The Effectiveness of Artificial Intelligence-Assisted Learning Stations for Differentiated Learning Based on Students' Learning Styles

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Abstract

The integration of learning stations in higher education continues to face challenges in effectively addressing diverse student learning styles. Although differentiated instruction offers substantial promise, its implementation is often hindered by limited resources and the complexity of delivering personalized learning experiences at scale. This study explores the effectiveness of artificial intelligence (AI)-enhanced learning stations in supporting differentiated instruction aligned with individual learning preferences. Using a mixed-methods explanatory design, the research involved 82 students from an Educational Technology Study Program, divided into an experimental group (utilizing AI-supported learning stations) and a control group (traditional stations without AI). Data collection methods included pre- and post-tests, structured observations, VARK learning style inventories, and semi-structured interviews. Quantitative results indicated statistically significant improvements in learning outcomes for the experimental group, reflected in higher post-test scores and greater normalized gains. T-test and ANOVA analyses confirmed the intervention's overall effectiveness, with no significant variation in learning gains across learning style categories within the experimental group. Qualitative findings supported these outcomes, with participants reporting that the AI-assisted environment fostered more personalized, relevant, and reflective learning experiences. Moreover, the integration of AI was associated with increased learner engagement, heightened motivation, and improved metacognitive awareness of learning preferences. This study contributes empirical evidence supporting the role of AI in enabling differentiated instruction within higher education contexts, highlighting its potential to provide scalable, personalized learning experiences. The findings suggest that AI-driven solutions may address key limitations in traditional instructional design by offering inclusive and adaptive strategies responsive to individual learner needs.

Keywords: Artificial Intelligence; Differentiated Learning; Learning Stations, Learning Styles

Abstrak

Penerapan learning station dalam konteks pendidikan tinggi menghadapi tantangan dalam mengakomodasi keragaman gaya belajar mahasiswa secara optimal. Pembelajaran berdiferensiasi menjadi pendekatan yang menjanjikan, namun implementasinya seringkali terkendala keterbatasan sumber daya dan kemampuan personalisasi instruksional. Penelitian ini bertujuan untuk menguji efektivitas learning station berbantuan kecerdasan artifisial (AI) dalam mendukung pembelajaran berdiferensiasi berdasarkan gaya belajar mahasiswa. Menggunakan pendekatan mixed-method eksplanatori, penelitian melibatkan 82 mahasiswa dari Program Studi Perpustakaan dan Sains Informasi yang dibagi ke dalam kelompok eksperimen (menggunakan AI) dan kelompok kontrol (tanpa AI). Data dikumpulkan melalui tes pretest dan posttest, observasi, kuesioner VARK, serta wawancara semi-terstruktur.

Hasil analisis kuantitatif menunjukkan bahwa kelompok eksperimen mengalami peningkatan hasil belajar yang signifikan dibandingkan kelompok kontrol, dengan skor posttest yang lebih tinggi dan peningkatan gain score yang lebih besar. Uji-t dan ANOVA mengonfirmasi bahwa intervensi AI berdampak positif tanpa menunjukkan perbedaan signifikan antar gaya belajar dalam kelompok eksperimen. Data kualitatif mendukung temuan ini, menunjukkan bahwa mahasiswa merasa kecerdasan artifisial membantu mereka belajar secara lebih relevan, personal, dan reflektif. Selain meningkatkan keterlibatan dan motivasi, AI juga memfasilitasi kesadaran metakognitif terkait preferensi belajar individu.

Kata Kunci: Gaya Belajar; Kecerdasan Artifisial; Learning Station; Pembelajaran Berdiferensiasi

Introduction

University students exhibit a wide range of characteristics, including varied learning styles. Learning style refers to an individual's preferred method of processing, absorbing, and applying new information. While some students learn more effectively through visual representations, others benefit more from verbal instructions or physical engagement. A mismatch between instructional strategies and students' learning styles may hinder the learning process and contribute to disparities in learning outcomes (Jääskä and Aaltonen, 2022; Pesovski et al., 2024; Yan and Fralick, 2022).

Consequently, there is a pressing need for flexible, adaptive, and data-driven instructional strategies that accommodate students' individual learning needs. The Learning Station model represents an innovative pedagogical approach designed to address the diverse learning styles of students. This strategy organizes the classroom into multiple learning zones or "stations," each tailored to varying levels of readiness, interests, and learning styles (Aydogmus and Senturk, 2019; Chien, 2017; Eickholt et al., 2021). Students are encouraged to select learning activities that align most closely with their personal preferences, thereby fostering a more personalized, active, and directed learning experience.

With instructors serving as facilitators, the Learning Station approach promotes student engagement and encourages autonomous learning (Darwesh and Fayed, 2024; Pho et al., 2021; Xiangze and Abdullah, 2023). In recent years, the integration of technology, particularly artificial intelligence (AI), has opened new avenues for enhancing instructional effectiveness. AI technologies enable scalable and data-driven personalization of learning, offering significant potential to enrich the Learning Station framework. By analyzing data such as survey responses, learning behavior patterns, and academic performance, AI systems can automatically identify individual learning styles (Bernard et al., 2017; Dominguez et al., 2025).

This capability allows for dynamic customization of learning stations to meet each student's specific needs more precisely (Feldman et al., 2015; Rasheed and Wahid, 2021; Sajja et al., 2023). Previous studies on the application of Learning Stations for differentiated instruction based on learning styles have yielded important findings. Meilinda's research, for example, emphasized that mapping students' visual, auditory, and kinesthetic learning styles contributes to improved learning quality, particularly in mastering mathematical concepts (Trifatmasari et al., 2023).

Another study compared the effectiveness of differentiated instructional strategies, including Learning Stations and Graphic Organizers, for students with visual learning preferences Additional research has shown that Learning Stations can meet the needs of diverse learners, including those with special needs, and foster higher-order thinking skills (Soselisa et al., 2020). However, these studies have primarily been conducted in traditional classroom settings without the integration of advanced technologies for personalizing learning activities. Darrow also highlighted the importance of differentiated instruction in music classrooms, particularly for students with diverse learning needs (Darrow, 2015). Further research has demonstrated the effectiveness of learning-style-based instruction in enhancing mathematical problem-solving abilities (HN et al., 2024). Gobiberia's study revealed that differentiated instruction improves motivation, engagement, and academic achievement in higher education contexts (Gobiberia and Kevkhishvili, 2021).

Similarly, differentiated learning strategies have been found to strengthen students' analytical skills in STEM education (Sulistiani et al., 2024). Nevertheless, few studies have examined the integration of artificial intelligence as a supporting tool for learning-style-based instruction within the Learning Station model, particularly in higher education settings. While prior research has mainly focused on primary and secondary education contexts, the potential of AI-enhanced Learning Stations for delivering differentiated instruction in universities remains underexplored. This gap indicates a need for empirical investigation into how AI can support personalized learning within flexible instructional frameworks in postsecondary education.

Unlike prior studies, this research empirically tests AI-based differentiated instruction in a higher education setting using a mixed-method explanatory design. This study offers a novel contribution by introducing an AI-driven differentiated learning approach that supports the implementation of Learning Stations in higher education, grounded in students' learning styles. Through the application of AI, instructors can more accurately identify student needs, manage learning processes more effectively, and evaluate outcomes with greater precision. The use of AI fosters a more adaptive, responsive, and relevant learning environment.

This study seeks to address several fundamental questions: (1) To what extent does the implementation of AI-supported Learning Stations improve students' learning outcomes compared to conventional Learning Stations? (2) How do students perceive the personalization features, engagement, and metacognitive support provided by AI-based Learning Stations? (3) Does the AI-supported Learning Station model produce balanced learning outcomes across different learning style categories? By addressing these questions, the study not only contributes to the theoretical development of AI-assisted differentiated learning but also offers practical guidance for educators and institutions seeking to implement scalable, data-driven personalization strategies in diverse higher education settings.

Method

This research employed an explanatory mixed-methods design by sequentially integrating quantitative and qualitative approaches to examine the effectiveness of AI-supported Learning Stations based on students' learning styles. The study involved 82 undergraduate students from the Educational Technology Study Program at a public university in Indonesia as the primary data source. Participants were purposively selected based on inclusion criteria such as active academic status, enrollment in the fifth semester, and willingness to complete the VARK learning style questionnaire. They were then randomly assigned into two groups: an experimental group that received AI-assisted Learning Station activities aligned with individual learning styles, and a control group that followed conventional Learning Station activities without AI support. Data collection techniques included pretest and posttest assessments to measure learning achievement, structured observations of learning activities, learning style identification using the

VARK questionnaire, and semi-structured interviews to explore students' learning experiences. The intervention was conducted over six weeks through weekly 150-minute sessions that facilitated differentiated learning. Quantitative data were analyzed using descriptive statistics, t-tests, and one-way ANOVA with SPSS version 26 to evaluate differences in learning outcomes between and within groups. Qualitative data were analyzed through thematic analysis, including transcription, coding, categorization of themes, and interpretation of students' narratives. The findings from both data sets were triangulated to ensure validity and provide a comprehensive understanding of the impact of AI-supported Learning Stations on student learning outcomes and experiences.

Result and Discussion

1. Distribution of Students' Learning Styles

The VARK questionnaire results revealed a varied distribution of learning preferences among the 82 participants: 19 Visual, 24 Auditory, 21 Read/Write, and 18 Kinesthetic learners (Table 1). This distribution served as the foundation for the AI-supported personalization system in the experimental group. Each profile informed the AI's adaptive logic to tailor content and learning activities that matched the student's dominant learning modality. This reflects the principles of differentiated instruction, which emphasize readiness-based instructional adaptation Goyibova et al., (2025), and aligns with studies highlighting how learning-style-based personalization enhances instructional relevance and cognitive efficiency (Hesham et al., 2020; Wu et al., 2024).

2. Effectiveness of the Intervention on Learning Outcomes

A comparative analysis of pretest and posttest scores (see Table 1) showed that both groups improved significantly, with the experimental group achieving a higher average posttest score than the control group. This difference was confirmed as statistically significant by an independent-samples t-test (Table 3). To ensure the validity of these tests, normality (Kolmogorov-Smirnov, $p > .05$) and homogeneity of variance (Levene's test, $p = .271$) were verified.

Table 1. Descriptive Statistics-Pretest And Posttest Scores

Group	N	Pretest (M ± SD)	Posttest (M ± SD)
Experimental	40	62.10 ± 6.75	81.40 ± 5.82
Control	42	61.60 ± 7.03	73.20 ± 6.44

In addition, paired-sample t-tests (Table 2) demonstrated statistically significant improvements within each group. While gain scores are not redundantly repeated here, the substantial within-group effect sizes, particularly in the experimental group, underscore the greater pedagogical impact of the AI-assisted Learning Station.

Table 2. Paired-Sample T-Test-Pretest vs. Posttest

Group	t	df	p-value
Experimental	18.94	39	< .001**
Control	10.72	41	< .001**

This aligns with findings by Yekollu et al., which demonstrated that AI-driven learning systems enhance cognitive performance through personalized instructional pathways (Yekollu et al., 2024). The intervention's effectiveness also resonates with constructivist learning theory, where learning becomes more meaningful when instructional approaches connect with students' preferred modes of engagement (Loughlin et al., 2021; Zajda, 2021). An independent-samples t-test on posttest scores (Table 3) further validated the difference between groups, demonstrating the statistically significant advantage of the AI-supported intervention over conventional methods.

These findings reinforce the claim that AI-based instructional systems, through learning-style-based personalization, can significantly enhance academic performance. The AI system not only tailored content delivery and activities but also enabled individualized learning pathways responsive to student characteristics. This supports constructivist principles, emphasizing the importance of instructional relevance and adaptive engagement Allen et al., (2016); Hunter (2015) and echoes evidence from adaptive learning literature on improved knowledge retention and transfer (Boudjemaa & Belkacem, 2024; Kellman et al., 2022).

Table 3. Independent-Samples T-Test-Posttest Scores

t	df	p-value
6.02	80	< .001**

Moreover, the learning gains observed in the experimental group were not only statistically superior but also pedagogically meaningful. The Personal Learning Path (PLP) generated by the AI allowed students to access material aligned with their cognitive strengths while reducing extraneous cognitive load from mismatched instruction. In this context, AI functioned not merely as an instructional tool but as an active facilitator in orchestrating differentiated, student-centered learning. This reflects of flexible grouping and responsive teaching, core to differentiated instruction (Tomlinson and Jarvis, 2009). These outcomes substantiate the argument that AI plays a critical role in improving learning effectiveness by aligning strategies with individual learner profiles.

3. The Role of Learning Styles in Intervention Outcomes

To assess whether students with different learning styles benefited equally from the intervention, a one-way ANOVA was performed on posttest scores within the experimental group (Table 4). This finding suggests that the AI system provided equitable and adaptive learning experiences across different learning styles, resulting in balanced learning outcomes. From a differentiated instruction perspective, this reflects the success of content, process, and product differentiation. Pedagogically, two interpretations can be offered. First, the AI system did not rigidly assign students to a single mode of learning but instead incorporated multimodal flexibility in content delivery. For example, auditory learners not only received auditory inputs but also benefited from discussions and audiovisual reinforcements. This cross-modal integration, according to Mayer Mayer, (2021), enhances retention through redundancy effects.

Table 4. Posttest Scores By Learning Style (Experimental Group)

Learning Style	N	Posttest (M ± SD)
Visual	10	80.10 ± 5.1
Auditory	11	82.00 ± 6.2
Read/Write	9	81.60 ± 5.4
Kinesthetic	10	82.40 ± 5.7

Second, the lack of significant differences implies that the quality of the intervention may override the influence of learning style preferences. As highlighted by Pashler et al., (2009) empirical support for strict learning-style matching remains inconclusive. However, in this study, the AI system served as a catalyst for delivering targeted, relevant, and efficient experiences, regardless of the learner's style, through real-time adaptation and feedback. From an instructional design perspective, these results underscore the value of adaptability over rigid classification.

Systems that confine learners to fixed learning style categories may overlook the increasingly multimodal and transformative nature of modern learners. In contrast, AI systems can dynamically accommodate this diversity, delivering holistic and context-aware learning experiences. Thus, the non-significant ANOVA results may be interpreted not as a limitation but as evidence of successful personalization, where all learners, regardless of style, are equally supported in achieving optimal outcomes. From a pedagogical perspective, these results substantiate key principles of both differentiated instruction and constructivist learning theory. The balanced outcomes across diverse learning styles suggest that the intervention successfully addressed the three core pillars of differentiated instruction, readiness, interest, and learning profile, through adaptive personalization. The AI system's ability to provide flexible pathways for accessing, processing, and applying knowledge aligns with Tomlinson's emphasis on modifying content, process, and product to meet individual learner needs (Tomlinson, 2017).

Moreover, the real-time responsiveness of the system exemplifies learner-centered pedagogy, where instruction is guided by formative feedback rather than predetermined categories (Aldino et al., 2025; Bhardwaj et al., 2025). In alignment with constructivist principles, the AI-supported learning environment enabled students to build knowledge actively through meaningful engagement with personally relevant tasks (Kolil et al., 2025; Nhan, 2025). The absence of significant variation in outcomes across learning styles reinforces the constructivist view that learning is most effective when learners are given autonomy, scaffolding, and opportunities for self-regulation.

Rather than enforcing fixed learning styles, the AI system acted as a dynamic mediator, supporting knowledge construction by allowing learners to interact with multimodal representations that resonated with their evolving cognitive strategies. In this way, the intervention operationalized a constructivist approach within a technologically mediated, differentiated learning model (Liu et al., 2025). Practically, these findings offer strong implications for the development of adaptive learning systems in higher education, particularly in contexts marked by learner diversity and limited instructional resources. Rather than relying on rigid manual differentiation, AI can be leveraged to create equitable, data-driven, and responsive learning environments at scale.

4. Student Perceptions of AI-Based Learning

To enrich the understanding of the intervention's effectiveness, this study explored students' perceptions through semi-structured interviews and non-participant classroom observations. A total of 12 students were selected as interview participants (6 from the experimental group and 6 from the control group), considering both learning style representation and academic performance. Thematic analysis of the qualitative data yielded three major themes: (1) perceptions of personalized learning, (2) increased engagement and motivation, and (3) metacognitive reflection and learning style awareness.

a. Personalized Learning Enhances Relevance and Satisfaction

Interview findings from the experimental group revealed that the AI-driven system consistently enhanced students' perceptions of learning relevance and comfort. Dominant sub-themes identified through open coding included: (a) access to content aligned with preferred learning styles, (b) personalized learning experiences, and (c) satisfaction with the ease of content navigation. To represent this theme, selected quotes from participants emphasized how AI-tailored materials improved comprehension and reduced confusion.

One of the participants strongly emphasized the impact of AI-driven materials on her understanding and learning flow. According to GC, a learner with a visual preference, the system promptly provided materials in the form of diagrams and images, which she reported as being highly supportive in enhancing her understanding (Interview, 14 May 2024). This statement reflects how learners experienced the AI system as an agent capable of adapting its instructional delivery to match their preferred modality. For visual learners, having information presented in image-based formats contributed not only to clarity but also to reduced cognitive strain. This aligns with Lin et al., (2024) who argued that real-time content adaptation can strengthen learners' perceived competence and self-efficacy, particularly when content delivery matches their cognitive preferences. A different participant, who identified as an auditory learner, highlighted how the integration of audio and real-life contextual examples significantly enhanced her comprehension. According to DN, a learner with an auditory preference, the system integrated audio content and real-life examples into the learning process, which she reported as enabling her to understand the material more quickly and without confusion (Interview, 14 May 2024).

This statement illustrates the system's ability to deliver instruction that resonates with the learner's habitual strategies. By aligning content with auditory preferences, the system likely reduced the learner's extraneous cognitive load Sweller (1994) improving the efficiency of information processing. This also reinforces the idea that personalization through AI not only supports cognitive functioning but also enhances engagement, as learners feel that the system "understands" their learning habits (Holmes and Tuomi, 2022; Yusuf et al., 2025). In a similar vein, DW, a student with a read/write preference, the AI system streamlined her learning process by eliminating the need to search for appropriate study materials.

She reported that the system provided content that precisely matched her preferences, making studying faster and less exhausting (Interview, 14 May 2024). This quote highlights the efficiency gains that AI-supported learning can offer. By automating content curation based on learners' profiles, the system reduced cognitive and emotional fatigue, allowing students to allocate more mental effort to learning rather than searching. This finding is in line with Davis' Technology Acceptance Model (1989), where perceived usefulness and ease of use significantly influence users' motivation to engage with a digital system. Furthermore, the reduction in learner frustration supports a more emotionally positive learning climate, which is essential for sustained motivation and engagement (Zawacki-Richter et al., 2019; Alam and Mohanty, 2023).

Collectively, these accounts illustrate that the AI-enhanced learning stations did more than deliver content, they served as intelligent pedagogical scaffolds capable of sensing and responding to learners' individual needs. As learners felt their preferences acknowledged and accommodated, their sense of autonomy, relevance, and satisfaction increased. This suggests that AI can function as a responsive agent in the learning process Majidah et al., (2025) supporting the transition from uniform instruction to truly differentiated, student-centered learning environments.

b. Increased Engagement and Motivation

In addition to content relevance, the AI-supported Learning Station model significantly enhanced engagement and motivation. Most participants described the learning process as "more engaging," "less monotonous," and "stimulating curiosity." Axial coding revealed two dominant themes: (a) active participation and (b) intrinsic motivation. One participant with a kinesthetic learning style, BD, emphasized how the variation of formats, such as switching between videos and simulations, stimulated his curiosity and reduced boredom. He stated, learning didn't feel boring because each session had a different format, sometimes videos, sometimes simulations. That made me more excited (Interview, 14 May 2024)

This statement suggests that the multimodal presentation of content catered to kinesthetic learners' need for interaction and variation. The reduction of monotony and the increased novelty of activities supported students' cognitive engagement and arousal, two key drivers of motivation in digital learning environments (Niemiec and Ryan, 2009).

This finding also echoes the argument of Humburg et al., (2024) who found that adaptive learning environments enhance student engagement by providing dynamic learning paths tailored to individual learners. Similarly, RN, an auditory learner, reflected on how the AI system helped her maintain focus during the learning process, the system supported her ability to maintain focus by aligning learning activities with her preferred style. She reported that, although she typically became easily distracted, the modality-matched approach helped her stay engaged throughout the learning process (Interview, 14 May 2024).

This statement reveals how personalization contributed to attentional regulation, a core aspect of autonomous motivation. By aligning tasks with learning styles, the system acted as a cognitive scaffold, supporting the learner's ability to concentrate and self-regulate, both of which are central to Self-Determination Theory (SDT) (Ryan and Deci, 2000). The learner's ability to stay focused was not a product of novelty alone, but of instructional compatibility with her internal learning rhythm. According to AN, a learner with a visual preference, the system fostered a sense of comfort and personal relevance by adapting to his learning style.

He reported that it felt as though the system was designed specifically for him, which increased both his comfort and motivation to engage with the material (Interview, 14 May 2024). His reflection underscores a shift in learner agency, from adapting oneself to the system, to being supported by it. This sense of belonging and autonomy directly feeds into intrinsic motivation, as posited by SDT (Niemiec and Ryan, 2009). Feeling "understood" by the system created a positive affective response, reinforcing persistence and satisfaction in the learning process. In line with these experiences, DW, a learner with a read/write preference, noted that the variation in tasks helped sustain her energy and engagement during online sessions.

She reported that, unlike typical online classes which often made her feel sleepy, this experience was different due to the continuous shift in task types (Interview, 14 May 2024). This highlights how task variety and multimodality function as energizers in online learning environments, preventing fatigue and supporting sustained engagement. These aspects of the AI system reflect what Ellikkal and Rajamohan (2025) describe as learner-sensitive design, a design approach where systems not only deliver content but adjust the flow and type of activity to maintain motivation.

Taken together, the findings support the idea that engagement and motivation are not solely outcomes of interactive or entertaining content. Rather, they are the result of deep alignment between the learner's personal identity, their cognitive preferences, and the instructional strategies provided by the system. The AI component of the learning station served not just as a delivery mechanism but as a catalyst for personalized engagement, helping students regulate focus, experience learning satisfaction, and remain motivated across sessions. This confirms the assertion that well-designed AI systems can become mediators between learner psychology and instructional design, enabling self-directed and emotionally resonant learning experiences (Hu and Zhang, 2017; Humburg et al., 2024).

c. Metacognitive Reflection and Learning Style Awareness

One of the most significant outcomes of the AI-supported Learning Station was the emergence of metacognitive reflection among students in the experimental group. Four of the six participants reported heightened awareness of their learning preferences and began consciously evaluating and adjusting their study strategies based on AI-generated feedback. According to DW, a learner with a kinesthetic preference, the system helped her identify the learning methods that were most effective for her. She reflected that she had come to realize she learns more efficiently through hands-on practice rather than by solely reading theoretical material, which subsequently led her to modify her study habits (Interview, 14 May 2024). This quote demonstrates how the AI-assisted environment served not only as a content provider but also as a metacognitive prompt, encouraging learners to evaluate the alignment between their preferred strategies and actual learning outcomes. DW's ability to identify the superiority of hands-on learning for herself represents a shift toward self-awareness and strategic adaptation, key components of metacognitive competence (Merikko and Kivimäki, 2022).

Her conscious shift in study behavior suggests the development of self-regulatory capacity, marking a transition from passive reception to intentional learning design. Similarly, AN, who initially identified as a read/write learner, shared that his exposure to varied formats in the AI-supported environment prompted a reassessment of his learning preferences. He explained that he had previously considered himself a reading-type learner, but the experience revealed a stronger alignment with auditory and discussion-based methods, allowing him to better understand what worked for him (Interview, 14 May 2024). This reflection illustrates how adaptive technologies can help challenge prior assumptions learners hold about themselves, leading to identity reconstruction as learners. AN's case reflects metacognitive recalibration, where learners refine their understanding of themselves through iterative experience and reflection (Benkhalfallah et al., 2024). The role of the AI system here was not merely corrective but transformative, helping students redefine their own learning logic based on feedback and lived experience. BD, a learner with a visual preference, also described a behavioral shift that emerged from a deeper understanding of his individual learning needs.

He noted that he had begun reorganizing his study approach, moving away from using arbitrary materials and instead focusing on resources that best matched his learning style (Interview, 14 May 2024). This shift reflects growing learner agency, the capacity to make strategic decisions about what, how, and when to learn. BD's narrative highlights the development of intentional learning behavior, which is central to the goals of adaptive learning systems. Rather than engaging in habitual or random study behaviors, students like BD began to curate and regulate their own learning process, a hallmark of self-directed learning. While most participants expressed positive cognitive transformations, one participant raised a critical concern. RN, a learner with an auditory preference, expressed caution regarding the potential for over-dependence on the AI system. He acknowledged that while personalized support was beneficial, he was concerned that full customization could lead to reduced adaptability. As a result, he made a conscious effort to incorporate other learning methods in order to remain flexible (Interview, 14 May 2024). This reflection introduces an important tension between personalization and overreliance. While personalization promotes comfort and efficiency, it may also reduce opportunities for cognitive flexibility and learning resilience if not designed with gradual release mechanisms.

RN's proactive attempt to balance system support with independent effort reflects high metacognitive maturity, as she actively seeks to preserve adaptability in her learning repertoire. As noted by Luckin et al., (2022) effective AI systems should serve not as permanent crutches but as temporary scaffolds, helping students internalize strategies before moving toward autonomous learning. Overall, these reflections underscore the role of the AI-supported system as a catalyst for metacognitive engagement. The system did not merely match content to preferences; it triggered reflection, prompted reevaluation, and supported the development of more adaptive and self-aware learners. This aligns with the broader pedagogical objective of intelligent learning environments: to move beyond content delivery and toward the cultivation of lifelong, reflective learners capable of navigating diverse and evolving educational demands (Strielkowski et al., 2025).

5. Integrative Interpretation of AI, Learning Styles, and Outcomes

To strengthen the connection between the quantitative and qualitative findings, a conceptual model is presented to illustrate the mechanism by which AI-based learning stations interact with student learning styles and influence learning outcomes. As shown in Figure 1, the model integrates AI-driven personalization with the VARK learning style framework, highlighting how individualized content delivery contributes to improved engagement, metacognitive awareness, and academic achievement.

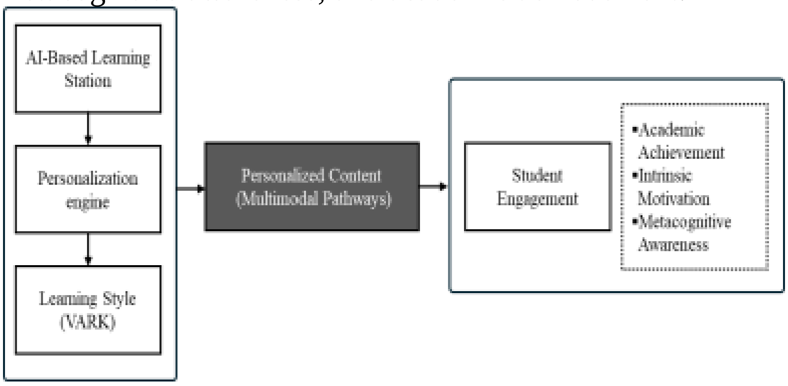

Figure 1. Integrative Model Illustrating The Relationship Between AI-driven Personalization, Learning Styles (VARK), And Learning Outcomes.

This model synthesizes the study's findings by positioning AI as the enabler of real-time differentiation based on individual learning styles. Personalized content delivery not only enhances academic achievement (as reflected in the posttest scores) but also drives engagement and metacognitive development, as supported by interview data. The flow aligns with differentiated instruction theory and constructivist learning principles, emphasizing learner-centeredness, adaptability, and self-regulation.

Conlusion

This study demonstrates that the integration of AI-supported Learning Stations into differentiated instruction effectively enhances student learning outcomes and promotes personalized learning experiences aligned with individual learning styles. The AI system functioned not only as a delivery mechanism but also as a pedagogical agent, dynamically adapting instructional content to diverse learner profiles, thereby supporting higher academic achievement, engagement, and metacognitive awareness. By employing a mixed-method explanatory approach, the research captured both measurable improvements in performance and students' subjective perceptions of the learning process, offering a comprehensive understanding of AI's role in higher education. These findings address the core problem of delivering scalable, personalized instruction in heterogeneous classrooms and highlight the practical need for institutional investment in adaptive learning technologies and faculty development. Future investigations should expand into interdisciplinary applications, assess impacts on 21st-century skill development, and explore ethical considerations surrounding AI-mediated educational environments.

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