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Perceived Forensic Auditing Learning, Digital Forensic Mindset, and Accounting Students' Self-Reported Cyber-Fraud Readiness

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ABSTRACT

Purpose: This study examines how perceived forensic auditing learning and a digital forensic mindset are associated, individually and jointly, with accounting students' self-reported readiness to address cyber fraud in the generative AI era.

Research Method: A quantitative survey involved 34 accounting students who had completed a Forensic Auditing course. Fifteen five-point Likert items measured the three constructs, and the responses were analyzed using descriptive statistics, item–total correlations, Cronbach's alpha, and multiple linear regression.

Results and Discussion: Both predictors had positive, statistically significant conditional associations with perceived readiness. The joint regression model was statistically significant, and the standardized coefficient for digital forensic mindset was numerically larger.

Implications: Accounting curricula may benefit from linking forensic auditing concepts to critical evaluation of electronic evidence and cyber-risk scenarios.

Originality: The study examines subject-specific forensic auditing learning alongside an investigative digital mindset in explaining variation in accounting students' perceived cyber-fraud readiness.

Keywords: Forensic Auditing; Digital Forensic Mindset; Accounting Education; Cyber Fraud; Generative Artificial Intelligence.

1. Introduction

Artificial intelligence and data-intensive systems are changing the information environments in which accounting evidence is generated, analyzed, and assessed. Automation may support audit procedures, but it can also alter the types of irregularities that professionals must recognize (Kokina & Davenport, 2017; Sutton et al., 2016). Machine-learning approaches to accounting-fraud detection illustrate the increasing analytical complexity of this environment rather than demonstrating that conventional professional judgment has become unnecessary (Bao et al., 2020). Audit research also identifies information overload, relevance assessment, and ambiguity as challenges when large datasets inform professional judgment (Brown-Liburd et al., 2015). These changes make the preparation of future accountants a question of both technical knowledge and disciplined evaluation of evidence.

The emergence of generative AI adds an important threat context. Synthetic images, video, and other manipulated media complicate judgments about authenticity, although their existence does not

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establish how frequently particular fraud schemes occur in accounting settings (Mirsky & Lee, 2021; Verdoliva, 2020). Broader discussions of AI identify both productive applications and concerns involving misuse, transparency, and trust (Dwivedi et al., 2021, 2023). For accounting students, the educational challenge is therefore not simply to become familiar with new software; it is also to question provenance, scrutinize anomalies, and recognize when evidence needs independent corroboration.

Forensic accounting education has long been proposed as a means of developing fraud-investigation competence (Rezaee & Burton, 1997). In Indonesia, academics have identified technology and data analytics as relevant components of forensic accounting education (Tarjo et al., 2021). Studies of accounting curricula further stress the inclusion of artificial intelligence, data analytics, and changing professional requirements (Qasim & Kharbat, 2020; Rawashdeh & Idris, 2025). However, the availability of curricular content should not be equated with students' ability to apply forensic reasoning in unfamiliar digital situations.

Existing studies address related but different educational outcomes. Kearns (2009, 2010) examined accounting students' perceptions of IT forensics and curriculum design, Hatane et al. (2025) investigated students' views of fraud-related subjects and whistleblowing, and Yaya et al. (2025) analyzed digital intelligence in relation to general work readiness. Their research provides a relevant basis for examining forensic preparation, but these outcomes are not interchangeable with perceived readiness for cyber fraud. The more specific question considered here is whether perceived forensic auditing learning and a digital forensic mindset have separate and joint associations with self-reported cyber-fraud readiness among students who have completed forensic auditing instruction. This context-specific comparison does not establish a training effect or objective fraud-detection competence.

The study focuses on students who had completed the Forensic Auditing course in the Accounting Study Program at Universitas Muslim Indonesia. It considers perceived learning in forensic auditing and digital forensic mindset as two related explanatory variables, with self-reported readiness to address cyber-fraud threats as the outcome. Its contribution lies in examining both perceived domains within one statistical model while distinguishing students' confidence in their preparedness from their demonstrated capacity to investigate digital fraud.

Three questions guide the analysis: whether forensic auditing learning is associated with perceived readiness, whether digital forensic mindset is associated with perceived readiness after accounting for forensic auditing learning, and whether the two predictors are jointly related to readiness. A quantitative survey and multiple linear regression were used to examine these relationships. Section 2 develops the literature-based rationale, Section 3 describes the measures and analytical procedures, Section 4 reports and interprets the empirical results, and Section 5 presents the main implications and limitations.

2. Literature Review and Hypothesis Development

2.1 *Forensic auditing and accounting education*

Forensic auditing combines accounting analysis with investigative procedures aimed at identifying, examining, and explaining suspected wrongdoing. Its educational value extends beyond memorizing fraud typologies: students must evaluate source reliability, reconstruct transactions, distinguish anomalies from evidence of misconduct, and communicate conclusions that remain open to challenge. Studies in professional settings relate forensic accounting and investigative auditing to fraud-detection

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or disclosure activities (Achmad et al., 2024; Khatimah et al., 2024), but those findings do not directly establish student competence. The distinction between professional practice and educational self-assessment is therefore important to the present research.

Curricular evidence is more directly relevant to the present study. Rezaee and Burton (1997) identified a rationale for integrating forensic accounting into accounting education. Research in Indonesia highlights the prospective value of technology and data-analytic skills for forensic accounting courses (Tarjo et al., 2021). Findings among educators and practitioners in another national setting likewise point to the importance of defining an appropriate forensic accounting skill set (Alzahrane, 2024). These contributions suggest that perceived mastery of investigative concepts may accompany a sense of preparedness, while leaving open whether self-reported mastery corresponds to observable performance.

2.2 *Digital forensic mindset*

A digital forensic mindset denotes a critical, investigative, and adaptive orientation toward digital evidence. It includes attention to data provenance, preservation and interpretation of electronic records, awareness of cybersecurity risks, and a willingness to reconsider explanations when evidence is incomplete. This orientation differs conceptually from completing a forensic auditing course: instructional content supplies investigative knowledge, while a mindset concerns the approach taken to uncertainty and digital traces. However, conceptual separation does not itself show that the corresponding self-report measures are empirically distinct.

The distinction matters when digital records can be manipulated at low cost. Research on synthetic media describes difficulties in establishing authenticity, making verification and professional skepticism relevant even when a document or image appears credible (Mirsky & Lee, 2021; Verdoliva, 2020). Kearns (2009, 2010) examined students' perceptions, interest, and curricular engagement in IT forensics; these investigations provide related educational context without independently validating the digital forensic mindset measured in this survey. Here, the construct represents a perceived investigative orientation rather than objectively assessed ability to use forensic software.

2.3 *Readiness for cyber fraud and prior evidence*

Readiness in this study denotes students' perceived knowledge, capacity to analyze digital fraud, willingness to use audit technology, and preparedness for AI-related fraud threats. This self-reported outcome is not equivalent to accuracy in detecting attacks, professional certification, or observed investigative performance. Some of its digital-analysis and technology themes are close to elements of the two predictors, so shared perceptions or overlapping item content may contribute to the statistical associations. Professional studies on fraud disclosure provide context (Achmad et al., 2024; Khatimah et al., 2024), whereas studies of accounting students speak more directly to education, fraud awareness, and professional skepticism (A'yuni et al., 2026; Hatane et al., 2025; Umenzekwe et al., 2023).

The literature does not suggest that course knowledge and mindset are interchangeable. Knowledge may supply the conceptual resources for investigation, while mindset may influence how consistently those resources are applied when digital evidence is uncertain. More generally, research on technology-related accounting competencies and work readiness supports the relevance of connecting professional learning with digital capability, without establishing equivalence between that broader

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outcome and cyber-fraud readiness (Yaya et al., 2025). The study therefore considers the two predictors together while retaining their distinct operational definitions.

2.4 *Research hypotheses*

The three hypotheses retain the study's original two-predictor framework. H1 concerns the partial association of perceived forensic auditing learning (X1) with readiness (Y), conditional on X2. H2 concerns the partial association of digital forensic mindset (X2) with readiness, conditional on X1. H3 concerns whether the two predictor coefficients are jointly different from zero. The individual t tests examine H1 and H2, whereas the model F test examines H3. All three are assessed as observational statistical relationships, not identified causal effects.

3. Research Method

3.1 *Research design, setting, and participants*

This research used a quantitative, observational survey design to examine associations among perceived forensic auditing learning, digital forensic mindset, and readiness to face cyber fraud. The setting was the Accounting Study Program, Faculty of Economics and Business, Universitas Muslim Indonesia. The target population comprised students who had completed the Forensic Auditing course. Since every respondent had undertaken the course, the design did not compare course participants with students who had not received forensic auditing instruction.

The study comprised 34 respondents purposively selected according to three stated criteria: active enrollment in the accounting program, completion of the Forensic Auditing course, and familiarity with basic accounting information systems and digital technology. These respondents constitute the achieved analytical sample rather than a probability sample. The purposive selection procedure does not provide known selection probabilities or a population-level response rate. The findings therefore primarily describe this group and cannot be assumed to represent all accounting students.

3.2 *Data collection and research procedure*

Primary data were collected with a 15-item questionnaire using a five-point Likert response scale, with scores from 1 to 5. The research also drew on scientific literature about forensic auditing, cyber fraud, and generative AI, as well as contextual documentation on accounting education. The research sequence included developing a conceptual framework and hypotheses, preparing the instrument, collecting responses, assessing item correlations and reliability, and analyzing the responses using SPSS multiple regression. All 34 reported questionnaires contained complete responses to the 15 analyzed items. The survey assessed respondents' own views rather than their performance on independently observed digital-fraud investigation tasks.

3.3 *Variables and measurement*

The first predictor, forensic auditing learning (X1), represents perceived understanding and application of forensic auditing concepts, fraud detection, digital investigation, and investigative audit techniques. The second predictor, digital forensic mindset (X2), represents critical thinking, digital-evidence analysis, adaptability to technology, cybersecurity awareness, and recognition of digital risks. The outcome, readiness to face cyber fraud (Y), covers perceived knowledge, analysis of digital fraud, readiness to use

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audit technology, and preparedness for AI-related fraud threats. Each construct was measured through five questionnaire items (X1.1–X1.5, X2.1–X2.5, and Y.1–Y.5); the five item scores were averaged to form MX1, MX2, and MY.

These variables are composites of self-reported responses. A higher Y score therefore indicates stronger perceived preparedness, not independently verified success in recognizing or investigating cyber fraud. Because digital analysis and fraud-related skills appear in more than one construct description, some conceptual overlap is possible. Establishing the distinctiveness of multi-item scales ordinarily requires attention to their conceptual boundaries, item content, and dimensionality as well as reliability (Boateng et al., 2018). The item correlations and internal-consistency estimates in this study evaluate limited aspects of the scales but do not independently establish their factor structure, content validity, or discriminant validity.

3.4 *Data analysis*

Descriptive statistics summarized variable scores and individual questionnaire items. Pearson correlations between each item and its variable total were compared with the reported critical value at the 5% significance level; Cronbach's alpha assessed internal consistency. The regression diagnostics comprised a normal P–P plot of standardized residuals, collinearity statistics, and a scatterplot of residuals against fitted values. These visual checks are useful for identifying conspicuous deviations but cannot alone prove that all model assumptions hold.

Multiple linear regression was estimated in SPSS with MY as the dependent variable and MX1 and MX2 as the predictors. The model was specified as $Y = \alpha + \beta_1 X1 + \beta_2 X2 + e$, where α is the intercept and e is the regression error. Two-sided t tests assessed individual coefficients, an F test assessed the joint regression model, and R^2 described the proportion of variation in the observed readiness scores accounted for by the predictors. The significance threshold was 0.05. Because the design is cross-sectional and nonexperimental, the estimates describe conditional associations rather than causal effects.

4. Results and Discussion

4.1 Analysis Results

4.1.1 *Descriptive statistics*

All 34 respondents provided complete answers to 15 items. Each composite score was calculated as the mean of the five items belonging to its construct. Table 1 reports the minimum, maximum, mean, and standard deviation for the three composite variables. Average responses were concentrated toward the upper end of the five-point scale, while perceived forensic auditing learning showed the greatest dispersion.

Table 1. Descriptive statistics for the research variables (N = 34).

Variable	Min	Max	Mean	Std. deviation	Category
Forensic Auditing (X1)	1.40	5.00	4.1941	0.64664	High
Digital Forensic Mindset (X2)	2.60	5.00	4.2353	0.57095	Very high
Readiness to Face Cyber Fraud (Y)	3.00	5.00	4.2412	0.49916	Very high

Source: Authors' analysis of primary data (SPSS output).

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Item-level responses, presented in Table 2, help describe differences obscured by the composite means. Within X1, item X1.3 had the highest mean (4.412) and X1.1 the lowest (3.882). For X2, the corresponding items were X2.5 (4.382) and X2.1 (4.088); for Y, they were Y.3 (4.441) and Y.1 (4.000). The proportion selecting scores 4 or 5 is also reported. The High and Very high labels serve as descriptive categories; the observed means and response percentages provide a more transparent basis for comparison than categories without an independently established competency threshold.

Table 2. Item descriptive statistics and item–total correlations.

Item	Mean	% scoring 4–5	Category	Item–total r	Criterion met
X1.1	3.882	82.4	High	0.713	Yes
X1.2	4.147	88.2	High	0.842	Yes
X1.3	4.412	91.2	Very high	0.825	Yes
X1.4	4.235	91.2	Very high	0.850	Yes
X1.5	4.294	88.2	Very high	0.719	Yes
X2.1	4.088	88.2	High	0.864	Yes
X2.2	4.206	91.2	High	0.847	Yes
X2.3	4.265	91.2	Very high	0.848	Yes
X2.4	4.235	85.3	Very high	0.784	Yes
X2.5	4.382	94.1	Very high	0.751	Yes
Y.1	4.000	82.4	High	0.593	Yes
Y.2	4.324	91.2	Very high	0.699	Yes
Y.3	4.441	91.2	Very high	0.752	Yes
Y.4	4.206	85.3	High	0.841	Yes
Y.5	4.235	82.4	Very high	0.760	Yes

Source: Authors' analysis of primary data (SPSS output).

4.1.2 *Item correlations and internal consistency*

The reported item–total Pearson correlations exceeded the study's critical value of 0.339 (N = 34, df = 32), and the reported two-tailed significance values were below 0.001. Correlations ranged from 0.593 to 0.864 across the 15 items in Table 2. These results meet the stated item-correlation screening criterion, but a correlation between an item and a scale total containing that item can be inflated by part–whole overlap. Accordingly, the coefficients should not be treated as evidence of corrected item–total discrimination without the corresponding calculation. More broadly, correlations and internal consistency do not substitute for content and dimensionality assessment of a multi-item measure (Boateng et al., 2018; Sijtsma, 2009).

Cronbach's alpha values were 0.847 for X1, 0.873 for X2, and 0.779 for Y (Table 3), all above the 0.70 benchmark employed in the analysis. The pattern indicates acceptable internal consistency in this sample, with the highest reported alpha for the digital forensic mindset scale. Internal consistency is not equivalent to evidence of a single underlying factor or of predictive validity.

Table 3. Internal-consistency reliability.

Variable	Cronbach's alpha	Items	Remark
Forensic Auditing (X1)	0.847	5	Reliable
Digital Forensic Mindset (X2)	0.873	5	Reliable
Readiness to Face Cyber Fraud (Y)	0.779	5	Reliable

Source: Authors' analysis of primary data (SPSS output).

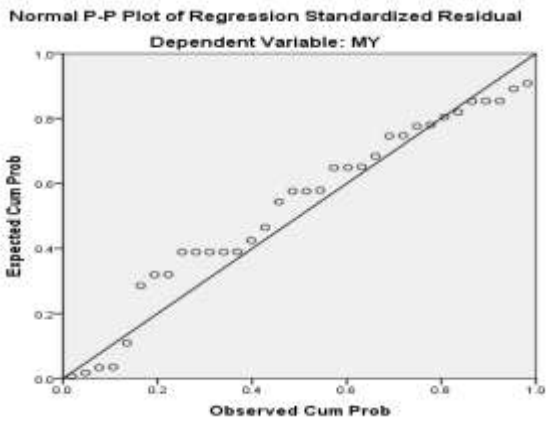
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4.1.3 Regression diagnostics

The P-P plot of standardized regression residuals (Figure 1) shows observations near the diagonal, with visible departures in the middle of the distribution. This pattern permits only a qualitative assessment of residual normality: visual proximity to the line does not establish that the distributional assumption is satisfied. The regression estimates and significance tests are therefore interpreted with the limits of the reported diagnostics in view.

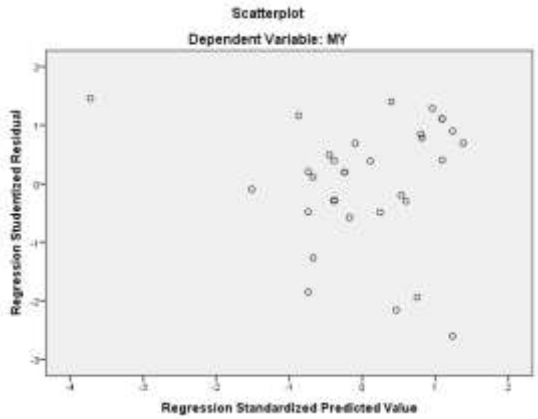
Figure 1. Normal P–P plot of standardized residuals (dependent variable: MY).



Source: Authors' analysis of primary data (SPSS output).

The two predictors each had a tolerance of 0.414 and a variance inflation factor (VIF) of 2.416; the maximum reported condition index was 25.774. These statistics are below commonly used high-collinearity alert values, although the predictors retain some shared variation. The residual-versus-fitted scatterplot (Figure 2) showed no obvious funnel pattern. Because such a plot is only a visual diagnostic, the absence of a clear pattern should not be interpreted as proof of homoscedasticity.

Figure 2. Studentized residuals against standardized predicted values (dependent variable: MY).



Source: Authors' analysis of primary data (SPSS output).

4.1.4 Regression coefficients

Table 4 reports the multiple-regression estimates. The fitted equation was Y = 1.210 + 0.292X1 + 0.426X2. Holding the other predictor constant, a one-unit difference in the X1 composite was associated

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with an estimated 0.292-point difference in Y (t = 2.339, p = 0.026). A one-unit difference in X2 was associated with an estimated 0.426-point difference in Y (t = 3.010, p = 0.005). Both conditional associations were positive and statistically significant under the stated 5% criterion.

Table 4. Multiple-regression coefficients (dependent variable: MY).

Variable	B	Std. error	Beta	t	p
(Constant)	1.210	0.395	–	3.068	0.004
Forensic Auditing (X1)	0.292	0.125	0.379	2.339	0.026
Digital Forensic Mindset (X2)	0.426	0.142	0.487	3.010	0.005

Source: Authors' analysis of primary data (SPSS output).

The standardized coefficient for X2 (β = 0.487) was numerically greater than that for X1 (β = 0.379). This describes the ranking of the point estimates; it is not a separate statistical test of whether the two population coefficients differ. The intercept has limited practical meaning because the questionnaire composites take values from 1 to 5 rather than zero.

4.1.5 *Joint model and hypotheses*

The joint regression test was statistically significant, $F(2, 31) = 30.574$, $p < 0.001$ (Table 5). The model had $R = 0.815$, $R^2 = 0.664$, and adjusted $R^2 = 0.642$, with a reported standard error of the estimate of 0.29871. Thus, the two predictors accounted for 66.4% of the observed variation in perceived readiness within this sample. This in-sample explanatory proportion does not establish predictive accuracy in other groups or identify the causes of the remaining variation.

Table 5. Regression analysis of variance.

Source	Sum of squares	df	Mean square	F	p
Regression	5.456	2	2.728	30.574	< 0.001
Residual	2.766	31	0.089		
Total	8.222	33			

Source: Authors' analysis of primary data (SPSS output).

The reported t tests and joint F test provide evidence for the three statistical hypotheses in the observed sample (Table 6). For H1 and H2, support denotes positive conditional regression associations; for H3, support denotes a jointly significant model. These findings should not be interpreted as effects of experimentally changing course exposure or student mindset.

Table 6. Summary of hypothesis tests.

Hypothesis	Test statistic	p	Decision
H1: X1-Y association	t = 2.339	0.026	Supported
H2: X2-Y association	t = 3.010	0.005	Supported
H3: joint X1/X2–Y association	F = 30.574	< 0.001	Supported

Source: Authors' analysis of primary data (SPSS output).

4.2 Discussion

4.2.1 *Forensic auditing learning and perceived readiness*

The positive conditional association between X1 and readiness is consistent with the argument that conceptual familiarity with fraud examination may accompany students' confidence in dealing with

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cyber-related threats. Forensic auditing learning combines transaction analysis, investigation, and evidence-based explanation. This aligns with the educational value attributed to forensic accounting in Indonesia (Tarjo et al., 2021), while findings from professional fraud investigations provide contextual but not directly comparable evidence (Achmad et al., 2024; Khatimah et al., 2024). Professional samples, outcomes, and research questions differ from the student self-assessments analyzed here.

An important boundary follows from the sample definition. All respondents had already taken the Forensic Auditing course, and X1 measured their responses about learning-related competence. Consequently, the coefficient does not estimate what would happen if a university introduced the course or increased its hours. A more defensible interpretation is that students reporting stronger forensic auditing competence also tended to report higher readiness after their digital forensic mindset scores were statistically taken into account. Testing instructional effectiveness would require performance measures and a design capable of comparing educational conditions.

4.2.2 *Digital forensic mindset and perceived readiness*

The association between digital forensic mindset and perceived readiness was also positive after accounting for X1. This finding is compatible with an educational account in which critical thinking, awareness of cyber risk, and scrutiny of electronic evidence are distinct from memorized investigative procedures. Kearns (2009, 2010) reported that motivation, interest, and skills are salient in accounting students' engagement with digital forensics. More recent evidence concerning accounting students' fraud awareness and professional skepticism also underscores the relevance of dispositions alongside knowledge (A'yuni et al., 2026).

In a generative AI environment, such dispositions could be useful when apparently authentic messages, documents, or visual records contain manipulated content. Work on deepfake creation and detection indicates why evidence evaluation cannot rely solely on surface plausibility (Mirsky & Lee, 2021; Verdoliva, 2020). Nevertheless, the questionnaire did not require respondents to identify a deepfake, preserve a forensic image, or analyze a simulated phishing incident. The result is therefore most accurately understood as an association between two self-reported constructs, not proof of capability against a specific attack technique.

4.2.3 *Joint interpretation and alternative explanations*

Considered jointly, forensic auditing learning and digital forensic mindset were related to a substantial proportion of the observed differences in students' readiness scores. Their standardized coefficients suggest a numerically larger conditional association for digital forensic mindset. Nevertheless, a claim that this predictor is definitively stronger in the population would require testing the difference between coefficients and considering their uncertainty; comparing point estimates alone does not perform that test (Gelman & Stern, 2006). The two predictors also shared some variation, as indicated by the collinearity statistics, so their coefficients should not be treated as wholly independent educational contributions.

Several alternative explanations remain plausible. Students with greater general technological confidence might rate both their digital forensic mindset and their readiness more highly. The same respondents answered all predictor and outcome items within one questionnaire; shared response tendencies could therefore strengthen observed correlations. Research on common-method variance explains why single-source measurement deserves attention while also cautioning against assuming

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that it necessarily invalidates every association (Fuller et al., 2016; Podsakoff et al., 2003). Neither those influences nor the possible overlap in question content were independently assessed in this study. Consequently, high in-sample model fit does not demonstrate causal effects or predictive accuracy beyond the surveyed group.

4.2.4 *Implications for accounting education*

The findings support a practical rationale for teaching forensic auditing as more than a set of conventional detection procedures. Accounting programs could link transaction analysis and investigative audit principles with structured exercises on source authentication, electronic-evidence handling, suspicious digital transactions, and AI-generated content. Students could learn to distinguish an apparent anomaly from a substantiated fraud conclusion and to communicate the limitations of available evidence. Such curriculum development is consistent with recommendations for modernizing accounting education in response to technological change (Qasim & Kharbat, 2020; Rawashdeh & Idris, 2025).

Case-based learning, investigation simulations, digital forensic laboratories, seminars, and collaboration with practicing auditors or cybersecurity professionals are possible implementation routes. Practical experience and training have also been examined in relation to auditors' fraud-detection capabilities (Ramadhani et al., 2025). Yet these recommendations are implications rather than interventions evaluated by the present survey. To determine whether a revised curriculum improves competence, future assessments should include behavioral tasks, transparent scoring rubrics, independent evaluation of digital evidence, and, where feasible, comparisons across instructional conditions.

5. Concluding Remarks and Recommendation

This study investigated whether perceived learning in forensic auditing and a digital forensic mindset were associated with accounting students' self-reported readiness to face cyber fraud. In the surveyed group of 34 students, both constructs showed positive conditional associations with readiness, and the joint regression model was statistically significant. The digital forensic mindset coefficient was numerically larger than the forensic auditing learning coefficient, but the difference was not subjected to an independent statistical test. The results describe perceived preparedness among students who had completed forensic auditing instruction; they do not establish that the course or mindset caused greater fraud-detection ability.

The principal educational contribution is to consider investigative knowledge and digital evidence-oriented thinking together rather than as interchangeable competencies. Forensic auditing instruction can provide conceptual and procedural foundations, while digital forensic reasoning draws attention to the authentication, scrutiny, and interpretation of electronic evidence. Integrating these elements into case-based accounting education is a defensible curricular direction, although its effectiveness needs to be evaluated using observed performance rather than perception measures alone.

The study is limited by its small purposively selected sample from one accounting program, its cross-sectional self-report measures, and the absence of known selection probabilities for estimating population representativeness. The measures of learning, mindset, and readiness may share content

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and response-method influences, while the item-total correlations and Cronbach's alpha values do not constitute a complete assessment of construct validity. The reported diagnostic figures provide visual information only, and the regression does not independently establish causal or out-of-sample effects. Future research should justify its sample size prospectively (Lakens, 2022), describe the original instrument and recruitment procedure in full, assess discriminant measurement properties where feasible, compare multiple institutions, and include observed fraud-investigation tasks or longitudinal educational comparisons. Internship experience, training intensity, technological literacy, and cybersecurity practice warrant examination as additional potential contributors.

Statement of Use of Generative AI

During the preparation of this work, the author used generative artificial intelligence tools to support the scientific writing process. Grammarly was used to check grammar, refine writing style, and improve clarity in scientific writing. All interpretations, analyses, and conclusions presented in this study are the sole responsibility of the author.

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