Development of AI-Based Algorithm Learning Media with a Personalized Learning and Mediated Learning Experience Framework

Eki Nugraha*, Salman Haykal Ramadhan

Universitas Pendidikan Indonesia, Dr. Setiabudhi St. No. 229, Bandung, West Java, 40154, Indonesia
*Corresponding author, email: ekinugraha@upi.edu

https://doi.org/10.17977/um065.v6.i7.2026.5

Article history
Submitted: 12 April 2026
Revised: 15 May 2026
Accepted: 15 May 2026
Published: 16 May 2026

Keywords
AI learning media
Personalized learning
Mediated learning experience
SUS
Phase E Informatics

Abstract
Algorithm learning in Informatics at Phase E requires media that can adapt to the individual needs of students. However, most conventional media remain static and one-directional. This study develops an AI-based algorithm learning medium that integrates the principles of personalized learning and Mediated Learning Experience (MLE) using the ADDIE model. It also evaluates usability through the System Usability Scale (SUS) and thematic analysis involving 22 tenth-grade high school students. The MLE principles intentionality, meaning, transcendence, and competence are translated into system features through a Socratic AI dialogue architecture. The average SUS score is 77.39 (SD = 12.87; 95% CI [71.68, 83.10]), which falls within the Acceptable range (Grade B–C). Thematic analysis identifies five main themes, with appreciation for content personalization (41%) and technical constraints (36%) emerging as the most prominent findings. The main contribution of this study is conceptual and design-oriented. It proposes a framework that maps personalized learning and MLE principles into concrete features within AI-based educational media.

1. Introduction

Digital transformation has changed how learning is designed and delivered. Instead of offering the same learning path for all students, current educational technology makes it possible to provide learning support that is more adaptive and responsive to individual needs. AI plays an important role in this shift because it can analyze student responses, support personalized learning pathways, and provide timely assistance during learning (Bhutoria, 2022; Fortuna et al., 2025). This change is relevant to Informatics education, where students are expected to develop computational thinking, or the ability to define problems and build logical and structured solutions (Wing, 2006).

In Indonesia, Informatics is introduced in Phase E of the Merdeka Curriculum as part of efforts to strengthen students' digital and computational competencies (Kepmendikbudristek No. 56/M/2022). One important topic in this phase is algorithm learning, which requires students to understand steps, patterns, conditions, and problem-solving procedures. However, algorithms are often difficult for students because the concepts are abstract and require them to connect visual representation, logical reasoning, and procedural thinking (Andrzejewska & Stolińska, 2022; Gonda et al., 2022). As a result, students need learning media that can guide them gradually and help them apply algorithmic ideas to new problems.

The current learning media used in algorithm learning are still often static and less responsive to different student needs. Initial observations showed that students tended to depend on step-by-step examples from the teacher and had difficulty solving new algorithmic problems independently. This condition is in line with Pujakesuma et al. (2024), who found that low learning interest can be related to lecture-based methods and limited interactive learning media. These limitations show the need for learning media that can provide immediate feedback, support independent reasoning, and adjust learning activities to student progress.

AI-based learning media can respond to these needs because AI can act as an adaptive tutor that provides personalized feedback, real-time scaffolding, and adaptive assessment. Generative AI can adjust content based on learner responses (Pesovski et al., 2024), and adaptive learning has been shown to support engagement and learning outcomes (Du Plooy et al., 2024). However, personalization should not only focus on content adjustment. It also needs a clear pedagogical basis so that students are guided to think, explain, and reflect rather than only receive answers.

ISSN: 2797-3174

Mediated Learning Experience (MLE) provides a relevant pedagogical basis for this purpose. In MLE, learning is supported through intentional interaction, meaning-making, transcendence, and the development of competence (Ashizuka, 2023; Zehr, 2023). When applied to AI learning media, MLE can help position AI as a mediator of thinking. This means that the system should ask guiding questions, encourage students to explain their reasoning, and help them transfer what they learn to different algorithmic problems. Therefore, combining personalized learning and MLE may create an AI-based learning medium that is adaptive while still pedagogically meaningful.

Several gaps can be identified from previous studies. Research on AI in education has grown rapidly, but studies on the design of interaction between AI and learners are still more limited than general discussions of AI use in education (Labadze et al., 2023; Crompton & Burke, 2023). In addition, the development of AI-based media for algorithm learning has mostly focused on higher education, while the context of Phase E Informatics remains underexplored (Mardeli et al., 2025). Existing studies on AI tutors and dialogic AI have also not clearly connected Feuerstein's MLE framework with dialogue structures in AI systems for algorithm learning (Lin et al., 2023; Tang et al., 2024).

Based on these gaps, this study aims to address two questions: (1) how to develop an AI-based algorithm learning medium that integrates personalized learning and MLE using the ADDIE model, and (2) how usable the developed medium is based on user evaluation using the System Usability Scale (SUS). This study contributes a design framework that maps personalized learning and MLE into concrete features of AI-based educational media, and it provides initial usability evidence for further development of the medium.

This study integrates personalized learning and Mediated Learning Experience (MLE) as the foundation for developing an AI-based algorithm learning medium. As shown in Figure 1, personalized learning is represented through content generation, runtime adaptation, and adaptive assessment. Meanwhile, MLE is applied through intentionality and reciprocity, mediation of meaning, transcendence, and mediation of competence. These two approaches are connected through Socratic dialogue to shape the AI learning medium, principle-learn. The developed medium is then evaluated using the System Usability Scale (SUS) and thematic analysis, and the evaluation results are used as the basis for design iteration.

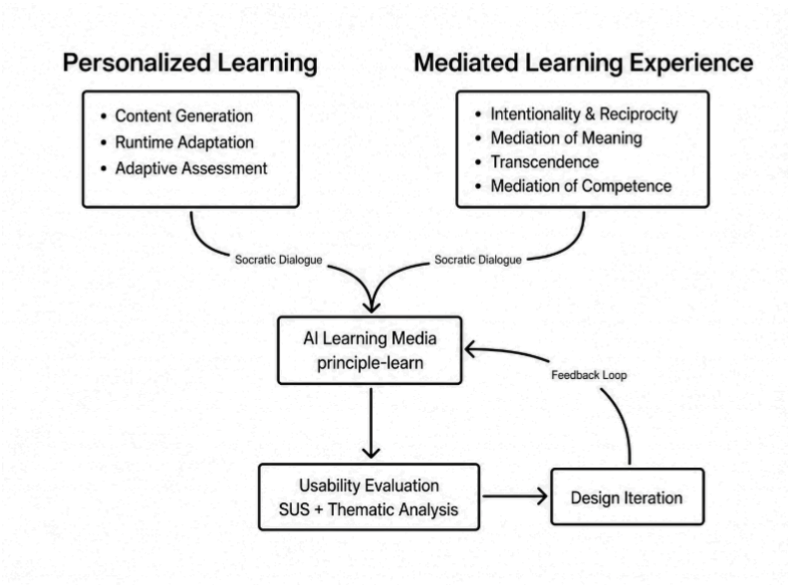

Figure 1. Conceptual Framework of the Study

2. Method

This section explains two main aspects of the research methodology. The first is the design and development process of the learning medium using the ADDIE model. The second is the evaluation procedure, which applies a mixed-method approach as described by Creswell and Creswell (2018). This approach combines the System Usability Scale (SUS) with thematic analysis of participants' open-ended responses.

2.1. Media Design and Development

The learning medium was developed based on the ADDIE model (Branch, 2009), as this model provides a systematic process and supports the documentation of design decisions from the needs analysis stage to evaluation. In this study, the evaluation focused on interaction usability (Leacock & Nesbit, 2007) by using the System Usability Scale (SUS) together with qualitative data from participants' open-ended responses. This study

ISSN: 2797-3174

did not conduct formal expert validation because the main focus was user-based evaluation as a basis for design improvement (Brooke, 1996). Within the ADDIE framework, formative evaluation involving target users is still considered a valid part of the media development process (Branch, 2009).

However, the absence of expert validation is recognized as a limitation, since content validity and pedagogical suitability were not assessed independently. Therefore, the findings should be understood as an initial evaluation that emphasizes practicality and user experience. The media development process followed the five ADDIE phases: analysis, design, development, implementation, and evaluation. Each phase had a different focus and output, ranging from identifying learning needs, translating personalized learning and MLE principles into media features, developing a web-based application prototype, conducting trials with students, and evaluating usability. The details of each phase and its development focus are presented in Table 1.

Table 1. ADDIE Phases and Media Development Focus

Phase	Focus/Output
Analysis	Identifying learning needs, aligning the media with Phase E learning outcomes, and defining the initial design principles
Design	Mapping personalized learning (PL) and Mediated Learning Experience (MLE) concepts into media features, and designing the Socratic dialogue structure
Development	Developing a web-based application prototype, integrating OpenAI GPT, and refining the media through internal iterations
Implementation	Conducting a trial involving 22 tenth-grade high school students in Phase E
Evaluation	Evaluating usability using the System Usability Scale (SUS) and conducting thematic analysis of participants' open-ended responses

Based on Table 1, the analysis phase shows that the available algorithm learning media were still mostly static, while students had difficulty reasoning independently. From the analysis of Phase E learning outcomes, four core competencies were identified and used as the basis for formulating three main design principles: adaptive learning, dialogic interaction, and gradual scaffolding. In the design phase, these pedagogical principles were translated into two main layers. The first layer is personalized learning, which focuses on content adjustment, while the second layer is Mediated Learning Experience (MLE), which emphasizes the quality of mediation in learning dialogue. A more detailed mapping of these two layers is presented in Table 2.

Table 2. Mapping of Personalized Learning and MLE Principles to Media Features

Principle		Media Feature	Technical Implementation
Personalized Learning	Content Personalization	Personal course creation	AI generates learning materials based on the prompts provided by users when creating a course
	Runtime Adaptation	Real-time difficulty adjustment	AI adjusts the depth of scaffolding based on users' responses
	Adaptive Assessment	Adaptive quizzes and challenges	Questions are adjusted based on users' previous answer history
Mediated Learning Experience	Intentionality	Challenge Thinking	Each session begins with a clear statement of learning objectives
	Meaning	Context-based course	AI connects algorithm concepts with relevant real-life situations
	Transcendence	Reflective prompts	AI encourages users to transfer their understanding to new contexts
	Competence	Positive feedback and progress tracking	The system strengthens students' sense of competence through explicit recognition of their progress

The two layers are integrated through a Socratic dialogue architecture that consists of two main components: an engineered system prompt and a structured application flow. The engineered system prompt is designed to apply MLE principles during the interaction, while the structured application flow guides the learning process in sequence, starting from concept introduction, guided practice, independent practice, and reflection. As shown in Figure 2, the medium was developed as a web-based application called "principle-learn" version 0.2.0, using Next.js 15, React 19, Supabase PostgreSQL, and the OpenAI GPT API. The application includes seven main features: onboarding, personal course creation, Ask Question, Challenge Thinking, adaptive quizzes, reflection journal, and progress tracking.

ISSN: 2797-3174

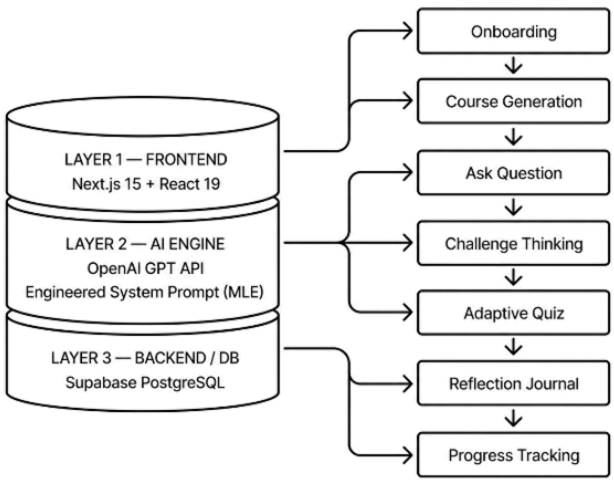

Figure 2. System Architecture of Principle-Learn

The system flow starts from Layer 1 (Frontend), which serves as the main interaction point between users and the system. At the beginning, users go through onboarding to provide basic information. The interface, built with Next.js 15 and React 19, not only displays information but also manages user input and sends it to the next layer. After this initial process, the system moves to course generation, where the user's choices or learning needs collected from the frontend are sent to Layer 2 (AI Engine). In this layer, the OpenAI GPT API, supported by an engineered system prompt based on MLE, processes the request by understanding the context, interpreting the learning goals, and generating suitable learning content.

The interaction then continues through the Ask Question and Challenge Thinking features. As shown in Figure 3, the Challenge Thinking feature applies MLE-based Socratic dialogue by encouraging students to respond to reflective questions after learning the material. In this feature, AI not only provides answers but also guides students to think more deeply through follow-up questions or challenging scenarios. Next, in the adaptive quiz stage, shown in Figure 4, the system generates quizzes based on the user's ability, learning progress, and responses. The quiz results, answers, and reflection journal entries are stored in Layer 3 (Backend/Database) using Supabase PostgreSQL, so the data can be reused for further analysis and personalization. Finally, in the progress tracking stage, the system retrieves the stored data and presents it back to users through the frontend, allowing them to monitor their learning progress continuously. Overall, this flow shows how the frontend, AI engine, and backend work together to create an adaptive and continuous learning experience.

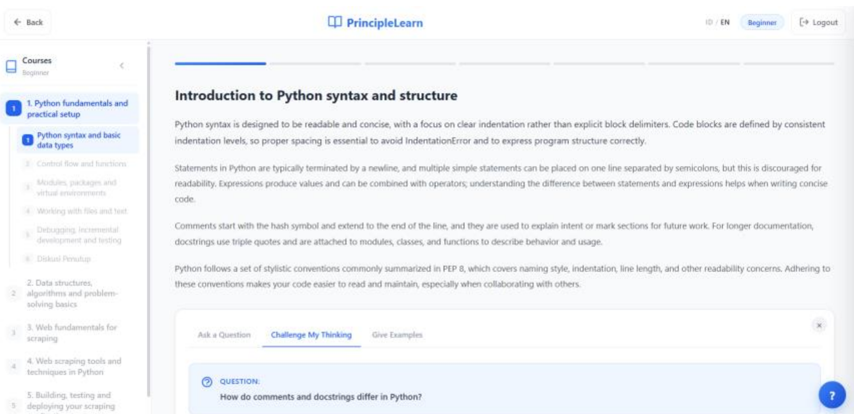

Figure 3. Challenge Thinking Feature (MLE-Based Socratic Dialogue)

ISSN: 2797-3174

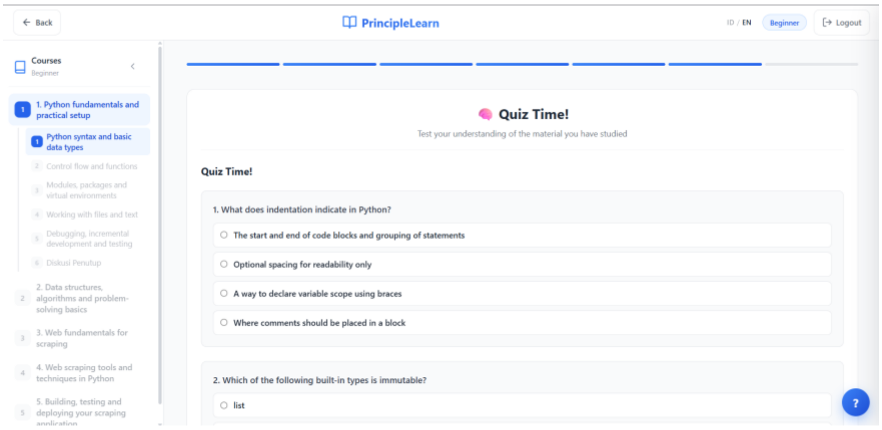

Figure 4. Adaptive Quiz Feature (Personalized Learning-Based Assessment)

2.2. Usability Evaluation

The evaluation used a mixed-method approach by combining the System Usability Scale (SUS) to measure usability quantitatively with three open-ended questions to explore users' experiences qualitatively. Participants were selected purposively based on two criteria: they were studying Informatics in Phase E and had used the developed media. All responses were included in the analysis, including those from participants whose experience with the media was not fully complete, in line with the SUS principle that measures users' perceptions at the time of response (Brooke, 1996). The SUS instrument consists of 10 statements using a 1–5 Likert scale, with odd-numbered items written as positive statements and even-numbered items written as negative statements. The scores were then converted into a 0–100 scale (Brooke, 1996). The interpretation of the SUS results followed the grading framework used by Vargas-Arteaga and Gravini-Donado (2024), as presented in Table 3, with an average score of 68 used as the reference point.

Table 3. SUS Score Interpretation Framework

Grade	Score Range	Adjective Rating	Acceptability Zone
A	> 80.3	Excellent	Acceptable
B	74.0–80.3	Good	Acceptable
C	68.0–73.9	Okay	Acceptable
D	51.0–67.9	Marginal	Marginal
F	< 51.0	Poor	Not Acceptable

In addition to SUS, participants were asked to answer three open-ended questions at the same time as the questionnaire. These questions covered: comments or suggestions about the use of the media, the most helpful part of the media, and the main difficulties experienced by users. A total of 66 qualitative response units, consisting of 22 participants × 3 questions, were analyzed using the six-phase thematic analysis model by Braun and Clarke (2006). The analysis was conducted by the main researcher and supported by an audit trail that connected the codes to the final themes. Meanwhile, the quantitative data were analyzed through SUS score calculation, descriptive statistics, the Shapiro–Wilk normality test, item-level analysis, and reliability testing using Cronbach's alpha. The results from both types of data were then triangulated by comparing the qualitative themes with the score patterns of each SUS item.

3. Results and Discussion

The application of the ADDIE model in this study resulted in the development of "principle-learn," which was based on three main design decisions. First, personalization was designed in three layers: content generation, runtime adaptation, and adaptive assessment. This structure allows for more detailed learning differentiation than a single personalization approach (Pesovski et al., 2024). Second, the principles of Mediated Learning Experience (MLE) were integrated into the Socratic dialogue architecture, which distinguishes this medium from conventional AI chatbots. Third, the learning flow was organized in a clear sequence, starting from concept introduction, guided practice, independent practice, and reflection, so that each session maintained a clear pedagogical direction. During the development stage, one challenge was maintaining the consistency of AI responses. The varied outputs generated by generative AI required several iterations of the system prompt to keep the interaction aligned with MLE principles. The descriptive statistics of SUS scores from 22 students are summarized in Table 4.

ISSN: 2797-3174

Table 4. Descriptive Statistics of SUS Scores (N = 22)

Statistic	Value
Mean	77.39
SD	12.87
Median	77.50
95% CI	[71.68; 83.10]
Range	50–100
Skewness	−0.08
Kurtosis	−0.26
Shapiro-Wilk W	0.974 (p = 0.805)
Cronbach's α	0.614

The score distribution was close to normal based on the Shapiro–Wilk test ($p = 0.805$), indicating that parametric analysis could be applied. The internal reliability test showed a Cronbach's alpha value of 0.614, which is below the commonly used threshold of 0.70 (Zakariya, 2022). The item-level analysis showed that Item 3, "easy to use," had a negative corrected item-total correlation (−0.16), while Item 10, "need to learn many things," had the highest correlation (0.63). This moderate alpha value may have been influenced by the small sample size (N = 22) and differences in participants' digital experience. Ikhsanudin et al. (2024) show that, in small samples, alpha coefficients can vary considerably across test groups and tend to become more stable when the number of respondents exceeds 80 for a 10-item scale. Therefore, the alpha value in this study should be interpreted carefully because the sample size may increase the possibility of sampling error and make the reliability value appear artificially lower. In addition, Zakariya (2022) emphasizes that the 0.70 threshold should not be applied universally without considering the instrument context, number of items, and sample characteristics. The distribution of individual SUS scores by grade is presented in Table 5.

Table 5. Distribution of SUS Scores by Grade (N = 22)

Grade	Adjective Rating	n	%	Zone
A	Excellent	8	36.4	Acceptable
B	Good	4	18.2	Acceptable
C	Okay	4	18.2	Acceptable
D	Marginal	5	22.7	Marginal
F	Poor	1	4.5	Marginal

Based on the SUS grade distribution presented in Table 5, most participants were in the Acceptable usability zone. A total of 8 students (36.4%) achieved Grade A, 4 students (18.2%) were categorized as Grade B, and 4 students (18.2%) were categorized as Grade C. Meanwhile, 5 students (22.7%) were in Grade D, and 1 student (4.5%) fell into Grade F. Overall, 72.7% of participants were in the Acceptable zone, while 54.5% achieved Good or Excellent ratings. These results indicate that the developed media was generally perceived as usable by most students, although some users still experienced difficulties that need to be addressed in the next design iteration.

Table 6. Mean Per-Item Contribution Scores of the SUS

Item	Aspect	Mean Contribution Score
Item 1	Frequency of use	3.27
Item 2	Complexity	2.95
Item 3	Ease of use	3.41
Item 4	Technical support	3.05
Item 5	Function integration	3.27
Item 6	Inconsistency	2.77
Item 7	Learnability	3.23
Item 8	System cumbersomeness	2.95
Item 9	Confidence	3.45
Item 10	Learning curve	2.59

3.1. Qualitative Findings

Open coding of 66 response units produced 34 initial codes, which were then grouped into five main patterns. Two patterns appeared in more than 30% of participants' responses and represented the main user experiences: appreciation of content personalization and technical difficulties. The other three patterns, which appeared in 14% to 18% of responses, showed areas that still need improvement, including initial confusion, dialogic interaction, and the need for visual content.

The strongest positive response was related to content personalization, which appeared in 9 of 22 participants' responses (41%). Students felt that the media helped them learn more independently and create

ISSN: 2797-3174

learning topics that matched their needs. R15 stated that the material adjustment feature "makes it easier for users to learn independently." A similar response was given by R8, who said that "the course feature is very helpful for independent learning." R4 also noted that the media "helps users create learning topics quickly, in detail, and in a structured way." These responses indicate that the prompt-based content generation feature made the learning experience feel more personal and useful for students.

Technical difficulties formed the second major pattern and appeared in 8 of 22 participants' responses (36%). The reported problems were mainly related to slow loading time, scrolling issues, and inconsistent mobile display. R12 suggested that "the loading duration should be made faster," while R17 noted that the media "requires a fast and stable internet connection." R3 reported that users "could not scroll after the AI process was completed," and this issue was also mentioned by R14. R9 added that "some parts of the mobile interface are still inconsistent and not comfortable to view." These responses show that technical stability is an important part of the user experience, especially when students interact with AI-generated content in real time.

Some students also experienced confusion during their first use of the media. This pattern appeared in 4 of 22 responses (18%) and was consistent with the lower score on Item 10, which relates to the need to learn many things before using the system confidently. R6 suggested that "an initial overview of the media should be provided, because not everyone can immediately understand the concept." R13 gave a similar comment, stating that "at the beginning, it was still confusing because I was not used to it." These responses suggest that the Socratic dialogue approach needs clearer onboarding, especially for students who are new to AI-based learning interactions.

In addition to the challenges, students also responded positively to the dialogic interaction provided by the media. This pattern appeared in 4 of 22 responses (18%). R18 highlighted features such as "challenging understanding, providing examples, and asking questions." These responses reflect several principles of Mediated Learning Experience (MLE), especially intentionality and competence. The interaction did not only deliver information, but also encouraged students to think, respond, and evaluate their understanding during the learning process.

The final pattern was the need for more visual content, which appeared in 3 of 22 responses (14%). Some students felt that the learning material would be easier to understand if it included more visual support. R17 stated that "the learning content is still in text form without images" and added that the media would be "very powerful" if supported by visualizations. R7 also suggested that the content should be "visualized more." This finding is important because algorithm learning often requires visual representation to help students understand abstract concepts more easily (Andrzejewska & Stolińska, 2022).

3.2. Discussion

The SUS results show that principle-learn was generally perceived as usable by the students. The mean score of 77.39 was above the acceptable threshold of 68, and the lower bound of the 95% confidence interval, 71.68, also remained in the acceptable range (Vargas-Arteaga & Gravini-Donado, 2024). This finding is important because usability is the first condition for students to benefit from an AI-based learning medium. At the same time, the wide score variation (SD = 12.87; range = 50-100) shows that the user experience was not yet equally smooth for all students. The Cronbach's alpha value of 0.614 should also be read carefully because reliability values can be affected by sample size, item characteristics, and the context in which an instrument is used (Ikhsanudin et al., 2024; Zakariya, 2022). Therefore, the results suggest that the prototype is promising, but still needs design refinement before it can be considered stable for broader use.

Students' positive responses to content personalization help explain why the medium received an acceptable usability score. This aspect appeared in 41% of participants' responses and showed that students valued features that allowed them to create learning topics and study more independently. These findings suggest that personalized learning becomes more meaningful when it is presented through concrete features, such as course generation, adaptive content, and feedback that follows learner needs. In this study, personalization made the medium feel more flexible and helped students learn algorithms at a pace that was closer to their level of understanding. This finding is in line with previous studies showing that generative AI and adaptive learning can support engagement and learning outcomes when they are connected to clear learning activities (Pesovski et al., 2024; Du Plooy et al., 2024).

The MLE-based Socratic dialogue also contributed to students' learning experience, although it still needs clearer support for first-time users. Several students noticed that the media challenged their understanding, provided examples, and asked questions during learning. This response indicates that MLE principles, particularly intentionality, meaning, and competence, were reflected in the interaction design. The high scores on Item 9, which relates to confidence, and Item 3, which relates to ease of use, also support this interpretation. At the same time, the lower score on Item 10 shows that some students still needed time to understand how to use the system. This suggests that Socratic dialogue can encourage deeper thinking, but students need a clearer

ISSN: 2797-3174

introduction, so they understand why the AI asks guiding questions instead of giving direct answers. This finding is in line with Tang et al. (2024), who emphasize the value of dialogic AI, and Darvishi et al. (2024), who warn that overly direct AI assistance may reduce learner agency.

The technical and visual findings are also important for evaluating the quality of the prototype. Students reported several problems, including slow loading, scrolling issues, and inconsistent mobile display. These problems affected their learning experience, while the low score on Item 6 also pointed to concerns about system consistency. Such issues are important because technical barriers can distract students from the learning process, even when the pedagogical design is appropriate. In addition, students expected more visual content to support their understanding. This is relevant in algorithm learning because abstract ideas are often easier to understand when they are supported by visual representations and step-by-step procedures (Andrzejewska & Stolińska, 2022; Gonda et al., 2022). Therefore, improving technical stability and adding visual support should be seen as part of the learning design, not only as interface improvements.

3.3. Implications

Theoretically, this study shows that personalized learning and Mediated Learning Experience (MLE) can be combined as a design basis for AI-based learning media. The contribution is not limited to using AI as a content generator. More importantly, the study shows how AI can be guided by pedagogical principles so that it supports thinking, reflection, and gradual learning. By mapping personalized learning to content generation, runtime adaptation, and adaptive assessment, and by mapping MLE to Socratic dialogue, this study offers a practical way to connect learning theory with AI interaction design.

For Informatics teachers, principle-learn can be understood as a pedagogical partner that supports students during algorithm learning. The medium can help students practice reasoning through guided questions, receive feedback, and revisit learning content at their own pace. However, the teacher's role remains central. Teachers are still needed to set the learning context, explain the purpose of the AI interaction, monitor student understanding, and connect the media activities with classroom goals. In this sense, AI-based learning media should support teacher mediation rather than replace it.

The findings also have implications for the next design iteration. The onboarding process needs to explain the learning flow and the purpose of Socratic dialogue more clearly, especially for students who are not familiar with AI-based learning interactions. The media also needs stronger visual support for algorithm topics, because visual representation can help students connect abstract concepts with concrete procedures. In addition, loading performance, scrolling behavior, and mobile display consistency should be improved so that technical issues do not interrupt the learning process. These improvements would make the personalization and MLE features easier for students to experience in practice.

3.4. Limitations

This study has several limitations. The evaluation focused on usability and did not measure learning effectiveness. As a result, the findings show how students perceived and used the medium, but they do not yet show whether the medium improved students' algorithm learning outcomes. Future studies need to include pre-test and post-test designs or other learning performance measures to examine the educational impact more directly.

The study also has limitations related to validation and generalization. Formal expert validation was not conducted, so the content quality and pedagogical suitability of the medium were not assessed independently by experts. The participants were limited to 22 students from one school, which means the findings may not represent students from other schools or learning contexts. In addition, the media was used independently outside a fully controlled classroom setting, so differences in internet access, device quality, and user attention may have influenced the results.

There are also technical and instrument-related limitations. The medium depends on the OpenAI GPT API, and the behavior of the AI model may change when the model is updated. This means that future versions of the same medium may not always produce identical interactions. The SUS reliability result also needs further examination because the Cronbach's alpha value of 0.614 was below the conventional threshold. A larger and more homogeneous sample would help test whether this value reflects the instrument's consistency in this context or is mainly influenced by sample size and differences in students' digital experience.

4. Conclusion

This study developed principle-learn, an AI-based algorithm learning medium for Phase E Informatics, using the ADDIE model and a dual-layer design that combines personalized learning with Mediated Learning Experience (MLE). Personalized learning was implemented through content generation, runtime adaptation, and adaptive assessment, while MLE was translated into Socratic dialogue that guides students through

ISSN: 2797-3174

intentional interaction, meaning-making, transcendence, and competence. The usability evaluation with 22 tenth-grade students showed a mean SUS score of 77.39, placing the prototype in the Acceptable category; 72.7% of participants were in the acceptable range and 54.5% reached Good or Excellent ratings. These findings indicate that students generally accepted the medium and valued its personalization and dialogic support, although onboarding, technical consistency, and visual content still need improvement. Overall, this study provides an initial design framework and usability evidence for AI-based algorithm learning media, while future work should examine learning effectiveness with broader samples and more controlled classroom use.

Author Contributions

All authors contributed equally to the conception, design, data collection, analysis, and writing of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declaration of Conflicting Interests

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration on AI Use

The authors declare that artificial intelligence (AI) tools, specifically OpenAI GPT API, were used as part of the developed learning media. No AI tools were used in the writing or analysis of this manuscript.

Acknowledgement

The authors would like to thank the students and teachers who participated in this study, as well as the school administration for their support during the data collection process.

References

Andrzejewska, M., & Stolińska, A. (2022). Do structured flowcharts outperform pseudocode? Evidence from eye movements. *IEEE Access, 10*, 132965–132975. https://doi.org/10.1109/ACCESS.2022.3230981

Aripin, J. J., Suryana, Hendrayati, H., Sulistyowati, R., Muhamat, A. A., & Rafliansyah, F. M. (2026). AI integration in entrepreneurship education: A systematic review of the mediating role of self-efficacy. *Jurnal Pembelajaran, Bimbingan, dan Pengelolaan Pendidikan, 6*(4). https://doi.org/10.17977/um065.v6.i4.2026.4

Ashizuka, E. (2023). Who is like a teacher and mediator? *Mediated Learning Experience: International Practices and Advances, 1*(1). Feuerstein Institute.

Bhutoria, A. (2022). Personalized education and Artificial Intelligence in the United States, China, and India: A systematic review using a Human-In-The-Loop model. *Computers and Education: Artificial Intelligence, 3*, 100068. https://doi.org/10.1016/j.caeai.2022.100068

Branch, R. M. (2009). *Instructional design: The ADDIE approach*. Springer. https://doi.org/10.1007/978-0-387-09506-6

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & I. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). Taylor & Francis.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, 22. https://doi.org/10.1186/s41239-023-00392-8

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education, 210*, 104967. https://doi.org/10.1016/j.compedu.2023.104967

Du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon, 10*(21), e39630. https://doi.org/10.1016/j.heliyon.2024.e39630

Fortuna, A., Prasetya, F., Kaya, D., Raihan, M., Samala, A. D., Andriani, W., Rawas, S., Safitri, D., Criollo-C, S., & Nabawi, R. A. (2025). Artificial intelligence in personalized learning: A global systematic review of current advancements and shaping future opportunities. *Social Sciences & Humanities Open, 12*, 102114. https://doi.org/10.1016/j.ssaho.2025.102114

ISSN: 2797-3174

Gonda, D., Ďuriš, V., Tirpáková, A., & Pavlovičová, G. (2022). Teaching algorithms to develop the algorithmic thinking of informatics students. *Mathematics, 10*(20). https://doi.org/10.3390/math10203857

Ikhsanudin, I., Subali, B., Retnawati, H., & Istiyono, E. (2024). Estimation of Cronbach reliability based on sample size, gender, and grades. *International Journal of Evaluation and Research in Education (IJERE), 13*(2), 759–766. https://doi.org/10.11591/ijere.v13i2.24895

Kepmendikbudristek No. 56/M/2022 tentang Pedoman Penerapan Kurikulum dalam Rangka Pemulihan Pembelajaran. Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia.

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education, 20*(56). https://doi.org/10.1186/s41239-023-00426-1

Leacock, T. L., & Nesbit, J. C. (2007). A framework for evaluating the quality of multimedia learning resources. *Educational Technology & Society, 10*(2), 44–59. https://www.sfu.ca/~jcnesbit/articles/LeacockNesbit2007.pdf

Lin, C.-C., Huang, A. Y. Q., & Lu, O. H. T. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: A systematic review. *Smart Learning Environments, 10*, 41. https://doi.org/10.1186/s40561-023-00260-y

Mardeli, Sari, J. P., Setyaningsih, K., Fauzi, M., Fitri, E., Ballianie, N., & Novianti, R. (2025). Generative AI in personalized learning: A systematic review of implementation in Indonesia. *EDUKASIA: Jurnal Pendidikan dan Pembelajaran, 6*(2), 989–1002. https://doi.org/10.62775/edukasia.v6i2.1672

Pesovski, I., Santos, R., Henriques, R., & Trajkovik, V. (2024). Generative AI for customizable learning experiences. *Sustainability, 16*(7), 3034. https://doi.org/10.3390/su16073034

Pujakesuma, D., Ningrum, G. D. K., & Umami, A. A. (2024). Implementasi teknologi augmented reality dalam pengembangan media pembelajaran interaktif untuk siswa kelas X. *Jurnal Pembelajaran, Bimbingan, dan Pengelolaan Pendidikan, 4*(6). https://doi.org/10.17977/um065.v4.i6.2024.4

Tang, K. S., Cooper, G., Rappa, N., Cooper, M., Sims, C., & Nonis, K. (2024). A dialogic approach to transform teaching, learning & assessment with generative AI in secondary education: A proof of concept. *Pedagogies: An International Journal, 19*(3), 493–503. https://doi.org/10.1080/1554480X.2024.2379774

Vargas-Arteaga, J., & Gravini-Donado, M. L. (2024). Evaluating the usability of a gamified virtual course designed to teach cultural heritage. *International Journal of Emerging Technologies in Learning, 19*(4), 48–57. https://doi.org/10.3991/ijet.v19i04.45053

Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33–35. https://doi.org/10.1145/1118178.1118215

Zakariya, Y. F. (2022). Cronbach's alpha in mathematics education research: Its appropriateness, overuse, and alternatives in estimating scale reliability. *Frontiers in Psychology, 13*, 1074430. https://doi.org/10.3389/fpsyg.2022.1074430

Zehr, J. M. (2023). The master teacher. *Mediated Learning Experience: International Practices and Advances, 1*(1). Feuerstein Institute.

ISSN: 2797-3174