	4.95311	52.6838	56.3829

According to the preceding table, the analytical learning style has a higher mean score, which indicates that it is significant.

The fourth hypothesis was approved and reformulated as follows in light of the aforementioned:

The main effect of the type of electronic test (adaptive/non-adaptive) favors the adaptive test, regardless of the learning style (holistic/analytical), resulting in a statistically significant difference at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale.

Research Question 5:

How do students who study educational technology feel about the test in relation to their learning style (holistic vs. analytical)?

The Following Hypothesis Was Examined in Order To Respond To This Query:

Regardless of the type of electronic test (adaptive or non-adaptive), the main effect of learning style (holistic versus analytical) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale, favoring the analytical learning style.

It is evident from Table (7) that, independent of test type, the main effect of learning style (holistic/analytical) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale. At the (0.05) level, the F-value of 44.057 indicates statistical significance.

This suggests that regardless of the kind of electronic test, students' pleasure with it is significantly impacted by their learning style.

In order to ascertain the direction of the difference, it was discovered that the analytical learning style group's mean score was 63.0000, but the holistic learning style group's mean score was 54.0333.

Table (9):

Student satisfaction with the test	Mean	Std. Error	Std. Error	95% Confidence Interval for Mean	
				Lower Bound	Upper Bound
Holistic	54.0333	5.02053	.91662	52.1586	55.9080
analytical	63.0000	11.28319	2.06002	58.7868	67.2132

According to the preceding table, the analytical learning style has a higher mean score, which indicates that it is significant.

The fifth hypothesis was approved and rephrased as follows in light of the aforementioned: Regardless of the type of electronic test (adaptive or non-adaptive), the main effect of learning style (holistic versus analytical) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale, favoring the analytical learning style.

Research Question 6:

What impact does the interplay between the learning style (holistic/analytical) and the type of electronic test (adaptive/non-adaptive) have on students' test satisfaction among educational technology students?

The following hypothesis was examined in order to respond to this query: The interaction effect between the kind of electronic test (adaptive/non-adaptive) and learning style (holistic/analytical) results in statistically significant variations at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale.

It is clear from looking at Table (7) that the interaction between the type of electronic test (adaptive/non-adaptive) and learning style (holistic/analytical) results in statistically significant differences at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale. At the (0.05) level, the F-value of 70.798 indicates statistical significance.

This suggests that students' happiness with the test is significantly influenced by the interaction between the type of electronic test and their preferred method of learning.

Table 10 displays the results of the Tukey post hoc test, which was used to ascertain the direction of the differences.

Table (10):

groups	N	Subset for alpha = 0.05	
		1	2
1.00	15	52.3333	
4.00	15	53.3333	
3.00	15	55.7333	
2.00	15		72.6667
Sig.		.294	1.000

The table makes it clear that Group 2 (adaptive test with analytical learning approach) had the highest mean score.

The sixth hypothesis was approved and rephrased as follows in light of the aforementioned:

The interaction effect between the kind of electronic test (adaptive/non-adaptive) and the learning style (holistic/analytical) results in statistically significant variations at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale.

Discussion And Interpretation of The Results:

The following interpretation of the findings can be made based on the presentation of the statistical analysis results testing the research hypotheses:

First: Interpretation Of the Results Related To Self-Efficacy

The results of the statistical analysis showed that, independent of learning style (holistic or analytical), the main effect of the type of electronic test (adaptive versus non-adaptive) favors the adaptive test, resulting in a statistically significant difference between the mean scores of students on the Self-Efficacy Scale at the (0.05) level.

This finding is consistent with behaviorist theory, which holds that because the adaptive exam is founded on the ideas of stimulus gradation and behavioral regulation based on performance level, it increases students' self-efficacy. Students feel successful and accomplished when they are given questions that are appropriate for their present skill level. This reinforces good behaviors and boosts performance.

This steady rise in difficulty maintains learner motivation, builds self-confidence, and balances challenge and capability in a way that shapes behavior. Thus, the adaptive test's efficacy is consistent with behaviorist ideas in that it gradually shapes and reinforces academic behavior to reach the required degree of self-efficacy.

Moreover, the findings demonstrated that, independent of test type, the major influence of learning style (holistic vs. analytical) led to a statistically significant difference at the (0.05) level between the mean scores of students on the Self-Efficacy Scale in favor of the analytical learning style.

Constructivist theory, which holds that analytical learners typically gain their knowledge by dissecting situations into smaller bits and comprehending the relationships among parts to construct the complete picture, can be used to explain this outcome. Their perceived self-efficacy rises as a result of this analytical process, which raises awareness of thought processes and achievements.

According to constructivism, learning happens when students actively absorb and organize information, increasing their awareness of their comprehension, analytical, and problem-solving skills. Therefore, regardless of the exam type, the analytical learning style boosts students' self-efficacy by encouraging progressive knowledge creation and fortifying their sense of control over their learning process.

The findings also showed that self-efficacy was significantly impacted by the type of electronic test and learning style.

Constructivist theory can also be used to interpret this data, indicating that adaptive testing and holistic/analytical learning styles interact to produce a dynamic learning environment that enables students to independently build their knowledge based on their aptitudes. Students' perception of competence and control over their education is increased by adaptive exams, which give them assignments that are harder in proportion to their achievement.

From distinct angles, both analytical and holistic learning styles aid in the organizing and comprehension of knowledge: the former builds understanding through part-to-whole analysis, while the latter derives meaning from the entire structure. Both gain from adaptive testing's constructivist and interactive features, which promote introspection, strategy modification, and knowledge creation.

Through better self-awareness and comprehension of their skills, students gain more self-efficacy as a result of this engagement.

The findings from (du Plooy, Casteleijn, &

Franzsen, 2024), (Okafor, 2025), (Wolniak & Stecuła, 2024), (Katona & Gyonyoru, 2025), (Yan, Chiu, & Ko, 2020), (Yaseen et al., 2025), (Contrino et al., 2024), and (Lee & Jia, 2024) are in agreement with these findings.

Second: Interpretation Of the Results Related To Students' Satisfaction With The Test:

Due to the major effect of test type (adaptive/non-adaptive), the statistical analysis results showed a significant difference at the (0.05) level between the mean scores of students on the Students' Satisfaction with the Test Scale, favoring the adaptive test independent of learning style.

This might be read in the context of behaviorist theory, which holds that because adaptive testing is founded on the ideas of stimulus gradation and learning environment management based on learner performance, it results in higher levels of pleasure. Students respond favorably to the learning process when they are given questions that are appropriate for their level because they feel less frustrated or anxious and more successful and accomplished.

The behaviorist idea of positive reinforcement is supported by this steady increase in difficulty, which serves as behavioral shaping by boosting confidence and satisfaction via recurrent success. As a result, regardless of learning style, adaptive test design that takes individual characteristics into account makes learning more rewarding and interesting. Furthermore, the results indicated that, independent of test type, the major effect of learning style (holistic versus analytical) was significantly different at the (0.05) level in favor of the analytical learning style.

This can be explained in the context of constructivist theory, which contends that analytical learners are more satisfied with their education because they actively and methodically participate in learning activities, building knowledge through question analysis and conceptual relationship comprehension. The constructivist idea that learning is an active, self-directed process built on interaction and individual meaning-making is reflected in this method.

Regardless of the type of test, analytical learners also like assignments that foster problem-solving, logical thinking, and exploration since these activities provide them a stronger sense of control over their education and increase their level of pleasure. This interpretation is therefore consistent with the constructivist viewpoint, which holds that active engagement and individual knowledge creation lead to satisfaction and successful learning.

The findings also showed that student satisfaction was significantly impacted by the type of electronic test and learning method.

From a behaviorist standpoint, this can be explained as follows: adaptive testing enhanced positive responses and pleasure by fostering a learning environment with increasing complexity, which decreased anxiety and frustration while encouraging repeated success. In line with the ideas of behavioral regulation and gradual reinforcement, students felt more competent and in charge.

From a constructivist standpoint, students were able to organize knowledge and construct understanding based on their cognitive style through the interplay between test type and learning style. While holistic learners profited from observing broad conceptual linkages, analytical learners profited from the sequence of questions for further in-depth contemplation and analysis. Through active engagement and individual meaning-making during assessment, this constructivist interaction increased satisfaction.

These findings align with research by (Mate & Weidenhofer, 2021), (Wang et al., 2022), (Tong, Uyen, & Ngan, 2022), (Du, Liu, & Zhao, 2025), (Neil-Sztramko, Caldwell, & Dobbins, 2021), (Burr et al., 2023), (Frey, Liu, Fink, & König, 2024), and (Lacko et al., 2023). These findings support the importance of both adaptive and non-adaptive electronic testing, as well as their interaction with holistic and analytical learning styles, in enhancing learner satisfaction.

5. CONCLUSION

According to the study's findings, one of the best strategies for enhancing students studying educational technology's experience with academic assessments is adaptive electronic testing. Compared to non-adaptive assessments, this kind of assessment improved academic satisfaction and self-efficacy.

Additionally, the results demonstrated that while the test type had no effect on holistic learners, the analytical learning style was more suitable with adaptive testing and resulted in improved academic achievement.

These findings highlight how crucial individual adaptation is in learning and evaluation settings. The efficacy of the educational process is increased by taking into account various learning styles. The results are in line with current developments in educational artificial intelligence, which highlight how intelligent systems, including educational chatbots and adaptive assessments, can raise students' motivation and competency through individualized interaction and real-time feedback.

The study suggests using adaptive analytics to measure students' performance in real time and incorporating AI technology into university evaluation designs. Fairer and more accurate assessment practices that encourage lifelong learning and inspire students to succeed and be creative can result from this.

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