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Developing an AI-assisted multimodal critical reading instructional model to enhance problem-solving and metacognitive literacy

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Abstract: The low learning outcomes in multimodal critical reading across 12 Study Programs in the Indonesian Language Course constitute a major issue among four universities in Bali. An effort made to address the low level of students' critical thinking skills was the development of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) model. This model was designed to enhance students' critical thinking abilities in analytically, evaluatively, and reflectively understanding multimodal texts. This study employed the Research and Development (R&D) method, with the model design stages referring to the ADDIE framework. The AI-OBHL model comprises six main syntax stages: (1) Determination of Learning Outcomes, (2) Exploration of Problems in the Text, (3) Formulation of Hypothesis, (4) Testing of Hypothesis, (5) Sharing and Response to Arguments, and (6) Reflection of Learning Outcomes. The results of the model's content and construct validity showed that Aiken's V values were highly valid. The effectiveness of the OBHL model was demonstrated through a significant improvement in students' critical reading skills of multimodal text, categorized as a large effect, compared to the control group, which showed only a small to moderate effect. These findings reinforce the urgency of implementing AI-OBHL as a strategic innovation in multimodal-based critical reading learning.

Keywords: *AI-Assisted learning, Critical reading, Metacognitive literacy, Multimodal text, Problem-solving.*

1. Introduction

The paradigm of twenty-first-century education has reformulated the concept of literacy as a multidimensional competence that integrates critical, creative, metacognitive, and problem-solving abilities essential for navigating the complexities of the digital information ecosystem [1-3]. In this context, critical reading was no longer confined to understanding linear texts but had evolved into the ability to interpret multimodal composition texts that combined verbal, visual, auditory, and interactive elements [4, 5]. This shift gave rise to the concept of critical multimodal literacy, which positions readers as interpreters who analyze the ideological, visual, and algorithmic layers of meaning embedded in digital media [6].

The rapid integration of artificial intelligence (AI) in education also revolutionized literacy practices, creating new forms of interaction, adaptive learning, and cognitive reflection [7, 8]. In AI-mediated learning ecosystems, literacy was no longer limited to mastery of reading and writing skills but also encompassed understanding how algorithms, data visualizations, and digital multimodality shaped thinking patterns, perceptions, and decision-making. Consequently, AI-assisted critical multimodal reading became a core literacy skill for developing higher-order thinking and reflective reasoning in the era of intelligent learning systems [9, 10].

Although global scholarly awareness of the importance of multimodal literacy has continued to rise, challenges in Indonesia remain significant. The Program for International Student Assessment 2022 indicated that Indonesia's reading literacy score (359) remains far below the OECD average (476),

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reflecting weak critical and reflective reasoning skills among students [11]. A similar pattern appears in higher education. Diagnostic evaluations of twelve study programs across four universities in Bali, Universitas PGRI Mahadewa Indonesia, Universitas Pendidikan Ganesha, Universitas Warmadewa, and Universitas Mahasaraswati, show low levels of analytical reasoning, inferential ability, and metacognitive reflection.

This condition indicated that university students were not yet fully able to critically interpret multimodal information, regulate their thinking strategies, or apply reflective reasoning to solve complex problems. Pedagogical practices had long focused on content comprehension rather than exploring meaning structures and reflective thinking [12-14]. In the digital context, problem-solving ability and self-regulated reasoning became key indicators of twenty-first-century learning needs [15-18]. For this reason, a learning model that connects critical multimodal reading with the development of reflective reasoning strategies and problem-solving skills, supported by AI technologies, was urgently needed [19-21].

A number of studies have examined the relationship between multimodal literacy, digital learning, and critical thinking skills [22-24]. Other studies highlighted the role of AI in enhancing cognitive reflection through adaptive feedback and generative tutoring systems [8, 25-27]. However, research in the Asian region remained dominated by technology development, implementation aspects, and personalization of learning systems [27-29]. Empirical studies in Asia generally focus on user acceptance of AI tools and descriptive analyses of implementation processes [30, 31]. Meanwhile, strong empirical evidence regarding the effectiveness of AI-assisted multimodal reading interventions in improving problem-solving skills and metacognitive literacy remains limited. In Southeast Asia, research findings showed that problem-based learning and multimodal instruction could enhance learning engagement and conceptual understanding [23, 32, 33]. Meanwhile, strong empirical evidence regarding the effectiveness of AI-assisted multimodal reading interventions in improving problem-solving skills and metacognitive literacy remains limited. In Southeast Asia, research findings showed that problem-based learning and multimodal instruction could enhance learning engagement and conceptual understanding [33-36]. This gap demonstrated the absence of a pedagogical model integrating AI-assisted multimodal reading, problem-solving literacy, and metacognitive literacy within a coherent learning framework.

To address this gap, the present study developed and validated the AI-Assisted Outcome-Based Hypothesis Learning Model (AI-OBHL) as an innovative pedagogical framework that synthesizes Outcome-Based Teaching and Learning (OBTL) and Hypothesis-Driven Learning (HDL) with AI-Assisted Learning support. This model introduced three key innovations. First, an integrative design that connected hypothesis formulation, multimodal interpretation, and metacognitive reflection within a single learning cycle. Second, AI-based scaffolding that utilized artificial intelligence to provide adaptive feedback, automated multimodal text analysis, and reflective dialogue to strengthen learners' metacognitive awareness. Third, a learning-outcome-oriented framework that ensured all instructional activities and assessments were aligned with twenty-first-century competencies such as critical, creative, adaptive, and ethical thinking.

Theoretically, this study extended the discourse on AI-mediated multimodal literacy pedagogy by integrating cognitive, reflective, and technological dimensions within an outcome-based learning framework. Practically, it offered a substantial contribution to higher education in Indonesia by presenting an empirically tested model capable of improving problem-solving literacy and metacognitive literacy through AI-assisted critical multimodal reading instruction. Thus, this study not only addressed the challenge of low reflective literacy in the local context but also contributed globally to the development of adaptive twenty-first-century literacy pedagogy that emphasized the integration of learning outcomes, reflective thinking, and AI-enhanced learning [37, 38].

2. Method

2.1. Research Design

This study employed a Research and Development (R&D) design by adapting the ADDIE model. The ADDIE model consisted of five systematic stages selected based on its structured and iterative workflow, which was suitable for producing a theoretically grounded and empirically tested learning model. The implementation of ADDIE began with a needs and problem analysis related to the critical reading of multimodal texts across four universities in Bali. The analysis was conducted through interviews and initial observations. The findings served as the basis for formulating a model design relevant to the higher-education learning context.

The design stage focused on developing the initial prototype of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) model, which included learning syntax, instructional tools, and evaluation instruments for problem-solving and metacognitive literacy. The AI-OBHL model was developed through formative evaluations consisting of one-to-one evaluations, small-group evaluations, and field trials. Feedback from each stage was used to refine the instructional components of the model.

The implementation of the AI-OBHL model was carried out through a quasi-experimental study using a pretest–posttest non-equivalent control group design. The final stage of the trial involved assessment using MANOVA and effect size analyses to measure the model's effectiveness.

2.2. Research Sites and Trial Subjects

The needs and problem analysis were conducted at four higher education institutions: Universitas PGRI Mahadewa Indonesia, Universitas Pendidikan Ganesha, Universitas Warmadewa, and Universitas Mahasaraswati. These institutions were selected based on the uniform implementation of Outcome-Based Education (OBE) in the Indonesian language courses.

The study involved two groups of subjects: (1) expert validators for the model validation process, and (2) students for the effectiveness trial. The expert team consisted of three specialists recruited based on their expertise and publication track record in language education and instructional design. These included an expert in instructional design, an expert in technology-enhanced Indonesian language learning, and an expert in critical literacy. The validation procedure was conducted in two stages: content validation and construct validation, using Aiken's V formula.

The total number of student participants across the four universities was 182. However, the effectiveness trial utilized only two classes: Class C9 of the Management Study Program at Universitas Warmadewa and Class A of the Economics Education Study Program at Universitas PGRI Mahadewa Indonesia.

Table 1.
Composition of Trial Subjects by Group and Gender.

Class	Group	Learning Model	Number of Participants (n)	Female (%)	Male (%)
C9 Management study program	Experiment	AI-Assisted Learning Based OBHL Model	49	31	18
An Economic Education Study Program	Control	Group-Based Discussion Learning Model	40	13	27

Group division was carried out using a matching technique with two equivalence indicators, namely the students' average scores in the previous Indonesian Language course and their pre-test scores on multimodal critical reading skills.

2.3. Data Collection Procedure

The study was conducted over one semester in the Indonesian Language course, with each meeting lasting 100 minutes. The data collection procedure consisted of two main components: an expert validation questionnaire and a learning outcome test.

The validation questionnaire was used to assess the content and construct validity of the model, while the learning outcome test was used to measure the model's effectiveness. The expert validation instrument was adapted to the context of the AI-OBHL model. The questionnaire consisted of 15 statement items using a four-point Likert scale: (1) not valid, (2) moderately valid, (3) valid, and (4) highly valid.

The validation process involved three experts: a learning design expert, an Indonesian language education expert, and a critical literacy expert. In addition to providing quantitative scores, the experts were also asked to give qualitative feedback in the form of comments, critiques, and suggestions for improvement for each indicator.

2.4. Data Analysis Procedure

The data analysis in this study used a mixed methods approach, combining qualitative and quantitative analyses to produce more comprehensive and interpretatively valid results. Qualitative data in the form of comments, critiques, and suggestions from content and construct validation experts were analyzed thematically to refine the model design prior to empirical testing.

Quantitative data included the model validation results and the learning effectiveness test. The construct validity of the AI-OBHL model was calculated using Aiken's V formula. Before hypothesis testing, prerequisite tests were conducted, namely a normality test and a homogeneity test. The effectiveness of the OBHL model was tested using MANOVA statistical analysis. All statistical analyses were performed using SPSS version 26.

The interpretation of effect sizes followed Cohen's [39] criteria: 0.1 = small effect, 0.5 = medium effect, 0.8 = large effect.

3. Findings

3.1. The Design of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) Model in Critical Reading of Multimodal Texts

The AI-Assisted Outcome-Based Hypothesis Learning (OBHL) model for teaching critical reading of genre-based multimodal texts consists of a sequence of structured activities designed as an operational guide for classroom learning. This activity structure is divided into a series of core stages, each representing a key step in the learning process. The model comprises six instructional syntaxes: (1) *Determination of Learning Outcomes*, (2) *Exploration of Problems in the Text*, (3) Formulation of Hypotheses, (4)

Testing of Hypothesis, *(5) Sharing and Response Argument*, dan *(6) Reflection of Learning Outcomes.*

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Table 2.
Syntax of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) Model in the Teaching of Critical Reading of Multimodal Texts.

Phase	Description of Learning Activities	Problem-Solving and Metacognitive Competencies
Phase 1: *Determination of Learning Outcomes*	The lecturer, assisted by the AI system, established specific and measurable learning outcomes related to students' critical and reflective reading abilities of multimodal texts. The AI Assistant generated adaptive learning objectives based on initial data and students' reading profiles. Students explored examples of editorial texts through an AI-curated database to identify multimodal compositions (verbal, visual, spatial, and auditory). The lecturer emphasized that the goal of critical reading was not merely to understand the content but also to evaluate the reliability, bias, and persuasive effects of multimodality.	Identified problems through clarification of learning objectives. Conducted initial metacognitive planning regarding what, why, and how they learned.
Phase 2: *Exploration of the Problem in the Text*	Students, guided by the AI Assistant, analyzed multimodal texts to identify the main issues, points of view, and informational bias through interactive pre-reading activities. The AI highlighted the relationship between verbal and visual modes so that students could visualize how meaning was constructed. The lecturer facilitated guiding questions generated by the AI to deepen the interpretation of the text.	Performed cognitive monitoring by tracking their understanding and recognizing areas of confusion. Strengthened problem-solving skills by conducting interpretations through guided multimodal analysis.
Phase 3: *Formulation of Hypothesis*	Students formulated interpretive hypotheses based on the results of text analysis with support from the AI brainstorming feature. The AI helped students refine their hypotheses by tracing patterns of linguistic, structural, and visual evidence. Students, working in groups, determined the most relevant hypothesis with the support of the AI's analytical summary.	Engaged in analytical problem solving by generating and comparing logical alternative interpretations. Exercised metacognitive control by evaluating the quality and rationality of the hypotheses they formulated.
Phase 4: *Testing of Hypothesis*	Students tested their hypotheses by searching for supporting and contradicting data using AI-based search tools. The AI helped evaluate the validity of arguments, detect logical fallacies, and visualize data reliability. Students conducted intertextual comparisons based on AI recommendations and performed critical annotations on verbal and visual modes. The lecturer facilitated the verification process using critical discourse theory and visual semiotics.	Carried out evaluative problem solving by assessing the strength of arguments and the credibility of evidence. Engaged in metacognitive monitoring by adjusting reading strategies based on AI feedback and self-reflection.
Phase 5: *Sharing and Response Argument*	Each group presented the results of their analysis using AI-supported presentation media. The AI summarized the main arguments from various groups to facilitate comparative discussions. Students conducted a peer review using critical question prompts generated by the AI. The lecturer moderated a reflective discussion that emphasized evidence-based argumentation and logical reasoning.	Conducted collaborative problem solving by constructing and sustaining arguments within an academic discussion context. Practiced metacognitive evaluation by developing awareness of the strength of reasoning and clarity of communication.
Phase 6: *Reflection of Learning Outcomes*	Students wrote reflective essays or learning logs with AI support. The AI provided personalized metacognitive feedback regarding students' reading processes, thinking strategies, and learning outcomes. The lecturer synthesized the reflection results to determine the direction of subsequent learning improvements.	Performed metacognitive reflection by assessing their learning strategies and individual achievement outcomes.

3.2. Validity of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) Model in Multimodal Critical Reading Learning

The development stages began with a validation phase conducted through expert judgment. The model's validity involved both construct and content validity. Each type of validity was assessed by three experts, consisting of experts in Indonesian language education, critical literacy, and educational technology.

Table 3.
Construct Validity of AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) Model in Critical Reading Learning of Multimodal Texts.

Aspect	Indicator	V	Category [40]
Theoretical Alignment	The model was aligned with contemporary theories of critical reading and metacognition.	1.00	Highly Valid
	It integrated AI-assisted scaffolding in accordance with outcome-based learning principles.	0.89	Highly Valid
Learning Model Syntax	The AI-OBHL instructional syntax was structured systematically and practically to support multimodal critical reading.	1.00	Highly Valid
	The sequence of learning steps was logical, facilitating the formation, testing, and reflection of hypotheses with AI-generated feedback.	0.89	Highly Valid
Social System	It encouraged active collaboration among students through AI-facilitated discussions and exploration.	1.00	Highly Valid
	AI functioned as an adaptive learning mediator that promoted participation from all students.	1.00	Highly Valid
	The model accommodated students' diverse abilities through adaptive recommendations and difficulty levels generated by AI analytics.	1.00	Highly Valid
Reaction Principles	AI provided real-time feedback that helped students independently validate their hypotheses.	0.89	Highly Valid
	It promoted the strengthening of positive learning behaviors through AI-driven reflective recommendations.	1.00	Highly Valid
	The AI Assistant provided metacognitive prompts to help students monitor their thinking processes.	0.89	Highly Valid
Support System	The model was equipped with an interactive AI-based digital learning guide that was easily accessible to both instructors and students.	1.00	Highly Valid
	Technical support and an online learning system compatible with the AI Assistant were available.	0.89	Highly Valid
Instructional and Accompanying Impact	The model effectively guided students in analyzing and evaluating multimodal texts critically using AI tools.	1.00	Highly Valid
	It fostered social-emotional skills and collaborative abilities as students shared their AI-facilitated analyses.	0.78	Valid
	The model enhanced students' problem-solving abilities and metacognitive awareness through adaptive feedback.	1.00	Highly Valid
		0.95	Highly Valid

The results of the construct validity test of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) model in multimodal critical reading instruction showed that the model had a very high level of validity, with an average Aiken's V score of 0.95. The AI-OBHL model was determined to meet the aspects of theoretical validity, instructional syntax, social system, reaction principles, supporting system, as well as instructional effects and nurturant effects.

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Table 4.
Content Validity of the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) Model in Critical Reading Learning of Multimodal Texts.

Aspect	Indicator	V	Category [40]
Curriculum Alignment	The model was aligned with the competency framework for critical reasoning skills and multimodal literacy in the compulsory Indonesian Language course.	0.89	Highly Valid
	The model supported the learning objectives of critical reading through the integration of AI-based scaffolding and adaptive feedback.	0.89	Highly Valid
Suitability with Student Characteristics	The model accommodated students' cognitive strategies in analyzing multimodal texts through AI-assisted guidance.	0.89	Highly Valid
	It promoted exploratory learning personalized by AI according to students' learning styles.	0.89	Highly Valid
	The model strengthened multiperspective reading skills and reflective reasoning through AI-based comparative text analysis.	1.00	Highly Valid
Clarity of Learning Indicators	The indicators explicitly measured students' problem-solving and metacognitive abilities with the support of AI analytical tools.	0.89	Highly Valid
	The indicators assessed critical understanding through the processes of hypothesis formulation, AI-assisted validation, and evidence-based testing.	0.89	Highly Valid
	The evaluation stages integrated an AI-assisted assessment to monitor the achievement of problem-solving and metacognitive indicators in critical reading.	0.89	Highly Valid
Validity of Materials and Learning Resources	The reading materials were enriched with AI-curated sources to develop students' problem-solving abilities and metacognitive reflection.	0.89	Highly Valid
	The model utilized AI to connect intertextual sources and verify hypotheses in multimodal texts.	1.00	Highly Valid
	The model integrated various genres of multimodal texts enriched with AI annotation and visualization features.	0.89	Highly Valid
Alignment with 21st Century Learning Skills	It strengthened problem-solving and metacognitive skills through AI support.	1.00	Highly Valid
	It fostered collaboration and AI-based peer feedback in discussing and refining text analysis results.	1.00	Highly Valid
	It encouraged creativity and evidence-based argument construction through AI-generated prompts.	1.00	Highly Valid
	It developed communication skills and digital literacy through discussion forums, debates, and presentations.	0.89	Highly Valid
		0.93	Highly Valid

The results of the content validity analysis for the AI-Assisted Outcome-Based Hypothesis Learning (AI-OBHL) model in the context of critical reading of multimodal texts indicated a "Highly Valid" category, with an average Aiken's V score of 0.93. This outcome reflects that the AI-OBHL model demonstrates high feasibility in terms of curriculum alignment, student characteristics, learning indicators, learning materials, and relevance to 21st-century skills.

3.3. Effectiveness Text

To measure the effectiveness of the AI–Outcome Based Hypothesis Learning (OBHL) model in multimodal critical reading for improving university students' problem-solving and metacognitive abilities, a trial was conducted in two classes: Class C9 of the Management Study Program at Universitas Warmadewa and Class A of the Economics Education Study Program at Universitas PGRI Mahadewa Indonesia. Before the study was carried out, an equivalence test of the pre-test results was first administered. This equivalence test was statistically analyzed to ensure that both groups had comparable initial ability levels prior to receiving the experimental treatment.

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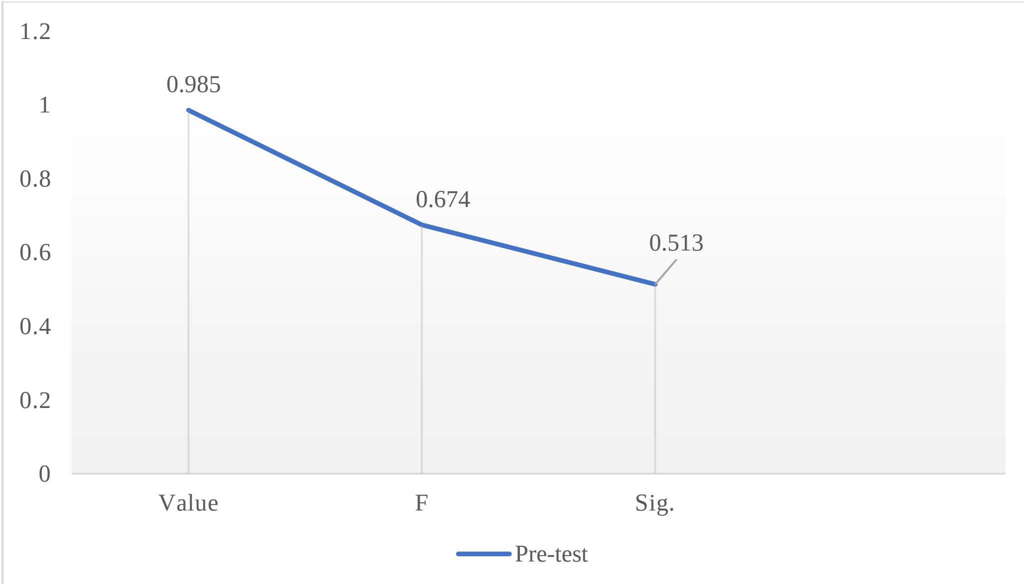

Figure 1.
The Results of the Pre-Test Equivalence Test.

Based on the results of the initial equivalence test using MANOVA on the two dependent variables, problem-solving ability and metacognitive ability, the analysis yielded Wilks' Lambda = 0.985, F = 0.674, and p = 0.513. The significance value greater than 0.05 indicated that there was no significant difference between the experimental and control groups on the pre-test scores of both variables. Both groups had equivalent initial abilities in problem solving and metacognition before the treatment was administered. These data met the assumption of initial equivalence, confirming that both groups were appropriate to be used as research samples for the subsequent treatment phase.

Table 5.
Descriptive Statistics.

	Class	Mean	Std. Deviation	N
Problem-Solving	Control	72.72	2.264	40
	Experiment	75.02	2.116	49
Metacognitive	Control	75.52	2.641	40
	Experiment	77.76	2.634	49

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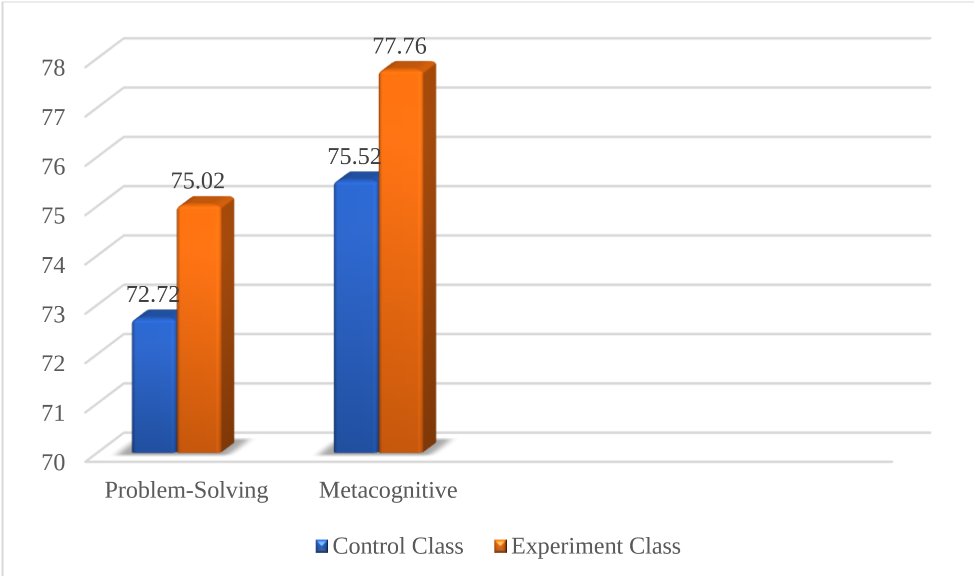

Figure 2.
Descriptive Statistics.

The mean score of problem-solving ability in the control class was 72.72 with a standard deviation of 2.264, while the experimental class achieved a higher mean score of 75.02 with a standard deviation of 2.116. This indicates that students in the experimental class demonstrated better problem-solving abilities compared to those in the control class. The metacognitive ability score in the control class was 75.52 with a standard deviation of 2.641, whereas the experimental class scored 77.76 with a standard deviation of 2.634. These results show that the experimental class also had higher metacognitive ability than the control class.

3.3.1. Tests of Normality

The normal distribution test was conducted using SPSS version 27.0 with the Shapiro–Wilk statistical method because the sample size was fewer than 50.

Table 6.
Results of the Normality Test.

Variable	Class	Shapiro-Wilk		
		Statistic	**df**	**Sig.**
Problem-Solving	Control	0.965	40	0.251
	Experiment	0.957	49	0.071
Metacognitive	Control	0.951	40	0.081
	Experiment	0.966	49	0.162

Based on the results of the Shapiro–Wilk normality test, the significance values for all variables were greater than 0.05. Thus, the data on problem-solving and metacognitive abilities in both the experimental and control groups were normally distributed. The normality assumption was met, allowing the MANOVA analysis to proceed.

3.3.2. Homogeneity of Variance Test

The homogeneity of variance test was conducted on the data for problem-solving and metacognitive abilities, both jointly and separately. The overall homogeneity analysis used Box's M test, calculated with the assistance of SPSS software.

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Table 7.
Results of Box's M Homogeneity Test.

Box's M	**0.790**
F	0.257
df1	3
df2	3727078.020
Sig.	0.857

After the homogeneity test using Box's M, the data were further examined for individual homogeneity using Levene's test with the assistance of SPSS version 27.0.

Table 8.
Results of Levene's Homogeneity Test.

Variable	**Levene Statistic**	**df1**	**df2**	**Sig.**
Problem-Solving	0.219	1	87	0.641
Metacognitive	0.044	1	87	0.835

The results of Box's M test showed a significance value of 0.857, which was greater than the 0.05 significance threshold. Likewise, Levene's test indicated that the significance value for problem-solving ability was 0.641 and for metacognitive ability was 0.835. These findings demonstrated that all significance values in both Box's M and Levene's tests exceeded the 0.05 threshold. Therefore, it can be concluded that the research data had homogeneous variances across both groups, whether tested simultaneously or separately for each variable.

3.3.3. Effects on the Two Dependent Variables

The correlation analysis between the dependent variables was conducted on two datasets, namely the problem-solving and metacognitive abilities of students enrolled in the Indonesian Language course using the AI–Outcome Based Hypothesis Learning (AI-OBHL) model, and those of students who learned through the Group-Based Discussion approach.

Table 9.
Results of the Test of Effects on Dependent Variables.

		Problem-Solving	**Metacognitive**
Problem-Solving	Pearson Correlation	1	0.493
	Sig. (2-tailed)		0.001
	N	89	89
Metacognitive	Pearson Correlation	0.493	1
	Sig. (2-tailed)	0.001	
	N	89	89

The correlation analysis results in the table above showed a positive, moderate relationship between problem-solving ability and metacognitive ability. Metacognitive skills, such as awareness of thinking, strategic planning, and self-evaluation, contributed significantly to the improvement of problem-solving skills when students engaged with the AI–Outcome Based Hypothesis Learning (AI-OBHL) model in multimodal critical reading. The correlation results indicated a positive relationship; therefore, the data analysis was continued using the MANOVA test.

Table 10.
Results of the MANOVA Test for the Dependent Variables.

		F	**Sig.**
Variable	Problem-Solving	24.328	0.001
	Metacognitive	15.749	0.001

Based on the table above, the results of the MANOVA test using SPSS version 27.0 were as follows:

1. An F-value of 24.328 with a significance level (Sig.) = 0.001 < 0.05 indicated that there was a significant difference in problem-solving ability between students who learned using the AI–Outcome Based Hypothesis Learning (AI-OBHL) model and those who learned using the Group-Based Discussion model.
2. An F-value of 15.749 with a significance level (Sig.) = 0.001 < 0.05 indicated that there was a significant difference in metacognitive ability between the two groups taught using the AI–Outcome Based Hypothesis Learning (AI-OBHL) model and the Group-Based Discussion model.
3. There was a significant difference in both problem-solving and metacognitive abilities between students who used the AI–Outcome Based Hypothesis Learning (AI-OBHL) model and those who used the Group-Based Discussion model, with an F-value of 14.546 and a significance level (Sig.) of 0.001, which is less than 0.05.

4. Discussion

The AI–Outcome–Based Hypothesis Learning (AI-OBHL) model developed in this study represents an instructional innovation that integrates Outcome-Based Education (OBE), Hypothesis-Driven Inquiry, and Artificial Intelligence (AI)-supported scaffolding. The model was designed to strengthen students' problem-solving and metacognitive abilities in critically and reflectively interpreting Indonesian multimodal texts. AI-OBHL aligns with the framework of AI-based reflective learning, which emphasizes that the integration of artificial intelligence in learning enables adaptive and personalized processes of reflection and metacognition [41]. Similarly, AI-driven feedback systems significantly enhance students' metacognitive awareness through reflective feedback-based interventions [42]. AI-driven adaptive feedback and analytics also improved metacognitive skills by providing reflective prompts, guiding evidence exploration, and facilitating hypothesis verification [43].

The validity of the AI-OBHL model was supported by a design grounded in constructive alignment, which emphasized coherence among learning objectives, instructional strategies, and assessment [44]. In practice, AI-OBHL effectively connected learning goals with activities that stimulated problem-solving and metacognitive skills, thereby meeting the demands of 21st-century education focused on critical thinking and digital literacy [45]. The model demonstrated high relevance in the context of multimodal text reading. Readers of multimodal texts no longer relied solely on linguistic features; such texts required the interpretation of multiple representational modes, visual, spatial, and gestural, that were integrated into a unified meaning structure. Critical reading of multimodal texts, therefore, required the ability to integrate information from different semiotic channels, a skill central to contemporary digital literacy [46]. AI-OBHL adopted a hypothetico-deductive approach beginning with hypothesis formulation, followed by testing through the exploration of textual evidence. This strategy strengthened cognitive structures and trained both problem-solving and metacognitive skills. AI as a learning assistant supported adaptive feedback and problem-solving cues, which enhanced students' metacognitive monitoring. AI-generated scaffolding also promoted deeper cognitive engagement and improved the quality of critical thinking processes during analytical tasks. Moreover, the hypothesis-validation process within AI-OBHL encompassed multimodal dimensions, broadening critical literacy from verbal text analysis to the simultaneous interpretation of visual and contextual meanings. The dialogic component of AI-OBHL also played a crucial role in achieving learning outcomes. Group discussions, multiperspective reading, and collective reflection supported by AI-assisted scaffolding provided opportunities for students to negotiate meaning and develop critical stances toward texts. This aligned with dialogic pedagogy, which emphasized the importance of active learner engagement in meaning-making through social interaction [47].

The effectiveness test demonstrated a positive correlation between problem-solving and metacognitive abilities, supporting the theoretical perspective that metacognition acts as a mediator for problem-solving competence [48]. This indicated that the implementation of the AI-OBHL model contributed not only to the improvement of individual skill domains but also to the dynamic integration of mutually reinforcing aspects. Enhanced metacognitive capacity awakened awareness to monitor, evaluate, and regulate learning processes [49]. These metacognitive abilities directly contributed to strengthened problem-solving skills, particularly when students engaged in evidence analysis and hypothesis formulation. The interconnectedness between problem-solving and metacognitive abilities in AI-assisted critical reading instruction thus reflected a reciprocal relationship essential for effective multimodal text comprehension.

The implementation of the OBHL model in practice encountered several challenges. First, its success heavily depended on lecturers' readiness to facilitate dialogic and multimodal instruction. Second, students' reliance on AI as a learning mediator risked creating overreliance, leading to reduced autonomous critical reasoning when scaffolding was not gradually withdrawn. Therefore, AI-assisted instruction needs to implement a gradual-release mechanism to ensure the internalization of metacognitive strategies and critical reasoning skills [50-52]. Third, effectiveness depended on infrastructure readiness, the quality of AI-curated multimodal corpora, and instructors' ability to design tasks that optimally utilized AI feedback. Structural barriers, such as limited time allocation and dense curricula, also posed challenges. The integration of multimodal literacy into the curriculum remained constrained by the dominance of conventional textual instruction [53, 54]. These conditions indicate the need for systemic support to provide space for innovative instructional approaches such as AI-OBHL to foster students' problem-solving and metacognitive literacy on a sustained basis.

5. Conclusion

The development of the AI Assistant–Outcome-Based Hypothesis Learning (AI-OBHL) model in teaching critical reading of multimodal texts demonstrated positive outcomes consistent with the demands of 21st-century literacy education. From a design perspective, the model was systematically constructed through structured learning phases oriented toward enhancing problem-solving and metacognitive competencies. Each phase actively engaged students in observing, formulating hypotheses, examining evidence, revising arguments, and synthesizing ideas based on the understanding of textual modalities with the support of AI as a learning assistant. The construct and content validity of the OBHL model showed high results, both in terms of coherence among model components and learning objectives and in its practical feasibility. These findings confirmed that the AI-OBHL model possessed strong theoretical and didactic foundations. In terms of effectiveness, the AI-OBHL model proved to be significantly more successful in improving students' critical reading skills compared to conventional instructional models. The large correlation values indicated strong and meaningful pedagogical impact. The model was also highly relevant to evidence-based learning, higher-order thinking skills, and metacognitive literacy in addressing the complexity of multimodal texts.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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