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DESIGNING A PERSONALIZED LEARNING ENVIRONMENT BASED ON ANALYTICAL LEARNING (INFERENCE/ MEASUREMENT /CONSTRAINTS) TO DEVELOP SYSTEMS ANALYSIS AND DESIGN SKILLS AMONG COMPUTER TEACHER PREPARATION STUDENTS

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ABSTRACT

This project aims to promote systems analysis and design skills among computer teacher preparation students by building a tailored learning environment based on analytical learning in its three forms: inference, Measurement, and constraints. Drawing on theories of meaning-based learning, deep learning, and constructivism—all of which stress the significance of offering learning pathways customized to learners' needs—the study investigated the role of instructional analytics in facilitating personalized learning. The research adopted a quasi-experimental design with a pre- and post-test on three experimental groups (N=48). Within a customized learning platform, each group was assessed using a distinct instructional analytics pattern: inference, measurement, and limitations. The results showed statistically significant differences between the pre- and post-tests in favor of the post-test in all three patterns. The inference group recorded the highest post-test mean (M=32.375), followed by the Measurement group, and then the restrictions group. The findings of the one-way ANOVA also demonstrated the superiority of the inferential analytic strategy, a finding verified by Tukey's post-tests. The study comes to the conclusion that students' proficiency in systems analysis and design skills can be effectively increased through individualized learning environments that are supported by educational analytics, especially inferential analysis. The research recommends adopting the inferential analytical learning approach in designing personalized learning environments for students, given

its high effectiveness in developing systems analysis and design skills and achieving better academic results compared to other approaches.

KEYWORDS: Analytical Learning, Personal Learning Environment (PLE), System Analysis and Design Skills, Inference, Measurement, Constraints.

1. INTRODUCTION

In recent years, the area of education has witnessed an increasing emphasis on personalized learning, where instructional tactics are adapted to match the specific requirements of pupils. By taking into account learners' prior knowledge, learning pace, and preferences, personalized learning environments are created to maximize student engagement, motivation, and accomplishment (Pishtari et al., 2023). The incorporation of Learning Analytics (LA) into educational settings has been essential in offering data-driven insights that advise both learners and instructors. Learning Analytics encompasses the gathering, measurement, analysis, and interpretation of data connected to learners' interactions within educational systems, enabling educators to make informed decisions that enhance the learning experience (Mukred, Mokhtar, Hawash, AlSalman, & Zohaib, 2024).

One successful strategy for bridging the gap between educators and intelligent technologies is Model-Based Learning Analytics (MbLA). By making student learning models and instructional tactics public, MbLA helps educators to understand learning progress, foresee challenges, and plan adaptive interventions (Pishtari et al., 2023). Such transparency promotes a collaborative atmosphere in which teachers may provide focused support, while intelligent algorithms offer automatic guidance based on real-time student data. This strategy is especially pertinent to higher education, as mastering intricate abilities like Systems Analysis and Design (SA&D) necessitates a thorough comprehension of both conceptual and practical knowledge domains (du Plooy, Casteleijn, & Franzsen, 2024).

The demand for systems analysts in the digital era has expanded dramatically. Organizations must use systems analysis and design (SA&D) to streamline operations, boost productivity, and provide technological solutions that support strategic goals (Irwansyahputra & Khairot, 2025). However, research has shown that there are gaps between the skills taught in SA&D courses and those needed in professional settings, especially in areas like agile development approaches, software testing, and system modeling (Rahmawati, Rahayu, & Safitrah, 2022). This mismatch underlines the need for novel teaching strategies that ensure computer teacher preparation students not only obtain theoretical knowledge but also develop practical, industry-relevant competencies.

Personalized learning environments informed by Learning Analytics can play a vital role in solving this skills gap. By continuously monitoring students' performance, engagement, and learning restrictions, educators can adjust instructional tactics to individual learner profiles (Khor & Mutthulakshmi, 2023), (Pishtari et al., 2023). For instance, dashboards and adaptive learning architectures allow teachers to monitor student progress, identify areas of weakness, and execute targeted interventions in real-time (Pishtari et al., 2023). Moreover, the use of inference-based analytics helps instructors to anticipate future learning issues and give scaffolding before students meet substantial difficulty. This predictive competence is vital for developing complex analytical abilities in domains like SA&D, where problem-solving, system modeling, and decision-making are interrelated.

Computer teacher preparation programs do more than just educate technical skills. Future teachers must develop critical thinking, analytical, and problem-solving abilities through these curricula (English, 2021). By embedding personalized learning strategies and analytics-driven feedback into the curriculum, teacher preparation programs can foster the development of critical competencies, such as requirement gathering, data flow analysis, system modeling, and the application of design patterns (Douglas College, 2025) Additionally, students can apply theoretical information in real-world situations through experiential learning through projects, case studies, and simulations, which strengthens skill acquisition and fosters deeper comprehension.

Integration of Learning Analytics in tailored contexts also fosters metacognitive development among learners. Students are encouraged to reflect on their own learning patterns, evaluate strengths and limitations, and adapt tactics accordingly (Pishtari et al., 2023). This reflective process not only promotes comprehension of SA&D principles but also enables future educators to use evidence-based teaching practices in their classrooms. Furthermore, the adaptive nature of such environments accommodates varied learning styles, prior knowledge levels, and cognitive limits, offering equitable opportunity for all learners to succeed (Simplilearn, 2025).

The construction of tailored learning environments for SA&D training involves a full understanding of both pedagogical concepts and technology affordances. To develop learning platforms that incorporate assessment frameworks, adaptive material distribution, and real-time feedback mechanisms, systems analysts and instructional designers must work together (GeeksforGeeks, 2025; Dias, 2024). By leveraging these tools, teacher preparation programs can provide scaffolded learning experiences that progressively improve analytical, technical, and professional competencies. Furthermore, incorporating ongoing assessment via Learning Analytics guarantees that the instructional design stays adaptable to students' changing demands, improving overall efficacy and efficiency (Namacha, 2024).

Implementing individualized learning environments for SA&D skill development presents a number of hurdles, despite the potential advantages. Data privacy issues, the requirement for analytics interpretation training for teachers, and the alignment of adaptive content with curriculum objectives are some of these difficulties (Pishtari et al., 2023; English, 2021). Overcoming these problems demands a coordinated approach among educational institutions, technology suppliers, and legislators to create best practices and assure sustainable, scalable solutions that really improve learning results.

In conclusion, creating a customized learning environment based on analytical learning—which includes measurement, inference, and learning constraints—offers a viable strategy for helping students preparing to become computer teachers gain SA&D competencies. By integrating Learning Analytics, adaptive instructional methodologies, and reflective practices, instructors may provide individualized support that promotes student engagement, mastery, and readiness for professional positions in systems analysis and design. Adopting data-driven, learner-centered approaches is essential for equipping future computer educators with the skills, knowledge, and critical thinking abilities needed in today's dynamic IT world as higher education continues to change in response to technology breakthroughs.

2. MOTIVATION

The constantly changing field of computer education necessitates a change from traditional teaching methods to more individualized, data-driven approaches in order to prepare future instructors. The intricate field of systems analysis and design (SA&D) blends theoretical understanding with real-world problem-solving and analytical abilities. However, typical SA&D courses sometimes fail to address individual learner differences, resulting to gaps between student competences and the skills expected in professional situations (Rahmawati, Rahayu, & Safitrah, 2022). Personalized learning environments, enabled by Learning Analytics, offer a promising answer by customizing instruction to the learner’s needs, offering real-time feedback, and enabling predictive insights (Pishtari et al., 2023).

1. **Bridging the Skills Gap:**

The actual skills needed in industry, such as system modeling, requirement analysis, software testing, and agile development approaches, are known to differ from the theoretical information taught in SA&D courses (Misic & Russo, 1999; Rahmawati et al., 2022). A tailored, analytics-driven environment can assist bridge this gap by targeting specific learner deficiencies and personalizing education accordingly.

2. **Enhancing Engagement and Motivation:**

To boost engagement, personalized learning makes use of students' interests, learning styles, and past knowledge. Adaptive systems support motivation and perseverance in learning difficult SA&D concepts by offering scaffolding, prompt feedback, and predictive interventions (Pishtari et al., 2023; English, 2021).

3. **Developing Critical Analytical Skills:**

SA&D needs high-level analytical thinking, including problem-solving, system analysis, decision-making, and application of design patterns. Learning environments that incorporate measurement, inference, and constraint analysis facilitate the development of these competencies (Douglas College, 2025; IBM, 2025).

4. **Promoting Reflective Learning:**

Analytics-informed environments empower students to monitor and reflect on their learning behavior, recognize strengths and limitations, and make educated modifications. This metacognitive growth is necessary for future educators to apply successful teaching strategies and continuously enhance their own skills (Pishtari et al., 2023; English, 2021).

5. **Preparing Future Educators for Modern Classrooms:**

Computer teacher preparation programs are not only concerned with technical training but also with equipping students to teach successfully in digitally enhanced and learner-centered classrooms. Both training and demonstration tools for students' future teaching practices are provided via personalized and analytics-driven learning models. (Osorio Vanegas, Sobrino Morías, and Segovia Cifuentes, 2025)

The necessity to update SA&D education with individualized, analytics-informed learning environments is the driving force behind this study. By addressing skill gaps, improving motivation, developing critical thinking, fostering reflective learning, and preparing students for modern educational situations, such environments have the potential to greatly increase the quality of computer teacher preparation. This strategy is in line with the more general educational objective of developing highly skilled, flexible, and evidence-based teachers who can satisfy the changing needs of the IT and educational sectors.

3. RESEARCH PROBLEM

Students enrolled in computer teacher preparation programs find it challenging to successfully acquire Systems Analysis and Design (SA&D) skills that meet the demands of the labor market given the speed at which information technology is developing and the growing need to provide computer teachers with advanced technical and analytical skills. The practical skills needed in the workplace, such as systems modeling, requirements analysis, software testing, and the use of agile development methodologies, clearly differ from what is taught in SA&D courses, according to recent studies (Rahmawati, Rahayu, & Safitrah, 2022; Misic & Russo, 1999).

Furthermore, research has demonstrated that traditional educational environments are unable to accommodate individual student variances in learning styles and deliver standardized curriculum that fails to incorporate students' past knowledge, learning pace, and analytical thinking ability. This weakness leads to limited cognitive and skill development among some students, restricting their capacity to apply theoretical concepts in practical circumstances (Pishtari et al., 2023; English, 2021).

Therefore, the need arises to develop a tailored learning environment based on analytical learning, focusing on tactics of reasoning, measurement, and limitations analysis. This seeks to tailor the learning process to each student's level and offer ongoing assistance so they may acquire practical and analytical skills in systems analysis and design. It is also clear that there aren't many practical studies that show how these analytical techniques work in individualized learning settings, especially for students preparing to become computer teachers. This raises doubts regarding the influence of these strategies on strengthening their SA&D skills and selecting the most successful approaches.

4. RESEARCH QUESTIONS

4.1. Main Question

What impact does analytical learning (inference, measurement, and limitations) have on the development of systems analysis and design abilities in students preparing to become computer teachers?

4.2. Sub-Questions

1. How does analytical learning with inference affect students preparing to become computer teachers in terms of their ability to build systems analysis and design skills?
2. What is the effect of analytical learning with measurement on developing systems analysis and design skills among computer teacher preparation students?
3. How do analytical learning with limitations affect students preparing to become computer teachers in terms of their ability to build systems analysis and design skills?
4. Which analytical learning strategy—inference, measurement, and constraints—is best for helping students preparing to become computer teachers build their systems analysis and design skills in a personal learning setting?

4.3. Research Hypotheses

1. The analytical-inferential learning strategy in the development of systems analysis and design abilities is responsible for the statistically significant difference between the pre- and post-test mean scores of computer teacher preparation students, favoring the post-test.
2. There is a statistically significant difference between the pre- and post-test mean scores of computer teacher preparation students attributed to the analytical-measurement learning technique in building systems analysis and design skills, favoring the post-test.
3. The analytical-constrained learning strategy in the development of systems analysis and design abilities is responsible for the statistically significant difference between the pre- and post-test mean scores of computer teacher preparation students, favoring the post-test.
4. There are statistically significant differences between the mean scores of computer teacher preparation students attributable to the different analytical learning approaches (inference/measurement/constraints) in developing systems analysis and design skills, favoring the group that studied using the analytical-inferential learning approach.

5. CONTRIBUTIONS

1. Contribution to the Development of Theoretical Knowledge:

By showing how analytical learning techniques (inference, measurement, and restrictions) affect the development of systems analysis and design skills among students preparing to become computer teachers, this study contributes to science. This gives a deeper knowledge of the link between analytical learning methodologies and the technical and cognitive skills required in the modern workplace (Pishtari et al., 2023).

2. Contribution to the Design of Personalized Learning Environments:

This research adds to creating a viable model for a personalized learning environment based on analytical learning. This model is defined by its flexibility in adapting to individual student differences and its use of reasoning, measurement, and constraints analysis to guide learning and facilitate the gradual and effective acquisition of skills (du Plooy et al., 2024).

3. Improving Learning Outcomes in Teacher Preparation Programs:

Research helps develop novel teaching approaches that contribute to boosting students' professional competence by enhancing analytical thinking, problem-solving, systems modeling, and evidence-based decision-making abilities, thereby satisfying labor market expectations (Rahmawati, Rahayu, & Safitrah, 2022).

4. Contributing to Educational Practice:

Research presents a practical foundation for instructors and academic supervisors to adopt analytical learning in individualized learning settings. This permits monitoring student progress, identifying shortcomings, and delivering targeted educational interventions, hence boosting the effectiveness of the educational process and encouraging self-directed and adaptive learning (Khor & Mutthulakshmi, 2023).

5. Supporting Data-Based Educational Decision-Making:

By merging inferential, measurement, and constraint analysis approaches, research gives precise data on student performance. In order to enhance instructional design and guarantee that it is in line with students' requirements and learning levels, this aids educators in making evidence-based decisions (Mukred et al., 2024).

6. SEARCH TERMS

According to Dabbagh and Kitsantas (2012), a personal learning environment (PLE) is a system that integrates educational tools and data analysis techniques to support self-directed and adaptive learning, allowing learners to control their learning resources and methods, tailored to their individual needs and skill level.

In the context of individual learning, analytical learning promotes critical thinking and evidence-based decision-making by utilizing reasoning, measurement, and constraint analysis techniques to support a thorough comprehension and methodical analysis of information (Reis et al., 2020).

System Analysis and Design Skills: These are the technical and mental aptitudes required to comprehend complicated issues and create suitable software and technical solutions. They are critical abilities for computer science professors to provide students with best practices in information technology (Rahmawati, Rahayu, & Safitrah, 2022).

Inference: This is a computational or logical process aimed at generating inferences or predictions from given facts or information. It helps students comprehend relationships and patterns in educational content through analytical learning (Du, Zhang, Jiang, Zeng, & Lu, 2025).

Measurement: This is a quantitative assessment procedure of abilities, knowledge, or performance. It is used in personalized learning environments to determine a learner's progress and alter educational content accordingly (du Plooy et al.). (2024)

Constraints: Factors or restrictions that affect the design and implementation of a learning environment, such as time constraints, equipment capabilities, and learner characteristics, which must be considered to ensure the efficacy of the learning environment (Haron et al., 2021).

Designing and Managing a Personal Learning Environment:

Designing a personal learning environment involves establishing a personalized e-learning environment that allows learners to collect and organize various learning resources according to their needs and learning style. These environments are based on the principle of learner-centeredness, where the learner is responsible for organizing information and managing their learning content in collaboration with their teachers and peers, thus promoting self-directed and organized learning (Klasnja Milicevic, Ivanovic, & Stantic, 2020). According to Education Elements (2024), a personal learning environment is a method that tailors the curriculum, pace of instruction, and learning environment to each student's needs, interests, and objectives. By allowing students to select their own learning paths and promoting personalized education, this strategy seeks to increase student autonomy and motivation. The paper underlines the significance of technology in allowing adaptive learning experiences that help students realize their academic potential.

Designing a personal learning environment entail examining learners' characteristics in terms of cognitive, informational, and affective skills, coupled with knowing their educational needs and the difficulties they confront. In addition to offering learning strategies that support learner-centered learning and assist them in achieving their learning objectives, learning content, educational tools, and digital services are arranged within an integrated environment that makes it easier to access and control content (du Plooy, Casteleijn, & Franzsen, 2024). Managing these environments relies on instructing learners on how to utilize the tools and services, providing different learning resources to assist them achieve their goals, and assuring their active involvement through ongoing assessment and feedback. In the context of the individual learning environment, the function of the teacher also changes from that of a knowledge provider to that of a mentor and facilitator who helps students along their learning path (Sande & Burnett, 2023). A study by Xu et al. (2024) highlighted the advantages and difficulties of personal learning environments by analyzing the results of 53 research studies. In addition to issues including teachers' lack of digital literacy, reliance on self-directed learning, unequal resource distribution, and privacy concerns, the study highlighted the absence of a common definition for this kind of setting. It also recognized the limited impact of these environments on developing non-academic skills and made recommendations for building more successful educational systems. Using complexity theory and NVivo data analysis, Gunawardena et al. (2024) investigated Australian secondary school teachers' perspectives on implementing individualized learning. Teachers exhibited a mix of enthusiasm and caution, acknowledging its potential benefits against obstacles linked to classroom management, pedagogy, and the needs of the school system. The study finds that a complexity perspective helps in comprehending these problems and establishing individualized learning strategies suited to the educational context.

Prescott (2024) also highlights the necessity to adapt instruction to suit the individual learning styles, preferences, and needs of each student. Key tactics include the use of individualized evaluations and feedback, personalized learning plans, personalized education systems, and progress tracking. Strong teacher-student connections and parental involvement are recognized as crucial for encouraging student engagement, motivation, and academic success. This method strives to provide a student-centered learning environment that encourages continual academic progress and empowers individuals to realize their greatest potential.

6.1. Designing A Personalized Learning Environment Based on Analytical Learning:

Creating an educational system that gives students control over their learning materials and adapts them to their unique requirements and ability levels while utilizing educational analytics to promote efficient learning is known as designing a personalized learning environment. Personalized learning environments are noted for their flexibility, interactivity, and different learning materials, enabling learners to proceed in a way that suits them and fosters self-directed learning processes (Tuo et al., 2025).

In the context of analytical learning, strategies of inference and measurement are employed, along with identifying constraints that affect the learning process. This provides an accurate analysis of the learner's needs and performance level, helping to design a learning environment that dynamically adapts to individual differences. This methodology not only distributes content but also incorporates the systematic and continuous monitoring and analysis of student performance to help them along their learning journey (Jabbour et al., 2025).

Ingkavara et al. (2022) and Zhang et al. (2023) emphasize the relevance of personalized learning environments in encouraging learner autonomy by leveraging information and communication technology to tailor learning experiences to students' needs and interests. They also mention the global growth of these environments, particularly in the United States, the United Kingdom, and China, highlighting important implementation problems such as scalability, integration, and pedagogical adaption. They underline the necessity for significant methodological revisions to ensure the effectiveness and sustainability of these approaches in the future.

Students' critical and analytical thinking abilities are strengthened by creating a customized learning environment based on analytical learning, particularly in challenging subjects like systems analysis and design. This needs the ability to assess and characterize issues and design solutions systematically, which allows the successful application of professional and technical abilities (du Plooy et al., 2024).

Analytical Learning Strategies in Personalized Learning Environments:

The foundation of individualized learning environments is analytical learning strategies, which improve students' analytical and critical thinking abilities. In order to enhance comprehension and successfully direct learning within a customized learning environment, these tactics rely on learning analytics, which involves monitoring student performance using inferential and benchmarking techniques (Guo et al., 2024). Learners can design their own learning experiences by active engagement with content and interaction with peers and instructors, encouraging systematic information analysis and problem-solving skills (Hardianti et al., 2024).

According to Fajriyah and Afifah (2025), analytical learning strategies include methods like interpretive reasoning, ongoing skill evaluation, using constraints to pinpoint areas that require more assistance, and using in-depth analysis of educational data to customize individual learning experiences.

These tactics help students become more motivated and better at controlling their learning, which promotes the growth of their systems analysis and design abilities, especially in challenging technical courses.

By utilizing these techniques in personalized learning settings, learners' past knowledge can be incorporated into learning routes that are tailored to their individual performance and understanding levels, increasing educational efficacy. According to Hakim, Jastacia, and Al-Mansoori (2024), this has a favorable effect on learning outcomes and helps prepare computer science teacher preparation students for the demands of contemporary education and vocational training.

6.2. Learning Analytics (La)

Learning analytics is described as the use of educational data to enhance the learning process by collecting and analyzing data and offering actionable insights for both teachers and students (Khalil & Ebner, 2015). It emphasizes transparency, security, ownership, and accuracy in data use with the goal of fostering engagement and self-directed learning (Khalil & Ebner, 2015). Key concerns include security, ethical, and policy limits that may limit the effectiveness of LA in educational contexts.

Recent studies indicate that integrating learning analytics with artificial intelligence (AI) should be human-centered, incorporating students and teachers at all stages of the design process to ensure trust and reliability (Riordan et al., 2024). This approach emphasizes a balance between technical capabilities and acceptable behaviors, while also addressing safety and human control in AI-driven educational systems (Cukurova, 2024).

According to research, AI may be used in a variety of educational settings, such as inclusive primary education in STEAM subjects (Sointu et al., 2024) and online university education (Liu, 2024; Nguyen & Karunaratne, 2024). Techniques such as model-based learning analytics (ML) can be utilized to foster partnerships between instructors and intelligent teaching systems, as transparent models of student and teacher behaviors enable successful educational decision-making (Pishtari et al., 2023).

Personalized learning contributes to adapting content and learning pace to students' needs, boosting their independence and academic motivation (Zahran et al., 2025; Van den Bogaard & De Vries, 2017). Integrating learning analytics into personalized learning systems enables the provision of individualized recommendations to students and the enhancement of learning activity design to correspond with each learner's learning style and needs (Kurday & Vladova, 2025; Liu et al., 2025).

When putting Learning Analytics (LA) into practice, privacy and security are crucial factors. Approaches such as Differential Privacy can preserve student data while keeping the utility of analytics (Liu et al., 2025). In order to promote confidence in educational systems, researchers stress the necessity of responsible frameworks that integrate student rights protection with academic success (Kaliisa, 2022).

6.3. Constraints Analysis in Personal Learning Environments

Constraints analysis in personal learning environments refers to analyzing and identifying the elements that affect the design and implementation of these settings in order to improve their educational effectiveness. These restrictions include things like the difficulty of navigating instructional materials, a lot of learning possibilities that could lead to cognitive overload, and time and technical constraints that prevent students from reaching their full potential (Berbel Gimenez & Borras-Gene, 2023). According to Cronin-Golomb and Bauer (2023), learners may experience uncertainty or frustration in the environment due to the quantity of available paths and resources, which can result in a reduction in focus and accomplishment, particularly when faced with new or complicated instructional content.

To solve these issues, personal learning environments require the provision of electronic support systems that intelligently guide learners along their learning journey, reducing distractions, boosting focus, and enhancing interactive learning. Individual differences among learners must also be considered while building limitations to flexibly fulfill each learner's demands. (Okolugbo et al., 2025)

This constraints analysis plays a critical role in building personalized learning environments (PLEs) that are practically useable and appropriate from both a technology and human perspective, therefore leading to more effective continuous learning and skill development. (Ahmed and others, 2025)

6.4. Analyzing Student Performance in A Personal Learning Environment

With an emphasis on enhancing students' analytical and design capabilities, assessing student performance in a personal learning environment entails quantifying and evaluating the degree to which students use this learning environment to gain the desired knowledge and skills. Studies reveal that individualized learning environments based on learning analytics allow students to study individually at their own speed, with the option to regularly review knowledge to encourage mastery. As a result, abilities are better retained in long-term memory and are easier to use in real-world scenarios (Yildirim et al., 2024).

Research also indicates that continuous interaction between the student and the learning environment, along with the various activities implemented, contributes to enhancing students' ability to apply acquired skills spontaneously, resulting in more structured and effective performance (Guerra-Macías & Tobón, 2025). Teachers and researchers can improve the learning environment to better suit the different requirements of learners by using performance analysis to identify strengths and shortcomings in the learning process (Ponomariovienė et al., 2025).

According to a study by Wang et al. (2024), incorporating AI into customized learning settings improves cognitive abilities and motivation, but it also presents issues with bias, accuracy, over-reliance, and privacy. The findings show the necessity for a student-centered strategy and appropriate teacher training to enable the effective deployment of artificial intelligence. The study emphasizes how crucial it is to address data privacy and ethical concerns in future teaching methods.

Analyzing student performance in personal settings helps provide a reliable database on the effectiveness of different learning strategies and their suitability for enhancing students' skills, particularly in disciplines such as computer science teacher preparation, which requires the development of highly efficient technical and analytical skills (He, Chen, & Mo, 2024).

6.5. Educational Data Analysis in Personalized Learning Environments

Educational data analysis involves gathering and analyzing information linked to student activities and interactions inside a customized learning environment (PLE). Enhancing student performance and raising the standard of the educational process are the objectives. PLEs offer sophisticated capabilities for evaluating student data, such as tracking progress, recognizing learning challenges, and assigning educational resources to fit individual needs, thus dramatically increasing learning outcomes (Gonzalez & Chiappe, 2024).

The study includes a variety of data kinds, such as inferential analyses to assist well-informed educational decisions, predictive analyses to discover future trends, and descriptive analyses to evaluate the existing situation (Dibekulu, 2020). Learner behavior analytics are also utilized to personalize learning experiences and promote engagement and involvement, therefore fostering active and effective learning (Weng & Zhang, 2025).

Analyzing educational data provides the provision of instant and tailored feedback to students, allowing for the improvement and adaption of courses to their performance. This enhances computer science instructors' training and helps them build their analytical and practical skills (Wang & Liang, 2025).

6.6. Improving Learners' Personal Learning Environment

Enhancing the efficiency of education and helping students develop their skills requires improving their personal learning environment. Offering a thorough, individualized learning environment is essential to promoting self-development. It boosts their ability to plan consistently and employ innovative learning strategies that correspond with their unique demands (Akyuz, 2022). Furthermore, building learners' self-awareness through performance evaluation and identifying strengths and weaknesses contributes to refining their skills and improving their engagement with learning content, which positively impacts the quality of their educational experience (Padayao & Bantulo, 2024).

Improving the learning environment also involves providing digital tools and modern technologies that help learners track their progress and effectively analyze their learning outcomes, in addition to supporting continuous development through specialized training courses and workshops (Evolvetosuccess, 2025). Additionally, educational assistance is essential to establishing an engaging learning environment that fosters creativity and boosts students' motivation to finish assignments (Abbasi et al., 2025).

The influence of this better environment extends to engaging learners and boosting their self-directed learning by providing flexible learning models that cater to individual characteristics and consider their various degrees and skills. Students preparing to become computer teachers benefit from improved learning outcomes and the development of systems analysis and design skills (Subandiyah et al., 2025).

Improving students' personal learning environment is a significant aspect in improving learning motivation and raising the quality of academic success. This technique relies on offering interactive learning environments that allow learners to control the selection of educational activities and applications that meet their particular needs, thus boosting their ability to self-regulate and learn independently (Subandiyah et al., 2025). Personalized, collaborative learning environments also give possibilities for social contact and cooperation among students, contributing to the development of flexible thinking abilities and creativity (Almulla, 2023).

Strategies for improving the learning environment include providing psychological and social support for students, building relationships based on trust and respect between teachers and students, and diversifying teaching methods to accommodate individual differences, such as group work and individual activities. This guarantees that every student participates actively and inspires them to learn. Furthermore, it highlights a commitment to connecting with parents to assist the educational process and provide a comprehensive learning environment across all areas of the student's life. (Zenebe & Assefa, 2024)

These improvements lead to a classroom environment that fosters creativity and interaction, enhancing learning outcomes and developing students' skills comprehensively and holistically, particularly in advanced fields such as systems analysis and design within the context of computer science teacher training (Lewis, 2025).

A method for combining student interaction data in customized learning environments with a learning style model to forecast academic performance using machine learning models was presented in a study by Nazempour and Darabi (2023). The findings demonstrated that students scored higher when their learning behaviors matched the anticipated learning styles. The study recommends techniques for leveraging these insights to facilitate tailored learning and increase academic success.

(Digital Promise ,2023) explored techniques for strengthening individualized learning environments by connecting learning to students' interests, guaranteeing inclusion, and growing the learner's voice and talents. It emphasizes the role of work-based learning and partnerships with employers, teachers, and families in bridging theoretical knowledge with practical application. In order to encourage individualized learning that equips students for study, employment, and community involvement, best practices including competency-based curricula, practical projects, and educational technologies are emphasized.

6.7. Challenges Of Personalized Learning Environments for Teachers and Students

The efficacy of personalized learning environments for both teachers and students are impacted by a number of issues. One of the most significant issues is the difficulty students encounter in self-regulating within a learning environment that offers many courses without direct direction, which can lead to student burnout and lack of motivation (Barrera Castro et al., 2025). Some teachers also suffer from a lack of awareness regarding the usefulness of virtual learning tools, in addition to a paucity of the requisite technical abilities to use these technologies successfully. This makes it more difficult for them to adjust and create new learning opportunities (Xu et al., 2024). Furthermore, budgetary and operational obstacles restrict the delivery of rich and innovative educational content. Problems linked to the maintenance and preservation of virtual learning tools also negatively impact the continuous usage of personal learning environments (Deroncele-Acosta & Ellis, 2024). The different abilities and developmental characteristics of pupils also constitute an impediment to achieving a homogeneous and secure learning environment. For all kids to integrate and engage in constructive interactions, teachers must offer the proper psychosocial support (Barrera Castro et al., 2025). To address these challenges, studies recommend providing ongoing training for teachers to enhance their technical and pedagogical skills, offering comprehensive technical support for the learning environment, and fostering a positive learning culture that includes effective communication and psychological support for students. This contributes to increasing educational performance and accomplishing the aims of personal learning environments. (Alabdouli, 2025).

A study by (Wongwatkit & Panjaburee ,2024) underlines the problems of establishing personalized learning environments and suggests a dual-adaptive system that provides tailored learning content and modifies learning activities based on students' real-time behavior. This method was used in a system to promote secondary school students' digital literacy, and a trial with 336 students showed notable increases in motivation and performance when compared to conventional instruction. The outcomes demonstrate multi-level adaptation's efficacy and its potential to advance more customized learning environments.

(Everett,2023) asserts that the implementation of personalized learning in personalized learning environments relies on positive forces such as teacher-student relationships, interdisciplinary teaching, and technology that enables flexible learning and real-time progress tracking. Conversely, it is hindered by traditional institutional structures, teachers' limited capacity to produce personalized resources, and a lack of a unified vision among stakeholders. The article emphasizes the importance of understanding these forces to design effective and scalable personalized learning environments.

7. METHODOLOGY

First: Research Method:

This research adopted a quasi-experimental design based on a three-group experimental design. Each of the three experimental groups of students used one of the analytical learning techniques in a private learning setting:

1. Learning Analytics Based on Inference.

2. Measurement-Based Learning Analytics.

3. Learning Analytics Based on Constraints.

This design intends to examine the impact of each analytical learning technique on developing students' systems analysis and design skills.

Second: Research Population and Sample

1. Research Population:

The research population comprises of all students enrolled in the Computer Teacher Preparation Program at the Faculty of Specific Education, Kafrelsheikh University, who were registered in the Systems Analysis and Design course during the academic year 2024/2025.

2. Research Sample:

A purposeful sample of (48) male and female students was recruited to guarantee homogeneity of educational and knowledge backgrounds across the groups. They were divided into three experimental groups as follows:

Group 1: Inference Method, 16 students.

Group 2: Measurement Method: 16 students.

Group 3: (16) students - Constraints Method

Third: Research Instruments:

The researcher employed different equipment to collect data and measure the impact of the experimental treatments. These included:

1. A System Analysis and Design Skills Test (SA&D Skills Test)

This test comprises the following sub-skills:

a) Systems Analysis Skills.

Field	main Skills
Understanding Business and Processes	Understanding organizational goals, policies, procedures, and user needs
Gathering Requirements	Conducting interviews, observation, analyzing surveys, and analyzing current problems and opportunities
Analyzing Data	Identifying data types, creating DFD diagrams, and analyzing ERD relationships and entities
Problem Solving and Decision Making	Identifying the root cause of problems, evaluating alternatives, and selecting the most appropriate solutions
Modeling Skills	Using DFDs, BPMN, and UML (Use Case, Class Diagram(
Effective Communication	Simplifying technical concepts for users and writing clear and understandable reports

b) Systems Design Skills.

Field	main Skills
Interface Design	Design user-friendly interfaces, prioritizing user experience.
Database Design	Create diagrams, define tables, relationships, and primary keys.
Process Design	Define task execution, inputs, and outputs for each process.
Technical Architecture Design	Select appropriate software and tools.
Basic Programming Skills	Understand programming languages or communicate with the development team.

System Testing	Prepare test cases, test performance and functionality, and ensure system quality

Scoring Scale: 40 points, each question worth 1 point.

- Validity and reliability were verified using expert reviews and Cronbach's Alpha > 0.85.

C) Achievement Test:

- Question Type: Multiple choice, 40 questions.
- Objectives: To test higher-order thinking skills, analytical thinking, inference, data analysis, and process design.
- Diversity of Thinking Levels: This ensures that higher-order thinking skills are measured by covering Bloom's Taxonomy (knowledge, comprehension, application, analysis, and assessment).
- Validity and reliability: Cronbach's Alpha > 0.85 with expert evaluation.
- The test was used for pre- and post-testing for each group.

Procedures:

- Based on the analytical learning approach, students were split up into three groups.
- **The training program was implemented in the Moodle environment:**
- Theoretical and practical tutorials for each ability were uploaded.
- Interactive exercises like surveys, quizzes, forums, and assignments were created.
- **Analytical learning methodologies were supported:**
- **Reasoning:** Step-by-step problem-solving and analysis activities were incorporated.
- **Measurement:** Applying norms and standards to real challenges.
- **Constraints:** Step-by-step activities to help pupils toward right responses.
- After the training completed, post-testing was conducted for all groups.

Group Homogeneity:

Table (1): Descriptives Degree.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Inference	16	9.5625	1.63172	.40793	8.6930	10.4320	6.00	12.00
Measurement	16	9.0625	1.73085	.43271	8.1402	9.9848	6.00	11.00
Constraints	16	9.6875	2.12034	.53008	8.5577	10.8173	6.00	13.00
Total	48	9.4375	1.82076	.26280	8.9088	9.9662	6.00	3.00

Table (2): ANOVA Degree.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.500	2	1.750	.517	.600
Within Groups	152.313	45	3.385		
Total	155.813	47			

- All groups had a pre-test mean score of less than 10.
- ANOVA on the pre-test: F = 0.517 → No statistically significant changes
- This guarantees that any subsequent differences in the post-test are due to the analytical learning style rather than variations in the students' primary levels.

Statistical Analysis

- Paired-samples t-test: This method compares each group's pre-test and post-test means.
- One-way ANOVA: Comparing the means of the three groups after implementation to determine the optimum technique.
- Significance level: $\alpha = 0.01$

Fourth - Setting up the Personal Learning Environment (PLE) Analytics Platform

Steps for setting up the Personal Learning Environment (PLE) Analytics Platform

This comprises the following and is based on inferential analysis, standard analysis, and constraints analysis using the Moodle platform:

A: Needs analysis and design requirements assessment, which includes:

1. Analyzing the characteristics of computer teacher preparation students in terms of their technical background, learning styles, tendency towards self-learning, and competence level in using digital platforms.
2. Analyzing the abilities targeted for systems analysis and design.
3. Defining user roles: Student – Faculty Member – System.

4. Compiling the learning analytics specifications required to tailor the platform's learning routes in accordance with the three types:

Measurement/Comparative Analytics; Inference Analytics; Constraints-Based Analytics B: Designing the entire platform architecture, which includes:

1. **Outlining the Structure of the Platform:** User interface – Learning dashboard – Instructor dashboard – Learner database – Activity repository
2. **Designing the Data flow Between System Components;** how student learning data is gathered, analyzed, and returned as pathways.

3. Defining the Learning Models for Each Sort of Analysis:

- Inference model
- Model of measurement
- The model of constraints

A: Creating a Learner Profile Database by developing a personal learning profile that includes:

1. Basic information (age, technical background, specialism).
2. Previous performance level, student efforts, and learning points.
3. Learning preferences: video, simulation, practical exercises, and text.
4. Analytical data that is utilized in the three categories of analytics.

D: Applying the three forms of learning analytics within the platform, which includes:

(1) Inference Analytics

The learner is steered to learning information relevant to their learning preferences using inference analysis to infer what the student requires based on their behavior inside the platform and to develop an automatic tailored learning path that is updated after each learning session.

(2) Comparative Analytics and Measurement

Using comparison analysis, a comparison model is created that compares each student's performance with that of their peers and creates customized tasks to address any weaknesses found through comparison, guiding the student to learning content appropriate to their learning preferences. (3) Constraint-Based Analytics

Students are led toward learning content suited to their learning preferences via constraints analysis. This entails establishing the prerequisites and guidelines for mastering a skill and then evaluating mistakes in light of these limitations. Additionally, mastery learning is used to make sure that students only advance after meeting the minimal skill requirements.

E: Designing user interfaces, which comprises:

1. A user-friendly interface showcasing the particular learning path.
2. A dashboard for student progress.
3. An instructor dashboard that incorporates group statistics and gap analysis.

Fourth: Experimental Procedures

1. Preparation Phase:

- Analyzing learner characteristics and the course's technical requirements.
- Designing the individual learning environment according to the ADDIE instructional design technique.

Three learning paths representing various forms of analytical learning have been developed within the system.

Assessment instrument preparation and validation.

2. Implementation Phase:

The pilot program was carried out using the following procedures from March 23, 2025, to May 4, 2025:

A. First Group: Inference Method:

- The system tracked student learning patterns.
- It offered guided support for problem-solving and error prediction.

B. Second Group - Measurement Approach:

- It measured student performance in real-time across various skills.

Dashboards were used to give instant quantitative feedback.

- It automatically altered tasks based on achievement levels.

C. Third Group - Constraints Approach:

- It investigated elements impeding student learning (time, difficulty, resources).

It offered different learning paths according to each student's unique learning limitations.

- It supplied adaptive solutions when knowledge gaps were detected.

3. Phase of Evaluation

Research Results:

1. Analytical learning through reasoning:

Table (3): Group Statistics.

	group	N	Mean	Std. Deviation	Std. Error Mean
degree	Pre-test	16	9.5625	1.63172	.40793

	Post-test	16	32.3750	.95743	.23936

Post-Test Mean M=32.375 Vs. Pre-Test 9.5625 → Statistically Significant Difference P < 0.01.

Interpretation:

This result reveals that a personalized learning environment based on inferential analytics was the most successful in enhancing student performance. This is owing to the nature of this strategy, which relies on inferring each learner's needs and monitoring their interaction patterns inside the platform to arrive at accurate learning decisions.

According to constructivist learning theories, learners tend to create their knowledge when they receive constant feedback and learning pathways that adjust directly to their performance. Inferential analytics reinforced this principle through:

1. Content distribution based on conclusions drawn from real learning data (association rules, Bayesian inference).
2. Automatically guiding students to remedial resources that correlate with their errors.
3. Real-time adaptability, which improved achievement and motivation.

This result is in line with earlier research showing how well inferential analytics may promote tailored learning, including:

According to (Akyüz, 2022), learning environments built on learner data analysis offer more precise suggestions that boost performance.

(Siemens & Baker, 2021) discovered that the best way to forecast performance and make early corrections is to use inference models.

Therefore, the significant superiority in the post-test average can be explained by the fact that the inference approach provides the deepest level of personalization, which is consistent with previous studies that have confirmed that inference reflects a higher level of "analytical intelligence" compared to measurement or constraints.

2. Analytical Learning by Measurement:

Table (4): Group Statistics.

	group	N	Mean	Std. Deviation	Std. Error Mean
degree	Pre-test	16	9.0625	1.73085	.43271
	Post-test	16	31.1250	.71880	.17970

Post-Test Mean M=31.1250 Vs. Pre-Test 9.0625 → Statistically Significant Difference P < 0.01.

Interpretation:

Benchmarking, which compares student performance to that of peers or a benchmark, was found to significantly boost student performance.

This confirms the findings of Bandura's social learning theories, which suggest that learners are naturally motivated to improve their performance through comparative learning.

Benefitting also helps to:

1. Determine any learning gaps in relation to the benchmark level.
2. Increase the student's motivation by demonstrating their place in the group.
3. Establish a clear path for development (benchmarking path).

Previous research, such as (Verbert et al. ,2020), demonstrate that benchmarking boards raise learners' awareness of their performance and make learning more transparent, which positively impacts skill acquisition.

However, the drawback of this method compared to reasoning derives from the fact that it does not offer tailored recommendations regarding the accuracy of the reasoning, because it focuses on comparison rather than a deep understanding of the causes for the inaccuracy.

3. Analytical Learning with Constraints:

Table (5): Group Statistics.

	group	N	Mean	Std. Deviation	Std. Error Mean
degree	Pre-test	16	9.6875	2.12034	.53008
	Post-test	16	30.8125	.65511	.16378

Post-Hoc Mean M = 30.8125 Vs. Pre-Hoc Mean 9.6875 → Statistically Significant Difference P < 0.01.

Interpretation:

Constraints analysis is based on establishing precise guidelines for a skill (such as analytic procedures, system design guidelines, and problem-solving guidelines) and then comparing student performance to these guidelines to find mistakes.

This is consistent with the cognitive learning hypothesis, which contends that rule-based feedback lowers mistakes and fosters a logical comprehension of the skill.

Studies such as Mitrovic (2019) have revealed that constraints analysis is particularly successful in tasks requiring unambiguous steps since it highlights the phase where the student made a mistake and provides a correct example.

However, this method's shortcomings in comparison to measurement and inference result from:

1. Its reliance on fixed rules that do not change with context.
2. Its inability to offer intricate, customized learning pathways such as inference.
3. Its limited ability to predict learner behavior compared to inference.

4. Comparison of the three methods after application:

Table (6): ANOVA Degree.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	21.875	2	10.938	17.617	.000
Within Groups	27.938	45	.621		
Total	49.813	47			

ANOVA After Application: F=17.617, P<0.01 → Best Reasoning Style.

To determine the best style, Tukey's test was applied, which indicates that analytical reasoning learning is the best style.

Table (7): Tukey Hsda.

group	N	Subset for alpha = 0.05	
		1	2
Constraints	16	30.8125	
Measurement	16	31.1250	
Reasoning	16		32.3750
Sig.		.506	1.000

Interpretation:

Following implementation, the ANOVA test results show distinct differences between the three methods, with inferential analysis being favored.

The study results indicated the evident usefulness of a tailored learning environment design based on the three learning analysis styles (inference, measurement, and constraints analysis) in improving systems analysis and design skills among computer teacher preparation students. The findings indicated that there were statistically significant differences between the pre- and post-tests, with all groups favoring the post-test. This confirms the learning environment's ability to increase academic achievement regardless of the sort of analysis performed.

However, a more in-depth assessment of the differences among the three ways demonstrated the superiority of inferential analytical learning compared to the other two, reaching the highest post-test mean. This was supported by the findings of the one-way ANOVA and Tukey's test. This advantage demonstrates the ability of inferential analysis to give a greater level of adaptive personalization by inferring student needs and delivering intelligent recommendations that correlate with their actual performance. Although measurement and limitations analysis techniques have been successful in raising performance, their comparative and rule-based character has restricted their influence in comparison to inference's capacity to forecast mistakes and provide students with dynamic guidance.

The superiority of inference over other methods can be explained as follows:

1. Inference Is More Personalized

It is more in line with the idea of individualized learning that is stressed in the theoretical framework because it is based on examining the student's real learning habits.

2. Inference Provides Higher Learning Intelligence

While constraints analysis relies on predefined rules and measurement on comparison, inference incorporates artificial intelligence models capable of comprehending the fundamental cause of problems, not only identifying them.

3. Inference Enables Real-Time Adaptation

Adaptive learning theories lend credence to this, as research indicates that quick responses to student performance boost motivation and success (Azevedo, 2020). 4. Higher-Order Thinking Is Supported by Reasoning:

This coincides with the aims of systems analysis and design skills. Additionally, because reasoning approaches rely on facts and the real-world context of learner performance, they are among the most effective.

This result is in line with research by Siemens

(2022), Romero & Ventura (2021), Akyüz (2022), and Verbert et al. (2020), which shown that prediction and reasoning models outperform comparative or rule-based analyses in enhancing student learning. Overall, this study provides solid empirical evidence that incorporating educational analytics into a tailored learning environment significantly enhances student performance, and that reasoning analysis is the most efficient strategy in this setting. This creates a wide range of research and application options for creating learning environments that are more intelligent and adaptable.

8. RECOMMENDATIONS

1. To guarantee precise and customized learning paths for every student, implement personalized learning environments based on inferential and benchmarking analytics and constraints analysis within courses.
2. Encourage instructional designers to employ instructional analytics models when creating digital content to guarantee the quality of learning and to base design choices on actual data rather than conjecture.
3. Develop analytical dashboards within online platforms that allow students and instructors to assess academic achievement in real time and change learning paths according to clear performance markers.
4. Redesign assessment procedures inside university courses to be linked to the outputs of inferential and benchmarking analytics, ensuring objective measurement of systems analysis and design skills.
5. Turn on limitations analysis algorithms to identify typical mistakes made by students in online learning environments and immediately reroute them to remedial activities based on data.
6. Provide training programs for faculty members on using all three types of instructional analytics and how to interpret learning data into practical actions within traditional and virtual classrooms. 7. Conduct comprehensive trials of AI-powered tailored learning environments to evaluate their efficiency across multiple academic fields and develop models that are more flexible to students' talents and requirements.

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