JIHAD: Jurnal Ilmu Hukum dan Administrasi
Vol. 8 No. 3 September 2026
p-ISSN : 2745-9489, e-ISSNl 2746-3842
DOI: *10.36312/jihad.v8i2.10804/*https://ejournal.mandalanursa.org/index.php/JIHAD/issue/archive

Developing an AI-Assisted Case-Based Learning Model to Improve Students' Political Literacy

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Article Info

Article history:
Accepted: 17 June 2026
Publish: 1 September 2026

Keywords:
AI-Assisted Learning;
Case-Based Learning;
Political Literacy;
Plomp Model;
Higher Education.

Abstract

Political literacy among university students has become a pressing concern in the age of digital democracy, yet the way it is currently taught often falls short. This study set out to develop and test an AI-Assisted Case-Based Learning (AI-CBL) model for the Introduction to Political Science course at STKIP Taman Siswa Bima. We followed the three-phase Plomp development model: preliminary research, prototyping, and assessment. Participants included three expert validators, three course lecturers, and 32 first-year students from the 2024/2025 academic year. We gathered data through validation sheets, practicality questionnaires, and a political literacy test, then analysed them using descriptive statistics, percentage scoring, and the N-Gain formula. Four findings stand out. First, the model proved highly valid, with a mean expert score of 3.84 on a 4-point scale. Second, the feasibility check returned an average index of 91.5%, placing the model in the "highly feasible" range. Third, both lecturers (89.7%) and students (88.4%) rated the model as highly practical. Fourth, students' political literacy improved sharply, with a mean N-Gain of 0.62 and 65.6% of them reaching the high-gain category. Taken together, these results suggest that AI-CBL works as a valid, feasible, practical, and effective approach for strengthening political literacy in higher education. The model also offers a concrete way of bringing generative AI into political education without sidelining the deliberative, case-based reasoning that the field requires.

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1. INTRODUCTION

Indonesia has become a thoroughly digital democracy. The Digital 2024 Indonesia Report by We Are Social shows that more than 167 million Indonesians use social media, and most of them now get their political news through digital channels rather than print or television. That shift has raised the stakes for political literacy. Knowing the names of the country's institutions is no longer enough; today's students need to read political information critically, weigh competing claims, and act on what they find (Tam, 2016; Cassel & Lo, 1997). For university students in particular, this is more than an academic exercise. They are first-time voters, future civil servants, and online opinion-makers all at once.

The Introduction to Political Science course is meant to lay the groundwork for that kind of thinking. It is normally one of the first political-science subjects students encounter, and it covers basic ideas about the state, power, political systems, and ideology. The course should also help students connect these ideas to what they see in the news every day. Our own observations at STKIP Taman Siswa Bima between March and July 2024 told a less optimistic story. Teaching still leans heavily on lectures and slide presentations, leaving students as passive listeners. A diagnostic test we administered to 60 students returned a mean political-literacy score of only 48.7 out of 100, with the weakest results in critical analysis of contemporary political issues.

Other Indonesian researchers have reported much the same pattern. Ridha and Riwanda (2020) found that the political literacy of first-time voters sits at the low-to-medium level, particularly when it comes to identifying credible information and spotting hoaxes. Sumanto and Dharma (2019) reported that civic education courses at university have not done as much as they could to raise political literacy, in large part because the teaching methods remain conventional. These results point in the same direction: we need an approach that does more than transmit content.

Case-Based Learning (CBL) is one well-tested option. Across disciplines, students who learn through real cases tend to think more analytically, solve problems better, and stay more engaged than those who only attend lectures (Lavi & Marti, 2023; Arab & Saeedi, 2024; Hmelo-Silver, 2004; Guo et al., 2024). CBL fits political science especially well, because politics is messy and context-dependent in ways that lend themselves to case analysis. However, running a CBL course is harder than the literature sometimes suggests. Lecturers struggle to keep cases up to date with fast-moving events, and even more so to give every student individual feedback on their reasoning (Lavi & Marti, 2023).

This is where generative AI tools such as ChatGPT and Claude become interesting. A growing body of work suggests that AI assistants can help personalise learning, broaden access to information, and provide just-in-time scaffolding for student thinking (Bettayeb et al., 2024; Zhai et al., 2021; Adiguzel et al., 2023). In a CBL context, the same tools can help lecturers generate fresh cases pegged to current events, give students rapid feedback on draft analyses, and pull together perspectives from a wider range of sources than any single instructor could cover. Critically, used well, AI does not replace the reasoning students are supposed to be learning; it makes more of that reasoning possible.

Despite this promise, studies that bring CBL and AI together in one model are rare, and most of the existing work is in medicine, nursing, or business education (Yu et al., 2019; Zhu et al., 2020; Liu, 2024). We could find no published model that integrates the two for political science education in Indonesia, and no model that has been developed and tested using the kind of systematic procedure that would let other lecturers adopt it with confidence. That gap is what this study addresses.

Specifically, we ask four questions about the AI-Assisted Case-Based Learning (AI-CBL) model we developed: (1) Is it valid in the eyes of subject-matter experts? (2) Is it feasible in conceptual, content, and technical terms? (3) Is it practical for the lecturers and students who actually use it? (4) Is it effective in raising students' political literacy? Answering these four questions is the main contribution of the paper. The model itself is the secondary contribution: a worked example of how generative AI can be folded into a deliberative, case-based pedagogy without turning the classroom into a chatbot demonstration

2. METHOD

2.1 Research Design

This is a Research and Development (R&D) study following Plomp's three-phase model (Plomp & Nieveen, 2013). We chose Plomp because it is iterative by design, which suits the messy reality of working out a teaching model that has to be valid for experts, feasible for institutions, practical for users, and effective in the classroom. The three phases are preliminary research, prototyping, and assessment. Each phase ends with a round of formative evaluation that feeds back into the next.

Figure 1 sets out the full procedure, including the main activities and the outputs produced at each phase.

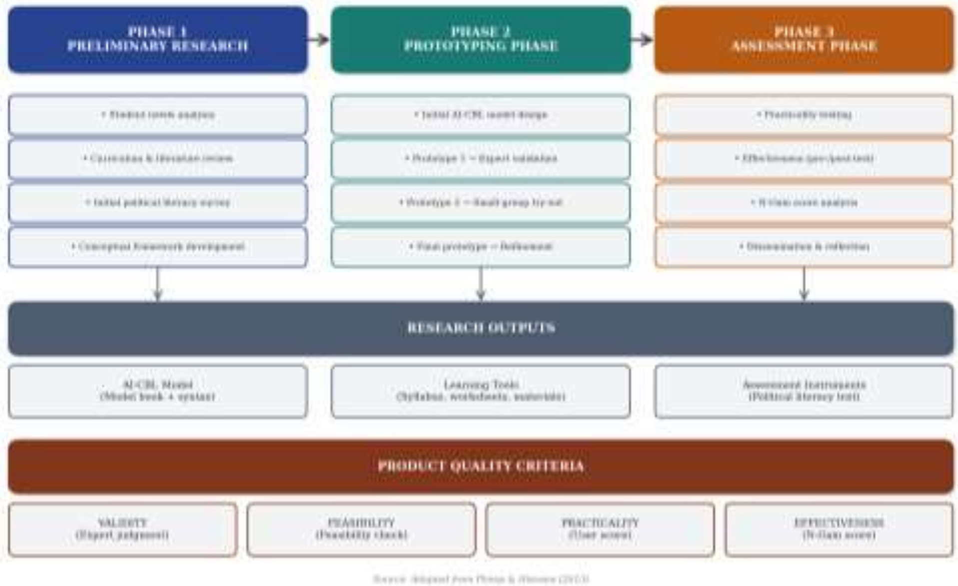

Figure 1. Plomp Development Model Procedure (adapted from Plomp & Nieveen, 2013)

2.2 Research Subjects and Setting

Table 1 summarises who took part in the study and where it took place.

Table 1. Research Subjects and Setting

No.	Component	Description
1	Setting	STKIP Taman Siswa Bima, Bima City, West Nusa Tenggara, Indonesia
2	Time frame	March 2024 – February 2025 (12 months)
3	Course	Introduction to Political Science (3 credits, Semester 1, Department of Education)
4	Expert validators	3 validators: (a) political science content expert; (b) instructional design / learning expert; (c) AI-in-education expert
5	Course lecturers	3 lecturers who currently teach Introduction to Political Science (practicality raters)
6	Student participants	32 first-semester students of the Department of Education, 2024/2025 cohort
7	Sampling	Purposive sampling for validators; total sampling for the student class

2.3 Research Procedure

Table 2 breaks the three Plomp phases down into specific activities and the outputs that each phase produced.

Table 2. Research Procedure Across the Three Plomp Phases

No.	Plomp Phase	Activities	Outputs
1	*Preliminary Research* (initial investigation)	Student needs analysis; review of the syllabus; systematic review of literature on CBL, AI in education, and political literacy; identification of teaching problems; development of the theoretical and conceptual framework	User-needs profile; research-gap map; conceptual framework of the AI-CBL model

2	*Prototyping Phase* (prototype development)	Design of Prototype 1 → expert validation by three reviewers → revision → Prototype 2 → small-group try-out (n = 8) → refinement → final prototype ready for classroom use	Model book; five-step lesson syntax; syllabus, student worksheets, and reading materials with AI integration; assessment instruments
3	*Assessment Phase* (evaluation)	Practicality rating by 3 lecturers and 32 students; effectiveness check using a one-group pretest-posttest design; N-Gain analysis; limited dissemination to peers	Practicality data (quantitative and qualitative); effectiveness data (pretest, posttest, N-Gain); final development report

2.4 The Conceptual Model

The conceptual framework that emerged from the preliminary research and prototyping phases is shown in Figure 2. It has four working layers input, process, AI-assist, and output and treats political literacy as the main outcome, divided into cognitive, affective, and psychomotor dimensions

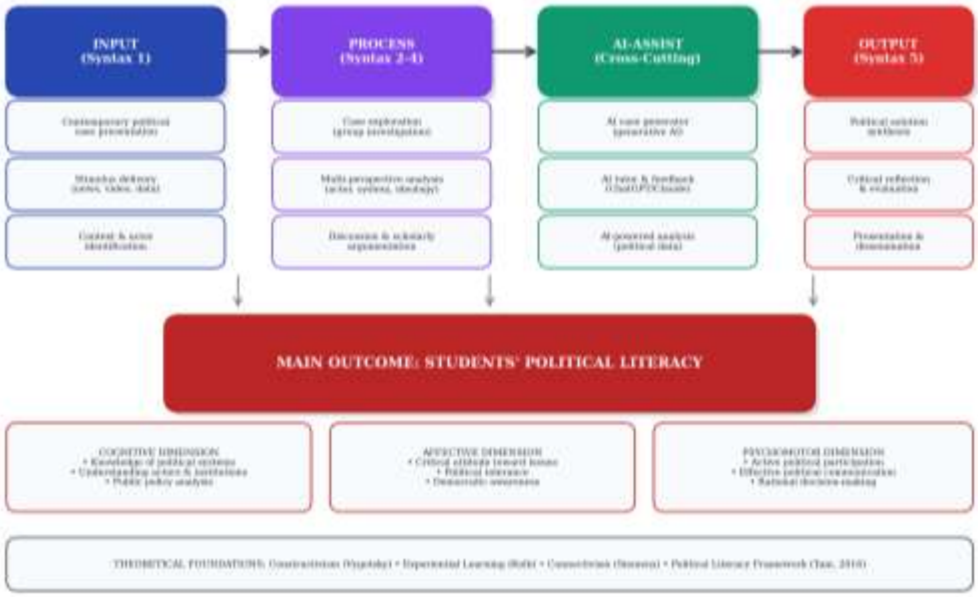

Figure 2. Conceptual Framework of the AI-Assisted Case-Based Learning (AI-CBL) Model

2.5 Instruments and Validation

We used six instruments to measure the four product-quality dimensions (validity, feasibility, practicality, and effectiveness). Table 3 lists them along with their purpose, respondents, and the techniques we used to check their psychometric quality.

Table 3. Research Instruments and Their Validation

No.	Instrument	Purpose	Respondents	Validation / Reliability

1	Model validation sheet	Rates the validity of content, construction, language, pedagogy, and AI integration	3 expert validators	Content Validity Index (CVI); Aiken's V
2	Feasibility rating sheet	Rates feasibility across conceptual, content, technical, and implementation aspects	3 expert validators	4-point rubric based on Nieveen (1999)
3	Lecturer practicality questionnaire	Captures how practical the model is from the teaching side	3 lecturers	5-point Likert scale; construct validity + Cronbach's α = 0.87
4	Student practicality questionnaire	Captures how practical the model is from the learning side	32 students	5-point Likert scale; Cronbach's α = 0.89 (highly reliable)
5	Political literacy test (pretest–posttest)	Measures effectiveness across the cognitive, affective, and psychomotor dimensions	32 students	Item validity (product–moment r); KR-20 reliability = 0.87
6	Classroom observation sheet	Tracks whether the syntax of the model is actually being followed in class	2 observers	Inter-rater reliability (Cohen's Kappa = 0.82)

2.6 Data Analysis

We analysed the data in three ways. First, validity scores were averaged on a 1–4 scale and matched against the categories in Table 4. Second, practicality scores were converted into percentages using Riduwan's (2015) cut-offs, with ≥80% counted as highly practical, 60–79% as practical, 40–59% as moderately practical, and <40% as not practical. Third, effectiveness was checked using Hake's (1999) Normalized Gain (N-Gain) formula: N-Gain = $(S\_post - S\_pre) / (S\_max - S\_pre)$. Values of $g \geq 0.70$ are taken as high, $0.30 \leq g < 0.70$ as medium, and $g < 0.30$ as low.

Table 4. Validity Score Categories

No.	Score Range	Validity Category	Action
1	$3.25 \leq x \leq 4.00$	Highly valid	Use as is, no revision needed
2	$2.50 \leq x < 3.25$	Valid	Use after minor revision
3	$1.75 \leq x < 2.50$	Marginally valid	Major revision required
4	$1.00 \leq x < 1.75$	Not valid	Cannot be used

3. RESULTS AND DISCUSSION

This study produced an AI-Assisted Case-Based Learning (AI-CBL) model for the Introduction to Political Science course. In what follows we work through the four research questions in turn, presenting the relevant quantitative data, the supporting figures, and the comparisons with the existing literature.

3.1 Validity of the AI-CBL Model

Three experts validated the model. Each came from a different angle: Validator 1 (V1) is a doctor of political science; Validator 2 (V2) specialises in educational technology; and Validator 3 (V3) works on AI in education. All three rated five aspects of the model on the 1–4 scale defined in Table 4. Table 5 reports the full set of scores.

Table 5. Validation Scores from the Three Expert Validators

No.	Validation Aspect	V1 (Politics)	V2 (Pedagogy)	V3 (AI)	Mean
1	Content (conceptual accuracy, alignment with learning outcomes)	3.85	3.78	3.70	3.78
2	Construction (syntax, social system, support system)	3.78	3.88	3.80	3.82
3	Language and communication (clarity, precision of terms)	3.90	3.85	3.75	3.83
4	Pedagogy (fit with learning theory, ZPD, scaffolding)	3.82	3.92	3.85	3.86
5	AI integration (purpose, ethics, relevance of AI's role)	3.75	3.95	3.96	3.89
	Overall mean	3.82	3.88	3.81	3.84
	Validity category	*Highly Valid*			

Figure 3 plots the same data so the pattern across validators is easier to see. Every score sits above the 3.25 cut-off for "highly valid".

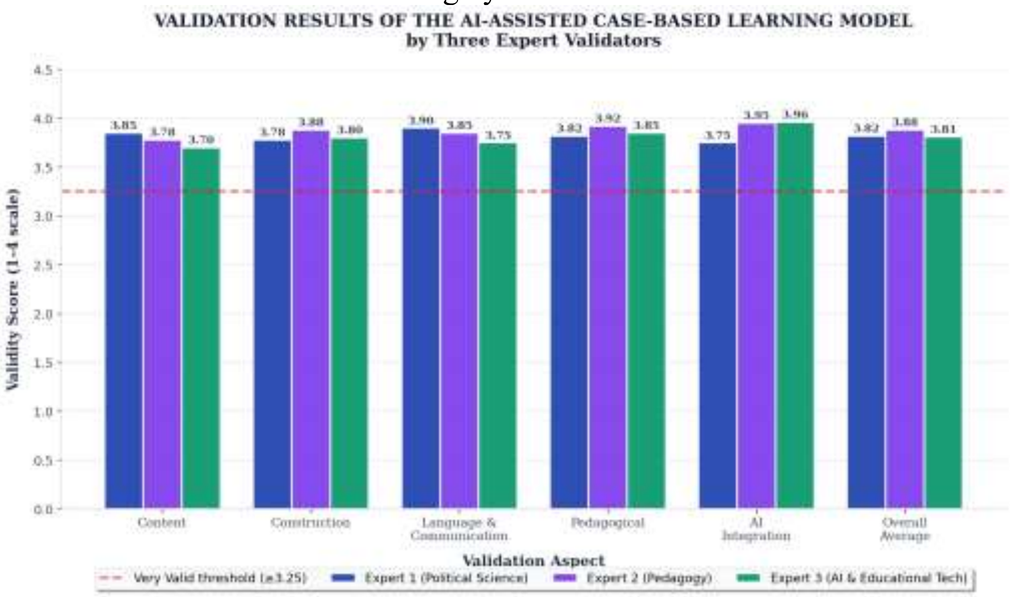

Figure 3. Validity Scores for the AI-CBL Model by Three Expert Validators

Several things stand out. The overall mean is 3.84 out of 4.00, comfortably inside the highly valid band. No aspect, and no validator, dropped below 3.70. By the standards of Nieveen's (1999) framework for product quality in educational design research, the model has both construct and content validity.

The AI-integration aspect drew the highest mean score (3.89), which is interesting on its own. V2 and V3 the pedagogy and AI specialists were almost unanimous (3.95 and 3.96), while V1 the political-science specialist was a step behind at 3.75. We read this as a useful warning: the way AI is built into the model works on educational and technical grounds, but the political-science framing of the AI use could still be stronger. That echoes Adiguzel et al. (2023), who argue that AI integration in any subject succeeds or fails on how well it is contextualised within that subject, not on the technology alone.

Pedagogy (3.86) and language (3.83) also came in high, which suggests the model rests on a coherent theory of learning and is described clearly enough for other lecturers to follow. The lowest mean, content at 3.78, is still solidly in the highly valid band; the experts' written comments pointed mainly to opportunities to fold in more Indonesian political cases, rather than to anything wrong with what was there.

Inter-rater agreement was tight: the three overall means (3.82, 3.88, 3.81) span only 0.07 points. We take this as evidence that the model holds up when viewed from quite different disciplinary angles, which is part of what Bettayeb et al. (2024) and Zhai et al. (2021) call trustworthiness in expert validation.

3.2 Feasibility of the AI-CBL Model

Feasibility was rated on four aspects following Nieveen (1999): conceptual, content, technical, and implementation. The full results are in Table 6.

Table 6. Feasibility Ratings for the AI-CBL Model

No.	Aspect	Indicators	Score (%)	Category
1	Conceptual	Strength of theoretical grounding; internal consistency of the syntax; coherence among model components	92.8	Highly feasible
2	Content	Alignment of cases with learning outcomes; recency and local relevance of political material; cross-disciplinary integration	90.5	Highly feasible
3	Technical	Ease of access to AI tools; reliability of the platform; compatibility with campus infrastructure	89.3	Highly feasible
4	Implementation	Fit with the 3-credit timetable; lecturer workload; potential for institutional adoption	93.2	Highly feasible
Overall feasibility index			91.5	Highly feasible

Every aspect cleared the threshold for "highly feasible", with an overall index of 91.5%. The strongest score went to implementation (93.2%), which matters more than it might look: a model that is theoretically elegant but impossible to run is, in Plomp and Nieveen's (2013) terms, not really feasible at all.

The conceptual score (92.8%) reflects the way the model knits together four theoretical sources Vygotsky's constructivism, Kolb's experiential learning, Siemens's connectivism, and Tam's (2016) political literacy framework. Pulling from several theories is unusual for a single course-level intervention, and it adds complexity, but it also lets the model meet the different demands of cognitive, affective, and psychomotor learning at once. Karisma et al. (2024) report a similar finding in a different setting: multi-theory designs tend to score well on feasibility because they make room for student variation.

The lowest score, technical at 89.3%, is still in the highly feasible range, but the experts' notes are worth taking seriously. Most of their concerns were about the digital divide uneven internet access and varying student devices. Adiguzel et al. (2023) and Romero, Reyes, and Kostakos (2024) make the same point in broader terms: AI in education only works if the infrastructure works. We addressed this in the prototype by adding a low-bandwidth mode and an offline-first option, so that classroom activities can still run when the connection drops.

3.3 Practicality of the AI-CBL Model

Practicality was rated from two sides: three lecturers as users-as-teachers, and 32 students as users-as-learners. Six aspects were measured: ease of use, clarity of instructions, lesson implementation, usefulness of AI, time efficiency, and case appeal. Table 7 gives the full picture.

Table 7. Practicality Ratings of the AI-CBL Model

No.	Practicality Aspect	Lecturers (n=3) %	Students (n=32) %	Mean	Category
1	Ease of use	88.5	86.8	87.65	Highly practical
2	Clarity of instructions	91.2	87.5	89.35	Highly practical
3	Lesson implementation	89.3	88.9	89.10	Highly practical
4	Usefulness of AI	92.8	94.2	93.50	Highly practical
5	Time efficiency	85.6	83.4	84.50	Highly practical
6	Case appeal	90.4	92.1	91.25	Highly practical
	Overall practicality score	89.7	88.4	89.05	Highly practical

Figure 4 puts the lecturer and student ratings side by side. The two groups largely agreed, and the small gaps that did appear are themselves informative.

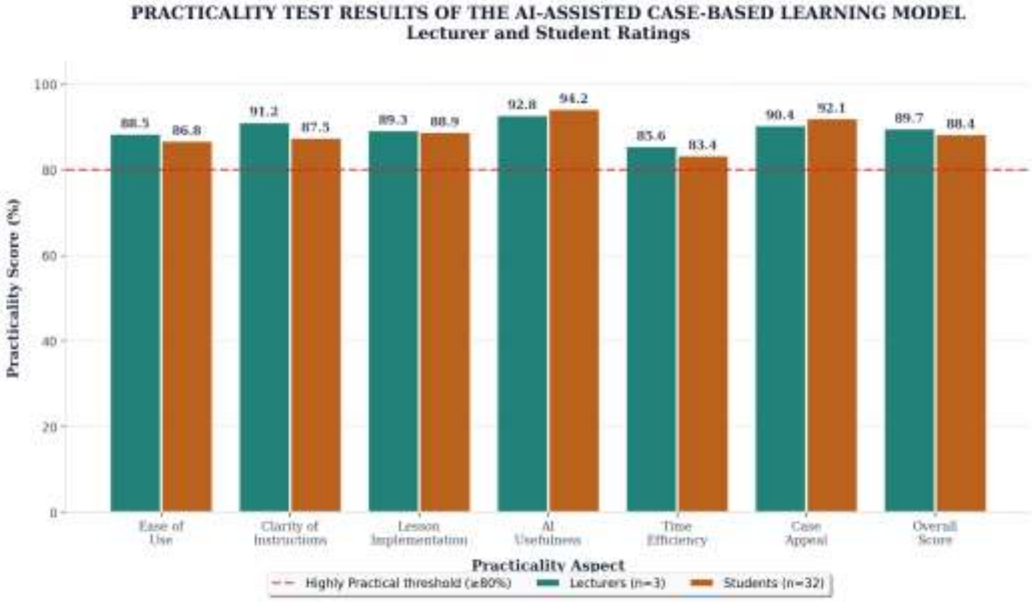

Figure 4. Practicality Ratings from Lecturers and Students

The headline number is the overall practicality score of 89.05% (89.7% from lecturers, 88.4% from students), which sits firmly in Riduwan's (2015) highly practical category. The two sides of the classroom rate the model within 1.3 percentage points of each other, which is unusual and suggests the design works for both teaching and learning.

The single highest score, 93.50% for usefulness of AI, is interesting in its own right because students (94.2%) rated this even higher than lecturers (92.8%). That gap is small but it points to something real: students saw the value of AI as a learning companion more strongly than their lecturers did. Bettayeb et al. (2024) report similar patterns in other studies, and the obvious explanation is the one they offer — students who grew up online are quicker to treat AI as a useful tool, while lecturers tend to be more cautious. From the student side, an AI assistant is patient, available outside class, and non-judgmental in a way a human teacher with thirty students cannot reasonably be (Zhai et al., 2021).

Case appeal also scored well (91.25%), which was good news for the model because outdated cases are one of the standard criticisms of CBL (Lavi & Marti, 2023). With an AI assistant on hand, the lecturers were able to refresh cases as the news shifted examples from the 2024 election cycle, ongoing regional elections, and even local-government cases from Bima ended up in classroom discussions during the trial. Students mentioned this in their open-ended feedback as one of the things they liked best.

The lowest score, time efficiency at 84.50%, is more revealing than it looks. Students rated it 83.4%, slightly below the 85.6% from lecturers. In follow-up interviews, students explained that the AI-CBL classes simply took longer than the lectures they were used to: there was more reading, more discussion, and more drafting. This matches what Burucu and Arslan (2021) and Liu (2024) have found in other CBL contexts the method is more demanding by design, but the trade-off is deeper learning. The practical implication for lecturers is to build in explicit time-management scaffolding so students do not feel they are losing ground.

3.4 Effectiveness of the AI-CBL Model

Effectiveness was tested with a one-group pretest-posttest design on all 32 students who took the course. The political literacy test (KR-20 = 0.87) covered the three dimensions of cognitive, affective, and psychomotor literacy. Table 8 shows the pretest scores, posttest scores, score gains, and N-Gain values.

Table 8. Effectiveness of the AI-CBL Model on Students' Political Literacy (n=32)

No.	Dimension of Political Literacy	Pretest	Posttest	Gain	N-Gain	Cat.
1	Political cognition (knowledge of systems, actors, policy)	52.3	83.6	+31.3	0.66	Med.
2	Political affect (critical attitude, tolerance, democratic awareness)	48.7	79.4	+30.7	0.60	Med.
3	Political psychomotor (participation, communication, decision-making)	45.2	77.8	+32.6	0.59	Med.
	Political literacy (overall)	48.7	80.3	+31.6	0.62	Med.

Table 9 then breaks the same students down by N-Gain category, which shows how widely (or narrowly) the benefit was distributed.

Table 9. Distribution of Student N-Gain Scores (n=32)

No.	N-Gain Category	Score Range	Students	Percentage
1	High	$g \geq 0.70$	21	65.6%
2	Medium	$0.30 \leq g < 0.70$	10	31.3%
3	Low	$g < 0.30$	1	3.1%
	Total	—	32	100.0%

Figure 5 brings these two tables together, with the pretest-posttest comparison on the left and the N-Gain distribution on the right.

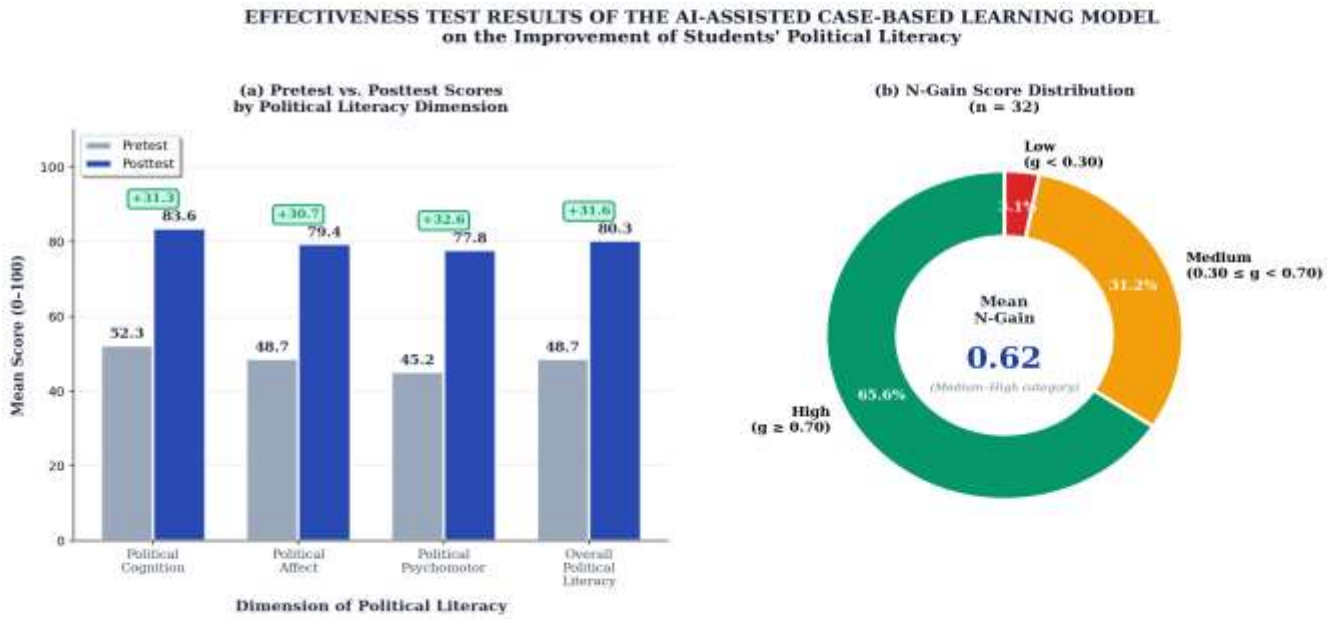

Figure 5. Effectiveness of the AI-CBL Model: (a) Pretest vs. Posttest by Dimension; (b) N-Gain Score Distribution

Four findings deserve attention. First, every dimension of political literacy improved. The overall mean climbed from 48.7 to 80.3, a gain of 31.6 points or roughly 65% in relative terms, and the overall N-Gain of 0.62 sits in the medium-high band. This is well above the 0.38 (medium) that Ridha and Riwanda (2020) reported using more conventional approaches, which is a useful point of comparison: the gap between the two studies is the strongest indirect evidence we have that the AI-assist genuinely adds something beyond what good case-based teaching already delivers.

Second, the largest gain came in the psychomotor dimension (+32.6 points), followed by cognition (+31.3) and affect (+30.7). That ordering is, frankly, a little surprising. Psychomotor outcomes actually doing politics, not just knowing about it are usually the hardest thing to move through a single classroom intervention. The fact that they moved most here suggests the simulated cases, supported by AI feedback, gave students enough of a near-authentic experience that they could practise the moves themselves. This lines up well with Kolb (1984): concrete experience is what builds action competence, and the AI-CBL classroom gave students more concrete experience than a lecture course can.

Third, the spread of N-Gain scores is positive but not uniform. Twenty-one of the 32 students (65.6%) reached the high category, ten landed in the medium category, and one was in the low category. By comparison, the recent meta-analysis in Frontiers in Medicine (2025) reports that CBL studies typically place 40–55% of students in the high N-Gain band, so our distribution is at the upper end of what the literature would predict. The most likely explanation is the personalised scaffolding that the AI assistant provides: students who came in with weaker preparation got more iterations of feedback before tackling the posttest, which seems to have helped most of them catch up.

Fourth, the single student who ended up in the low category warrants a closer look. Following up on their case showed that the issue was not the model itself: this student missed more than 30% of the class meetings and reported repeated internet outages at home that made it hard to use the AI tools outside class. The lesson is straightforward enough the model works when the basics are in place, and it cannot rescue a student who has lost the basics. As Adiguzel et al. (2023) note, AI-enabled teaching only delivers if the institutional supports for attendance, infrastructure, and engagement deliver too.

Taken together, the four findings support the broader claim that AI-Assisted Case-Based Learning is more than the sum of its parts. Contemporary political cases, a structured CBL syntax, and an AI assistant each have their own evidence base; what this study adds is empirical support for combining them in the specific domain of political science education in Indonesia. That extends the line of argument made by Bettayeb et al. (2024) and Tahiru (2021) about AI's potential in higher education, and it puts new evidence on the table in a subject area where such evidence has so far been thin.

Looking ahead, the model offers a starting point that other lecturers can adapt for related courses political sociology, contemporary Indonesian politics, modern political thought, even civic education at the secondary level. The five-step syntax is intentionally generic at the structural level (authentic case → multi-perspective analysis → AI-assisted scaffolding → synthesis → reflection), which should make adaptation reasonably straightforward provided that the cases are localised and the AI prompts are tuned to the discipline.

4. CONCLUSION

The four research questions can be answered briefly. First, the AI-Assisted Case-Based Learning (AI-CBL) model is highly valid: the mean expert score was 3.84 on a 4-point scale, and inter-rater agreement was tight (range = 0.07). Content, construction, language, pedagogy, and AI integration all came out in the highly valid band. Second, the model is highly feasible, with an overall feasibility index of 91.5%. The strongest score went to implementation (93.2%), which is the test that matters most in practice: a model that cannot run in real classrooms is not a useful model.

Third, the model is highly practical. Lecturers gave it 89.7% and students gave it 88.4%, with usefulness of AI as the single highest-rated aspect (93.50%). Fourth, the model is effective. The mean N-Gain was 0.62 (medium-high), with 65.6% of students reaching the high-gain category and gains spread across all three dimensions of political literacy cognitive (+31.3 points), affective (+30.7), and psychomotor (+32.6).

These results carry two kinds of implication. Theoretically, the study contributes a conceptual framework that brings together four established sourcesVygotsky's constructivism, Kolb's experiential learning, Siemens's connectivism, and Tam's political literacy framework and integrates generative AI into a working classroom design. Practically, the model gives political science lecturers a concrete template for AI use that supports, rather than replaces, the deliberative reasoning that the discipline requires. We also see the model adapting reasonably well to related courses in the social sciences and humanities.

Two limitations should be noted. The study used a single-group, single-institution design, so the inferences are necessarily local; a multi-site quasi-experiment with a control group would be a useful next step. The trial also ran over a single semester, which leaves the longer-term durability of the political literacy gains an open question. Both points are good candidates for follow-up research..

5. ACKNOWLEDGMENTS

The author wishes to thank the leadership and academic community of STKIP Taman Siswa Bima for institutional support throughout the study. Sincere thanks also go to the three expert validators the political science content expert, the instructional design specialist, and the AI-in-education expert whose detailed feedback shaped the model. The author is grateful to the first-semester students of the Department of Education (2024/2025 cohort) who took part as research participants, and to the three lecturers of the Introduction to Political Science course who collaborated during the prototyping and assessment phases.

Finally, the author thanks his family for their unwavering support, and everyone who contributed to the study but is not named here..

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