SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 11, No. 4, (2025), pp. 2337-2366
Open Access. Online & Print

DOI: 10.5281/zenodo. 18422007

THE EFFECT OF THE INTERACTION BETWEEN LEARNING STYLE (SURFACE / DEEP) AND CONTENT PRESENTATION MODE (CONDITIONAL / FLEXIBLE) IN AN ADAPTIVE LEARNING ENVIRONMENT ON ACQUIRING COMPUTER MAINTENANCE SKILLS AND DEVELOPING ANALYTICAL THINKING AMONG EDUCATIONAL TECHNOLOGY STUDENTS

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Received: 11/11/2025
Accepted: 18/12/2025

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ABSTRACT

The necessary adjustments the objective of this study is to examine how students studying educational technology develop their analytical thinking and computer maintenance skills in an adaptive learning environment by interacting with their learning style (deep/surface) and content presentation mode (conditional/flexible). The necessity to create electronic learning environments that take into account the unique characteristics of each student and modify content in accordance with their cognitive levels and learning styles led to the study. A 2×2 factorial experimental design was used in the study, which involved 56 first-year students from Kafrelsheikh University's Department of Educational Technology, Faculty of Specific Education. When compared to the surface learning style, the results showed statistically significant differences favoring the deep learning style in the development of computer maintenance abilities and analytical thinking. Furthermore, in terms of improving students' overall performance, the flexible material presentation option fared better than the conditional method. Since students with a deep learning style who studied using flexible content attained the highest levels of analytical thinking and practical abilities, the results also showed a strong relationship between learning style and content presentation manner. These findings highlight how crucial it is to use adaptive learning environments in higher education since they offer individualized learning experiences that take into consideration students' learning preferences and foster their independence and drive

to study. Additionally, to attain more profound and long-lasting learning outcomes, adaptive and AI-based technologies can be included into contemporary teaching methodologies.

KEYWORDS: Adaptive Environments – Learning Style – Content Presentation – Surface Learning – Deep Learning – Conditional Presentation – Flexible Presentation – Computer Maintenance Skills – Analytical Thinking – Educational Technology – E-Learning.

1. INTRODUCTION

The significance of emphasizing how students learn rather than just what they learn or acquire is becoming more and more apparent in contemporary educational practices. In order to accommodate individual differences among learners, overcome obstacles they encounter, and improve the processing, retention, and comprehension of acquired knowledge, there is an increasing awareness of the necessity of diversifying learning methods, tactics, and approaches. Additionally, instead of just passively absorbing knowledge, these developments urge students to actively engage in the educational process (Fadieieva, 2023; Katsaris & Vidakis, 2021).

A notable development in e-learning is adaptive learning systems, which offer individualized learning experiences tailored to the requirements and educational background of each student. These systems enhance learning effectiveness and comprehension by adapting educational content and presentation to the learner's skills (Brusilovsky & Peylo, 2003; Gomes, 2024). Adaptive environments also encourage cooperative involvement and knowledge exchange among students by fostering interactive and collaborative learning.

Students' engagement with instructional information is significantly influenced by their learning styles. According to Entwistle's (1981) paradigm, learning orientations can be divided into three categories: achievement, reproduction, and personal. These categories correlate to deep, surface, and strategic learning styles, respectively. The relationship between motivation and learning styles is further highlighted by Biggs (1987), who distinguishes surface, deep, and achievement-oriented approaches. While deep learners are inherently driven and seek conceptual understanding and practical application of knowledge, surface learners frequently rely on external incentive and rote memorization (Biggs & Tang, 2011; Talbi & Ouared, 2022; Kamberi, 2025).

Deep learners exhibit critical thinking, active involvement, and sophisticated cognitive processing, which enhances retention and expands their capacity to apply knowledge in novel circumstances (Marton & Säljö, 1976; Ramsden, 2003). In contrast, surface learners prioritize repetition and little academic standards, which hinders their understanding and long-term memory (Howie & Bagnall, 2013; Donnison & Penn-Edwards, 2012). Deep learning strategies are regularly linked to improved academic performance, mastering motivation, and intellectual curiosity, according to research (Bakhtiarvand et al., 2011; Floyd, Harrington, & Santiago, 2009; Pacak-Vedel, 2016).

By providing environments that adapt to learners' preferences, skills, and progress, adaptive learning enhances our understanding of learning styles. Adaptive systems offer customized learning routes, interactive feedback, and information that takes individual characteristics into account, in contrast to conventional "one-size-fits-all" e-learning systems (Hammad, Hariadi, Purnomo, & Kurniawan, 2018; Wang, Wang & Huang, 2008; Weber, 2019). Adaptive learning systems are better equipped to track learner performance over time, forecast future behavior, and optimize content delivery when artificial intelligence and data analytics are integrated (Kruger, 2021; Girault, 2020).

Additionally, adaptive learning environments provide psychological advantages by establishing stimulating and secure locations where students may voice their thoughts, accept difficulties, and persevere through assignments. By offering ongoing feedback and learning experiences that are suitably paced, they promote motivation, independence, and a positive attitude toward learning (El-Sabagh, 2021; Stein, 2019; Kurt, 2021). Students can access content in adaptive settings based on their preferred learning styles and cognitive levels thanks to their flexibility and interaction, which improves engagement, comprehension, and achievement (Paramythis & Loidl-Reisinger, 2003; Costa et al., 2021).

One essential component of adaptive learning systems is content adaptation. Conditional and flexible content delivery are examples of adaptive presentation techniques that try to match content to learners' levels and preferences in order to minimize cognitive overload and preserve learning coherence (Bunt, Carenini, & Conati, 2007; Gligorea, Cioca, Oancea, & Tudorache, 2023). While flexible presentation enables learners to access extra explanations or links to enhance understanding, conditional presentation arranges content according to learner needs and past knowledge, encouraging learner autonomy and active involvement (Brusilovsky, Kosba & Negdi, 2007; Saarsar, 2018).

The significance of tailoring the way that content is presented to the requirements of learners is supported by theoretical underpinnings like as behaviorist, cognitive, constructivist, motivational, and cognitive load theories. These ideas emphasize that in order to maximize educational outcomes, learner control, cognitive processing, and motivation must be balanced (Burhanuddin, Ahmad, Said, & Asimiran, 2021; Gagné; Keller, 2010; Kalyuga, 2000).

The usefulness of adaptive learning environments has been shown by empirical research in a variety of educational situations, such as language acquisition, programming, 3D animation, and mathematics. Learner performance, critical thinking, problem-solving abilities, and usability satisfaction are all enhanced by these settings (Agustini, 2017; Yao, Zhong, & Cao, 2025; Holthaus, Pancar & Bergamin, 2019; Hamadtoh, Gohar, & El-Ghool, 2016).

1.1. Motivation

Because of the speed at which computer technologies have advanced in recent decades, students studying educational technology now need to be proficient in computer maintenance. In addition to keeping up with technological developments, mastering these skills will enable students to troubleshoot and resolve technical issues that could impede efficient learning or the use of technology in classrooms. However, the sequential nature and procedural complexity of computer maintenance make it difficult to learn. This emphasizes the significance of creating adaptive learning environments that may enable effective skill development and accommodate learners' individual characteristics.

Among these variations, learning style is thought to be a key element in predicting learning success. Students that have a surface learning style typically rely on external direction and rote memory, concentrating mostly on task performance with little interest in deeper comprehension. Students with a deep learning style, on the other hand, are more likely to understand, make connections between concepts, analyze issues, and create meaning. These variations have a significant impact on how students engage with and gain from different approaches to material delivery.

The way that the knowledge is presented is also crucial because it helps to organize the learning process. Conditional presentation ensures orderly development and cumulative knowledge accumulation by requiring learners to meet predetermined objectives or prerequisites before moving on to new content. Conversely, flexible presentation increases learners' independence and intrinsic motivation by giving them more freedom to explore the material as they see fit.

Therefore, it is anticipated that the efficiency of adaptive learning environments will be significantly influenced by the interaction between learning style (surface vs. deep) and content presentation mode (conditional vs. flexible). For example, flexible presentation may be better suited for exploration, analysis, and meaningful knowledge integration for deep learners, whereas conditional presentation may be more advantageous for surface learners since it offers structured guidance and minimizes distractions. Therefore, it is essential to analyze this interaction in order to optimize adaptive learning design.

Furthermore, the goal of higher education is to foster the development of analytical thinking abilities as well as practical skills, which allow students to assess issues critically, consider other options, and come to well-informed conclusions. Important insights into instructional design will come from examining the ways in which learning style and material presentation mode interact to influence the development of computer maintenance skills as well as the improvement of analytical thinking. It is anticipated that the results of this study will aid in the creation of adaptive learning systems that strike a balance between learner autonomy and structured instruction, thereby improving cognitive and practical learning outcomes.

1.2. Contributions

Several noteworthy theoretical and practical contributions are anticipated from this study:

1. Theoretical Contributions

- **Adding to the body of knowledge about adaptive learning environments:** The study offers empirical evidence on how individual differences impact the efficacy of adaptive instructional design by examining the relationship between learning style (surface vs. deep) and content presentation mode (conditional vs. flexible).
- **Enhancing knowledge of content presentation techniques:** The study clarifies the varying effects of conditional and flexible material presentation on students with different learning styles, highlighting their pedagogical significance.
- **Connecting cognitive and skill-based outcomes:** This study examines the development of analytical thinking and computer maintenance abilities at the same time, integrating both aspects in contrast to studies that only concentrate on the acquisition of cognitive or technical skills.
- **Offering a structure for next studies:** For further research that examines additional learner attributes (such as motivation and cognitive style) in connection to adaptive learning systems, the study provides a

conceptual and methodological foundation.

2. Practical Contributions

- **Enhancing educational technology instructional design:** The results will help teachers and instructional designers choose the best way to deliver content based on students' preferred learning methods, resulting in more efficient skill development.
- **Supporting the creation of computer maintenance curricula:** By finding efficient methods for instructing computer repair, the study helps create training materials that are both organized and flexible, improving students' preparedness for professional practice.
- **Developing higher-order thinking skills:** The study highlights how adaptive learning helps students think analytically, which supports colleges' efforts to give students the critical thinking and problem-solving skills they need in real-world situations.
- **Improving learner-centered education:** The study offers useful insights for developing adaptable and customized learning experiences that can be used in both in-person and virtual settings by highlighting the significance of matching instructional tactics with learners' preferences.

3. Methodological Contributions

- In order to provide more nuanced insights into adaptive learning, the study uses an experimental design that captures interactions. This design enables the examination of both the primary effects and the interaction effects of learning style and content presentation.
- Dual outcome measures: The study guarantees a thorough assessment of learning efficacy by evaluating both cognitive (analytical thinking) and practical (computer maintenance skills) results.

1.3. Problem Statement

Several factors contributed to the study's issue. The researchers noticed that first-year students have a lot of trouble using and maintaining computers while teaching theoretical and practical courses in Kafrelsheikh University's Department of Educational Technology and Computer Science. The intricacy of some maintenance abilities, which call for analytical reasoning, forecasting, and methodical problem-solving, is the root cause of many of these challenges. The traditional teaching techniques did not adequately address the requirements and abilities of the students, despite their high desire in learning computer maintenance, which they considered to be one of the important professional capabilities for their area.

The researchers used a sample of 24 first-year students in an exploratory investigation to validate this problem. According to the results, 95.42% of the students showed a weak degree of mastery across critical maintenance abilities, 4.58% attained a moderate level, and none of the students showed a high level of competence. However, 97.91% of students indicated that they were willing to learn these abilities, compared to 2.08% who were neutral and 0% who were unwilling, demonstrating that students were highly motivated to do so. These results indicated that while students suffer from a major shortage in both knowledge and practice, they also possess high preparedness and good attitudes towards learning computer maintenance.

A review of previous research revealed the dearth of studies examining the relationship between content presentation modes (conditional vs. flexible) and learning styles (surface vs. deep) in adaptive learning environments, particularly in relation to computer maintenance and the development of analytical thinking. Additionally, the recommendations of a number of national and international conferences, such as the 17th Scientific Conference of the Egyptian Association for Educational Technology (2020), the First Scientific Conference of the International Association for E-Learning and Educational Technology (2021), and the 19th Conference of the Arab Association for Educational Technology (2022), highlighted the importance of integrating modern technologies, especially adaptive learning environments, to improve learning outcomes and enhance skill acquisition.

Since first-year students in Kafrelsheikh University's Department of Educational Technology and Computer Science have poor computer maintenance abilities, the current study aims to remedy this issue. Its objective is to investigate how well adaptive learning environments that integrate both learning styles (deep vs. surface) and content presentation modes (conditional vs. flexible) help students develop the computer maintenance and analytical thinking skills that are essential for their future employment.

1.4. Research Questions

The present study seeks to answer the following main question:

What is the impact of the interplay between surface/deep learning style and conditional/flexible content presentation mode in an adaptive learning environment on students studying educational technology's development of analytical thinking and computer maintenance skills?

From this main question, the following sub-questions are derived:

1. How do first-year students in the Department of Educational Technology and Computer Science develop computer maintenance skills in relation to their learning style (deep vs. surface)?
2. How do first-year students in the Department of Educational Technology and Computer Science learn computer maintenance skills in relation to the conditional or flexible style of material presentation?
3. How do first-year students in the Department of Educational Technology and Computer Science learn computer maintenance skills when their learning styles (deep/surface) and material presentation modes (conditional/flexible) interact?
4. How do first-year students in the Department of Educational Technology and Computer Science develop their analytical thinking skills in relation to their learning style (deep vs. surface)?
5. How do first-year students in the Department of Educational Technology and Computer Science enhance their analytical thinking skills in relation to the conditional or flexible style of content presentation?
6. How does the relationship between the content presentation mode (conditional / flexible) and learning style (surface / deep) affect the growth of analytical thinking in first-year students in the Department of Educational Technology and Computer Science?

1.5. Research Hypotheses

1. The primary effect of learning style (deep vs. surface) results in a statistically significant difference at the level ($\alpha \leq 0.05$) between the mean scores of students on the performance observation checklist of computer maintenance skills, favoring the deep learning style independent of the mode of content presentation.
2. The main effect of the content presentation mode (conditional / flexible) favors the flexible presentation mode regardless of the learning style, resulting in a statistically significant difference at the level ($\alpha \leq 0.05$) between the mean scores of students on the performance observation checklist of computer maintenance skills.
3. The interaction between learning style (surface/deep) and content presentation mode (conditional/flexible) results in statistically significant differences ($\alpha \leq 0.05$) between the mean scores of students on the computer maintenance skills performance observation checklist, favoring the deep learning style in conjunction with the flexible presentation mode.
4. Regardless of the form of content presentation, the main effect of learning style (deep vs. surface) results in a statistically significant difference at the level ($\alpha < 0.05$) between the mean scores of students on the analytical thinking scale, favoring the deep learning style.
5. The major effect of the content presentation mode (conditional / flexible) favors the flexible presentation mode independent of the learning style, resulting in a statistically significant difference at the level ($\alpha < 0.05$) between the mean scores of students on the analytical thinking scale.
6. The interaction between learning style (surface / deep) and content presentation mode (conditional / flexible) results in statistically significant differences at the level ($\alpha \leq 0.05$) between the mean scores of students on the analytical thinking scale, favoring the deep learning style in conjunction with the flexible presentation mode.

1.6. Research Objectives

The present study aims to:

1. Make a list of the computer maintenance abilities that first-year students in the Department of Educational Technology and Computer Science must possess.

2. Assess how learning type (deep or surface) affects:

- First-year students in the Department of Educational Technology and Computer Science are developing their analytical thinking skills.
- First-year students in the Department of Educational Technology and Computer Science are learning how to maintain their computers.

3. Assess the impact of the content presentation mode (flexible or conditional) on:

- First-year students in the Department of Educational Technology and Computer Science are developing their analytical thinking skills.
- First-year students in the Department of Educational Technology and Computer Science are learning how to maintain their computers.

4. Determine whether learning style—deep or surface—is best suited for:

- Fostering critical thinking in first-year students in the Department of Computer Science and Educational Technology.
- In the Department of Educational Technology and Computer Science, first-year students are learning how to maintain their computers.

5. Determine which conditional or flexible content presentation option is best suited for:

- Encouraging first-year students in the Department of Educational Technology and Computer Science to think critically.
- First-year students in the Department of Educational Technology and Computer Science are learning how to maintain their computers.

6. Examine how the surface/deep learning style and the conditional/flexible content display method interact to:

- First-year students in the Department of Educational Technology and Computer Science are developing their analytical thinking skills.
- First-year students in the Department of Educational Technology and Computer Science are learning how to maintain their computers.

1.7. Significance Of the Study

The following are anticipated benefits of the current study:

1. Teaching the Department of Educational Technology and Computer Science's first-year students how to maintain computers.
2. Helping first-year students in the Department of Educational Technology and Computer Science develop their analytical thinking skills, which will help them become proficient in computer maintenance.
3. Stressing the value of utilizing adaptive learning environments to help first-year students in the Department of Educational Technology and Computer Science learn how to maintain their computers.
4. Adding to the body of knowledge about the use of adaptive learning environments in the teaching and learning process in the field of educational technology.
5. Introducing learning through adaptive learning environments, one of the newest e-learning innovations.
6. Offering research resources that could help other researchers carrying out related investigations.

1.8. Delimitations Of the Study

The current investigation is restricted to the following:

1.8.1. Subject Delimitations

- The type of learning (deep or surface).
- Mode of content presentation (flexible/conditional).
- First-year students in the Department of Educational Technology and Computer Science are developing their analytical thinking skills.
- First-year students in the Department of Educational Technology and Computer Science learn how to maintain their computers.

1.8.2. Time Delimitations

The study's experiment was carried out over the course of four weeks, from October 15 to November 12, 2024, during the first semester of the academic year 2024–2025.

1.8.3. Human Delimitations

56 first-year students from Kafr El-Sheikh University's Department of Educational Technology and Computer Science, Faculty of Specific Education, made up the research sample. The selection of this sample was justified by the fact that the researchers were instructing this particular set of students, which made it easier to perform the study practically and concretely.

1.8.4. Research Instruments

The following tools were used in this study:

1. A scale for analytical thinking that the researchers created.
2. A computer maintenance skills checklist that the researchers created.
3. The researchers created an environment for adaptive learning.

1.8.5. Research Variables

The following variables are included in the study:

1.8.6. Independent Variables

1. Learning style (deep or surface).
2. Mode of content presentation (flexible/conditional).

1.8.7. Dependent Variables

1. First-year students in the Department of Educational Technology and Computer Science are able to think analytically.
2. The ability of first-year students in the Department of Educational Technology and Computer Science to maintain their computers.

1.8.9. Experimental Design

The factorial experimental design (2 × 2), which has four experimental groups in both pre- and post-measurements, was chosen by the researchers based on the research variables.

The results are displayed in the following table:

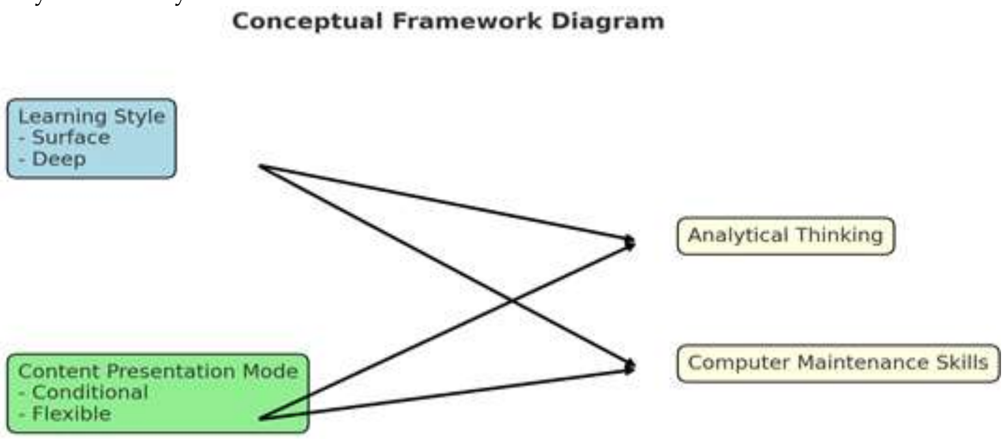

Table:

Experimental Design		
Learning Style / Conditional Content Presentation	Surface Learning	Deep Learning
Conditional	Group (1)	Group (3)
Flexible	Group (2)	Group (4)

Group (1) uses conditional content display in conjunction with the surface learning method. Group (2) uses variable content presentation in conjunction with the surface learning approach. Group (3) uses conditional material display in conjunction with the deep learning style. Group (4) uses variable content presentation in conjunction with the deep learning style.

The present study employed the following methodologies:

1. **Descriptive-Analytical Method:** Used to assess the literature, prior research, and related studies; define the study's theoretical framework; analyze content and make clear the relationships between its components; and create the experimental and measuring methods.
2. **Experimental Method:** This approach is used to evaluate research hypotheses and provide answers to research questions by analyzing the impact of the interaction between independent and dependent factors.

1.8.10. Research Procedures

The following sequential steps were used to conduct the current study:

1. A thorough analysis of pertinent Arabic and foreign literature, research, and earlier works that are directly related to the subject. The goal of this step was to develop the theoretical framework and provide guidance for the creation of experimental treatment materials and research instruments.
2. Development of a verified list of computer maintenance competencies needed by first-year students in the Department of Computer Science and Educational Technology. After experts examined the checklist, changes were made to finalize its content.
3. To divide the research participants into two groups—surface learners and deep learners—a learning style assessment was administered electronically.
4. The creation of a scale for analytical thinking,

which was reviewed by experts before being finalized.

5. Choosing the study sample, which included first-year students from Kafrelsheikh University's Faculty of Specific Education's Department of Educational Technology and Computer Science.
6. In accordance with the factorial design that was chosen, the participants were divided into four experimental groups based on the study's independent variables.
7. Creating educational scenarios for the adaptive learning environment that are specific to the two ways that content is presented (flexible and conditional).
8. Creating an adaptable learning environment with content that is compatible with both conditional and flexible presentation modes in order to promote computer maintenance skills. Experts verified the environment before it was finished with the required changes.
9. Performing a pilot study to determine possible difficulties or roadblocks during implementation, to guarantee the dependability of the research instruments, and to improve the processes.
10. **Using the factorial study methodology, the primary experiment was carried out in the following stages:**
    - Pre-tests for the research tools are administered.
    - Delivery of the experimental treatments in accordance with the designated modalities of content presentation and learning styles.
    - Post-tests are administered for the research instruments.
11. Documentation, statistical evaluation, and interpretation of the information gathered.
12. A discussion of the results in relation to the hypotheses and research topics.
13. Developing ideas and recommendations for additional study.

1.8.11. Key Terms of The Study

Surface Learning: A method of instruction where students prioritize memorization of computer maintenance-related facts and information over deeper comprehension. With minimal focus on fundamental principles, the primary goal is frequently restricted to passing tests or doing assigned work.

Deep Learning: A method of instruction where students work to gain a thorough understanding of computer maintenance techniques. This entails using knowledge in broader contexts and real-life scenarios, critically evaluating information, and tying new information to previously learned material.

Conditional Content Presentation: An approach to teaching in which students must fulfill specific requirements before moving on to new material. Prior to accessing further material, learners must successfully finish a predetermined set of tasks or develop a particular set of skills. The order of the content is determined by the performance or decisions of the learners.

A method of delivering teaching that gives students more autonomy in accessing the material is called flexible content presentation. Without being constrained by preconditions or predetermined sequencing, students are free to investigate computer maintenance abilities in whatever order they choose.

An adaptive learning environment is one that uses technology to tailor the educational process to each student's needs and preferred method of learning (deep or surface). It incorporates flexible and conditional material presentation methods and modifies tactics to aid in the development of learners. The major goal of this project is to improve the computer maintenance abilities of first-year students at Kafrelsheikh University's Department of Educational Technology, Faculty of Specific Education.

The technical skills necessary to disassemble, reassemble, troubleshoot, and repair computer systems, including precise issue identification and efficient tool use, are known as computer maintenance skills.

Analytical Thinking: A cognitive process in which students analyze data critically and break down computer maintenance issues into their most basic elements. To find practical answers, it entails recognizing connections, assessing the available data, and coming to logical conclusions.

2. LITERATURE REVIEW

2.1. Deep Learning and Surface Learning

Current educational trends stress that rather than concentrating solely on what pupils learn or acquire, attention must also be paid to how they learn. Diversifying learning approaches, strategies, and methods is becoming more and more popular as a way to address individual differences among students, solve their problems, and improve how well they absorb, retain, and comprehend the knowledge they have learned. Additionally, these developments motivate students to take an active role in their education.

With a number of advantages that improve students' experiences, adaptive learning systems are a major advancement in the e-learning space. By modifying the presentation and instructional materials in accordance with the demands and educational level of each learner, these systems offer individualized learning content. This leads to increased learning efficacy. Moreover, adaptive systems establish an interactive learning environment that encourages ongoing communication between the student and the material, which advances comprehension and deeper understanding. Additionally, by promoting collaboration, information sharing, and experience sharing, these settings help students learn collaboratively. Adaptive systems can provide varied and relevant content that makes it easier to comprehend complex material and increases the effectiveness of the learning process by evaluating student activities and determining their needs. In the end, adaptive systems improve the way content is delivered, make complex ideas easier to understand, and increase students' capacity to more successfully complete their coursework.

Since learning styles have a direct impact on the process of teaching and learning as well as the acquisition and application of knowledge, they have drawn a lot of attention. There are other theories and classifications of learning styles, including Entwistle's model (1981), which identifies three main orientations: achievement, reproduction, and personal. Three learning styles are distinguished by this classification: strategic, surface, and deep.

The learning strategies that children use throughout the learning process were also highlighted by Biggs (1987). His model identifies three main learning approaches, each of which is composed of two interrelated components—motivation and strategy—that work together to influence the learner's approach:

1. **Surface method:** Students who choose this method see education as a way to accomplish outside objectives like finding work. They concentrate on using rote learning and memorizing to meet academic criteria.
2. **Deep Approach:** Students are motivated by internal factors and a sincere desire to learn. They are highly skilled in interpretation, analysis, and summarization, and they have a thorough understanding of the subject, making connections between abstract concepts and practical applications. They are curious and passionate about their studies.
3. **Achievement/Strategic Approach:** Rather than delving thoroughly into the material, these students are more concerned with getting good scores. They exhibit excellent organizing abilities, effectively allocating their time and energy to succeed academically.

The following succinctly describes the traits of the surface learning style:

1. **Dependency on outside motivation:** Rather than an innate desire to learn, surface learners are largely motivated by outside incentives like grades or avoiding failure (Biggs, 1978).
2. **Emphasis on rote memorization:** This method reduces the application of information by emphasizing its mechanical storage without connecting it to conceptual or practical settings (Entwistle, 2000).
3. **Lack of critical engagement:** According to Ramsden (2003), surface learners frequently take instructions at face value without exercising critical judgment or reflective thought.
4. **Repetition and recall techniques:** They don't aim for profound comprehension or the development of conceptual connections; instead, they focus on mechanical repetition (Biggs & Tang, 2011).
5. **Poor knowledge transfer and retention:** This approach frequently leads to inadequate long-term information storage, which restricts the learner's capacity to remember or apply information in novel or unfamiliar situations. (Marton & Säljö, 1976).

The surface learning style, according to Talbi and Ouared (2022), is dependent on outside incentive, with learners aiming to accomplish career-related objectives. Their main goal is to complete the course requirements by memorizing, and they are motivated by the prospect of succeeding or failing. These students focus more on clues and signs than on gaining in-depth knowledge.

The deep learning approach, on the other hand, is predicated on genuine understanding of the material and internal motivation. Students using this method are engaged with the material and make an effort to comprehend and interpret it in ways that suit their preferences and areas of interest. Kamberi (2025)

Therefore, surface learning is a reflection of a learner's propensity to process knowledge superficially, which is frequently driven by a desire to please parents or a fear of failing. Deep learning, on the other hand, is motivated by internal factors. Through the use of abilities like interpretation, summarization, and analysis, students who favor the deep method engage with academic material more deeply. They relate everyday experiences to theoretical knowledge. (Mimoza, 2025)

In summary, the learner's attempt to understand the fundamental meanings of concepts and relate new information to past experiences and larger settings is referred to as the deep learning style (Biggs, 1978; Marton & Säljö, 1976).

A set of traits that emphasize the learner's quest for true comprehension and sophisticated cognitive processing reflects the qualities of the deep learning approach. The following is a summary of these:

1. **Intrinsic motivation and drive:** Two essential characteristics of deep learners are intellectual curiosity and a sincere desire to learn. Instead of being influenced or expected by others, their learning is driven by their own interests. (Biggs & Tang, 2011).
2. **Emphasis on conceptual understanding:** Rather than being restricted to absorbing discrete facts, deep learners aim to create interrelated meanings and cultivate a thorough understanding of concepts through analysis, critique, and interpretation (Entwistle, 2000).
3. **Active participation in the learning process:** This method is demonstrated by ongoing involvement with the material through questioning, conversing with others, and using information in novel and diverse circumstances (Ramsden, 2003).
4. **Development of higher-order thinking skills:** Deep learning enhances students' ability to think critically, analytically, and creatively, enabling them to approach difficult problems in a flexible and successful manner (Biggs, 1978).
5. **Transferable and sustainable knowledge acquisition:** This learning style leads to excellent information recall and retention, as well as the capacity to use knowledge successfully in a variety of contexts and novel learning scenarios (Marton & Säljö, 1976).

Conversely, surface learning is defined by repetition and rote memorization without a deeper comprehension of the material. This method is frequently driven by external factors, such as a fear of failing, a desire to please others, or pragmatic objectives like passing tests or landing a job (Biggs, 1978; Marton & Säljö, 1976).

Howie and Bagnall (2013) and Donnison and Penn-Edwards (2012) have pointed out that surface learners rely on a low level of cognitive activity that is not appropriate for the demands of the educational endeavor. In this instance, the learner prioritizes non-academic objectives over academic ones, relies on rote repetition to gain knowledge, and only wants to receive the minimal grades necessary to finish the course. Deep learners, on the other hand, use a high degree of cognitive activity that is in line with the requirements of the learning process, which promotes a favorable attitude toward the material. This in turn results from their tenacity and intense desire to study.

Comparison between Deep Learning and Surface Learning

Table:

Dimension	Deep Learning	Surface Learning
Definition	Seeks to understand meanings and relationships between concepts	Relies on rote memorization and repetition without deep understanding
Motivation	Intrinsic (love of knowledge, curiosity	Extrinsic (success, fear of failure
Strategies	Linking ideas Critical analysis Search for meaning	Memorization by heart Repetition Focus on isolated facts
Learner's Role	Active (inquirer, analyst, participant)	Passive (receiver of information)
Type of Knowledge	Deep Long-lasting Transferable	Shallow Easily forgotten Non-transferable
Thinking	Analytical Evaluative	Non-analytical Non-critical
Learning Outcomes	Sustainable understanding High skills in analysis and problem-solving	Temporary achievement Weakness in problem-solving
Relation to Prior Knowle-dge	Connects new knowledge with previous experiences	Does not rrolate to prior experiences
Assessment Focus	Competent learner Capable of creativity	Learner memorizes for the exam

In a 2011 study, Bakhtiarvand, Ahmadian, Delrooz, and Farahani examined surface and deep learning strategies and how they relate to mastery motivation and academic success. The findings showed that among groups using the deep learning approach, accomplishment levels and mastery motivation were positively and statistically significantly correlated. Additionally, the study demonstrated that the two independent variables—learning technique and gender—had a statistically significant impact on mastery motivation. Additionally, in the deep learning group, mastery motivation was found to differ across males and females, with the results favoring the females.

The interaction between learning scaffolds in a web-based learning environment and learning approaches (surface/deep) in relation to academic achievement and students' capacity to choose relevant learning resources for educational situations was investigated in the study by Dolmans, Loyens, Marcq, and Gijbels (2016). Because learning scaffolds helped these kids accomplish better academically, the results validated the superiority of the experimental group pupils employing surface/deep learning techniques.

The goal of the study by Howie and Bagnall (2013) was to assess the degree of surface and deep learning approaches among students at the Islamic University and the University of Babylon using Biggs' model. Additionally, it examined statistically significant variations in learning styles by specialization (scientific against humanities), gender (male versus female), and university (Babylon versus Islamic). Furthermore, the study investigated the relationship between students' intellectual curiosity at both universities and surface and deep learning methodologies (Biggs' model). While there were no statistically significant differences in the surface learning technique between students at the two universities, there were substantial disparities in the deep learning strategy, with the results favoring males. The study also found that students' intellectual curiosity and the deep learning technique were positively correlated.

The most crucial affective strategies in college students' learning processes were examined in the study by Floyd, Harrington, and Santiago (2009), along with the nature of the connection between affective strategies and surface and deep learning techniques. With the exception of the effort avoidance strategy, the results demonstrated a statistically significant correlation between the deep learning approach and every aspect of emotional strategies in learning processes. Students' deep and surface learning approaches differed statistically significantly, with the deep learning approach being preferred. Furthermore, all emotional learning strategies—aside from effort avoidance and social image strategies—showed significant differences between students with high and low levels of deep learning methods, with the outcomes favoring those with greater levels of deep learning.

In addition to examining mean differences across gender, specialization, and academic level, the study by Pacak-Vedel (2016) sought to investigate the predictive power of the Big Five personality traits and the learning environment on surface and deep learning approaches. The findings showed that among students at Yarmouk University, the deep learning strategy was most popular. Gender and academic level were found to have significant effects, with the surface learning strategy preferring men and the deep learning approach favoring first-year students over fourth-year students and above.

Lastly, the study by Desierto, De Maio, O'Rourke, and Sharp (2018) examined how a sample of Tishreen University education students differed in terms of gender and academic year between surface and deep learning methodologies. The findings verified that neither the deep learning strategy nor the surface learning approach showed any statistically significant differences between males and females. Furthermore, there were no discernible variations in the surface learning strategy by academic year. However, there were notable variations in the deep learning strategy by academic year, with fourth-year students being favored.

2.2. *Adaptive Learning*

Since it focuses on offering a customized and individualized learning experience that fits the needs and characteristics of each student, adaptive learning is regarded as one of the most significant contemporary trends in the world of education and training. Content, activities, interaction strategies, and evaluation can all be modified in adaptive learning environments to suit each learner's preferred learning style.

The ability to adjust to the various circumstances of learners is referred to as adaptive. Because it helps to develop the learning process and makes it more dynamic and flexible, adaptive learning has emerged as a viable alternative to traditional e-learning. In order to improve performance in accordance with a set of preset criteria, this is accomplished by tailoring and modifying the content to each student. Students can select the learning components they require, including their chosen learning style, thanks to adaptive learning solutions (Hammad, Hariadi, Purnomo, & Kurniawan, 2018).

Adaptive learning systems are a new alternative to existing systems that are based on the idea that "one size fits all." Adaptive learning systems, on the other hand, are founded on the idea that "one size does not fit all," since they consider the unique characteristics of each learner. This is accomplished by creating a customized model for every student that takes into account their objectives, needs, and traits. This enables the content of instruction to be tailored to each student's specific needs (Wang,

Wang & Huang, 2008, p.249).

Two primary factors contributed to the development of adaptable learning environments: the increasing popularity of web-based learning and intelligent tutoring systems. Similar to the function of a traditional instructor, these settings seek to assist the student throughout the learning process. They are made to respond to the unique characteristics or chosen learning method of the learner, as well as to their level and ability. This is achieved by gathering data about the student and keeping it in a specific profile that is updated on a regular basis. As a result, multiple students can be taught the same content, but they will be presented differently (Brusilovsky & Peylo, 2003). Gomes (2024).

Adaptive learning is one of the teaching strategies that accommodates the many learning styles and traits of students, including their specific learning preferences, whether they are electronic or traditional, according to Katsaris & Vidakis (2021). This is accomplished by offering a suitable learning environment and content that adjusts to each student's unique requirements and preferred learning style.

An interactive electronic educational system that allows for the personalization and modification of digital content, learning models, and peer interactions according to the needs, abilities, individual characteristics, learning styles, and preferences of learners is another definition of adaptive learning. With the goal of supporting their learning process based on their past experiences and recently obtained knowledge, this helps to provide each learner with an appropriate learning experience (Fadieieva, 2023).

Higher education institutions are becoming more interested in the potential of adaptive learning as a data-driven strategy to improve teaching approaches, according to (Mirata, V., 2020). Despite the positive attitude of institutional leaders toward implementing this strategy and the encouraging initial findings about its efficacy, the practical use of adaptive learning in curricula is still somewhat limited.

According to Esichaikul, Lamnoi, and Bechter (2011), adaptive learning is "an innovative approach to learning that makes e-learning systems more effective and flexible by adapting the structure of different links and the content presentation methods for each learner based on their behavior, knowledge, and prior information." Additionally, they underlined that adaptive learning is founded on the idea that what works for one learner might not work for another, allowing for a more customized learning experience for every person.

In his research, (Yang, Hwang, & Yang, 2013) shows that a number of characteristics, such as thinking style, knowledge patterns, learning preferences, prior knowledge, self-efficacy, multiple intelligences, anxiety levels, motivation, and locus of control, may influence adaptive learning. These results provide the foundation for the current study, which uses learning preferences to dynamically modify the learning environment for every student in a customized manner that enhances the learning process.

According to (Weber, N., 2019), adaptive learning systems come in a wide range of forms, from straightforward systems that follow a set of fundamental rules to intricate systems that depend on self-learning algorithms. Nevertheless, there is still a dearth of empirical data on the effects of adaptive learning. With adaptive learning, students can openly voice their thoughts in a setting free from pressure, fear, and surveillance. Through tenacity and a love of difficulty, this kind of learning encourages students to stick with and finish their academic assignments. Additionally, it gives students enough time to learn, motivates them to keep studying, and gives them constructive criticism (El-Sabagh, 2021).

Both Stein (2019) and Kurt (2021) concur that adaptive learning is a component of interactive learning that attends to the needs of students and tailors' instruction to their aptitudes and preferences. This is accomplished by using individualized learning pathways and ongoing, useful feedback to track students' progress rather than implementing a generic curriculum for all. Additionally, the development of technology makes it easier to use adaptive learning in three key domains: adaptive evaluation, adaptive sequencing, and adaptive content.

Since adaptive learning gives students a customized educational experience based on their unique needs, traits, learning preferences, and styles, numerous studies have confirmed its efficacy. As demonstrated by the works of (Kara & Sevim, 2013), (Surjono, 2014, Holthaus, Pancar & Bergamin, 2019), (Kokoç, 2019), (Kim, Hong & Song, 2019), (Mebert et al., 2020), (Bernacki, Greene & Lobczowski, 2021), (Tetzlaff, Schmiedek & Brod, 2021), and (Gronseth, Michela & Ugwu, 2021), research suggests that adaptive learning is an effective tool for accomplishing educational goals.

It should be highlighted, nonetheless, that the scope of these studies has been constrained, concentrating only on one or two facets of content adaptation and related variables, such as adaptation in accordance with learners' educational preferences or thinking patterns. Other crucial elements and variables were not covered, such as the adaptive content presentation method, which can be flexible or conditional based on the surface or deep learning technique. This element is regarded as a novel variable that has not received enough attention in earlier research.

Due to substantial advancements in information and communication technologies, adaptive learning environments initially surfaced in the early 1990s. Although content adaptation was the main focus at first, these environments gradually developed to incorporate interactive interfaces, adaptive learning mechanisms, and a variety of interaction methods. Their development was significantly impacted by the rise of artificial intelligence since these environments could now thoroughly examine student characteristics and dynamically modify information according on those features (Kruger, D., 2021, pp. 93–116).

Systems that offer training methods, learning environments, or instructional materials that are especially tailored for each learner based on their unique characteristics—such as goals, preferences, interests, and past experiences—are known as adaptive learning environments (Froschl, 2005, p.11).

They are described as the creation of a customized learning experience for every student based on an analysis of their performance, interests, and personality in order to accomplish objectives like learner satisfaction, academic progress, and efficient learning procedures (Yaghmaie & Bahreininejad, 2011, p. 3280).

Educational settings that track students' activities and analyze them based on their cognitive models are known as adaptive learning environments. These settings are distinguished by their capacity to deduce the needs and interests of students. To support the learning process in accordance with particular learning requirements, they rely on the information that is already accessible about students and the instructional materials (Roy, S., & Roy, D., 2011).

A promising strategy for meeting the various needs of students in educational settings is the creation of adaptive learning environments, which present fresh chances to give each student a customized educational experience. They use artificial intelligence and data analytics to customize instruction to meet the needs of individual students. By offering individualized training, feedback, and support, adaptive learning environments also assist in overcoming the drawbacks of the conventional "one-size-fits-all" approach (Kerns, B. R., 2019).

Interactive electronic settings that employ artificial intelligence and data analytics to tailor instruction to the unique needs and features of each learner are known as adaptive learning environments (Girault, M., 2020). In these settings, the term "adaptation" refers to changing aspects of the learning process, such as activities, content, interaction, and evaluation, in response to information obtained from students' performance and interactions (Devilly, O. Z., 2021). The ability to accommodate the various needs of learners and offer each one individualized and significant learning experiences sets adaptive environments apart (Shemshack, A., 2022).

An adaptable learning environment is one in which the way the content is presented varies according to each student's unique reaction (Kommers, P., et al, 2015, pp. 334–359). It is regarded as a kind of online learning environment that offers the challenges required to meet the unique needs of each student and contributes to their pleasure.

According to (Bard, K. A., 2021), an adaptive learning environment is an electronic learning environment that, in order to provide a personalized educational experience, adjusts and customizes content and learning methods based on each learner's needs and unique characteristics, such as cognitive level and preferred learning styles. By doing this, students engage with materials and educational activities that are appropriate for their skills and requirements.

Electronic settings that modify and customize learning materials and approaches based on the requirements, preferences, and traits of individual students are known as adaptable learning environments. In order to increase learning effectiveness and improve results, they aim to give every student a customized, interactive educational experience that fits their skills and learning preferences. These settings offer interesting, customized learning experiences and cater to the various needs of students (Paramythis & Loidl-Reisinger, 2003; Costa et al., 2021).

(Sze-Yeng, F., 2013) emphasizes how adaptable learning environments help students build their capacity for self-directed and lifelong learning. According to Xuan (2020) and Yang (2019), adaptive learning environments use rewards and reinforcement to increase learner motivation.

Traditional e-learning systems, which usually displayed static web pages with the same material for every learner, faced difficulties that led to the development of adaptive learning systems.

Conversely, adaptive learning systems allow for the customization of presentation and content to suit each learner's unique needs and level, providing customized educational content. These systems can engage with each student in a personalized and autonomous way by fusing artificial intelligence with adaptive media technologies (Surjono, 2014, p.89).

The effectiveness of adaptive support as a design variable in e-learning environments for first-year students in the Department of Educational Technology to build programming abilities in Visual Basic.net was studied by (Agustini, 2017). The findings demonstrated that students' development of programming abilities in Visual Basic.net was significantly impacted by the adaptive assistance system built into the e-learning environment.

Similarly, (Yao, Zhong, & Cao, 2025) sought to investigate how well educational technology students could grow their 3D animation production talents by creating an adaptable environment based on intelligent agents. The research sample's pre-test and post-test mean scores on the accomplishment test and the observation checklist showed statistically significant changes in favor of the post-test at the 0.05 level, according to the data. Additionally, the research group's post-test scores on the product quality evaluation checklist and the hypothetical mastery level (80%) showed statistically significant differences at the 0.05 level, supporting the performance of educational technology students enrolled in the professional diploma program at Mansoura University's Faculty of Education.

Using Vermunt's (1994) classification of learning styles—which comprises four learning styles: reproduction-directed, meaning-directed, application-directed, and undirected—Boyle, Duffy, and Dunleavy (2003) developed a suggested learning analytics-based approach for creating digital content in adaptive learning environments. Four key components make up the paradigm for adaptive learning systems that the current study proposed:

1. Learner Model – containing all learner-related data used to guide adaptation processes.
2. Content Model – specifying mechanisms for content adaptation.
3. Domain Model – responsible for structuring adaptive learning systems.
4. Adaptation Model – responsible for managing and coordinating all adaptation processes. (Nguyen, Do, & Fröschl, 2008)

In light of Bloom's taxonomy of learning abilities, a study was undertaken by White (2020) to determine the efficacy of employing an adaptive learning environment in the field of information management for undergraduate students as opposed to traditional teaching techniques. Students studying information technology were included in the sample. Using McGraw-Hill's Connect LearnSmart platform, a correlation analysis was conducted between student performance on subject-specific assessments and the use of the adaptive learning environment. The results demonstrated no correlation between student performance on the subject tests and the use of the adaptive learning environment, suggesting that the adaptive learning environment is a preferred option for learning styles and offers user satisfaction without having a major effect on academic performance.

The impact of an e-learning environment based on Kolb's model on the development of problem-solving abilities in creating instructional settings was investigated in a study by Konak, Clark, and Nasereddin (2014). The results verified that, according to Kolb's learning styles, there were no statistically significant variations in the problem-solving abilities of Educational Technology students when it came to creating instructional scenarios.

In order to improve student learning, (Holthaus, M., Pancar, T., & Bergamin, P., 2019) sought to investigate the effects of incorporating easy-to-use adaptability into a university learning system. The instructional design, which was built on adaptive exercises in light of Cognitive Load Theory, was used in a basic mathematics course. Students who actively participated in these adaptive exercises performed better, according to the first data.

(Hamadtoh, R., Gohar, A., & El-Ghool, R. M., 2016) sought to assess the usability of this environment and investigate the effects of creating an adaptive learning environment on the development of English as a Foreign Language (EFL) writing skills among second-year English majors. Students were divided into groups using the Multiple Intelligences Theory, and each group received a different set of assignments according to their writing proficiency and favored intelligences. A collection of online resources, including Facebook, WhatsApp, Google Drive, and Hangouts, were used to provide the activities.

Sixty students made up the study sample; they were split into two groups: the experimental group and the control group. An environment usability scale and a writing skills test were given out. According to the findings, students' writing abilities improved as a result of the adaptive learning environment, which they also found to be user-friendly, beneficial for learning, and productive for engagement.

2.3. Characteristics Of Adaptive Learning Environments

According to (Kommers, P., et al. ,2008, pp. 351–365), (Van Schyndel, J. L. ,2015, p. 56) the characteristics of adaptive learning environments include:

1. To assess student data and offer individualized learning experiences catered to each learner's needs, adaptive learning environments rely on cutting-edge artificial intelligence technologies.
2. They make it simple and flexible for students to access educational resources from any location at any time.
3. To assist students, get the most out of the learning process, they offer a variety of learning materials and activities that are tailored to their skills and interests.
4. To guarantee success in their educational journeys, adaptive learning environments provide teachers and students with all-encompassing support, including intellectual, technical, and psychological support.
5. Through a variety of educational activities, these settings promote engagement and interaction, which promotes dynamic and efficient learning.
6. They offer tools for ongoing evaluation and helpful criticism to improve performance and boost student enthusiasm.
7. Using multimedia instructional materials and activities tailored to each person's needs, they provide a varied and customized learning experience.
8. These settings are distinguished by their reactivity to external stimuli and ability to successfully adjust to them.
9. They continue to be efficient and consistent in responding to changes in the environment while giving pupils a productive and inspiring educational experience.
10. By using learning data analytics and intelligent prediction, they can forecast how students will behave in the future.

Furthermore, there are several benefits to adaptable learning environments. They are able to determine each learner's unique learning style and pattern, which increases the effectiveness of the teacher. While taking into account each student's cognitive ability and offering suitable learning resources, these environments automatically monitor learners' progress in adaptive content and apply uniform standards to every learner without the need for human interaction. Chen, Wu, and Chen (2017).

2.4. The Advantages of Adaptive Learning Environments

The following benefits are associated with adaptive learning environments, according to Kara & Sevim (2013, p.112), Tetzlaff, L., Schmiedek, F., & Brod, G. (2021), Kim, Hong & Song (2019), Koç, M. (2019), Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021), Mebert et al. (2020), and Gronseth, S. L., Michela, E., & Ugwu, L. O., 2021).

1. Content Adaptation: Presenting content in numerous formats and media that correspond with the learner's style and traits, as well as adapting the modes of presentation through texts, photos, videos, and interactive activities.
2. Personalized Content Delivery: Personalized educational content can be given to each person based on their specific needs and educational level thanks to adaptive learning environments. This increases learning effectiveness and helps to more effectively accomplish learning goals. They accomplish this by examining the data, preferences, and learning styles of each student and then dynamically modifying the material and delivery method to fit the needs of each unique learner.
3. Flexibility: They offer adaptable learning opportunities, enabling students to readily access instructional resources at any time and from any location they see appropriate.
4. Interactive Learning Environment: Adaptive learning environments provide ongoing interaction between the student and the course material, improving understanding and concept assimilation and adding interest to the learning process.
5. Engagement and Motivation: Adaptive learning environments improve student engagement and motivation by tailoring educational experiences to each learner's choices and interests. They accomplish this by providing instructional exercises, feedback systems, and multimedia engagement resources that pique students' attention and encourage them to keep studying.
6. Student Activity Analysis: By analyzing student activities and determining their needs, they may provide relevant and varied content that streamlines difficult concepts and improves the efficacy of learning.
7. Better Content Delivery: Learners can better comprehend complicated information and accomplish educational objectives thanks to adaptive learning environments, which also

improve the way educational content is delivered.

Distraction is one of the main issues that students encounter in adaptive learning settings. Finding a suitable method of information presentation that fits the type and degree of learners is essential to overcoming this difficulty. As a result, content-presentation-based adaption patterns are essential for enhancing these environments' creation and design as well as their effectiveness in reaching certain learning goals.

2.5. The Importance and Systems of Content Adaptation in Adaptive Learning Environments

Addressing issues like student "distraction" requires adaptive presentation patterns in adaptive learning environments. Choosing the right presentation pattern based on contextual factors, such as the type and level of learners and the content's nature, is the answer. To guarantee dependable outcomes, these patterns must be designed with extreme precision. Continuous development of these patterns is also necessary to ensure successful approaches and successful learning results. The main objective of employing adaptive presentation patterns is to choose the best strategy that fits the needs and features of the learners. (Monterrat, George, and Lavoué, 2017)

Two primary mechanisms of adaptation in adaptive e-learning environments are identified by research in this area (Brusilovsky, 2005; Brown et al., 2007; Louca & Zacharia, 2008):

1. Adaptive Presentation, which concentrates on the way content pages display information.
2. Adaptive Navigation, which is concerned with how students navigate material sites.

Every one of these systems has distinct characteristics that set them apart, along with a variety of implementation techniques. The compatibility of the method's features with the learner's traits, the nature of the content, and the limitations of the learning environment determine which approach is best.

In a course created and developed with computer programs, adaptive material encompasses both cognitive and skill-related elements, claim Erazo, Esteve-González, and Vaca (2015). Depending on their requirements, skill levels, and capacities, learners can choose from a range of interactive media and learning tools, as well as freely traverse and explore this content.

According to (Brusilovsky, Kosba & Negdi, 2007, p. 127), adaptive presentation uses information from the user model to tailor instructional materials to the needs and cognitive level of the learner. Content can be divided into units that correspond with the best period for learning; for instance, experts are given more in-depth material, while beginners are given easier explanations. Additionally, the format of the text is altered to include multimedia components like pictures, videos, and graphics. By providing tailored and pertinent content, this method lessens the amount of information that is offered all at once, preventing "information overload" and enhancing the educational process.

According to Burgos (2006), p. 75, adaptive presentation aims to match the level of scientific material with the traits and preferred method of learning of the learner. The way that information is presented to students might vary depending on the aural stimuli, visual features, and font size and color. Adaptation is the process of changing content pages, including text, audio, visuals, and videos, to match learner preferences and the data in the learner model.

Adapting the presenting style to each learner's unique learning style, cognitive approach, and advancement level is the foundation of the adaptive presentation system. Additionally, it enables students to choose the portions of the course material that they find most appealing and to utilize various content types in ways that best fit their requirements (Knutov & Pechenizkiy, 2011, p. 45).

The learning path is significantly shaped by the manner instructional content is delivered. Content may become less effective if the presenting style does not satisfy the needs and expectations of the learners, not because it is wrong (Alabi, 2024)

By concealing information that might not be pertinent to the learner's current interests, the adaptive presentation system seeks to alter how visual components are displayed during education. Many adaptive display patterns, including conditional text, stretchtext, alternative pages, alternative fragments, and frame-based approaches, are used to accomplish this purpose (Bunt, Carenini, & Conati, 2007).

The conditional style and the flexible style are the two primary forms seen in adaptive learning environments aimed at seasoned learners, according to Pahl and Kenny's (2009) examination of numerous opinions and works on adaptive material presentation styles (p. 189). These two approaches make it easier for seasoned students to navigate these kinds of settings, which greatly aids in reaching the desired learning goals.

The significance of adaptation styles that depend on the way content is delivered is emphasized by (Brusilovsky, Kosba & Negdi, 2007), who primarily concentrate on changing the way that learners are given content or multimedia. This is accomplished by concealing information that is unrelated to their present interests. These styles are distinguished by their applicability for various content types and educational levels as well as their simplicity of use.

The conditional content style divides the content into parts or sections that correspond to particular learner model conditions. Only the sections that are pertinent to the learner's requirements and satisfy the learning condition—typically indicated by the learner's level of knowledge—are shown by the system.

The adaptable content style, on the other hand, gives students more details about a certain subject. Clicking on trending terms or active links can enlarge or shrink this style of hypertext. Jirasko and Duenser (2005)

Additionally, the conditional adaptive content presentation style presents instructional content in divided chunks, according to (Sayed, Noeman, Abdellatif, & El-Tantawy, 2022). Three levels of learners are distinguished: novice, intermediate, and expert. Their level of expertise determines how much information is given to them; experts are given the least amount, intermediates are given less, and beginners are given the most.

Additionally, the flexible adaptive material presentation style is a technique that gives students access to more information about a certain subject (Gligorea, Cioca, Oancea, & Tudorache, 2023). Students can explore content that aligns with their needs, skills, and past learning experiences by clicking on the links that are provided.

Table:

Property	Conditional Style	Flexible Style
Content Presentation	Displays specific parts based on learner conditions	Displays full content with interactive options
Information Control	High (only relevant content shown)	Moderate (full content available, details can be hidden
Learner Flexibility	Low, depends on system	High, learner chooses what to explore
Cognitive Load Reduction	Very effective	Less effective
Maintaining Context	May be segmented by conditions	Preserves full context

Both content formats are supported by a number of theories and viewpoints. Because Skinner stressed the significance of logically arranging content from the easiest to the most difficult while concentrating on information directly relevant to the particular unit purpose, the behaviorist theory supports the conditional content approach. Avoid including extraneous information that could divert students. Therefore, the conditional content style satisfies the needs of the learner. In 2021, Burhanuddin, Ahmad, Said, and Asimiran

However, some viewpoints suggest that the flexible style is a superior choice for preserving coherence and consistency, particularly when teaching concepts and standards, as the conditional content style may have a detrimental effect on the information flow. A learner's attention and comprehension may suffer if portions of the content are missing since there may be a lack of continuity (Solow, R. M., 2000, p. 202). As a result, the flexible style is thought to be better suited for preserving the content's overall context.

This method is also supported by the information processing theory, which notes that learning is an ongoing process that starts with the transfer of information through the senses, progresses to short-term memory, and may eventually reach long-term memory, as Gagné noted. A cognitive map that arranges knowledge in memory is the end product of this process. This hypothesis states that learners are better able to choose relevant connections in a flexible manner as opposed to a conditional content style (Shahid, Khan, & Ishtiaq, 2023).

This approach is also supported by the cognitive constructivist theory, which views thinking as an organizing and adapting process in which students engage with course material by integrating and coordinating new experiences with their preexisting cognitive frameworks. In order to adapt, a person must make an attempt to strike a balance between their past knowledge and newly discovered environmental occurrences. This is accomplished through simultaneous, interacting processes of assimilation and accommodation. This flexibility is evident in the flexible content style, which allows learners to engage with new experiences that complement their existing knowledge by providing access to more material (Saarsar, 2018).

The adaptable presentation approach is also supported by the Motivational Theory. In order to improve learner motivation and boost learning effectiveness, Keller established four general criteria that affect learner motivation: completeness, alignment, expectancy, and satisfaction. Expectancy and alignment highlight the learner's understanding of their own demands and their potential for success.

Keller (2010).

Because people's processing capacity is limited, theories like the Limited Capacity Model and Cognitive Load Theory emphasize how crucial it is to arrange the information that is provided in order to minimize memory load. The effectiveness of learning may be diminished by any surplus of information (Kalyuga, 2000, p. 165). Because it directly addresses the demands of learners, these theories prioritize the conditional content style.

Alrashedi (2020) asserts that adaptable educational content improves the learning process by offering comprehensive explanations of topics and illustrative examples that let students reveal or conceal information based on their requirements and preferred methods of learning. In order to minimize confusion and guarantee a seamless transition between levels, content also takes the learner's level and educational preferences into account. Additionally, by appropriately displaying information and offering tailored interactions based on the learner's preferences and background, it lessens cognitive overload.

(Bach, Hofer, & Bichler, 2024) also highlighted how adaptive educational content can serve a variety of purposes, including providing learners with comprehensive information about a concept and illuminating examples that allow them to reveal or conceal content based on their learning preferences and needs. This method minimizes cognitive overload that could arise from presenting all the knowledge at once, reduces misunderstanding, and ensures seamless development between levels by taking into account the educational preferences and levels of the learners. Additionally, it offers tailored interactions based on the learner's preferences and past knowledge.

According to (Milošević, 2006) and (Abd Halim, Mohemad, & Haji Ali, 2023), adaptable content should have the following traits:

- Alignment of objectives with learners' cognitive needs and learning styles.
- Consideration of individual differences among students.
- Ability to adapt to each learner's characteristics and abilities.
- Allowing learners to progress at their own pace.
- Quality, effectiveness, and ease of use.
- Free of linguistic and scientific errors.
- Usability and transferability across diverse educational environments.
- Integration of interactive multimedia to support learning.
- Ease of updating and development at any time.

In the unit "Geometry and Measurement," Bayuningsih, Usodo, and Subanti (2017) examined how employing instructional scaffolding affected the development of geometric thinking and certain analytical thinking abilities in first-year preparatory schoolgirls. The 79 students that made up the research sample were split into two groups: the experimental group, which included 38 students, and the control group, which included 41 students. The Van Hiele scale for geometric thinking levels and an analytical thinking abilities test were among the research instruments. The findings showed that the scaffolding technique had a beneficial effect on the development of geometric and analytical thinking abilities, as evidenced by the statistically significant differences in favor of the experimental group in the post-test of both analytical thinking skills and Van Hiele levels.

(Bataineh & Salah, 2017) sought to investigate how the theater technique affected the development of critical thinking abilities in Jordanian 10th graders. 40 students made up the sample, and they were split into two groups: one that received instruction using the drama tactic as an experimental group and the other that received instruction using more conventional techniques. The outcomes demonstrated the efficiency of the drama technique in developing analytical thinking abilities, with statistically significant differences favoring the experimental group who used it for their studies.

The goal of the study by Beniche, Larouz, and Anasse (2021) was to examine how the reasoning approach may be used to teach philosophy to secondary school students in order to foster their analytical thinking and cognitive flexibility as well as to look into the relationship between the two abilities. Sixty second-year secondary school students (30 in each group) were included in the sample. Eight skills related to analytical thinking were the focus of the curriculum. The results showed that the experimental group outperformed the control group in the post-test of analytical thinking, with statistically significant differences at the 0.01 level.

3. METHODOLOGY

3.1. Methodological Procedures of The Research

Given the research problem, questions, and hypotheses, this section outlines the methodological steps the researchers took to carry out the study. The research methodology, experimental design, research population and sample, instructional materials, adaptive learning environment, research instruments, implementation procedures, and statistical techniques are all included.

3.2. First Research Method

The current study adopted two main approaches:

1. **Descriptive Analytical Method:** To build the theoretical framework, prepare measurement instruments, and develop the adaptive learning environment, this method was utilized to examine and evaluate relevant literature and earlier research on the independent and dependent variables.
2. **Quasi-Experimental Method:** To assess the impact of the interaction between the independent variables (Learning Style: Surface/Deep × Content Presentation Mode: Conditional/Flexible) and the dependent variables (Computer Maintenance Skills – Analytical Thinking), the researchers used a factorial experimental design (2×2).

3.3. The Experimental Design of The Research

Second the research adopted a factorial design (2×2) as follows:

Table:

Learning Style / Conditional Content Presentation	Surface Learning	Deep Learning
Conditional	Group (1)	Group (3)
Flexible	Group (2)	Group (4)

Group (1) applies the surface learning style with conditional content presentation.

Group (2) applies the surface learning style with flexible content presentation.

Group (3) applies the deep learning style with conditional content presentation.

Group (4) applies the deep learning style with flexible content presentation.

Third: Research Population and Sample

Population: All first-year students at Kafr El-Sheikh University's Faculty of Specific Education, Department of Educational Technology and Computer Science.

Sample: Using the aforementioned methodology, a sample of 56 first-year students was chosen and split up into four experimental groups.

Reasons for the sample's selection:

This group was taught by the researchers, which made application and follow-up easier.

The degree of similarity between students' ages and academic backgrounds.

The sample size's suitability for the factorial design (2×2).

Fourth: Instructional Content

Only fundamental computer maintenance techniques appropriate for first-year students were covered. These were ascertained by:

1. Analyzing the department's curricula.
2. Reviewing related literature and previous studies.
3. Consulting experts and specialists.

The targeted skills included:

– Setting up and installing input/output devices (keyboard – mouse – monitor).
– Assembling and disassembling the system case.
– Assembling and disassembling the motherboard, RAM, and processor.
– Handling the power supply unit.
– Assembling and disassembling the cooling fan.
– Managing storage devices (hard disk).

Fifth: The Adaptive Learning Environment

To help pupils develop their analytical thinking and computer maintenance skills, an adaptive electronic learning environment was created. The following factors were considered in the design:

1. Learning Style (Surface/Deep):

For surface learners: Activities focusing on recall and direct understanding.

For deep learners: Activities emphasizing analysis, interpretation, and problem-solving.

2. Content Presentation Mode (Conditional/Flexible):

Conditional Mode: Students adhere to a predetermined order, only progressing to the next ability upon meeting prerequisites or passing tests.

Flexible Mode: There are no limitations on the students' ability to switch between talents.

3. General features of the environment:

- Interactive hands-on activities.
- Multimedia instructional videos.
- Short quizzes to measure progress.
- Technical support and gradual guidance.

Preparation and Development of the Adaptive Learning Environment Using Moodle

Since the Moodle Learning Management System

(LMS) is one of the most popular and adaptable platforms for e-learning and adaptive learning, the researchers used it to develop the adaptive learning environment.

The following structured phases comprised the preparatory process:

1. Preliminary Analysis of Content and Variables

- Identifying the computer maintenance skills (cognitive and practical) required for first-year students.
- Mapping learning activities and presentation styles to the surface/deep learning styles: Deep learners received extended content with analytical tasks and research-based exercises, while surface learners received simplified content backed by a series of brief quizzes.
- Outlining the characteristics of the conditional and flexible modes of material presentation: in the former, students can only move between modules after finishing certain assignments or tests, while in the latter, they have more flexibility in selecting the order and course of study.

2. Structuring the Course in Moodle

- Creating a course entitled “Computer Maintenance Skills”.
- Dividing the course into main instructional modules, each covering specific targeted skills (e.g., assembling and disassembling the motherboard, handling the power supply unit, installing RAM).
- Designing each module as a set of interactive learning activities, including videos, images, simulations, and PDF resources.

3. Implementing Adaptivity Mechanisms in Moodle

- Applying the conditional mode through the Activity Completion and Restrict Access features makes sure that students are unable to proceed to the next module until they have finished the necessary activities (such as watching the entire video or earning a specific grade on an exam).
- Using User Grouping and Adaptive Release to categorize students based on their surface/deep Learning Style Scale scores would enable differentiated or prolonged content delivery.
- By having all of the courses available at once, the flexible mode allows students to choose the study order that best suits them.

4. Designing Adaptive Assessment Tools

- Developing short quizzes at the end of each module to measure initial comprehension.
- Creating analytical assessments for deep learners to evaluate problem-solving and reasoning skills.
- Preparing a performance observation checklist to assess students’ practical application of maintenance skills.
- Enabling Moodle’s analytics and reporting tools (Logs & Reports) to monitor each student’s engagement and progression.

5. Support and Guidance within the Environment

- Incorporating discussion forums and chat rooms to foster interaction between students and instructors.
- Enabling instant feedback after quizzes, providing tailored guidance aligned with the learner’s style.

Sixth: Research Tools

The research employed the following tools:

1. Analytical Thinking Test consisting of (36) items (developed by the researchers).
2. Performance Observation Checklist for maintenance skills consisting of (114) items (developed by the researchers).
3. Learning Style Scale (Surface/Deep) by Biggs (2004) to classify students according to their learning style.

Seventh: Steps of Conducting the Research

1. Preparing a list of computer maintenance skills and validating it through expert review.
2. Preparing the research tools (tests – observation checklist – analytical thinking test) and validating them.
3. Applying the Learning Style Scale electronically to classify students into surface/deep learners.
4. Dividing the students into four groups according to the experimental design.
5. Designing the adaptive learning environment with both presentation modes (conditional/flexible) according to learning styles.
6. Conducting a pilot study to ensure clarity of the tools and the learning environment.
7. **Implementing the main experiment:**

Pre-testing students in analytical thinking and maintenance skills

Applying the experimental treatments (adaptive learning environment)

Post-testing using the same tools

8. Recording and statistically analyzing the results.
9. Discussing the findings and interpreting them in light of the hypotheses and previous studies.

Eighth: Statistical Methods Used

Research Results:

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 pre-application of the Computer Maintenance Skills Performance Observation Checklist. This was accomplished by comparing the pre-test results of the performance observation checklist for computer repair skills between the groups. For this, the one-way ANOVA approach was employed.

The results of the one-way ANOVA for the four experimental groups with respect to the Computer Maintenance Skills Performance Observation Checklist pre-test scores are displayed in the following table.

Table (2):

Tool		Sum of Squares	df	Mean Square	F	Sig.
Computer maintenance skills	Between Groups	38.643	3	12.881	1.432	.244
	Within Groups	467.857	52	8.997		
	Total	506.500	55			

The computed F-value was 1.432, which is not significant at the 0.05 level, indicating that there are no significant variations in the pre-test scores of the Computer Maintenance Skills Performance Observation Checklist between the four experimental groups (Table 2).

Consequently, the homogeneity test results show that the four experimental groups were equal prior to the experiment and that any discrepancies detected following the experiment are caused by the study's independent variables.

4. RESULTS ANALYSIS AND INTERPRETATION

The study sought to assess how students studying educational technology's development of analytical thinking and computer maintenance skills were impacted by the interplay between their surface/deep learning style and conditional/flexible content presentation style in an adaptive learning environment.

The findings are shown as follows:

1. Answering the Research Questions Related to Computer Maintenance Skills Among Educational Technology Students:

The researchers employed the two-way ANOVA method to determine the differences between the levels of the first independent variable, learning style (surface/deep), and the second independent variable, content presentation style (conditional/flexible), within the adaptive learning environment in order to test the research hypotheses regarding computer maintenance skills among students studying educational technology.

The purpose of this research was to ascertain the primary impacts of both independent variables and how they interacted to influence the students' acquisition of computer repair abilities.

The results of the two-way ANOVA for the effects of the adaptive learning environment's conditional/flexible content presentation style and surface/deep learning style on students studying educational technology's acquisition of computer maintenance skills, as well as their interaction effect, are shown in the following table.

Table (3):

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
learning_style	11687.161	1	11687.161	23.639	.000
presentation_mode	41856.446	1	41856.446	84.660	.000
learning_style presentation_mode	3762.161	1	3762.161	7.609	.008
Error	25709.214	52	494.408		
Total	7532669.000	56			
Corrected Total	83014.982	55			

First Research Question:

What is the effect of the learning style (surface/deep) on the development of computer maintenance skills among educational technology students?

To answer this question, the following hypothesis was tested:

First Hypothesis:

No matter the content presentation style (conditional/flexible), the main effect of the learning style (surface/deep) favors the deep learning style, resulting in a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

It is clear from looking at the preceding table that, independent of the way the content is presented, there is a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Observation Checklist due to the primary effect of the learning style (surface/deep).

At the (0.05) level, the computed F-value of 23.639 is significant. This suggests that, independent of the technique used to convey the content, there is a statistically significant variation in the mean scores of students as a result of the primary effect of the learning style (surface/deep).

The deep learning style group's mean score was 379.179, whereas the surface learning style group's mean score was 350.286. This information was used to establish the direction of the discrepancy.

Table (4):

learning_style	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
surface	350.286	4.202	341.854	358.718
deep	379.179	4.202	370.746	387.611

Since the deep learning style's mean score was greater, as indicated in the preceding table, the significance is in favor of it.

The first hypothesis was adopted in light of the aforementioned and can be expressed as follows: No matter the content presentation style (conditional/flexible), the main effect of the learning style (surface/deep) favors the deep learning style, resulting in a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

Second Research Question:

What is the effect of the content presentation style (conditional/flexible) on computer maintenance skills among educational technology students?

To answer this question, the following hypothesis was tested:

Regardless of the learning style (deep or surface), the main effect of the content presentation style (flexible vs. conditional) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

It is clear from looking at Table (3) that, independent of learning style, the main effect of the content presentation style (conditional/flexible) within the adaptive learning environment is responsible for the statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Observation Checklist.

At the (0.05) level, the computed F-value of 84.660 is significant. This suggests that, independent of learning style, the primary influence of the material presentation type (conditional/flexible) in the adaptive learning environment results in a statistically significant difference in the mean scores of students.

The flexible content presentation style group's mean score was 392.071, whereas the conditional content presentation style group's mean score was 337.393. This information was used to establish the direction of the discrepancy.

Table (5):

presentation_mode	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
conditional	337.393	4.202	328.961	345.825
flexable	392.071	4.202	383.639	400.504

According to the preceding table, the flexible content presentation method had a higher mean score, indicating that it was significant.

The second hypothesis was adopted in light of the aforementioned and can be expressed as follows: Regardless of the learning style (deep or surface), the main effect of the content presentation style (flexible vs. conditional) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

Third Research Question:

What impact does the interplay between the conditional/flexible material presentation style and the surface/deep learning style have on students studying educational technology in terms of their computer maintenance abilities?

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

The interaction effect between the surface/deep learning style and the conditional/flexible content presentation style results in statistically significant differences at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

It is clear from looking at Table (3) that the interaction between the learning style (surface/deep) and the content presentation style (conditional/flexible) results in statistically significant differences at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Observation Checklist.

At the (0.05) level, the computed F-value of 7.609 is significant.

This suggests that the relationship between the learning style (surface/deep) and the material presentation style (conditional/flexible) causes statistically significant changes in the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist.

The Tukey post hoc test was used to ascertain the direction of the difference, and the findings were as follows:

Table (6):

groups	N	Subset for alpha = 0.05		
		1	2	3
1.00	14	331.1429		
3.00	14	343.6429		
2.00	14		369.4286	
4.00	14			414.7143
Sig.		.452	1.000	1.000

According to the table, the fourth group, which employed the flexible material presentation style and the deep learning style, had the highest mean.

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

Regardless of the learning style (deep or surface), the main effect of the content presentation style (flexible vs. conditional) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Computer Maintenance Skills Observation Checklist.

2. Answering the Research Questions Related to Analytical Thinking among Educational Technology Students

The researchers employed a two-way analysis of variance (Two-Way ANOVA) to investigate the variations in the levels of the following in order to test the validity of the research hypotheses pertaining to analytical thinking among students studying educational technology:

The first independent variable is the surface/deep learning style.

The second independent variable is the conditional/flexible style of content presentation.

To ascertain their individual and combined effects on the growth of analytical thinking in students studying educational technology in the adaptive learning environment.

The findings of the two-way ANOVA on the impact of surface/deep learning style, conditional/flexible material presentation style, and their interaction on students' analytical thinking in educational technology are shown in the following table.

Table (7):

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
learning_style	1292.161	1	1292.161	26.661	.000
presentation_mode	4626.446	1	4626.446	95.458	.000
learning_style presentation_mode	407.161	1	407.161	8.401	.005
Error	2520.214	52	48.466		

Total	835289.000	56			
Corrected Total	8845.982	55			

Fourth Research Question:

What is the effect of the type of learning style (surface/deep) on the development of analytical thinking among Educational Technology students?

To answer this question, the following hypothesis was tested:

Hypothesis 4:

No matter the content presentation style (conditional or flexible), the main effect of the learning style (deep vs. surface) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Analytical Thinking Scale, favoring the deep learning style.

With reference to the preceding table, it is evident that the major influence of the learning style (surface/deep) on the mean scores of students on the Analytical Thinking Scale, independent of the content presentation style, results in a statistically significant difference at the (0.05) level. At the (0.05) level, the computed F-value of 26.661 is significan

This suggests that, independent of the manner in which the content is presented, there is a statistically significant variation in the mean scores of students on the Analytical Thinking Scale attributable to the learning style main impact.

The deep learning style group's mean score was 126.286, whereas the surface learning style group's mean score was 116.679, indicating the direction of the difference.

Table (8):

learning_style	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
surface	116.679	1.316	114.039	119.319
deep	126.286	1.316	123.646	128.926

The significance is in favor of the flexible content presentation style, as its mean score is higher, as shown in the previous table.

Based on the above, the fourth hypothesis was accepted and reformulated as follows:

Regardless of the conditional or flexible content presentation style, the main effect of the learning style (deep vs. surface) results in a statistically significant difference at the (0.05) level between the mean scores of students on the Analytical Thinking Scale in favor of the deep learning style.

Fifth Research Question:

What impact does the conditional/flexible content presentation style have on students studying educational technology in terms of their ability to think analytically?

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

The main effect of the content presentation style (conditional/flexible) favors the flexible content presentation style, independent of the learning style (deep/surface), and there is a statistically significant difference between the mean scores of students on the Analytical Thinking Scale at the (0.05) level.

It is clear from Table (3) that, independent of learning style, the main effect of the content presentation style (conditional/flexible) in the adaptive learning environment results in a statistically significant difference at the (0.05) level between the mean scores of students on the Analytical Thinking Scale. At the (0.05) level, the computed F-value of 95.458 is statistically significant.

This suggests that, independent of learning style, the main influence of the material presentation style in the adaptive learning environment is responsible for a statistically significant variation in the mean scores of students on the Analytical Thinking Scale.

The conditional content presentation group's mean score was 112.393, whereas the flexible content presentation group's mean score was 130.571, indicating the direction of the difference.

Table (9):

presentation_mode	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
conditional	112.393	1.316	109.753	115.033
flexable	130.571	1.316	127.931	133.211

According to the preceding table, the flexible content presentation method has a higher mean score, indicating that it is significant.

The fifth hypothesis was approved and rephrased as follows in light of the aforementioned: The main effect of the content presentation style (conditional/flexible) favors the flexible content presentation style, independent of the learning style (deep/surface), and there is a statistically significant difference between the mean scores of students on the Analytical Thinking Scale at the (0.05) level.

Sixth Research Question 6:

What impact does the interplay between the conditional/flexible material presentation style and the surface/deep learning style have on the growth of analytical thinking in students studying educational technology? **The following hypothesis was examined in order to respond to this query:**

The interaction effect between the learning style (deep/surface) and the content presentation type (conditional/flexible) results in statistically significant variations between the mean scores of students on the Analytical Thinking Scale at the (0.05) level.

It is clear from Table (7) that the interaction effect between the learning style (surface/deep) and the content presentation style (conditional/flexible) results in statistically significant differences at the (0.05) level between the mean scores of students on the Analytical Thinking Scale. At the (0.05) level, the computed F-value of 8.401 is statistically significant.

This suggests that the interaction between the learning style (deep/surface) and the content presentation type (conditional/flexible) results in statistically significant variations between the mean scores of students on the Analytical Thinking Scale.

To determine the direction of the differences, Tukey's post hoc test was applied, and the results were as follows:

(Table (10):

groups	N	Subset for alpha = 0.05		
		1	2	3
1.00	14	110.2857		
3.00	14	114.5000		
2.00	14		123.0714	
4.00	14			138.0714
Sig.		.387	1.000	1.000

The table makes it clear that Group Four, which received instruction utilizing both the flexible material presentation style and the deep learning approach, had the greatest mean score.

The sixth hypothesis was approved and rephrased as follows in light of the aforementioned: The main effect of the content presentation style (conditional/flexible) favors the flexible content presentation style, independent of the learning style (deep/surface), and there is a statistically significant difference between the mean scores of students on the Analytical Thinking Scale at the (0.05) level.

First: Interpretation of Results Related to Computer Maintenance Skills

The results of the statistical analysis used to test the research hypotheses showed that, independent of the style of content presentation, there is a statistically significant difference ($\alpha \leq 0.05$) between the mean scores of students on the Computer Maintenance Skills Performance Observation Checklist attributable to the main effect of the learning style (deep vs. surface).

This can be interpreted as follows:

constructivist Theory states that students who have a deep learning style perform better than those who have a surface learning style because they actively create their own knowledge through interaction with the material and learning environment. In order to improve deep cognitive representation and achieve optimal performance in computer maintenance skills—a domain that necessitates problem analysis and practical application—deep learning encourages learners to comprehend the connections between concepts and to relate them to their past experiences.

Effective learning happens when students actively create knowledge via practice and discovery, claim Piaget and Bruner. As a result, students using a deep learning approach actively create knowledge about repair, maintenance, and error detection processes.

Additionally, regardless of the learning style, the analysis showed that the main effect of the content presentation style (conditional/flexible) was responsible for a statistically significant difference at the ($\alpha \leq 0.05$) level between the mean scores of students on the Computer Maintenance Skills Checklist in favor of the flexible presentation style.

The superiority of the flexible presentation style can be explained by the fact that giving students varied stimuli, freedom of navigation, and flexibility in content sequencing improves their behavioral motivation, raises the percentage of correct answers, and consequently improves their practical performance in maintenance skills.

In contrast to the conditional style, which enforces a set path that restricts individual freedom and adaptive reinforcement, the flexible presentation style functions as a series of instructional stimuli that direct the learner's responses and continuously reinforce desired behaviors, resulting in more accurate and stable performance.

Last but not least, the findings also demonstrated statistically significant interaction effects between the surface/deep learning style and the conditional/flexible content presentation style, favoring the combination of the deep learning approach and the flexible presentation type.

Through the lens of constructivist theory, this result can be interpreted because deep learning and flexible content presentation combine to create an active learning environment that enhances comprehension and the practical application of computer maintenance skills by allowing learners to construct their own knowledge through experimentation, reflection, and exploration.

Additionally, Vygotsky's social constructivism—which emphasizes how social interaction promotes cognitive development and solidifies technical concepts—aligns with the flexible presentation method, which offers chances for engagement, discussion, and experience sharing.

Thus, enhanced practical performance and long-term skill development are encouraged by the combination of deep learning and flexible presentation.

The findings of the present study are in line with those of the following studies: Talbi & Ouared (2022); Kamberi (2025); Yao, Zhong, & Cao (2025); Mimoza (2025); White (2020); Howie & Bagnall (2013); Pacak-Vedel (2016); Weber (2019); Stein (2019); Erazo, Esteve-González, & Vaca (2015); Gligorea, Cioca, Oancea, & Tudorache (2023); and Kurt (2021). These studies highlight the role of surface and deep learning styles, as well as their interaction with conditional and flexible content presentation modes.

Second: Interpretation Of Results Related to Analytical Thinking Development

Prior statistical analyses testing the research hypotheses revealed that, independent of the content presentation style, there is a statistically significant difference ($\alpha \leq 0.05$) between the mean scores of students on the Analytical Thinking Scale attributed to the main effect of learning style (surface/deep). This difference favors the deep learning style.

The Behaviorist Theory, which sees learning as a modification in observable behavior brought about by the interplay of cues, responses, and reinforcement, might be used to interpret this conclusion. According to the Analytical Thinking Scale, pupils who choose a deep learning style do noticeably better, demonstrating more active and reliable cognitive reactions to learning stimuli. Positive reinforcement is more successful and long-lasting in forming their analytical behavior since they aim for comprehension and application rather than only memorizing.

From Skinner's point of view, deep learning is linked to repeated deliberate practice backed by instantaneous feedback, which results in the development of consistent cognitive behavior patterns such information analysis, comparison, and conceptual relationship recognition. Surface learners, on the other hand, depend on reflexive answers devoid of thought, which lessens the effect of reinforcement. Thus, in accordance with the tenets of successful behavioral learning, the dominance of the deep learning style indicates that practice, motivation, and regular reinforcement all help to develop a sophisticated analytical cognitive behavior.

Additionally, the findings showed that, independent of learning style, there was a statistically significant difference ($\alpha \leq 0.05$) in the mean scores of students on the Analytical Thinking Scale between the main effect of content presentation style (conditional/flexible) in favor of the flexible presentation style.

The principle of the stimulus-response relationship provides a behavioral explanation for this. In contrast to the conditional approach, which enforces a specific learning path, the flexible presenting style offers a range of educational stimuli, giving students numerous chances for active and adaptable answers that improve their analytical skills. Learners' attention and focus are increased by the variety of stimuli in the flexible presentation, which also encourages comparison, analysis, and the identification of conceptual linkages.

As a fundamental tenet of behaviorist theory, which emphasizes the significance of appropriate and logically ordered stimuli in directing behavior toward desired responses, the flexible presentation style also permits content adaptation to the learner's performance level and pace, making the learning process more gradual and cognitively organized. In line with behaviorist perspectives of learning as a process of behavioral regulation and control through stimuli, learners' superior performance under the flexible mode thus suggests that structuring and varying instructional stimuli improves analytical thinking processes and cognitive performance.

This is explained by the fact that while the flexible presentation style provides a learning environment that lets students manage their learning path and select activities that are appropriate for their pace and skill level, deep learning encourages learners to look for meaning, comprehend relationships between concepts, and connect theoretical knowledge to practical application. More chances for introspection, comparison, and analysis are therefore presented.

Higher-order cognitive skills like analysis, inference, and problem-solving are strengthened when these two methods are used together because students become more interested in the material and more able to consciously and independently organize their information.

Therefore, compared to other learning and presentation styles, the superiority of the deep learning–flexible presentation combination suggests that flexibility in content delivery supports deep cognitive processing mechanisms, activates organized and logical thinking, and ultimately results in a more effective and sustainable development of analytical thinking.

The outcomes of the present study are also consistent with those of the following studies: (Shahid, Khan, & Ishtiaq, 2023); (Abd Halim, Mohemad, & Haji Ali, 2023); (Bayuningsih, Usodo, & Subanti, 2017); (Beniche, Larouz, & Anasse, 2021); (Kamberi, 2025); (Alabi, 2024); and (Erazo, Esteve-González, & Vaca, 2015). These studies support the development of analytical thinking in adaptive learning environments.

5. CONCLUSION

The study came to the conclusion that creating adaptive learning environments that effectively consider various learning styles and content presentation techniques enhances learning quality and fosters the growth of both technical proficiency and critical thinking. The findings showed that flexible content presentation provides more options for autonomy and involvement, which improves proficiency in performing computer maintenance skills, and that deep learning produces more effective and long-lasting learning than surface learning. Furthermore, it was found that the combination of flexible presentation with deep learning was twice as successful in accomplishing skill-based and cognitive goals.

According to the study, adaptive environments—which integrate individualization and ongoing feedback while encouraging students to actively participate in knowledge construction—represent a viable future path for higher education. In order to give students flexible, individualized learning experiences that encourage critical thinking and creativity, it also suggests integrating these environments with learning analytics and artificial intelligence systems in technical and practical courses.

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