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AI Social Interaction, Experience, and AI Literacy in Identifying AI Content among Jabodetabek Users

Dani Surya Wijaya[1*], So Yohanes Jimmy[2], Trihadi Pudiawan Erhan[3]
[1,2,3]Universitas Multimedia Nusantara, Tangerang, Banten, Indonesia
[1]*dani.surya@student.umn.ac.id , [2]yohanes.jimmy@lecturer.umn.ac.id , [3]trihadi.pudiawan@umn.ac.id

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***Corresponding Author**

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ABSTRACT

Background: Generative AI has intensified the circulation of synthetic visual content and increased the need for users to identify AI-generated content. Prior studies have examined deepfake detection, AI literacy, AI experience, and social interaction separately, but empirical evidence on how these factors jointly shape identification ability remains limited. Objective: This study investigates the effects of AI Social Interaction and AI Experience on AI Content Identification Ability, with AI Literacy positioned as a mediating mechanism. Methods: A quantitative survey was conducted with 270 social media users in Jabodetabek. AI Social Interaction, AI Experience, and AI Literacy were measured using a five-point Likert questionnaire, while identification ability was measured through a 30-item objective performance test consisting of AI-generated and authentic images and videos. Data were analyzed using partial least squares structural equation modeling with SmartPLS 4.0. Results: AI Experience had a positive effect on AI Literacy. AI Literacy and AI Social Interaction had significant direct effects on AI Content Identification Ability. AI Experience did not directly affect identification ability, but its indirect effect through AI Literacy was significant, indicating full mediation. Conclusion: AI use experience does not automatically improve the ability to identify synthetic content. Experience must be converted into evaluative and ethical AI Literacy, while social interaction may support direct pattern recognition through digital exposure.

INTRODUCTION

Generative artificial intelligence has shifted digital media production from a specialized technical activity into an everyday practice. Images and videos can now be generated, modified, and distributed with limited production cost, while the visual quality of the output increasingly resembles authentic documentation. This condition creates a new challenge for social media users because realistic visual content can no longer be automatically treated as evidence of a real event. The issue is especially relevant in Indonesia, where internet and social media use are embedded in daily information seeking, learning, commercial activity, and social interaction (Asosiasi Penyelenggara Jasa Internet Indonesia, 2024).

The problem is not limited to technological novelty. Synthetic visual content can be used for entertainment and creative work, but it can also be misused for misinformation, impersonation, fraud, and reputational harm. Indonesian public institutions have increasingly warned citizens about AI-enabled scams, deepfakes, and hoaxes (Kementerian Komunikasi dan Digital Republik Indonesia, 2025; Otoritas Jasa Keuangan, 2025). Prior research also shows that people often overestimate their ability to distinguish authentic from AI-synthesized content, especially when synthetic content appears visually realistic (Bray et al., 2023; Casu et al., 2025; Diel et al., 2024; Nightingale & Farid, 2022).

Previous research has approached the issue from several directions. Technical studies have developed automatic detection methods, while human-centered studies have examined AI literacy, technology familiarity, trust, and users' ability to evaluate AI outputs. However, empirical evidence remains limited regarding how AI Social Interaction, AI Experience, and AI Literacy jointly explain users' ability to identify AI-generated visual content. This gap matters because users may learn about AI not only by operating AI tools, but also by observing, discussing, and evaluating AI-related content within their social environment.

This study addresses the gap by examining whether AI Social Interaction and AI Experience influence AI Content Identification Ability directly and indirectly through AI Literacy. AI Social Interaction refers to social exposure and exchange related to AI, such as discussing, asking about, and receiving information about AI in a digital environment. AI Experience refers to prior use and familiarity with AI technologies. AI Literacy refers to users' evaluative and ethical understanding of AI, including their ability to judge outputs, recognize limitations, and consider risks. AI Content Identification Ability is measured not as self-perceived skill but as actual performance in distinguishing AI-generated and authentic visual content.

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The contribution of the study is threefold. First, it integrates the social learning perspective and AI literacy literature to explain how direct experience and social exposure may operate through different learning pathways. Second, it tests a mediated model using PLS-SEM with data from 270 social media users in Jabodetabek. Third, it uses an objective performance-based test, reducing reliance on self-assessed ability and providing a more behaviorally grounded view of human AI content identification.

LITERATURE REVIEW

The social learning perspective explains learning as a process shaped by observation, modeling, reinforcement, and direct experience (Bussey, 2023). In a digital media environment, individuals do not learn about AI only from formal instruction. They also learn by watching how other users react to suspicious images, receiving explanations from peers, and repeatedly encountering AI-generated content in online spaces. This perspective supports the assumption that AI Social Interaction may influence how users recognize visual cues, interpret content authenticity, and decide whether content is synthetic or authentic.

AI Literacy provides the cognitive foundation for more deliberate evaluation of AI systems and outputs. Long and Magerko (2020) define AI literacy as competencies that enable people to critically evaluate, communicate with, and use AI. Ng, Leung, Chu, and Qiao (2021) further emphasize that AI literacy includes understanding what AI can and cannot do, recognizing ethical issues, and evaluating the consequences of AI use. More recent studies also position AI literacy as a competency related to user understanding, evaluation, and responsible use (Allen & Kendeou, 2024; Grassini, 2024; Wang, Rau, & Yuan, 2023). In the present study, AI Literacy is operationalized through evaluative and ethical dimensions because identifying AI content requires technical awareness and critical judgment.

AI Experience is expected to support AI Literacy because repeated use of AI tools may expose users to the strengths, limitations, and typical artifacts of AI outputs. Prior use can help users understand prompting, output variation, hallucination, image generation patterns, and system limitations. Familiarity may also increase users' ability to recognize when an output looks plausible but lacks coherence or contains subtle anomalies. Studies on generative AI adoption and user experience indicate that direct interaction with AI systems shapes user perceptions, trust, and perceived competence (Christensen et al., 2025; Kim, Kim, & Baek, 2025; Wang et al., 2025). Nevertheless, experience alone may not be sufficient because frequent use does not always produce critical understanding.

Human detection of AI-generated content remains difficult. Nightingale and Farid (2022) showed that AI-synthesized faces can be perceived as realistic and trustworthy. Bray, Johnson, and Kleinberg (2023) found that human ability to detect deepfake face images is limited and shaped by judgment. Maiano et al. (2024) compared human and machine detection of AI-generated images and emphasized that both approaches have different strengths and weaknesses. Jeong Ha et al. (2024) showed different error patterns when artists, crowdworkers, and automated detectors distinguish human art from AI-generated images. Casu et al. (2025) further demonstrated the role of impostor bias and automation bias in human judgment. These findings suggest that AI content identification involves perceptual skill, literacy, attention, and bias management.

Based on these arguments, this study proposes that AI Social Interaction and AI Experience may influence AI Content Identification Ability through distinct mechanisms. AI Experience may primarily support identification ability indirectly by developing AI Literacy. In contrast, AI Social Interaction may contribute either to AI Literacy or directly to identification ability through social exposure, examples, and pattern recognition. The conceptual framework is presented in Figure 1.

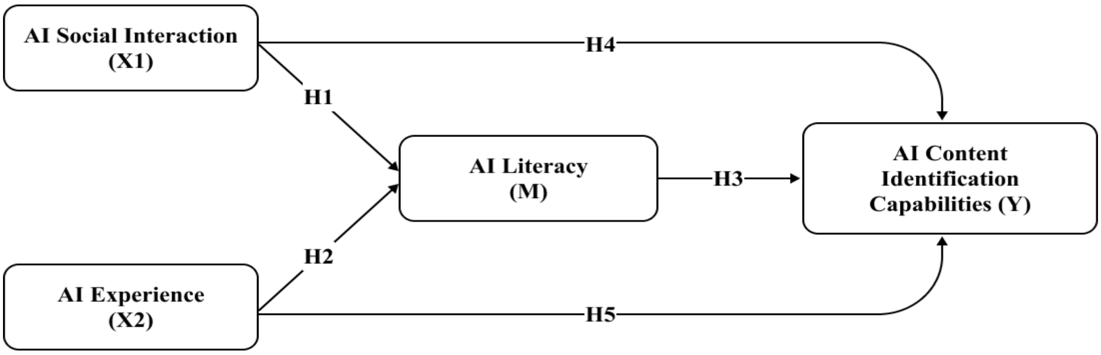

Figure 1. Conceptual framework of the study

METHOD

This study used a quantitative design under a positivist paradigm because the objective was to test hypothesized relationships among measurable constructs. The research was conducted using a cross-sectional survey and an objective performance test. The population consisted of social media users in Jabodetabek who had prior exposure to AI tools. A purposive sampling technique was used to ensure that respondents were relevant to the research context. The final

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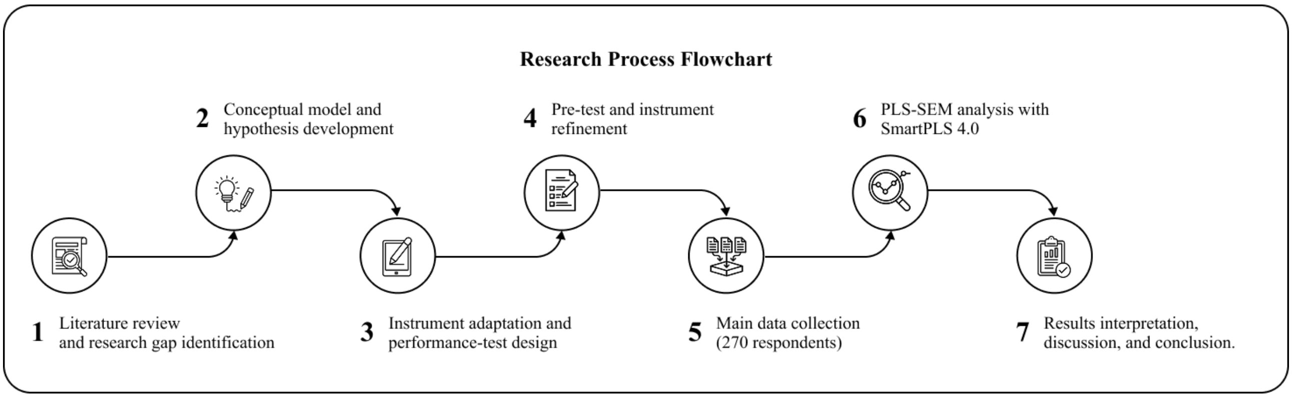
sample consisted of 270 valid respondents, exceeding the minimum sample size requirement for the PLS-SEM model based on the inverse square root method discussed by Hair et al. (2022).

The instrument consisted of two components. The first component was a structured questionnaire using a five-point Likert scale to measure AI Social Interaction, AI Experience, and AI Literacy. AI Experience was modeled as a higher-order construct formed by AI Prior Use and AI Familiarity. AI Literacy was modeled as a higher-order construct formed by Evaluation and Ethic. The second component was a performance-based test used to measure AI Content Identification Ability. In this test, respondents evaluated 30 visual stimuli consisting of seven AI-generated videos, seven authentic videos, eight AI-generated images, and eight authentic images. The score reflected the number of correct answers and represented actual identification performance rather than self-perceived ability.

The research process is summarized in Fig. 2. The process began with identifying the research gap and developing the conceptual model. The instruments were then adapted and refined through a pre-test before main data collection. After obtaining 270 valid responses, the data were analyzed using SmartPLS 4.0, followed by interpretation of the measurement model, structural model, mediation results, and performance-test outcomes.



The flowchart summarizes the empirical procedure from research gap identification to interpretation of the PLS-SEM and performance-test results.

Figure 2. Research process flowchart

Table 1 summarizes the operationalization of the constructs. AI Social Interaction captured the extent to which respondents interacted socially about AI-related content. AI Experience captured prior use and familiarity with AI tools. AI Literacy captured respondents' evaluative and ethical understanding of AI. AI Content Identification Ability captured actual accuracy in distinguishing AI and non-AI visual content. The single performance score was used as a concrete and objective indicator, consistent with the view that PLS-SEM can accommodate directly observed measures when the construct is specific and unambiguous (Hair et al., 2022; Sarstedt, Ringle, & Hair, 2021).

Table 1. Operationalization of Research Constructs

Construct	Dimension	Measurement Approach	Main Adaptation Source
AI Social Interaction	-	Social exposure, discussion, inquiry, and information sharing about AI-related content using a five-point Likert scale.	Zhang et al. (2025); Liao et al. (2020)
AI Experience	AI Prior Use; AI Familiarity	Prior use and familiarity with AI tools using a five-point Likert scale; modeled as a higher-order construct.	Christensen et al (2025)
AI Literacy	Evaluation; Ethic	Ability to evaluate AI output and consider ethical implications using a five-point Likert scale; modeled as a higher-order construct.	Long and Magerko (2020); Ng et al. (2021); Wang et al. (2023)
AI Content Identification Ability	-	Objective performance score based on correct answers across 30 visual stimuli.	Bray et al. (2023)

Source: Processed by the author based on thesis instrument (2026)

Data analysis was conducted using SmartPLS 4.0 with partial least squares structural equation modeling. The measurement model was evaluated using outer loading, Average Variance Extracted, Cronbach's Alpha, Composite Reliability, Fornell-Larcker Criterion, cross loading, and Heterotrait-Monotrait Ratio. The structural model was

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evaluated using collinearity statistics, path coefficients, t-statistics, p-values, coefficient of determination, effect size, predictive relevance, and specific indirect effects. The significance of direct and indirect effects was assessed through bootstrapping with a threshold of t-statistic greater than 1.96 and p-value less than 0.05 (Hair et al., 2022).

RESULT

The measurement model indicated that the retained constructs met the main requirements for validity and reliability. As presented in Table 2, AI Experience obtained Cronbach's Alpha of 0.743, Composite Reliability of 0.886, and AVE of 0.795. AI Social Interaction obtained Cronbach's Alpha of 0.748, Composite Reliability of 0.855, and AVE of 0.664. AI Literacy obtained Cronbach's Alpha of 0.628, Composite Reliability of 0.833, and AVE of 0.716. Although the Cronbach's Alpha of AI Literacy was below the ideal threshold of 0.70, its Composite Reliability value exceeded the recommended threshold, indicating that the construct remained acceptable in a PLS-SEM context. Discriminant validity was also supported by the Fornell-Larcker Criterion, cross loading, and HTMT results. The structural model did not indicate collinearity problems.

Table 2. Measurement Model Summary

Construct	Cronbach's Alpha	Composite Reliability	AVE	Interpretation
AI Experience	0.743	0.886	0.795	Reliable and valid
AI Social Interaction	0.748	0.855	0.664	Reliable and valid
AI Literacy	0.628	0.833	0.716	Acceptable due to CR and AVE values

Source: Processed by the author based on SmartPLS output (2026)

The structural path results are presented in Table 3. AI Experience had a positive and significant effect on AI Literacy, indicating that respondents with greater prior use and familiarity with AI tended to demonstrate higher AI literacy. AI Literacy had a positive and significant effect on AI Content Identification Ability. AI Social Interaction also had a significant direct effect on AI Content Identification Ability. However, AI Social Interaction did not significantly influence AI Literacy, and AI Experience did not have a significant direct effect on AI Content Identification Ability.

Table 3. Path Coefficient, Mediation, and Hypothesis Decision

Hypothesis	Relationship	Coefficient	T-statistic	P-value	Decision
H1	AIS → AIL	0.032	0.702	0.241	Rejected
H2	AIE → AIL	0.652	14.902	0.000	Accepted
H3	AIL → KIA	0.283	3.799	0.000	Accepted
H4	AIS → KIA	0.196	3.586	0.000	Accepted
H5	AIE → KIA	0.116	1.526	0.064	Rejected
H6	AIS → AIL → KIA	0.009	0.665	0.253	Rejected
H7	AIE → AIL → KIA	0.184	3.620	0.000	Accepted

Source: Processed by the author based on SmartPLS output (2026)

The mediation results show that AI Literacy significantly mediated the relationship between AI Experience and AI Content Identification Ability. The indirect effect of AI Experience through AI Literacy was positive and significant. In contrast, the indirect effect of AI Social Interaction through AI Literacy was not significant. This means that AI Experience contributes to identification ability primarily when it is translated into AI Literacy, while AI Social Interaction contributes more through a direct pathway. Based on the combination of a nonsignificant direct effect and a significant indirect effect, the relationship between AI Experience and AI Content Identification Ability can be interpreted as full mediation or indirect-only mediation.

Table 4 presents the explanatory and predictive results. The coefficient of determination for AI Literacy was 0.447, while the coefficient for AI Content Identification Ability was 0.239. This indicates that the model explained 44.7% of the variance in AI Literacy and 23.9% of the variance in AI Content Identification Ability. The relatively low R-square for the performance outcome suggests that identification ability is shaped by additional factors beyond the three predictors tested in the model. Predictive relevance was positive for both endogenous constructs, with Q-square of 0.437 for AI Literacy and 0.184 for AI Content Identification Ability. The objective performance test showed a mean score of 18.219 out of 30, with a median of 18, minimum of 8, maximum of 29, and standard deviation of 3.787. This indicates that respondents generally performed above chance, but their ability varied considerably.

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Table 4. Explanatory Power, Predictive Relevance, and Performance Test Result

Construct/Indicator	R-square	Adjusted R-square	Q-square	Mean	Standard Deviation
AI Literacy	0.447	0.443	0.437	-	-
AI Content Identification Ability	0.239	0.231	0.184	-	-
KIA performance score	-	-	-	18.219	3.787

Source: Processed by the author based on SmartPLS output and performance test (2026)

DISCUSSION

The results support the argument that direct experience with AI is an important foundation for AI Literacy. This finding aligns with the idea that AI literacy is not only obtained from conceptual exposure but also from repeated interaction with AI systems. Users who have used AI more frequently are more likely to observe output variability, limitations, bias, hallucination, and the relationship between input and output. This strengthens the evaluative and ethical dimensions of AI Literacy, which are central to the ability to judge synthetic content. The result is consistent with AI literacy frameworks that place critical evaluation and responsible use at the center of user competence (Long & Magerko, 2020; Ng et al., 2021; Wang, Rau, & Yuan, 2023).

The insignificant relationship between AI Social Interaction and AI Literacy suggests that social exposure alone may not be sufficient to build structured knowledge about AI. Social interaction may provide information, examples, or opinions, but the quality of that information can vary. Discussions about AI on social media may be fragmented, informal, or focused on trend-based usage rather than on critical evaluation. In social learning terms, observation does not automatically produce deep learning unless it is supported by attention, retention, meaningful coding, and reinforcement (Bussey, 2023).

The significant effect of AI Literacy on AI Content Identification Ability confirms the importance of cognitive and evaluative competence in the age of generative AI. Users with stronger AI Literacy are more likely to understand that AI outputs can be realistic yet flawed, biased, or ethically problematic. They may also be more aware of common anomalies in AI-generated content and more cautious when assessing content authenticity. This finding is consistent with studies showing that detection performance depends not only on exposure but also on evaluative skill, domain understanding, and attention to content cues (Bray et al., 2023; Casu et al., 2025; Jeong Ha et al., 2024; Maiano et al., 2024).

The direct effect of AI Social Interaction on AI Content Identification Ability provides a different interpretation. Although social interaction did not form AI Literacy significantly, it may still expose users to examples, warnings, corrections, and collective judgments about AI content. Such exposure can support implicit pattern recognition. In other words, users may become better at noticing suspicious visual cues because they have repeatedly encountered AI-related discussions or examples, even when this exposure does not become explicit AI Literacy. This finding suggests that social learning in digital communities can operate through an experiential and pattern-based route.

The nonsignificant direct effect of AI Experience on AI Content Identification Ability is particularly important. It indicates that being familiar with AI tools does not automatically make users better at identifying AI-generated content. Some users may use AI frequently for writing, productivity, or entertainment without developing the evaluative awareness needed for visual detection. The significant indirect effect through AI Literacy shows that experience must be transformed into critical understanding before it becomes useful for identification. This full mediation result clarifies why experience and literacy should not be treated as interchangeable constructs.

The relatively low R-square for AI Content Identification Ability indicates that the outcome is complex. Human detection may be affected by critical thinking, visual literacy, media literacy, attention to detail, cognitive bias, trust in AI, platform context, and the quality or difficulty of the stimulus (Pennycook & Rand, 2021). The performance test used in this study reduced the problem of self-report bias for the dependent variable, but the predictors were still measured through self-report at one point in time. The study was also limited to social media users in Jabodetabek and to visual stimuli consisting of images and videos. Future research should include longitudinal designs, broader samples, multimodal content such as audio deepfakes and AI-generated text, and additional cognitive or perceptual variables.

CONCLUSION

This study examined the influence of AI Social Interaction, AI Experience, and AI Literacy on AI Content Identification Ability among social media users in Jabodetabek. The results show that AI Experience significantly increases AI Literacy, while AI Literacy and AI Social Interaction significantly increase the ability to identify AI-generated content. AI Experience does not directly improve identification ability, but it influences the ability indirectly through AI Literacy. Therefore, AI Literacy functions as a full mediator in the relationship between AI Experience and AI Content Identification Ability, but it does not mediate the relationship between AI Social Interaction and the same outcome.

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The study contributes theoretically by showing that AI content identification is shaped by two learning pathways. The first is a cognitive pathway in which direct experience with AI becomes useful only when it develops into AI Literacy. The second is a social exposure pathway in which AI Social Interaction can directly support identification ability through examples, observation, and pattern recognition. Practically, the findings suggest that public education should move beyond encouraging AI use. Users need programs that strengthen evaluative and ethical AI Literacy, while online communities and platforms should support credible information sharing, corrective feedback, and collective awareness about manipulative AI content.

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