Mapping the learning styles of pre-service environmental science education in interaction with artificial intelligence on the topic of electric fields

Jadnika Dwi Rakhmawan Amrullah[1]*, Nur Ahmad[1], Rhischa Assabet Shilla[2]

[1]Departement of Science Education, Faculty of Teacher Training and Education, Universitas Jember, Kalimantan Street No 37 Jember, 68121, Indonesia

[2]Departement Center for Educational Measurement and Assessment, Faculty of Arts and Social Sciences, The University of Sydney, Camperdown New South Wales, 2050, Australia

*Corresponding author, email: brontok26.fkip@mail.unej.ac.id

Article History
Received: 21 July 2025
Revised: 19 August 2025
Accepted: 26 August 2025
Published: 1 September 2025

Keywords
Artificial Intelligence
Electric Fields
Learning Styles
Multimodal Learning
Pre-Service Teachers

Abstract
The integration of Artificial Intelligence (AI) in education offers new opportunities to address complex science concepts, yet its interaction with learning styles remains underexplored. Objectives: This study aimed to identify the learning styles of pre-service environmental science teachers and examine how AI-based instruction supports their understanding of electric fields. Using a mixed-methods design, 72 undergraduate students completed the VARK questionnaire, pre- and post-tests on electric field concepts, and participated in interviews. The findings showed significant improvement in conceptual understanding after AI-based learning, with visual and kinesthetic learners benefiting most from simulations and interactive tasks, while aural and read/write learners showed limited gains. Implications: The study highlights the potential of AI to enhance learning through multimodal engagement, but also emphasizes the need for inclusive designs that move beyond learning styles toward broader pedagogical frameworks.

How to cite: Amrullah, J. D. R., Ahmad, N., & Shilla, R. A. (2025). Mapping the learning styles of pre-service enviromental science education in interaction with artificial intelligence on the topic of electric fields. Article Title. *Journal of Environment and Sustainability Education, 3*(3). 377-386. doi: 10.62672/joease.v3i3.118

1. Introduction

In the last decade, Artificial Intelligence (AI) has increasingly permeated educational research and practice, with claims that it can revolutionise personalised learning, formative assessment, and student engagement (Holmes et al., 2022; Zawacki-Richter et al., 2023). AI is no longer confined to rudimentary automation but encompasses sophisticated applications including natural language processing, adaptive feedback systems, multimodal simulations, and intelligent tutoring systems (ITS). However, despite this promise, scholarly debate continues regarding the conceptual, pedagogical, and ethical integration of AI in education (Chen et al., 2023; Roll & Wylie, 2024). In particular, the use of AI-based tutoring systems defined here as interactive, computerised environments that adapt instructional content and scaffolding to learners' responses in real-time—raises important questions about their alignment with established learning theories and their capacity to support diverse learner profiles (Luckin & Cukurova, 2023).

One of the most widely adopted but also heavily contested frameworks in education is the theory of learning styles, specifically the VARK model (Visual, Aural, Read/Write, Kinesthetic). For decades, learning styles theory has been invoked to justify differentiated instructional strategies, with the assumption that aligning teaching methods to a learner's dominant modality leads to improved outcomes (Pashler et al., 2009; Kukul, 2024). Yet, recent literature has mounted significant critiques of this assumption, arguing that empirical evidence does not substantiate the effectiveness of tailoring instruction solely on the basis of learning style categories (Newton & Miah, 2017; Aslaksen et al., 2022). Large-scale reviews and experimental studies suggest that while learners may express preferences for particular modes of instruction, there is no consistent evidence that such alignment improves academic performance (Kirschner, 2017; Knoll et al., 2021). In fact, perpetuating the learning styles myth may risk oversimplifying the complexities of cognition and diverting attention from more robust pedagogical frameworks such as cognitive load theory, self-regulated learning, and multimodal learning principles (Cuevas, 2020; Coffield, 2023).

doi: 10.62672/joease.v3i3.118
© 2025 The Authors
This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License
ISSN: 3025-0714

This tension between the popularity of VARK in educational practice and its weak empirical foundations highlights a critical issue: to what extent can learning style taxonomies still provide meaningful insights when coupled with emerging AI technologies? Some scholars contend that while VARK lacks predictive validity, it can still function as a heuristic for exploring learner diversity, particularly when integrated within multimodal digital environments that flexibly support different forms of engagement (Dekker & Jolles, 2023). AI-based tutoring systems, with their adaptive algorithms and multimodal delivery capacities, may offer a context in which the limitations of learning styles theory are mitigated by richer, more dynamic learning interactions (Chen et al., 2022; Lee & Zhai, 2024).

However, a clear definition of what constitutes an AI-based tutoring system remains necessary. Unlike conventional e-learning platforms that provide static content, AI tutoring systems are characterised by their capacity to (a) diagnose learners' current understanding, (b) deliver adaptive scaffolding and multimodal representations, (c) engage in interactive dialogue, and (d) monitor learning progress over time (Roll & Wylie, 2024; Graesser et al., 2023). Examples include systems capable of real-time physics simulations, personalised feedback in natural language, and adaptive questioning strategies aligned with a learner's reasoning trajectory (Luckin & Cukurova, 2023). Such systems thus occupy a unique space at the intersection of cognitive psychology, pedagogy, and computational modelling. Nevertheless, their integration into pre-service teacher education remains limited, particularly in subject domains like electromagnetism, where abstract concepts pose persistent learning challenges (Miftah et al., 2024; Dai et al., 2023).

The challenge of conceptualising electric fields illustrates this pedagogical gap. Physics education research consistently identifies electric field theory as one of the most conceptually difficult topics for learners, who often harbour misconceptions about vector representation, field strength, and force interaction (Zhang et al., 2024). Conventional instructional approaches, such as lectures and textbook-based exercises, often fail to address these difficulties due to the abstract and invisible nature of the phenomena (Yeo & Gilbert, 2023). Here, AI-based tutoring systems offer significant affordances: real-time visualisation of field interactions, multimodal simulations that allow manipulation of charges, and adaptive feedback that can scaffold conceptual reasoning (Lee et al., 2023). These features align with the multimodal learning framework, which emphasises that learning is strengthened when content is delivered through complementary channels that engage multiple sensory and cognitive systems (Mayer, 2021).

Despite this potential, few studies have systematically examined how AI tutoring systems interact with the diverse learning preferences or self-reported modalities of pre-service teachers. This oversight is problematic because teacher education is a critical site where pedagogical technologies are not only consumed but also modelled for future classroom use (Tondeur et al., 2023). Pre-service teachers' engagement with AI systems may shape not only their own conceptual understanding but also their readiness to integrate such technologies into their future teaching practice (Nyaaba et al., 2024). A stronger theoretical framework is therefore needed, one that goes beyond simplistic applications of VARK and integrates more robust theories of learning such as:

a. Cognitive load theory (Sweller, 2020), which explains how instructional design can reduce unnecessary processing and optimise schema acquisition.

b. Multimodal learning theory (Mayer, 2021), which highlights how learners benefit when information is presented through complementary channels.

c. Sociocultural theory (Vygotsky, as revisited in AI contexts), which foregrounds the role of scaffolding, dialogue, and collaborative meaning-making (Kozulin, 2022).

Positioning AI tutoring systems within these frameworks can clarify their unique educational affordances. For instance, adaptive AI can dynamically manage cognitive load by pacing information delivery; it can enrich multimodal engagement by combining visual, auditory, and interactive representations; and it can simulate collaborative scaffolding through intelligent dialogue. Such theoretical grounding not only strengthens the rationale for AI integration but also distinguishes this research from studies that rely narrowly on VARK categorizations.

The novelty of this research lies in its attempt to bridge contested theories of learning styles with the cutting-edge affordances of AI tutoring systems in a context where conceptual understanding is particularly challenging. Whereas prior studies have either critiqued VARK in isolation or investigated AI tutoring without attention to learner diversity, this study seeks to synthesise these domains by exploring how pre-service teachers' reported learning preferences interact with AI-mediated multimodal feedback on the topic of electric fields. By employing a two-tier diagnostic assessment, the study further contributes methodological innovation, as this instrument captures not only content knowledge but also the reasoning processes underlying conceptual change (Treagust, 2021).

Accordingly, this research positions itself at the nexus of three urgent conversations in education: (1) the critical interrogation of learning styles theory in light of empirical evidence, (2) the need for theoretically grounded integration of AI in teacher education, and (3) the demand for novel instructional models that address persistent misconceptions in complex science domains. Through this integration, the study contributes to the design of more inclusive, adaptive, and evidence-based learning environments for future science educators.

2. Method

This study employed a mixed-methods approach with a sequential explanatory design, combining quantitative and qualitative strands to map the learning styles of pre-service enviromental science education and examine their interaction with artificial intelligence (AI) in learning the topic of electric fields. A total of seventy-two undergraduate students from the Science Education Programme at the Faculty of Teacher Training and Education, University of Jember, participated in the study. The participants were purposively selected on the basis of their prior completion of introductory physics courses and their limited exposure to the concept of electric fields.

2.1. Instruments and Reliability

Three instruments were employed for data collection. The first was the VARK learning style questionnaire, adapted to the local educational context. Its internal consistency was confirmed in the present study, yielding a Cronbach's alpha coefficient of 0.81, which indicates acceptable reliability (Tavakol & Dennick, 2011). The second instrument was a two-tier conceptual test consisting of ten items designed to assess both knowledge of electric field concepts and reasoning ability. The reliability coefficient of this diagnostic instrument was $\alpha = 0.76$, demonstrating satisfactory internal consistency. Finally, semi-structured interview protocols were used to collect qualitative insights, and inter-rater reliability for thematic coding achieved a Cohen's kappa of 0.84, suggesting strong agreement.

2.1.1. Pilot Testing and Instrument Validation

Prior to the main study, a pilot test was conducted with a group of twenty pre-service teachers not included in the final sample. Feedback from the pilot led to minor revisions in wording and structure of the VARK questionnaire and refinement of distractors in the two-tier conceptual test. Expert validation was also sought from three senior physics education scholars, who reviewed the instruments for construct validity, alignment with learning objectives, and appropriateness for the pre-service context. Their recommendations were incorporated to ensure both content validity and contextual relevance (DeVellis & Thorpe, 2021).

2.1.2. AI System: Technology, Features, and Interfaces

The AI system utilised in this study was an adaptive tutoring platform developed to support conceptual learning in physics. It integrated a rule-based engine with natural language processing capabilities, enabling both automated feedback and guided problem-solving. Key features included interactive visualisations of electric field lines, dynamic simulations allowing manipulation of charge placement, and embedded formative quizzes that adapted difficulty levels according to learner performance. The interface was designed to be user-friendly, featuring multimodal elements such as drag-and-drop interactive tasks, animation-rich explanations, and limited audio narration. Importantly, the system also offered adaptive scaffolding: when students demonstrated misconceptions, the AI generated targeted hints or alternative representations (for example, switching from abstract diagrams to concrete animations). This ensured that learners' engagement was personalised and responsive to their cognitive needs.

2.1.3. Research Procedure

The research procedure followed a sequential flow to ensure both systematic data collection and methodological rigour. Initially, students completed the VARK questionnaire to establish their dominant learning styles. Subsequently, they undertook the pre-test of the two-tier conceptual instrument. Following this, the AI-based learning activity was administered, during which participants engaged with interactive simulations, adaptive tasks, and system-generated feedback. Observations and screen recordings were carried out concurrently to capture interaction patterns. Upon completion of the AI learning session, the post-test was administered to measure conceptual change. Finally, semi-structured interviews were conducted with twelve purposively selected students, representing different learning styles, in order to obtain richer qualitative insights into their experiences.

The flow of the research can be conceptualised as a structured cycle beginning with diagnostic profiling (VARK questionnaire), followed by baseline measurement (pre-test), intervention (AI-based learning), outcome assessment (post-test), and reflective exploration (interviews). This sequential progression ensured that the mixed-methods design captured not only measurable learning gains but also the nuanced experiences of students interacting with AI. The scheme of the research procedure is shown in Figure 1.

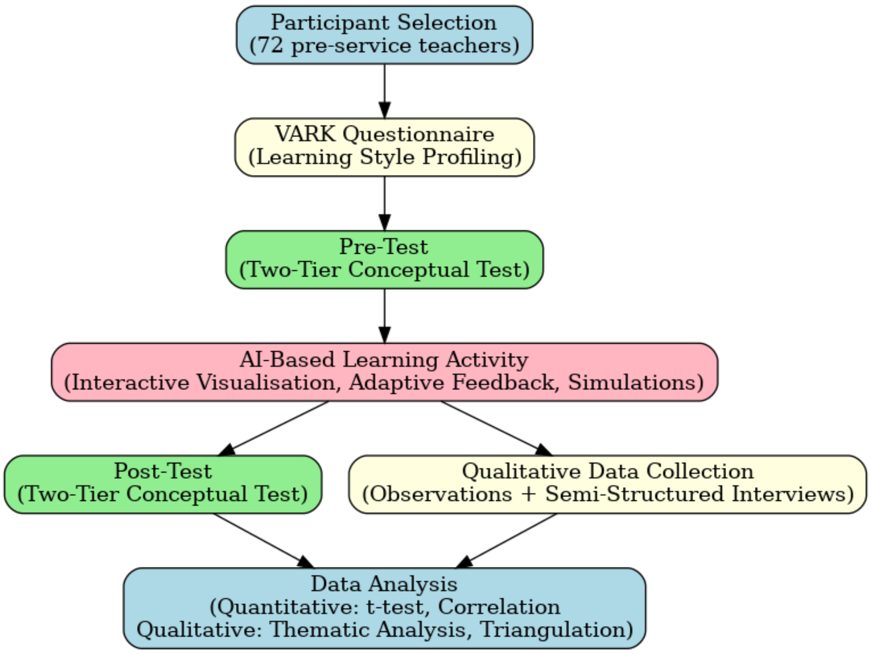

Figure 1. Research Procedure

2.1.4. Data Analysis

Quantitative data were analysed using descriptive statistics, paired-sample t-tests, and correlation analysis to examine relationships between learning styles and conceptual gains. Qualitative data from observations and interviews were subjected to thematic analysis, with triangulation applied to ensure trustworthiness. The study adhered to ethical standards established by the University of Jember's ethics committee, with all participants providing informed consent.

3. Results and Discussion

This study aimed to examine how different learning styles of pre-service science teachers interact with AI-based instruction in learning electric field concepts. The quantitative findings indicated a notable increase in students' conceptual understanding after the intervention.

3.1. Quantitative Results

Quantitative data were collected using the VARK learning style questionnaire and a two-tier conceptual test administered before and after the AI-based learning activity. The data were analyzed using SPSS, employing descriptive statistics, paired-sample t-tests, and correlation analysis. Below are the detailed findings.

3.1.1. Distribution of Students' Learning Styles Based on VARK

A total of 72 students completed the VARK questionnaire to identify their dominant learning style. The results of the analysis show the distribution in Table 1 and the diagram in Figure 2 as follows:

Table 1. Distribution of Students' Learning Style Based on Vark

Learning Style	Number of Students	Percentage
Visual	18	25.0%
Aural	15	20.8%
Read/Write	13	18.1%
Kinesthetic	14	19.4%
Multimodal	12	16.7%

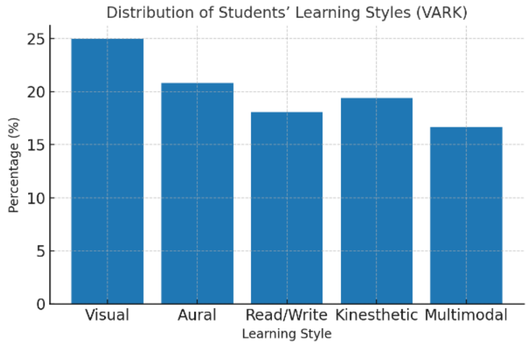

Figure 2. Distribution of Learning Style

3.1.2. Conceptual Understanding Before and After AI-Based Learning

Conceptual understanding was measured using a two-tier test administered before and after learning with an AI-based system. Table 2 and Figure 3 show the average results of the post-test and pre-test of students' conceptual understanding after learning

Table 2. Conceptual Understanding Before and After AI-Based Learning

Statistic	Pre-Test	Post-Test
Mean	4.03	7.24
Standard Deviation	1.71	1.36
N	72	72

The results of a paired-sample t-test indicated a significant difference between the pre-test and post-test scores ($t(71) = -15.827$, $p < 0.001$).

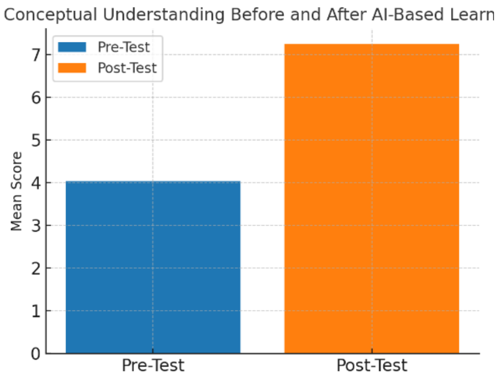

Figure 3. Conseptual Understanding Before and After AI-Based Learning

3.1.3. Relationship Between Learning Styles and Learning Gains

The analysis of the relationship between learning styles and learning gains in Table 3 and Figure 4 reveals a notable variation in the degree of influence among different learning preferences. Students with a visual learning style demonstrated a significant positive correlation ($r= 0.283$, $p= 0.017$), indicating that they experienced substantial improvement in learning outcomes following AI-based instruction. This is likely due to the presence of visual elements such as animations, interactive simulations of electric fields, and illustrative diagrams, which align closely with the way visual learners process information. Similarly, kinesthetic learners also showed a significant correlation ($r = 0.305$, $p = 0.012$), suggesting that the interactive features of the AI system particularly those allowing direct manipulation and virtual exploration provided a learning experience that resonated well with their preference for hands-on, physical engagement in conceptual understanding.

Table 3. Relationship Between Learning Styles and Learning Gains

Learning Style	Correlation (r)	Sig. (p)	Interpretation
Visual	0.283	0.017	Significant positive correlation
Aural	0.192	0.104	Not significant
Read/Write	0.096	0.414	Not significant
Kinesthetic	0.305	0.012	Significant positive correlation
Multimodal	0.222	0.081	Marginal

In contrast, students with an aural learning style did not exhibit a statistically significant correlation with learning gains (r = 0.192, p = 0.104). While there was a slight positive trend, the effect was not strong enough to reach statistical significance. This may be attributed to the AI system's limited emphasis on auditory elements, such as verbal narration or spoken explanations, which are essential for this learner group. Likewise, students with a Read/Write learning preference showed a very low and non-significant correlation (r = 0.096, p = 0.414), implying that they struggled to fully benefit from the predominantly visual and interactive content, particularly in the absence of detailed written explanations or text-based materials.

Multimodal learners demonstrated a marginal correlation (r = 0.222, p = 0.081), suggesting that while they possess the flexibility to adapt to various instructional formats, the gains they experienced were not as pronounced as those whose dominant learning styles aligned directly with the primary modes of the AI system. These findings underscore the importance of ensuring alignment between AI-based instructional design and students' cognitive preferences. While AI-enhanced learning environments have proven effective in enhancing conceptual understanding, their impact is significantly influenced by how well they cater to individual learning styles. For AI systems to support truly inclusive learning, their design must go beyond visual and interactive dominance, embracing a more balanced multimodal approach that accommodates the full spectrum of learners.

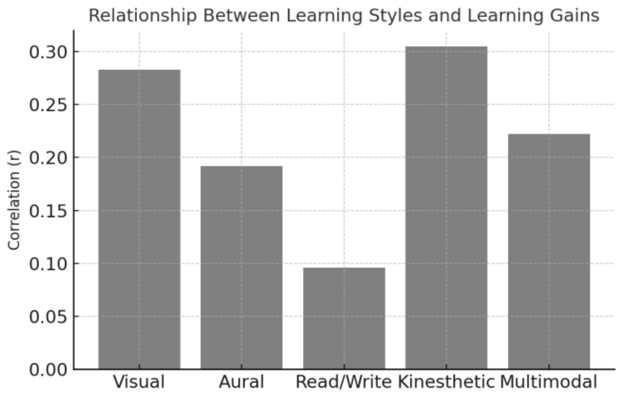

Figure 4. Relationship Between Learning Styles and Learning Gains

3.2. Qualitative Findings

The qualitative findings from interviews and observations of twelve students, each representing different learning styles, revealed a number of insightful patterns regarding their interactions with the AI-based learning system. Visual learners reported substantial benefits from the presence of interactive visualisations and electric field simulations, which helped them intuitively grasp abstract scientific concepts. Kinesthetic learners expressed a strong preference for the hands-on elements of the system, particularly the ability to manipulate charges and conduct virtual experiments, which offered a dynamic and exploratory learning experience. One kinesthetic respondent noted, "*The simulation helped me better understand the direction of electric forces. I could change the position of the charge and instantly see the effect.*"

In contrast, aural learners appreciated the inclusion of audio narrations and explanations but felt that the level of interaction lacked sufficient challenge or depth to fully engage them. For Read/Write learners, the experience was less favourable; they encountered difficulties in following the simulations due to the absence of detailed written explanations. As one respondent with this preference remarked, "I feel more comfortable when there is also a written explanation; sometimes visuals alone are not enough."

Multimodal learners demonstrated adaptability, being able to engage with the various features offered by the system. However, many still expressed a preference for a balanced combination of textual and visual materials, suggesting that while they could manage with the current design, their learning would be further enhanced by more varied content delivery. Overall, these observations underscore the need for AI learning systems to adopt a more inclusive, multimodal approach one that not only adapts to individual pace, but also caters to diverse cognitive preferences to ensure optimal learning experiences for all students.

3.3. Discussion

The results of this study show that the integration of AI-based instruction into the teaching of electric field concepts has a positive impact on pre-service science teachers' conceptual understanding, particularly among those identified through the VARK framework as visual and kinesthetic learners. These findings highlight the potential of AI as a transformative tool in science education but also raise critical questions regarding the theoretical assumptions underpinning learning styles, the validity of VARK as a diagnostic instrument, and the extent to which the observed gains can be attributed to genuine differences in learner typologies or to the instructional affordances embedded in the AI system. While VARK has long been used as a convenient tool to categorize learners into four broad groups visual, aural, read/write, and kinesthetic its empirical validity remains contested. Scholars increasingly argue that such frameworks oversimplify the complexity of learning processes, and recent studies in educational psychology and neuroscience have suggested that there is little robust evidence to support the notion that aligning instruction to specific styles consistently improves outcomes (Cuevas, 2023; Kirschner, 2021). Learners are not rigidly confined to a single mode of processing but rather display adaptive and flexible strategies depending on task demands, prior knowledge, and context. Consequently, while our study found that visual and kinesthetic learners benefited the most, these results should not be interpreted as direct evidence for the predictive power of VARK categories. Instead, they might reflect how the design of the AI system rich in simulations, diagrams, and interactive activities privileged certain types of engagement while underserving others.

An alternative interpretation of these findings can be grounded in well-established theories of learning such as cognitive load theory and dual coding. From the perspective of cognitive load, visualizations and interactive simulations are powerful tools for reducing extraneous processing by externalizing complex relationships that would otherwise overburden working memory (Sweller et al., 2019). The AI platform's strong reliance on animated representations of electric fields likely supported the construction of mental models for all learners, but particularly for those already inclined toward visual reasoning. Similarly, kinesthetic learners may have benefited not because of an inherent learning style advantage but because the platform provided embodied opportunities for manipulating charges and observing the resulting field interactions. Research in embodied cognition suggests that physical or simulated physical activity activates motor pathways that enhance conceptual understanding, particularly in science and mathematics education (Kontra et al., 2022). Thus, these results might be better understood as evidence of the effectiveness of active and multimodal learning design rather than confirmation of VARK's predictive validity.

In contrast, the comparatively modest gains for aural and read/write learners could be linked to limitations in the system design rather than weaknesses in those learners. The absence of comprehensive narrated explanations and detailed textual scaffolds deprived students who prefer linguistic engagement of important cognitive entry points. Prior work demonstrates that the integration of text and narration with visuals can enhance comprehension by appealing to multiple coding channels and supporting cross-modal reinforcement (Mayer, 2020; Fiorella & Mayer, 2021). Without such scaffolding, aural and textual learners may have struggled to engage as deeply with the predominantly visual and interactive design. This points to a larger issue in AI-enhanced education: the danger of overemphasizing certain modalities at the expense of others, thereby limiting inclusivity and equity.

The results should also be considered in light of several methodological and contextual limitations. The first concerns the reliance on the VARK questionnaire itself. As a self-report instrument, VARK captures learners' perceptions of their preferences, which may not accurately reflect their actual learning behaviors or most effective strategies (Cuevas, 2023). Moreover, the psychometric reliability of VARK has been questioned, with some studies finding inconsistent classification of learners across time and context. Second, the sample size of 72 students, drawn from a single institution, limits the generalizability of the findings. While sufficient for an exploratory study, broader and more diverse samples are needed to confirm whether similar patterns would hold across cultural and institutional contexts. Third, the design of the AI system was heavily weighted toward visual and kinesthetic features, which may have biased the results by amplifying benefits for certain learner groups while failing to provide equivalent affordances for others. Fourth, the outcomes were measured immediately after the intervention, leaving unanswered questions about long-term retention and transfer of knowledge. Durable learning is essential in science education, particularly when addressing abstract topics such as electric fields, and future research should incorporate delayed assessments to examine persistence of gains. Fifth, qualitative insights were drawn from only 12 participants, meaning that while valuable, they may not capture the full diversity of student experiences. Finally, the study did not account for other moderating variables such as prior knowledge, cognitive ability, motivation, or digital literacy, all of which could shape how learners interact with AI-based systems.

Despite these limitations, the study offers important implications for the design of inclusive AI learning environments. The uneven gains across different learner groups underscore the necessity of moving beyond narrowly defined modalities to embrace a multimodal approach that integrates visual, auditory, textual, and interactive elements. Recent developments in multimodal AI, supported by natural language processing, speech synthesis, and gesture recognition, suggest that it is increasingly feasible to create platforms capable of dynamically delivering content across multiple channels (Zhai et al., 2023; Lee & Zhai, 2024). Rather than attempting to match instruction to static learning style categories, AI systems should adopt the principles of Universal Design for Learning, which emphasize providing multiple means of representation, engagement, and expression (Al-Azawei et al, 2022). By offering learners flexible options for interacting with material, such systems can support diverse cognitive needs without confining them to predefined categories.

Furthermore, adaptive learning analytics can enable AI to personalize instruction in ways that go beyond VARK's limitations. Instead of relying on self-reported questionnaires, AI can analyze real-time data from learner interactions, identifying patterns of engagement and areas of difficulty, and then adjusting the modality and pacing of instruction accordingly (Vakili & Dianati, 2024). For example, if a student demonstrates difficulty with purely visual materials, the system could supplement these with additional textual or narrated explanations. Such dynamic responsiveness ensures that all learners, including those with strong linguistic preferences, are adequately supported. This approach shifts the focus from categorizing learners to empowering them through flexible, adaptive pathways that align with evolving needs.

For teacher education, these findings also carry broader implications. Pre-service teachers exposed to AI-based learning environments that transparently integrate multiple modalities may develop greater awareness of their own cognitive preferences and limitations. This metacognitive awareness can be invaluable in their future practice, enabling them to design lessons that accommodate diverse learners rather than defaulting to a "one-size-fits-all" approach. Encouraging pre-service teachers to critically reflect on the promises and pitfalls of AI in education prepares them to implement such technologies responsibly, ethically, and inclusively in their classrooms. At the same time, they must be cautioned against uncritically adopting frameworks such as VARK, which may reinforce myths rather than advance evidence-based pedagogy (Kirschner, 2021).

In summary, the results of this study should be interpreted less as confirmation of the efficacy of VARK-based personalization and more as evidence of the power of multimodal, interactive AI learning environments. While visual and kinesthetic learners demonstrated significant gains, these benefits likely reflect broader principles of cognitive load management, dual coding, and embodied cognition rather than the superiority of particular learning styles. The study's limitations underscore the need for more rigorous, large-scale, and longitudinal research to clarify the conditions under which AI most effectively enhances learning. Nonetheless, the implications are clear: to achieve inclusive and equitable outcomes, AI systems must integrate multiple modalities, dynamically adapt to learner needs, and align with universal design principles. In doing so, AI can move beyond the contested paradigm of learning styles to genuinely support the diverse and evolving needs of all learners.

4. Conclusion

This study demonstrated that AI-based instruction significantly improved the conceptual understanding of pre-service science teachers on the topic of electric fields, with visual and kinesthetic learners benefitting most from the system's reliance on simulations and interactive features. Nevertheless, several limitations must be acknowledged. The reliance on the VARK questionnaire as a measure of learning styles presents issues of validity and reliability, while the modest and localized sample size limits the generalizability of the findings. Furthermore, the design of the AI system, which strongly emphasized visual and interactive elements, may have biased the results toward certain learner groups. The absence of longitudinal measures also leaves unanswered questions about retention and transfer of knowledge.

Based on these considerations, several actionable recommendations emerge. First, future AI learning platforms should be designed to balance multiple modalities visual, auditory, textual, and kinesthetic ensuring that learners with diverse preferences and needs are equitably supported. Integrating narrated explanations, detailed textual scaffolds, and multimodal feedback would create more inclusive environments. Second, pre-service teacher education programs should incorporate explicit training on how to critically evaluate AI-based tools, equipping future educators to select and adapt systems responsibly. Third, system developers should embed adaptive analytics that continuously monitor learner engagement and performance, allowing real-time adjustments to instructional pacing, modality, and feedback.

Suggestions for future research also follow naturally from this work. Larger-scale and cross-cultural studies are needed to test the robustness of the findings across different educational contexts. Longitudinal research should explore whether conceptual gains achieved through AI persist over time and transfer to new problem-solving contexts. Future investigations might also move beyond VARK to explore other theoretical frameworks, such as cognitive load theory, dual coding, and universal design for learning, which may provide more robust explanations of learner differences. Finally, the ethical implications of deploying AI in teacher education including issues of equity, transparency, and data privacy should be systematically studied to ensure that technological innovation aligns with broader educational values.

In sum, this study highlights both the promise and the challenges of AI-assisted learning in science education. While demonstrating that AI can enhance learning outcomes, particularly for certain groups of learners, it also underscores the importance of moving toward multimodal, adaptive, and inclusive design principles. By addressing its current limitations and building upon its strengths, future research and practice can ensure that AI contributes not only to improved performance but also to more equitable and responsive educational experiences.

Author Contributions

All authors have equal contributions to the paper. All the authors have read and approved the final manuscript.

Funding

No funding support was received.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Al-Azawei, A., Serenelli, F., & Lundqvist, K. (2022). Universal design for learning (UDL): A content analysis of peer-reviewed journal papers from 2012 to 2020. *Educational Research Review, 35*, 100425. https://doi.org/10.1016/j.edurev.2021.100425

Aslaksen, H., Sälzer, C., & Stokke, A. (2022). The myth of learning styles: An evidence-based perspective. *Frontiers in Psychology, 13*, 928374. https://doi.org/10.3389/fpsyg.2022.928374

Chen, L., Xie, H., Zou, D., & Hwang, G. J. (2022). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, 100052. https://doi.org/10.1016/j.caeai.2022.100052

Chen, L., Huang, R. H., & Spector, J. M. (2023). Artificial intelligence in education: Promises and challenges. *Educational Technology Research and Development, 71*(1), 1–7. https://doi.org/10.1007/s11423-022-10162-9

Coffield, F. (2023). Why the learning styles myth persists. *Teaching in Higher Education, 28*(5), 623–635. https://doi.org/10.1080/13562517.2022.2103502

Cuevas, J. (2020). Is learning styles-based instruction effective? A comprehensive analysis. *Journal of Educational Psychology, 112*(2), 253–268. https://doi.org/10.1037/edu0000365

Cuevas, J. (2023). Re-examining the validity of learning styles theory: Implications for educational practice. *Frontiers in Psychology, 14*, 1173452. https://doi.org/10.3389/fpsyg.2023.1173452

Dai, Y., Chen, Y., & Wang, X. (2023). Intelligent tutoring systems for physics education: A review. *Journal of Science Education and Technology, 32*(6), 723–740. https://doi.org/10.1007/s10956-023-10024-4

Dekker, S., & Jolles, J. (2023). Do learning styles matter? Investigating the role of modality preferences in digital learning. *Learning and Instruction, 84*, 101745. https://doi.org/10.1016/j.learninstruc.2022.101745

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications* (5th ed.). Sage.

Fiorella, L., & Mayer, R. E. (2021). Eight ways to promote generative learning. *Educational Psychology Review, 33*(4), 1107–1133. https://doi.org/10.1007/s10648-020-09586-2

Graesser, A. C., Hu, X., Nye, B. D., & Sottilare, R. A. (2023). Intelligent tutoring systems: Past, present, and future. *International Journal of Artificial Intelligence in Education, 33*(1), 1–20. https://doi.org/10.1007/s40593-022-00291-6

Holmes, W., Bialik, M., & Fadel, C. (2022). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Kirschner, P. A. (2017). Stop propagating the learning styles myth. *Computers & Education, 106*, 166–171. https://doi.org/10.1016/j.compedu.2016.12.006

Kirschner, P. A. (2021). The learning styles neuromyth: Lack of evidence, persistence, and implications. *Educational Psychology, 41*(3), 231–243. https://doi.org/10.1080/01443410.2020.1864040

Knoll, A. R., Otani, H., Skeel, R. L., & Van Horn, K. R. (2021). Learning styles: Concepts and evidence. *Frontiers in Psychology, 12*, 640197. https://doi.org/10.3389/fpsyg.2021.640197

Kontra, C., Lyons, D. J., Fischer, S. M., & Beilock, S. L. (2022). Embodied learning in science education. *Trends in Cognitive Sciences, 26*(8), 677–689. https://doi.org/10.1016/j.tics.2022.05.006

Kozulin, A. (2022). Vygotsky's educational theory in cultural context revisited. *Cambridge Journal of Education, 52*(3), 341–356. https://doi.org/10.1080/0305764X.2021.1973821

Kukul, V. (2024). Revisiting the effectiveness of VARK in higher education. *Education and Information Technologies, 29*(1), 233–250. https://doi.org/10.1007/s10639-023-12058-0

Lee, M. K., & Zhai, X. (2024). Multimodal AI in education: The next frontier. *British Journal of Educational Technology, 55*(2), 351–370. https://doi.org/10.1111/bjet.13325

Lee, T. D., Chou, P. N., & Huang, Y. M. (2023). Adaptive AI tutoring systems for electromagnetism. *Journal of Educational Computing Research, 61*(3), 521–544. https://doi.org/10.1177/07356331221149020

Luckin, R., & Cukurova, M. (2023). Designing AI for education: Classroom implications. *Nature Human Behaviour, 7*(5), 617–627. https://doi.org/10.1038/s41562-023-01523-2

Mayer, R. E. (2020). *Multimedia learning. In L. Corno & E. M. Anderman (Eds.),* Handbook of educational psychology (3rd ed., pp. 305–321). Routledge.

Mayer, R. E. (2021). *Multimedia learning* (3rd ed.). Cambridge University Press. https://doi.org/10.1017/9781316941355

Miftah, M., Pratiwi, I. A., & Wulandari, R. (2024). Addressing misconceptions in electromagnetism using digital simulations. *Physics Education, 59*(2), 025014. https://doi.org/10.1088/1361-6552/acd245

Newton, P. M., & Miah, M. (2017). Evidence-based higher education: Is the learning styles 'myth' important? *Frontiers in Psychology, 8*, 444. https://doi.org/10.3389/fpsyg.2017.00444

Nyaaba, N., Boateng, R., & Mingle, J. (2024). Teacher education and AI: Preparing future educators. *Teaching and Teacher Education, 129*, 104070. https://doi.org/10.1016/j.tate.2023.104070

Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. (2009). Learning styles: Concepts and evidence. *Psychological Science in the Public Interest, 9*(3), 105–119. https://doi.org/10.1111/j.1539-6053.2009.01038.x

Roll, I., & Wylie, R. (2024). Evolution of intelligent tutoring systems: Current status and future directions. *Computers & Education, 195*, 104700. https://doi.org/10.1016/j.compedu.2023.104700

Sweller, J. (2019). Cognitive load theory and educational design: Recent developments. *Educational Psychology Review, 31*(2), 261–276. https://doi.org/10.1007/s10648-019-09465-5

Sweller, J. (2020). *Cognitive load theory*. Springer. https://doi.org/10.1007/978-3-030-47860-5

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tondeur, J., Scherer, R., & Siddiq, F. (2023). Preparing pre-service teachers for technology integration. *Journal of Computer Assisted Learning, 39*(1), 95–110. https://doi.org/10.1111/jcal.12692

Treagust, D. F. (2021). Diagnostic assessment in science education. *Studies in Science Education, 57*(2), 145–164. https://doi.org/10.1080/03057267.2021.1888043

Vakili, V., & Dianati, S. (2024). Adaptive learning analytics for personalised education. *Computers in Human Behavior, 152*, 107180. https://doi.org/10.1016/j.chb.2023.107180

Yeo, S., & Gilbert, J. K. (2023). Addressing misconceptions in electric field concepts. *International Journal of Science Education, 45*(1), 1–22. https://doi.org/10.1080/09500693.2022.2162007

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2023). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 1–27. https://doi.org/10.1186/s41239-023-00423-5

Zhai, X., Chu, H., & Lee, M. (2023). Multimodal AI for inclusive learning environments. *Computers & Education: Artificial Intelligence, 4*, 100119. https://doi.org/10.1016/j.caeai.2023.100119

Zhang, Y., Xu, H., & Chen, J. (2024). Student misconceptions in electric field learning: A review. *Physical Review Physics Education Research, 20*(1), 010101. https://doi.org/10.1103/PhysRevPhysEducRes.20.010101