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Economic Literacy as a Mediating Mechanism between Learning Motivation, AI-Oriented Learning Methods, and Students' Critical Thinking Skills

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Abstract: Evaluating macroeconomic claims requires students to apply economic concepts and assess the evidence behind them. This study examined whether economic literacy statistically accounts for part of the associations of learning motivation and artificial intelligence (AI)-oriented learning methods with critical thinking skills. A cross-sectional survey used a five-point Likert questionnaire with 165 undergraduates purposively sampled from Universitas PGRI Kanjuruhan Malang. Two ordinary least squares regressions and Sobel tests were used to estimate direct and indirect associations. Learning motivation ($\beta = .179$, $p = .011$) and AI-oriented learning methods ($\beta = .519$, $p < .001$) were positively associated with economic literacy. Economic literacy had the largest standardized coefficient in the model for critical thinking skills ($\beta = .434$, $p < .001$). The indirect associations via economic literacy were .078 for motivation ($p = .017$) and .242 for AI-oriented learning methods ($p < .001$). Both direct associations remained positive after adjustment for economic literacy. The cross-sectional, single-institution self-report design limits causal inference and generalizability. The findings identify economic literacy as a candidate pathway to examine in future evaluations of macroeconomics instruction.

Keywords: Economic Literacy, AI-Oriented Learning Methods, Learning Motivation, Critical Thinking Skills, Macroeconomics

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INTRODUCTION

Critical thinking skills help students judge the quality of evidence, question assumptions, and draw defensible conclusions. These skills matter in macroeconomics, where the same change in inflation or unemployment can support different policy responses depending on how students interpret the evidence. Research on critical thinking in higher education underscores the

importance of developing these skills explicitly, and work on argument-driven inquiry in Indonesian macroeconomics education illustrates how economic arguments can be built into course tasks (Anas et al., 2023; Van Damme & Zahner, 2022). In an Indonesian higher education case study, Pratama et al. (2024) found that students could understand basic economic concepts yet still struggle to apply them in everyday situations. This gap between knowing a concept and using it provides a reason to study economic literacy alongside critical thinking skills.

Economic literacy refers to understanding economic principles and using them to interpret economic information and evaluate choices (McCowage & Dwyer, 2022). In an Australian survey, abstract macroeconomic concepts were harder for respondents than questions grounded in everyday experience (McCowage, 2023). Domain knowledge can support critical thinking by helping students recognize which evidence is relevant and which conclusions follow from it. For example, distinguishing a lower inflation rate from a falling price level helps students assess whether a claim about household purchasing power is warranted. Domain-specific assessment research supports examining reasoning within the subject in which it is used (Tiruneh et al., 2017). Research in economics education also links economic literacy to critical thinking, although the two constructs concern different aspects of performance (Anistasia et al., 2025; Selviani et al., 2022).

Self-determination theory distinguishes students' reasons for engaging with coursework and links more autonomous forms of motivation to adaptive learning outcomes (Howard et al., 2021; Ryan & Deci, 2020). Studies of university students also connect learning motivation with engagement or academic outcomes (H. Li et al., 2020; S. Li & Yang, 2025). In macroeconomics, sustained engagement may give students more opportunities to develop economic knowledge. Motivation may also relate to critical thinking skills through a direct association if students invest effort in weighing evidence and revising arguments. The model therefore allows both associations.

AI-oriented learning methods refer here to students' perceptions of how AI is incorporated into course instruction. This construct concerns instructional use and is distinct from students' independent use of AI outside course activities or their personal AI literacy (Ng et al., 2021). AI applications in higher education can support feedback and tutoring, but their educational contribution depends on how they are used (Holmes et al., 2019; Zawacki-Richter et al., 2019). For macroeconomics, instructional activities that use AI to compare explanations could support conceptual understanding and provide opportunities to evaluate reasoning. Both associations are plausible, while evidence from other settings cautions that unrestricted access can encourage answer-seeking and undermine independent performance (Bastani et al., 2025).

Prior research has examined economic literacy as an intermediary between lecturer competencies and students' economic behavior (Narmaditya et al., 2024). The present study extends that question to critical thinking skills in macroeconomics by examining learning motivation and AI-oriented learning methods in the same model. Figure 1 shows the hypothesized positive associations of motivation (H1) and AI-oriented learning methods (H2) with economic literacy and of economic literacy with critical thinking skills (H3). The model specifies positive indirect associations via economic literacy for motivation (H4) and AI-oriented learning methods (H5), alongside positive direct associations with critical thinking skills after adjustment for economic literacy (H6 and H7, respectively). H6 and H7 denote the two adjusted direct associations included in the analytical model.

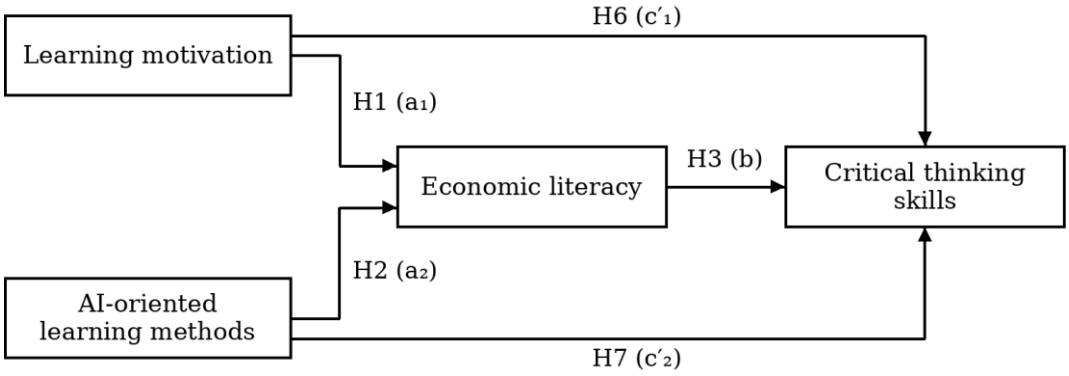

Figure 1. Conceptual model of direct and indirect associations

Note. H4 = a_1b and H5 = a_2b. Each indirect association combines the relevant path to economic literacy with the path from economic literacy to critical thinking skills.

METHOD

This quantitative study used a cross-sectional survey design. The target population comprised active undergraduates in the Faculty of Economics and Business at Universitas PGRI Kanjuruhan Malang who were enrolled in or had completed macroeconomics during the 2025/2026 academic year. Purposive sampling was used to recruit students with relevant coursework experience. The sample comprised 165 students. The enrollment criterion identifies the population to which the study pertains. Precision and generalizability must be considered separately from the number of participants (Lakens, 2022).

Students responded to a structured, closed-ended questionnaire using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Learning motivation was described in terms of internal drive, learning orientation, and academic perseverance. At the conceptual level, economic literacy concerns interpreting and applying economic concepts, and critical thinking skills concern analyzing arguments, evaluating evidence, and drawing warranted inferences. The AI-oriented learning methods score represents students' reports about instructional use of AI. These definitions establish the conceptual scope of the measures, while item-level evidence remains important for evaluating construct coverage and distinctiveness (Flake & Fried, 2020). Preliminary measurement checks involved Pearson product–moment correlations and Cronbach's alpha.

The analyses used two ordinary least squares regressions in IBM SPSS. Model 1 regressed economic literacy on learning motivation and AI-oriented learning methods. Model 2 regressed critical thinking skills on those two predictors and economic literacy. The reported models contain no additional covariates. The indirect association for each predictor was calculated as ab, where a is its unstandardized coefficient in Model 1 and b is the coefficient for economic literacy in Model 2. The adjusted direct coefficient c′ is the corresponding predictor coefficient in Model 2. The total association conditional on the other predictor was recovered as c′ + ab. The indirect share was calculated as ab/(c′ + ab) (Hayes & Rockwood, 2017).

Indirect associations were evaluated using two-sided Sobel tests at $\alpha = .05$. The sampling distribution of ab can be asymmetric, so the tests were supplemented with 95% Monte Carlo intervals rather than relying solely on normal-theory inference (MacKinnon et al., 2004; Preacher & Selig, 2012). Each interval used the 2.5th and 97.5th percentiles of 2,000,000 simulated products based on independent normal draws centered on the path estimates and their standard errors. This parametric approach assumes independent, normally distributed coefficient

estimates. The coefficients describe statistical mediation in the fitted models. Causal mediation would require evidence about temporal order and confounding that the survey design cannot establish (Maxwell & Cole, 2007).

RESULTS AND DISCUSSION

Research Results

Regression Diagnostics

Collinearity and residual diagnostics are summarized in Table 1. Variance inflation factors (VIFs) ranged from 1.300 to 1.743 across the two models, indicating limited variance inflation among the included predictors. The Kolmogorov–Smirnov test yielded p = .200, the residual scatterplot showed no evident pattern, and the Durbin–Watson statistic was d = 1.870. These residual diagnostics are interpreted cautiously because their records do not identify the corresponding regression model. For ordered residuals, Durbin–Watson interpretation depends on sample size, predictor count, and observation order. Consequently, the residual checks provide only partial evidence about the regression assumptions.

Table 1. Regression diagnostics for both response models

No.	Diagnostic	Model 1	Model 2
1	Collinearity (VIF)	Motivation 1.300, AI methods 1.300	Motivation 1.353, AI methods 1.743, economic literacy 1.643
2	Residual normality	Inconclusive	Inconclusive
3	Heteroscedasticity	Inconclusive	Inconclusive
4	Residual autocorrelation	Inconclusive	Inconclusive

Note. The Kolmogorov–Smirnov result (p = .200), residual plot assessment, and Durbin–Watson statistic (d = 1.870) are interpreted as general residual diagnostics rather than model-specific tests.

Economic Literacy as the Response

Table 2 shows that learning motivation was positively associated with economic literacy after adjustment for AI-oriented learning methods (B = .199, β = .179, p = .011), supporting H1. AI-oriented learning methods were also positively associated with economic literacy after adjustment for motivation (B = .619, β = .519, p < .001), supporting H2. The AI-oriented learning methods score had the larger standardized coefficient in Model 1.

Table 2. Model 1 regression with economic literacy as the response

Predictor	B	SE	β	t	p	VIF
Constant	.775	.292	—	2.655	.009	—
Learning motivation	.199	.077	.179	2.567	.011	1.300
AI-oriented learning methods	.619	.083	.519	7.432	< .001	1.300

Note. N = 165. Model-fit statistics derived from rounded regression parameters: R^2 = .39, adjusted R^2 = .38, and F(2, 162) = 51.9, p < .001.

Critical Thinking Skills as the Response

Table 3 shows that economic literacy was positively associated with critical thinking skills after adjustment for both predictors (B = .391, β = .434, p < .001), supporting H3. It had the largest standardized coefficient in Model 2. The direct coefficients for learning motivation (B = .219, β =

.220, p = .001) and AI-oriented learning methods (B = .233, β = .217, p = .003) remained positive with economic literacy in the model, supporting H6 and H7. The standardized direct coefficients were similar in magnitude.

Table 3. Model 2 regression with critical thinking skills as the response

Predictor	B	SE	β	t	p	VIF
Constant	.668	.238	—	2.808	.006	—
Learning motivation	.219	.063	.220	3.478	.001	1.353
AI-oriented learning methods	.233	.077	.217	3.029	.003	1.743
Economic literacy	.391	.063	.434	6.226	< .001	1.643

Note. N = 165. Model-fit statistics derived from rounded regression parameters: R^2 = .53, adjusted R^2 = .52, and F(3, 161) = 59.4, p < .001.

Table 4 presents correlations derived algebraically from the regression parameters using a common analysis sample of 165 students. In Model 1, predictor tolerance gives the magnitude of the correlation between learning motivation and AI-oriented learning methods. Its positive sign is consistent with the regression coefficients and the Model 2 tolerance for economic literacy. Correlations involving each response were calculated by multiplying the predictor correlation matrix by the corresponding vector of standardized coefficients. Model-fit statistics were obtained from the same parameter relationships.

Table 4. Correlations derived from regression parameters

Construct	1	2	3	4
1. Learning motivation	—			
2. AI-oriented learning methods	.48	—		
3. Economic literacy	.43	.61	—	
4. Critical thinking skills	.51	.59	.66	—

Note. Correlations were calculated from rounded coefficients and tolerance statistics using a common analysis sample.

Indirect Associations via Economic Literacy

Table 5 gives the indirect association of learning motivation with critical thinking skills via economic literacy. The product of the two paths was .078 (Sobel z = 2.386, p = .017, 95% Monte Carlo CI [.018, .147]), supporting H4. This estimate represents about 26% of the model-implied total association (.297) and is smaller than the direct coefficient (.219).

Table 5. Indirect association of learning motivation with critical thinking skills

Quantity	Estimate	Quantity	Estimate
a_1 (SE)	.199 (.077)	Sobel z	2.386
b (SE)	.391 (.063)	Two-sided p	.017
Indirect coefficient (a_1b)	.078	95% Monte Carlo CI	[.018, .147]
Direct coefficient (c'_1)	.219	Model-implied total	.297
Indirect share	26.2%	Sobel SE for a_1b	.0326

Note. Economic literacy is the mediator. Both regressions include AI-oriented learning methods.

Table 6 gives the corresponding indirect association of AI-oriented learning methods with critical thinking skills. The product of the two paths was .242 (Sobel z = 4.771, p < .001, 95% Monte Carlo CI [.150, .349]), supporting H5. This estimate represents about 51% of the model-implied total association (.475) and is similar in magnitude to the direct coefficient (.233). For both predictors, the estimates are consistent with partial statistical mediation. The study did not test the difference between the two indirect coefficients.

Table 6. Indirect association of AI-oriented learning methods with critical thinking skills

Quantity	Estimate	Quantity	Estimate
a_2 (SE)	.619 (.083)	Sobel z	4.771
b (SE)	.391 (.063)	Two-sided p	< .001
Indirect coefficient (a_2b)	.242	95% Monte Carlo CI	[.150, .349]
Direct coefficient (c'_2)	.233	Model-implied total	.475
Indirect share	51.0%	Sobel SE for a_2b	.0507

Note. Economic literacy is the mediator. Both regressions include learning motivation.

Discussion

Learning Motivation and Economic Literacy

The positive association between learning motivation and economic literacy fits the expectation that students who invest more effort in coursework have more opportunities to connect economic concepts with evidence. Research on undergraduates links motivation and learning strategies to academic performance, including in blended settings (Cosma et al., 2025; Liu et al., 2024). In macroeconomics, persistence may matter when understanding a policy question requires reconciling several mechanisms, such as the different ways demand and supply shocks can affect inflation. The present estimate identifies a relationship between students' questionnaire scores. It cannot specify which study habits produced it or distinguish autonomous motivation from other reasons for engagement.

AI-Oriented Learning Methods and Economic Literacy

The AI-oriented learning methods coefficient was larger than the motivation coefficient in the economic literacy model. This pattern is compatible with the idea that instructional design can make economic relationships easier to explore. An undergraduate physics trial found learning gains from a purpose-built AI tutor that used structured pedagogical guidance (Kestin et al., 2025). Aruleba et al. (2026) showed that prompt design changed the explanatory and ethical quality of model outputs in a financial learning setting. These studies illustrate different ways instructional design could matter. The first tested student learning and the second examined model outputs. The survey did not identify which AI-supported activities students experienced, so its coefficient cannot be attributed to tutoring, prompting, or simulations. Reviews of AI in higher education likewise call for clearer descriptions of pedagogy and stronger evaluation designs (Bond et al., 2024).

Economic Literacy and Critical Thinking Skills

Economic literacy had the largest standardized coefficient in the model for critical thinking skills. Students who can distinguish a measure from the phenomenon it represents are better placed to assess an economic argument. For instance, evaluating a claim that higher

interest rates immediately reduce inflation requires understanding transmission lags and checking which data support the claim. Research on critical thinking in higher education identifies student, instructional, and contextual factors that may shape such reasoning (Jaramillo Gómez et al., 2025). Studies of higher education pedagogy have examined the role of instructional design in supporting critical thinking, including through project-based learning in business education (Bhuttah et al., 2024; Dias-Oliveira et al., 2024). The observed association is compatible with the value of pairing conceptual instruction with explicit argument evaluation. It may also reflect overlap between self-reports of knowledge and self-reports of reasoning ability. Separate performance measures would clarify how much the two constructs share.

Direct Associations and the Role of Economic Literacy

The adjusted direct coefficients for learning motivation and AI-oriented learning methods were almost equal in standardized units. Motivation could relate to critical thinking skills through students' willingness to monitor their reasoning or revisit an initial answer. Research on self-regulated learning in university students identifies motivational strategies among the factors associated with regulation of learning (Ramos-Galarza et al., 2025). AI-supported activities could also give students opportunities to assess claims, provided that the task makes evaluation necessary. Online instructional design research has emphasized structuring learning tasks around critical thinking (Wardani et al., 2019), and work on critical thinking instruction in AI-supported language learning illustrates how reasoning can be taught explicitly in a different disciplinary context (Hajihasankhansary & Gilanlioglu, 2025). The present survey measured neither those behaviors nor the instructional sequences that could elicit them.

The two indirect shares tell different stories about the fitted model. Economic literacy accounts for roughly one quarter of the motivation association and roughly half of the AI-oriented learning methods association. In this sample, economic literacy captures a larger share of the AI-oriented learning methods association even though the direct coefficients are similar. These shares describe an algebraic partition of the fitted associations. Unmeasured factors, such as prior knowledge, could account for parts of both paths. Reverse ordering is also plausible. Students who already reason well about economics may perceive AI-supported instruction more favorably or rate their economic literacy more highly. The study's design leaves these explanations open (Maxwell & Cole, 2007; Rohrer, 2018).

Instructional Implications

One way to use these findings is to design a macroeconomics activity in which students first explain a policy concept, then evaluate an AI-generated claim about it against published data. In an inflation task, for example, students could check whether a model confuses disinflation with deflation, identify the series that resolves the ambiguity, and write an independent explanation. Formative feedback can address the conceptual error and the quality of the evidence students use. Requiring a short unaided explanation would help instructors distinguish students' reasoning from the assistance they receive. This distinction matters for both learning and assessment integrity when students have access to generative AI (Bastani et al., 2025; Cotton et al., 2024).

Limitations

The results come from a cross-sectional, purposively sampled survey at one institution. Shared self-report measurement can introduce common method bias, and the questionnaire scores do not establish performance on independent reasoning tasks (Podsakoff et al., 2024). The measurement evidence presented here is insufficient to establish fully whether economic literacy

and critical thinking skills were empirically distinguishable. Residual diagnostics offer only partial evidence about model assumptions, and the confidence intervals were based on rounded coefficients and standard errors. The models also do not account for differences in prior macroeconomics achievement or course progression. These limitations constrain interpretation of the magnitudes and the evidence for a temporal mechanism.

CONCLUSIONS

Learning motivation and AI-oriented learning methods were positively associated with economic literacy, and economic literacy had the largest standardized coefficient in the model for critical thinking skills. Both predictors also had positive direct associations with critical thinking skills after adjustment for economic literacy. The indirect associations via economic literacy were .078 for motivation and .242 for AI-oriented learning methods, representing approximately 26% and 51% of their respective model-implied total associations.

For macroeconomics instruction, the findings support examining course activities that develop economic knowledge and ask students to use it to judge evidence, including claims generated by AI. Interpretation is limited by the cross-sectional design, single institution, purposive sampling, and shared self-report measurement. Future studies could assess economic literacy and critical thinking skills at separate time points and use independent performance tasks. A multisite study that compares structured AI-assisted activities and documents students' prior macroeconomics achievement could examine whether the pattern holds across settings and whether changes in economic literacy precede changes in critical thinking skills.

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