

AI-Assisted Multimodal Discourse Analysis Learning Model to Enhance Critical Literacy Skills

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ABSTRACT

Background and Objectives: Critical literacy, a key four C's (4C) competencies, is essential for navigating digital complexities. In today's context, critical literacy goes beyond understanding texts, involving the ability to interpret meanings across modes, uncover underlying ideologies, and critically evaluate the intent and credibility of persuasive or manipulative messages. Yet discourse analysis in Indonesian universities remains confined to linear texts, limiting engagement with multimodal discourse. Emerging artificial intelligence (AI) offers promising opportunities, though its pedagogical applications remain underexplored. AI has the potential to serve as a learning assistant, capable of performing keyword extraction or topic modeling, bias analysis, image-text relation mapping, and sentiment analysis. Despite recognition of multimodal literacy and AI-assisted learning, structured pedagogical models are absent. This study introduces Discourse Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI) model, an AI-integrated model to scaffold reflection, enhance multimodal literacy, and enrich higher education.

Methodology: This study employed a research and development (R&D) design involving experts, lecturers, and 120 fourth- and fifth- semester students from four universities in Bali. Data collection focused on validity, practicality, and effectiveness. Model validation was conducted by five experts using Aiken's V, while practicality and effectiveness were examined through Likert-scale questionnaires and pre-post testing. Data analysis employed a mixed-methods approach, combining ANCOVA, effect size estimation, and thematic analysis to ensure comprehensive triangulation.

Results: The DISCERN-AI model comprises six phases, systematically designed as an operational framework for facilitating multimodal analysis in the classroom. Construct validity testing indicated a very high level, V value of 0.88, while content validity analysis yielded a mean coefficient of 0.86, categorized as very valid. Practicality testing by lecturers of the Discourse Analysis course further confirmed the model's

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applicability, obtaining a mean score of 3.90, categorized highly practical. Effectiveness was evaluated through effect size analysis using Cohen's *d*. Comparison of posttest results between experimental and control groups produced an effect size 1.32, which falls into the large category.

Discussions: The DISCERN-AI model brings together critical pedagogy, multimodal discourse analysis, and AI-assisted learning through responsive navigation and multimodal triangulation. Findings from empirical testing show high levels of construct and content validity ($V = 0.88$ & $V = 0.86$), strong practicality ($M = 3.90$), and notable effectiveness (Cohen's $d = 1.32$). These results highlight the model's solid potential to foster critical literacy skills in higher education, aligning with the growing global emphasis on technology supported critical pedagogy. This model guided students to examine textual representations across various modes—verbal, visual, and audiovisual—thereby fostering their interpretive, evaluative, and synthetic skills.

Conclusions: The DISCERN-AI model demonstrates strong theoretical validity, practical feasibility, and pedagogical effectiveness in enhancing students' multimodal critical literacy. Aligned with critical and multimodal discourse analysis frameworks and 21st-century competencies, the model contributes to theories of multimodal and critical digital literacy. Therefore, DISCERN-AI can be positioned as an innovative pedagogical model that addresses the demands of critical literacy in the digital era. The model also provides conceptual contributions to the theories of multimodal literacy and critical digital literacy.

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Introduction

21st-century education requires mastery of the four C's (4C) competencies, with critical literacy as a core skill for filtering, interpreting, and critiquing the flow of digital data and information (Kain et al., 2024). Critical literacy now encompasses the ability to connect meanings across modes to analyze ideologies, as well as to identify tendencies and the credibility of messages that are often packaged persuasively or manipulatively. Alongside the development of communication technologies, discourse increasingly appears in multimodal forms through combinations of text, visuals, audio, audiovisuals, gestures, and symbols that simultaneously construct meaning (Liu et al., 2024; Rahmanu & Molnár, 2024). However, the tendency in discourse analysis learning at Indonesian universities remains limited to linear texts, resulting in students often struggling to detect framing, visual bias, and ideological rhetoric in multimodal

texts. Simanjuntak et al. (2025) confirmed the low level of critical literacy among student in Indonesia, particularly in evaluating complex information. Preliminary interviews with lecturers and students at several universities in Bali, such as Universitas Pendidikan Ganesha, Universitas PGRI Mahadewa Indonesia, Universitas Mahasaraswati, and Institut Pendidikan dan Teknologi Markandeya also revealed the limited use of multimodal, artificial intelligence (AI)-based critical learning strategies in reading social media discourse and political advertisements. This condition highlights the need for a multimodal discourse analysis learning model. Simanjuntak et al. (2025) emphasized the urgency of technology-driven multimodal critical literacy as a response to disinformation, fake news, and post-truth politics.

On the other hand, the emergence of AI opens new opportunities to strengthen learning practices (Almaiah et al., 2022). AI has the potential to serve as a learning assistant, capable of performing keyword extraction or topic modeling, bias analysis, image–text relation mapping, and sentiment analysis. In addition, AI can provide automatic feedback on students’ analyses, so that lecturers’ roles are no longer limited to delivering materials, but rather focus on facilitating critical discussions and strengthening academic reflection (Owan et al., 2023). Nevertheless, the use of AI in pedagogical contexts, particularly in multimodal discourse analysis learning, remains relatively limited and has not yet been formulated into a structured and tested learning model.

The significance of multimodal literacy and the incorporation of digital technologies in education has been widely acknowledged. Dressen-Hammouda and Wigham (2022) introduced an evaluative framework for assessing multimodal literacy within academic and professional contexts, while Liu et al. (2024) validated a scale for generative AI literacy in multimodal composition. Tzirides et al. (2024) reported that the combination of human and AI roles can enhance literacy in education, while Tan et al. (2023) emphasized teachers’ challenges in integrating multimodal literacies with digital technology. However, these studies have not explicitly developed an AI-based multimodal discourse analysis learning model as scaffolding for critical reflection in higher education.

Based on these conditions and needs, this study considered it essential to develop an AI-integrated multimodal discourse analysis learning model as a learning assistant. The model, referred to as Discourse Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI), was developed to address the gap between the growing demand for multimodal critical literacy and the constraints of traditional teaching methods. Its theoretical foundation draws on Fairclough’s, critical discourse analysis, multimodal discourse analysis, along with key principles of AI-supported learning and critical pedagogy, which highlight the role of technology in fostering critical literacy. AI has the potential to serve as a learning assistant by providing scaffolding based on the principles of adaptive feedback, guided inquiry, and evidence-based reasoning. Through these mechanisms, AI can support students in identifying patterns, validating information, and reflecting critically on multimodal texts. Through this model, students are encouraged to build essential critical capacities, including the ability to interpret, analyze, evaluate, and reflect on ideologies or underlying perspectives present in multimodal discourse. Importantly, the integration of AI within the model is not intended to diminish students’ active role in the learning process, but rather to serve as a complementary tool that promotes reflection, dialogue, and the development of critical awareness.

Review of Literature

Artificial Intelligence (AI) in Education

The rapid advancement of AI has contributed significantly to the field of education, particularly through adaptive, personalized, and data-driven learning approaches (Wang et al., 2024). AI can function as a cognitive partner that supports interactive learning by providing instructional materials tailored to learners' levels of difficulty and individual needs (Goyal, 2025). Intelligent tutoring systems, which employ natural language processing (NLP) algorithms and machine learning techniques, have been shown to enhance both foundational literacy and digital literacy competencies. However, most current AI research remains focused on linear text processing and individualized adaptive learning, while the application of AI in discourse analysis remains relatively underexplored.

Multimodal Discourse Analysis (MDA)

Multimodal discourse analysis (MDA), grounded in social semiotic theory, emphasizes that meaning is constructed through the interaction of multiple modes, including visual, gestural, and auditory resources (Liu, 2022). In today's digital era, MDA has become an essential tool for enabling learners to critically engage with meaning-making processes embedded in multimodal texts such as advertisements, memes, videos, and infographics (Eisenlauer & Karatza, 2020). Through MDA, learners can develop critical interpretive skills that address social dimensions, ideologies, and identities. To date, MDA has primarily been employed as a linguistic and semiotic analytical method (Ope-Davies & Shodipe, 2023). Its potential as a pedagogical framework supported by AI-driven technologies has not yet been fully realized. Nevertheless, empirical studies integrating AI, multimodal discourse analysis, and critical literacy remain scarce in higher education discourse studies (Li & Wilson, 2025; Yusuf et al., 2025), indicating a significant research gap in the development of structured AI-assisted pedagogical models.

Critical Literacy

Critical literacy is rooted in the principles of critical pedagogy, which highlight the importance of "reading the world" as well as "reading the word." It focuses on cultivating learners' ability to identify ideologies, biases, and power relations embedded within texts. In the context of the contemporary digital era, characterized by the prevalence of misinformation, disinformation, and misleading content, critical literacy has become increasingly relevant (Brosseuk & Downes, 2024). The development of critical literacy should extend beyond written texts to encompass multimodal texts, enabling students to interpret, evaluate, and respond to meaning across diverse representational forms (Dwipayana et al., 2026). This expanded perspective underscores the urgent need for pedagogical frameworks that integrate multimodal critical literacy into educational practice, thereby addressing the challenges of meaning-making in complex digital environments.

Intersections AI, MDA, and Critical Literacy

Although AI, multimodal discourse analysis (MDA), and critical literacy have evolved as distinct domains, there is considerable potential to integrate them into a complementary pedagogical framework. Advances in multimodal machine learning increasingly necessitate the simultaneous analysis of textual, visual, and auditory modes within unified systems. AI can

scaffold students' interpretation of the complex meaning structures embedded in multimodal texts (Li & Wilson, 2025). Within the scope of critical literacy, AI can also be leveraged to identify bias, hidden ideologies, and dominant narratives in multimodal discourse. For instance, sentiment analysis of social media texts can provide an entry point for critical classroom discussions. In this way, AI functions as a mediational tool that fosters deeper critical reflection during academic dialogue. Despite this potential, empirical studies that explicitly integrate AI, MDA, and critical literacy into pedagogical models remain scarce in discourse analysis education (Yusuf et al., 2025). This research gap highlights the urgent need for pedagogical innovation aimed at advancing multimodal discourse analysis in higher education. Positioning AI, MDA, and critical literacy within an integrated pedagogical framework therefore offers a timely and valuable contribution to the literature, providing a solid foundation for future research and practice in higher education contexts.

Research Methods

Development Research Procedure

This study employed a research and development (R&D) approach based on the ADDIE framework, which encompasses the stages of analysis, design, development, implementation, and evaluation (Branch, 2009).

Analysis Phase

The analysis phase commenced with a needs assessment conducted through interviews with four lecturers teaching discourse analysis courses. The interviews aimed to identify instructional challenges, students' learning needs, and the potential use of AI in multimodal discourse analysis instruction. The findings of the needs assessment were subsequently used to formulate the learning objectives and determine the core components of the DISCERN-AI model.

Table 1

Results of the Problem Analysis and Needs Assessment for Multimodal Discourse Analysis Instruction

Problems Identified	Instructional Needs	Proposed Solutions
Students tend to describe the content of texts without identifying the underlying ideologies, power relations, and social representations embedded in multimodal discourse.	Instructional strategies that facilitate critical interpretation, evaluation, and reflection on multimodal texts.	Integration of critical literacy stages to enable students to identify, analyze, and evaluate the social meanings and ideologies represented in multimodal texts.
Students experience difficulties in connecting verbal, visual, auditory, and spatial elements to construct meaning in an integrated manner.	A systematic and practical multimodal analysis framework that can be readily applied in learning activities.	Development of a structured syntax for multimodal text analysis.

Table 1

(Cont.)

Problems Identified	Instructional Needs	Proposed Solutions
Students' use of AI is largely limited to information retrieval and summarization and has not been effectively utilized to support analytical and critical reflection processes.	Guidelines for the effective, critical, and ethical use of AI in academic analysis.	Integration of AI as a tool for data exploration, interpretation development, validation of findings, and critical reflection throughout the learning process.
Learning activities are predominantly characterized by content delivery and general discussion, resulting in relatively low student engagement in analytical processes.	Learning activities that promote investigation, collaboration, and active knowledge construction.	Implementation of case-based tasks, collaborative discussions, and reflective activities to enhance student participation and engagement.
No instructional model is currently available that comprehensively integrates multimodal discourse analysis, critical literacy, and AI utilization.	An instructional model that incorporates these three components within a coherent framework.	Development of the DISCERN-AI model for multimodal discourse analysis instruction.

Design Phase

The initial prototype of the DISCERN-AI model was designed based on the results of the needs analysis and literature review conducted in the preceding phase. The activities undertaken included the development of a conceptual framework, the formulation of instructional syntax, the design of learning materials and instructional resources, and the establishment of strategies for integrating AI into multimodal discourse analysis learning. The design process involved a research team in collaboration with five experts, comprising a discourse analysis expert, a critical literacy expert, an Indonesian language education expert, an educational technology expert, and a learning model development expert. These experts provided input regarding the model structure, the appropriateness of learning activities, and the coherence among the model's components. The outcome of this phase was an initial prototype of the DISCERN-AI model consisting of six instructional phases: (1) Problem Orientation, (2) Discourse Exploration, (3) Responsive Navigation, (4) Critical Interpretation, (5) Multimodal Triangulation, and (6) Reflection and Synthesis. This prototype subsequently served as the foundation for the further development and validation of the model in the subsequent phases.

Development Phase

The development phase focused on refining the DISCERN-AI model prototype through the development of various supporting materials, including an implementation guide, lesson plans, critical literacy assessment instruments, practicality response questionnaires, and model validation questionnaires. Prior to their use in the study, the construct validity, content validity, and practicality response instruments were subjected to content validation using the Gregory

formula based on evaluations provided by two expert reviewers. The statement items contained in these instruments were initially generated with the assistance of AI and subsequently reviewed and refined by the research team.

The analysis yielded validity coefficients of 0.87 for the construct validity instrument and 0.93 for the content validity instrument, indicating a very high level of validity. Once the instruments were confirmed to possess satisfactory validity, they were employed to collect data regarding the validity of the DISCERN-AI model from five experts representing the fields of discourse analysis, critical literacy, Indonesian language education, educational technology, and instructional model development. The experts' ratings were then analyzed using Aiken's V formula (1985) to determine the construct and content validity of the developed model.

In addition, the practicality of the model was evaluated through a practicality response questionnaire administered to four lecturers teaching discourse analysis courses at four different universities. The practicality data were analyzed using descriptive statistics by calculating the mean scores and the percentage of practicality attainment.

Furthermore, the reliability of the essay test instrument used to assess critical literacy skills in multimodal discourse analysis learning was examined using Cronbach's Alpha coefficient with the assistance of SPSS Version 27.0. This reliability testing was conducted to ensure the internal consistency of the instrument, thereby confirming that the data generated possessed an adequate level of reliability. After the instrument had been confirmed to be valid and reliable, it was administered to students in both the experimental and control groups to measure their critical literacy skills and to evaluate the effectiveness of the DISCERN-AI model. The results of the reliability analysis are presented in the following table.

Table 2

Cronbach's Alpha Reliability Analysis Results for the Multimodal Discourse Analysis Essay Test Instrument

Reliability Statistics	
Cronbach's Alpha	N of Items
0.921	7

The reliability analysis using Cronbach's Alpha yielded a coefficient of $\alpha = 0.921$, indicating that the test instrument possessed very high reliability. This result demonstrates that the seven essay items exhibited excellent internal consistency in measuring the construct of critical literacy skills in multimodal discourse analysis.

Implementation Phase

The DISCERN-AI model, which had satisfied the established validity criteria, was implemented in multimodal discourse analysis courses at four higher education institutions in Bali. This phase involved four course instructors and 120 fourth- and fifth-semester students from Universitas Pendidikan Ganesha ($n = 58$), Universitas PGRI Mahadewa Indonesia ($n = 15$), Universitas Mahasaraswati Denpasar ($n = 33$), and Institut Pendidikan dan Teknologi Markandeya ($n = 14$). All participants were enrolled in Indonesian Language and Literature Education programs and had relatively homogeneous academic backgrounds.

To evaluate the effectiveness of the model, participants were proportionally assigned to an experimental group ($n = 60$) and a control group ($n = 60$), comprising 76 male students (63%)

and 44 female students (37%). Prior to the implementation, the instructors received training on the instructional syntax of the DISCERN-AI model, the use of learning materials, and the integration of AI applications, namely ChatGPT, NVivo, Perplexity AI, Claude AI, Gemini, and Power BI Copilot, across each phase of the learning process.

The implementation was conducted over 10 instructional sessions, each lasting 100 minutes. The first session was devoted to learning orientation and the administration of the pretest to assess students' initial critical literacy skills in multimodal discourse analysis. Sessions two through nine focused on implementing the DISCERN-AI model, while the tenth session was used to administer the posttest for the experimental group. Meanwhile, the control group received multimodal discourse analysis instruction through conventional teaching methods routinely employed by the course instructors.

The effectiveness of the model was evaluated using a pretest-posttest control group design by comparing students' critical literacy performance before and after the intervention in both groups. Classroom observations were conducted during each instructional session to assess the fidelity of the model implementation. In addition, lecturer response questionnaires were administered to evaluate the practicality of the DISCERN-AI model.

The selection of multimodal discourse materials as learning resources was guided by three criteria: (1) semiotic density, (2) social relevance, and (3) measurability of critical literacy outcomes. These materials comprised news texts, advertisements, infographics, social media content, and audiovisual texts presenting diverse perspectives on contemporary social issues. This combination of learning resources enabled students to perform cross-source verification and critical comparison of multimodal information, thereby fostering cognitive processes that support the development of critical literacy skills.

Evaluation Phase

Data analysis employed a mixed-methods approach to evaluate the validity, practicality, and effectiveness of the DISCERN-AI model. Quantitative analysis was conducted to examine the model's effectiveness through four procedures: (1) normality testing, (2) homogeneity testing, (3) analysis of covariance (ANCOVA), and (4) effect size calculation using Cohen's *d*. Meanwhile, qualitative analysis was performed on expert validation results, field notes, implementation observations, lecturers' responses, and students' reflections using thematic categorization techniques to identify the strengths and limitations of the model.

Data integration was conducted at two levels. At the results level, quantitative findings, including p-values, adjusted ANCOVA means, and effect size values, were compared with qualitative findings derived from implementation observations, lecturers' perceptions, students' reflections, and field notes. At the interpretation level, these quantitative and qualitative findings were synthesized to explain the mechanisms and factors contributing to the effectiveness of the DISCERN-AI model in enhancing students' critical literacy skills. The integrated findings subsequently served as the basis for evaluating the model's validity, practicality, and effectiveness. Based on the evaluation results, the final refinement of each model component was undertaken, resulting in a DISCERN-AI model that is valid, practical, and effective for supporting AI-assisted multimodal discourse analysis learning.

Findings

Design of the Learning Model

The Discourse Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI) model consists of a series of structured activities designed as an operational guide in the classroom learning process. The model comprises six phase: (1) problem orientation, (2) discourse exploration, (3) responsive navigation, (4) critical interpretation, (5) multimodal triangulation, and (6) reflection and synthesis. The selection of AI tools integrated into the DISCERN-AI model was informed by their pedagogical affordances and alignment with the learning objectives associated with each instructional phase. Rather than being adopted merely for their technological novelty, these tools were incorporated based on their specific pedagogical contributions to fostering students' critical, analytical, and reflective engagement with multimodal discourse. Within the model, AI functions as a form of responsive learning navigation, assisting students in exploring information, examining alternative perspectives, verifying evidence, and connecting multiple sources and modes of meaning-making throughout the analytical process. In this sense, AI does not replace students' reasoning processes; instead, it provides navigational support that enriches learning and facilitates deeper critical inquiry. The pedagogical functions of the AI tools across the six phases of the DISCERN-AI model are summarized in Table 3.

Table 3

Phase of the Discourse Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI) Model

DISCERN-AI Phase	Learning Activities	AI Learning Assistant	Functions of AI Tools	Critical Literacy Competencies
Phase 1: Problem Orientation	a) Explain the goals of multimodal critical literacy. b) Students are presented with multimodal discourse. c) Identify issues, themes, and key problems within the multimodal discourse.	Chat-GPT	Facilitates topic modeling, the formulation of critical questions, and the development of contextualized problem summaries.	• Conceptual understanding • Problem identification
Phase 2: Discourse Exploration	a) Identify issues, actors, and events. b) Examine meaning representations in verbal, visual, and audiovisual modalities.	NVivo	Supports qualitative analysis based on codes, categories, and themes. Credibly applied in linguistic, semiotic, and	• Interpretive skills • Context sensitivity

Table 3

(Cont.)

DISCERN-AI Phase	Learning Activities	AI Learning Assistant	Functions of AI Tools	Critical Literacy Competencies
	c) Explore linguistic, semiotic, and social context elements.		multimodal context analysis.	
Phase 3: Responsive Navigation	a) Students use AI tools to search supporting data, literature, and fact validation. b) AI provides automatic feedback, such as highlighting bias and suggesting counter-literature.	Perplexity AI	Facilitates literature searches based on credible and verifiable sources.	- Analytical skills - Inferential skills
Phase 4: Critical Interpretation	a) Examine modality structures such as vocabulary, metaphors, layout, and visual perspective. b) Conduct intertextuality. c) Analyze meaning, ideology, and power relations.	Claude AI	Supports the interpretation of complex texts, deep understanding of discourse contexts, and the maintenance of consistency in critical analysis.	- Analytical skills - Evaluative skills - Explanatory skills - Argumentative reasoning
Phase 5: Multimodal Triangulation	a) Connect text, audio, and visuals for multimodal analysis. b) Conduct triangulation covering representational, interactive, and compositional activities. c) Group discussions to compare interpretation results, reinforced by AI feedback.	Google Gemini	Supports the triangulation of multiple multimodal representations, including text, images, audio, and video.	- Evaluative skills - Critical collaboration - Multimodal integration

Table 3

(Cont.)

DISCERN-AI Phase	Learning Activities	AI Learning Assistant	Functions of AI Tools	Critical Literacy Competencies
Phase 6: Reflection and Synthesis	a) Reflect on multimodal discourse regarding the relationship between text and social practices.	Power BI Copilot	Facilitates the interactive visualization of analysis results, encourages critical reflection, and supports the development of data-driven and evidence-based synthesis.	- Self-regulation - Metacognitive skills - Critical synthesis
	b) Synthesize analysis results, such as media bias, hidden ideology, and social implications.			
	c) Provide feedback to strengthen metacognitive awareness.			

Validity Results of Learning Model

The development of the model was carried out through a validation process using expert judgment. This validation covered both construct and content validity aspects, each reviewed by five experts: a discourse analysis expert, a critical literacy expert, an Indonesian language education expert, an educational technology expert, and a learning model expert.

Table 4

Construct Validity of the Model Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI)

Aspect	Indicator	Expert Judgment					V	Category (Aiken's, 1985)
		i	ii	iii	iv	v		
Theoretical Alignment	The DISCERN-AI model aligns with multimodal discourse analysis theory and critical discourse analysis theory.	4	4	4	3	4	0.93	High Validity
	Integrates AI technology as responsive navigation in accordance with recent developments in educational technology theory.	3	4	4	4	4	0.93	High Validity

Table 4*(Cont.)*

Aspect	Indicator	Expert Judgment					V	Category (Aiken's, 1985)
		i	ii	iii	iv	v		
Learning Model Syntax	The DISCERN-AI syntax is logical, systematic, and operational.	4	4	3	4	3	0.87	High Validity
	The integration of AI Learning Assistant is explicitly explained in each syntax stage to support critical thinking skills.	4	4	4	3	3	0.87	High Validity
Social System	Accommodates diverse student characteristics in learning styles and knowledge backgrounds in multimodal discourse analysis with AI support.	3	3	3	3	4	0.73	Acceptable Validity
	Encourages collaborative student interaction in analyzing and interpreting multimodal texts, fostering critical team-based discussion dynamics.	4	4	4	4	4	1.00	High Validity
	Provides equal access for students with varying levels of digital literacy in analyzing multimodal texts through AI assistance.	4	3	3	3	3	0.73	Acceptable Validity
Reaction Principle	This model includes adaptive feedback sessions via AI (feedback analytics, bias detector, counter-argument generator) to train critical literacy skills.	3	4	4	3	3	0.80	High Validity
	The model provides AI-facilitated argumentative discussion spaces to stimulate critical interaction and challenge opposing arguments.	4	3	4	4	4	0.93	High Validity
	The model integrates adaptive AI-based evaluation mechanisms to strengthen students' depth of critical thinking.	4	3	3	4	4	0.87	High Validity

Table 4*(Cont.)*

Aspect	Indicator	Expert Judgment					V	Category (Aiken's, 1985)
		i	ii	iii	iv	v		
Support System	The model is practically supported by AI tools as learning assistants (Chat-GPT, NVivo, Perplexity AI, Claude AI, Google Gemini, and Power BI Copilot).	4	4	4	4	4	1.00	High Validity
	Multimodal learning materials such as editorials, infographics, videos, and digital advertisements are available in a structured way to support discourse analysis.	4	4	4	4	4	1.00	High Validity
Instructional and Accompanying Impact	Guides students to analyze multimodal discourse content systematically, critically, and evidence-based.	4	3	3	4	4	0.87	High Validity
	Enhances students' skills in evaluating information credibility, analyzing ideology, and identifying bias in multimodal discourse with AI assistance.	4	3	4	4	4	0.93	High Validity
	Develops students' ability to conduct metacognitive reflection on the analysis process and synthesize critically across various multimodal discourses.	4	3	3	3	3	0.73	Acceptable Validity
Total Score							0.88	High Validity

The results of the construct validity of the DISCERN-AI model in multimodal discourse analysis showed that this model had a very high level of validity, with an average Aiken's V value of 0.88. This achievement confirmed that the DISCERN-AI model had fulfilled aspects of theoretical validity.

Table 5

Content Validity of the Model Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI)

Aspect	Indicator	Expert Judgment					V	Category (Aiken's, 1985)
		i	ii	iii	iv	v		
Curriculum Alignment	Aligns with the learning outcomes of the discourse analysis course, which emphasizes critical thinking and multimodal literacy skills.	3	4	4	4	4	0.93	High Validity
	Integrates the use of responsive AI-navigation in learning outcomes to support students' academic competencies.	3	4	4	3	4	0.87	High Validity
Student Characteristics Alignment	Provides space for differentiated learning styles through adaptive AI feedback.	4	3	3	4	3	0.80	High Validity
	Encourages students to construct critical interpretations from various social, cultural, and ideological perspectives in multimodal discourse.	3	4	4	3	3	0.80	High Validity
	Optimizes students' exploratory abilities with AI support to systematically navigate data, audiovisuals, texts, and visuals.	3	3	3	4	4	0.80	High Validity
Clarity of Learning Indicators	Indicators measure critical thinking skills such as evaluation, analysis, reflection, and synthesis in analyzing multimodal texts with AI support.	4	4	4	4	4	1.00	High Validity
	The model can assess the ability to examine arguments and detect bias with AI analytics support.	4	4	4	4	3	0.87	High Validity
	The evaluation reflects the achievement of AI-based critical literacy in multimodal discourse analysis.	3	4	4	3	3	0.73	Acceptable Validity
Validity of Materials and Learning Resources	Multimodal discourse sources are up to date, such as editorials, news, digital advertisements, infographics, videos, and political memes relevant to contemporary issues.	4	4	4	4	4	1.00	High Validity

Table 5*(Cont.)*

Aspect	Indicator	Expert Judgment					V	Category (Aiken's, 1985)
		i	ii	iii	iv	v		
	Employs intertextuality strategies with AI support to strengthen the validity of analysis.	4	3	3	3	4	0.80	High Validity
	Integrates various multimodal discourses that allow cross-comparison through AI navigation.	3	3	3	3	3	0.73	Acceptable Validity
Alignment with 21 st -Century Learning Skills	Emphasizes critical and creative thinking in interpreting multimodal discourse with AI-supported reasoning.	4	4	4	4	3	0.87	High Validity
	Utilizes various AI tools to foster reflective discussion.	4	4	4	4	4	1.00	High Validity
	Promotes argumentative creativity through AI counter-argument generators and visualization of analysis results with Power BI Copilot.	4	4	4	4	3	0.93	High Validity
	Develops academic communication skills in discussions, debates, and presentations with AI-driven feedback.	3	4	4	3	4	0.80	High Validity
	Total Score						0.86	High Validity

The content validity analysis of the DISCERN-AI model in multimodal discourse analysis demonstrated that it fell in the “High Validity” category with a mean Aiken’s V coefficient of 0.86. These results demonstrate that the DISCERN-AI Model in multimodal discourse analysis meets the validity aspects in terms of curriculum alignment, student characteristics, learning indicators, learning materials, and relevance to 21st-century skills.

Practicality of the Learning Model

The DISCERN-AI was evaluated by four lecturers responsible for teaching the Discourse Analysis course at each university, namely Universitas Pendidikan Ganesha, Universitas PGRI Mahadewa Indonesia, Universitas Mahasaraswati, and Institut Pendidikan dan Teknologi Markandeya.

Table 6

Practicality of the Model Interpretation through Systematic Critical Evaluation with Responsive AI-Navigation (DISCERN-AI)

Aspect	Indicator	Lecturer				Total
		i	ii	iii	iv	
Clarity of Model Syntax	The steps of the DISCERN-AI model are arranged sequentially, facilitating the learning process.	4	4	4	4	16
	The instructions in each syntax stage are easy to understand and provide systematic guidance for lecturers and students.	4	4	4	4	16
	The integration of AI-navigation in each syntax does not create technical or conceptual barriers.	4	4	4	4	16
Efficiency of Model Implementation	The model can be applied without requiring excessive resources.	4	4	4	4	16
	The time allocation for each syntax aligns with the course structure.	3	4	4	3	14
	Ability to adapt to the use of AI-support in multimodal discourse analysis.	4	4	4	4	16
Support of Materials and Learning Resources	The multimodal discourse materials are relevant to the learning outcomes.	4	4	4	4	16
	The integration of learning resources can be implemented smoothly.	4	4	4	4	16
	The AI tools used are easily accessible and user-friendly.	4	4	4	4	16
Evaluation and Monitoring	Instruments for measuring critical literacy skills are available in a structured manner.	4	3	4	4	15
	AI-feedback assists lecturers in monitoring student progress.	4	4	4	4	16
	The assessment of learning outcomes is aligned with multimodal critical literacy indicators.	4	3	3	4	14
Acceptance and Effectiveness of the Model	The model receives positive responses from students as it facilitates discussions, debates, and presentations.	4	4	4	4	16
	Motivates students to be actively engaged in multimodal discourse analysis.	4	4	3	4	15
	Overall, the DISCERN-AI model is practical and effective for use in multimodal discourse analysis lectures.	4	4	4	4	16
Total						234
Mean Score						15.53
Mean Score of the percentage						3.90
Category						High Practicality

The practicality test results conducted by lecturers of the Discourse Analysis course on the DISCERN-AI Model indicated a category of “High Practicality,” with an average score of 3.90. The main strengths of the model lie in the clarity of syntax, integration with AI tools, and support for collaborative learning processes. Nevertheless, there are areas that need further improvement, particularly in the aspects of time allocation and the structured design of evaluation instruments, to ensure the model’s optimal implementation.

Effectiveness Test

To evaluate the effectiveness of the DISCERN-AI learning model trials were conducted with two research groups, namely the control and the experimental. Each group consisted of 60 student from four universities in Bali. Prior to the implementation of the study, a class equivalence test was administered using the pretest scores of both groups in the Discourse Analysis course. The equivalence test was analyzed with the assistance of the SPSS software.

Table 7

Equivalence Test

Pretest Results of the Sample	Group	t	df	Sig. (2-tailed)
Initial Ability in Critical Multimodal Discourse Literacy	Control-Experiment	-1.188	118	0.237

The equivalence analysis of the initial abilities between the control and experimental groups was carried out using an independent t-test on the pretest scores of critical multimodal discourse literacy. The results showed a Sig. (2-tailed) of 0.237, which exceeded the threshold of 0.05. This indicates that there was no significant difference in the initial critical multimodal discourse literacy ability between the two groups, making them appropriate to be used as research samples. After the equivalence test, further analysis was conducted on the control and experimental groups using SPSS.

Table 8

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance
Pretest Control	60	19	59	78	4112	68.53	4.367	19.067
Posttest Control	60	22	60	82	4198	69.97	4.944	24.440
Pretest Experiment	60	20	60	80	4175	69.58	5.276	27.840
Posttest Experiment	60	16	68	84	4525	75.42	4.788	22.925

The control group’s average pretest score for critical literacy skills was 68.53, accompanied by std. deviation of 4.367, a variance of 19.067, a score range of 19, with the lowest score at 59 and the highest at 78. For the posttest, the mean score rose slightly to 69.97, with std. deviation of 4.944, a variance of 24.440, a range of 22, and scores spanning from 60 to 82. In the experimental group, the pretest yielded an average score of 69.58, with std. deviation of 5.276, a variance of 27.840, a score range of 20, the minimum at 60, and the maximum at 80. By comparison, the posttest mean score for the group instructed using the DISCERN-AI model reached 75.42, with a standard deviation of 4.788, a variance of 22.925, a score range of 16, a

minimum of 68, and a maximum of 84. The experimental group experienced an improvement of 5.84 points, which was notably higher than the gain observed in the control group.

Tests of Normality

The normality test of the critical literacy scores in multimodal discourse was conducted using the Kolmogorov–Smirnov technique with the assistance of SPSS.

Table 9

Tests of Normality Result

	Class	Kolmogorov–Smirnov			Remark
		Statistic	Df	Sig.	
Multimodal	Pretest Control	0.103	60	0.180	Normal
Discourse Critical	Posttest Control	0.103	60	0.181	Normal
Literacy	Pretest Experiment	0.104	60	0.164	Normal
	Posttest Experiment	0.088	60	0.200	Normal

All pretest and posttest data in both the control and experimental groups showed Sig. greater than 0.05. This condition indicates that the data distribution in each group met the assumption of normality.

Test of Homogeneity of Variance

The homogeneity test of students' critical literacy ability data was conducted using SPSS.

Table 10

Test of Homogeneity of Variance

F	df1	df2	Sig.	Remark
0.035	1	118	0.851	Homogeneous

Levene's Test of Equality of Error Variances for the posttest variable produced results of $F = 0.035$, $df1 = 1$, $df2 = 118$, and $Sig. = 0.851$ (> 0.05). The critical literacy skills data in multimodal discourse analysis were confirmed to meet the homogeneity assumption, thereby enabling further analysis using ANCOVA without any assumption violations.

Effect of the Independent Variable on the Dependent Variable

The impact of applying the DISCERN-AI model in multimodal discourse analysis learning on critical literacy skills was examined through ANCOVA. The results of the ANCOVA analysis examining the effect of the independent variable on the dependent variable using SPSS software are presented in Table 11.

Table 11

Effect of the Independent Variable with the Dependent Variable

Source	df	F	Sig.	Partial Eta Squared
Model	1	35.615	0.001	0.233
Pretest	1	7.878	0.006	0.063
Error	117			
$R^2 = 0.290$ (Adjusted $R^2 = 0.277$)				

Analysis of Covariance (ANCOVA) revealed a significant difference between the group that applied the DISCERN-AI model and the group that applied the conventional discourse analysis model on posttest scores after controlling for pretest scores. This result confirmed that the developed DISCERN-AI model made a substantial contribution to the enhancement of critical literacy skills. The pretest scores were found to have an effect on the posttest scores, $F(1,117) = 7.878$, $\text{Sig.} = 0.006$, $\eta^2p = 0.063$. These facts indicate that students' initial ability remained a factor affecting critical literacy in multimodal discourse analysis, although its effect was smaller than that of the DISCERN-AI instructional model.

Following the ANCOVA, the effectiveness of the DISCERN-AI model in multimodal discourse analysis learning was further examined using effect size analysis with Cohen's d . Based on the comparison of the experimental and control posttest data, the effect size was calculated as $\text{Cohen's } d = (75.42 - 68.97) / 4.87 = 1.32$. This result demonstrated that the effect size of the DISCERN-AI model on critical literacy skills in multimodal discourse analysis fell into the large category.

Discussions

The DISCERN-AI model possesses strong construct validity, practical feasibility, and pedagogical effectiveness in fostering students' critical literacy in the multimodal discourse analysis course. The high Aiken's V values for construct and content validity of 0.88 and 0.86, respectively indicate that this model is both theoretically well-founded and substantively aligned with curricular relevance. The integration of AI-driven tools, such as ChatGPT, NVivo, Perplexity AI, Claude AI, Gemini, and Power BI Copilot, strengthened students' differentiated learning experiences. This aligns with the principles of 21st-century skills emphasizing digital literacy and critical thinking (Kain et al., 2024; Thornhill-Miller et al., 2023). Accordingly, the validity of the DISCERN-AI instructional model demonstrates both theoretical and practical responsiveness to contemporary pedagogical needs that demand the integration of critical literacy and digital technology. This notion is reinforced by systematic review studies on critical digital literacy at the school level, the urgency of AI literacy and prompt engineering in modern education (Walter, 2024), and the critical and ethical training needs of teachers in AI utilization (Daher, 2025). Moreover, empirical studies have shown that AI literacy positively influences academic performance and collaborative engagement among students in AI-supported higher education contexts (Shi et al., 2025).

From the perspective of practical implementation, the mean score of 3.90, categorized as very practical, shows that DISCERN-AI can be effectively operationalized in multimodal discourse analysis lectures. The clarity of its syntax, efficient time allocation, and the use of contextual multimodal materials facilitated an interactive learning cycle. Furthermore, the pedagogical effectiveness analysis indicated a statistically meaningful variation between the experimental and control groups on posttest critical literacy scores after controlling for pretest scores, $F(1,117) = 35.615$, $p < .001$, $\eta^2p = 0.233$. The high partial eta squared value highlights the substantial contribution of DISCERN-AI to enhancing critical literacy, surpassing the influence of students' initial ability. This finding is reinforced by a large effect size (Cohen's $d = 1.32$), indicating that the results are not only statistically significant but also pedagogically meaningful in enhancing students' critical literacy skills.

The effectiveness of the DISCERN-AI model is supported by the implementation of AI-based scaffolding that functions as an epistemic scaffold, assisting students in navigating information, developing interpretations, and constructing reflective arguments without replacing the role of human reasoning. This finding highlights the importance of cognitive support in helping learners develop higher-order thinking strategies through processes of modeling, guidance, reflection, and articulation (Li & Wilson, 2025; Thornhill-Miller., 2023). Furthermore, the effectiveness of DISCERN-AI is strengthened by the integration of multiple AI platforms that are employed progressively and complementarily according to the analytical demands of each learning phase, ranging from concept exploration, source verification, and critical interpretation to multimodal triangulation and reflective visualization. Within this instructional model, AI serves as a support system that facilitates the representation and analysis of texts across multiple modes, including verbal, visual, and audiovisual forms, in a more in-depth, systematic, and critical manner (Goyal et al., 2024). These findings are consistent with the theory of distributed cognition, which views cognitive activity not as a process confined solely to the individual mind, but as one that is distributed across individuals, cognitive artifacts, and learning environments (Hutchins, 1995).

These results align with prior research demonstrating that the integration of AI significantly increases the occurrence of evaluative, reflective, and synthetic thinking among learners (Du et al., 2025). Similarly, the ISAR model highlights the transformative role of AI in fostering deeper student engagement with learning processes (Bauer et al., 2025). In addition, generative AI-based collaboration, such as with ChatGPT-4, enhances students' abilities in analysis, argument evaluation, solution creation, and self-regulation (Fan et al., 2025; Margono et al., 2024). Pedagogically, the DISCERN-AI model highlights the phases of responsive navigation and multimodal triangulation, which represent novel contributions to the field of multimodal discourse analysis. This approach guided students to examine textual representations across various modes—verbal, visual, and audiovisual—thereby fostering their interpretive, evaluative, and synthetic skills. This finding is consistent with multimodal literacy theory, which asserts that meaning-making is constructed through cross-modal semiotic interactions (Samuelsson, 2023). Furthermore, the integration of AI into multimodal discourse analysis practices enabled students to detect bias, evaluate the credibility of arguments, and construct evidence-based syntheses, in line with the frameworks of both critical thinking and critical digital literacy (Mills et al., 2022). Accordingly, the DISCERN-AI model offers theoretical contributions by advancing AI-based critical pedagogy in multimodal discourse analysis, while also providing practical contributions through the design of interactive and adaptive learning environments that strengthen students' critical literacy in the digital era.

Conclusions

This study demonstrates that the DISCERN-AI model is a valid, practical, and effective instructional model for fostering students' critical literacy in multimodal discourse analysis. The integration of AI as a form of responsive learning navigation enables students to engage more critically, analytically, and reflectively in exploring, interpreting, evaluating, and synthesizing meaning across diverse sources and modes of representation. These findings suggest that pedagogically designed AI integration can strengthen critical literacy learning processes in the digital era.

From a curricular perspective, the DISCERN-AI model provides a pedagogical framework for integrating critical literacy, digital literacy, and multimodal discourse analysis within higher education. The model offers an instructional alternative that aligns with the demands of twenty-first-century competencies, particularly in fostering critical thinking, information evaluation, and evidence-based decision-making skills. From a policy perspective, the findings underscore the importance of developing institutional guidelines and policies that support the ethical, responsible, and pedagogically meaningful integration of AI into teaching and learning practices. This study has several limitations: (1) the sample was limited to students enrolled in Indonesian Language and Literature Education programs at four universities in Bali, which may restrict the generalizability of the findings to other disciplines and educational contexts; (2) the study was conducted within the Indonesian context, and therefore the effectiveness of the model in different cultural and educational settings requires further investigation; (3) the implementation of the model relied on several specific AI tools whose characteristics and functionalities may evolve over time as AI technologies continue to develop; and (4) the relatively short duration of the intervention limited the ability to examine the long-term effects of the model on students' critical literacy development.

In light of these limitations, future research is recommended to examine the implementation of the DISCERN-AI model across broader and more diverse populations, encompassing different educational levels and cultural contexts. Further studies should also explore the impact of the model beyond cognitive outcomes, including its influence on affective, social, collaborative, and ethical dimensions of AI-assisted learning. In addition, longitudinal research is needed to evaluate the sustainability of the model's impact on the development of students' critical literacy over time.

Author Contributions

IKAD: Conceptualization, Methodology, Supervision, Project Administration, Writing–Review & Editing. IMS: Formal Analysis, Validation, Investigation, Writing–Review & Editing. IWS: Methodology, Resources, Validation, Writing–Review & Editing. IWA: Conceptualization, Investigation, Data Curation, Formal Analysis, Writing–Original Draft Preparation, Visualization.

Declaration of the Use of Generative AI

During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-5.0) to assist with language editing and polishing of the draft. The tool was used solely to improve the clarity, grammar, and overall readability of the manuscript. The authors carefully reviewed, verified, and revised all AI-generated suggestions as necessary to ensure accuracy, consistency, and alignment with the research objectives. The authors take full responsibility for the originality, integrity, and final content of the manuscript.

Ethics

This study involved minimal-risk educational research conducted in higher education institutions. Participation was voluntary, and informed consent was obtained from all participants prior to data collection. Participants were adequately informed about the objectives and procedures of the study. All personal information was anonymized and handled confidentially in accordance with established ethical principles for research involving human participants.

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