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AI-Enabled CTAS and Digital Tax-Fraud Detection: A PLS-SEM Study in Indonesia

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Abstract. This study investigates the factors determining digital tax fraud based on the New Fraud Star Theory, with great emphasis on the moderating role of AI-empowered CTAS. Data were collected from 107 corporate taxpayers in Indonesia through a structured survey and analyzed using Partial Least Squares Structural Equation Modeling. The results indicated that System Pressure, Technological Capability, and External Digital Pressure significantly heightened fraud attempts, while Digital Opportunity, AI Rationalization, Cyber Arrogance, Internal IT Governance, and Techno-Culture were not significant. The model explained a substantial variance in the effectiveness of fraud detection with $R^2 = 0.723$. Moderation analysis showed that AI-powered CTAS significantly weakened the effects of System Pressure (X1×CTAS), Technological Capability (X4×CTAS), Internal IT Governance (X6×CTAS), and External Digital Pressure (X7×CTAS). These findings identify CTAS's strategic role in improving compliance by enabling real-time data integration, anomaly detection rules, and strengthened access control. Implications are that digital governance reforms should give full attention to the establishment of robust AI-empowered monitoring systems to minimize the risk of tax fraud effectively.

Keywords: anomaly detection, ctas, digital governance, fraud detection, tax administration.

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1. Introduction

The fast-developing digital technologies have changed public administration around the world, and taxation is no exception. Governments around the world increasingly use AI, big data analytics, and integrated information systems to enhance transparency and efficiency in administration, as well as the monitoring of compliance. Tax fraud remains one of the most important challenges for both developed and developing countries. In Indonesia, the digitalization of tax administration via Core Tax Administration System (CTAS) has been launched in a bid to mitigate risks of evasion, but systemic vulnerabilities remain [1]. The persistence of fraud calls attention to the fact that the effectiveness of digital tools should be assessed together with behavioral and organizational factors interacting with these technologies.

Previous studies emphasize that digital transformation, as it happens within tax systems, enhances compliance because opportunities to manipulate a tax return are minimized and, at the same time, detection risks increase, as previous works have proved for e-invoicing [2], digital reforms [3], and AI integration for anomaly detection [4], together with predictive analytics in finance [5]. But technology cannot address psychological and cultural enablers of fraud like rationalization [6] or arrogance [7]. Findings also hint that such systems as CTAS, effective against structural fraud loopholes [8], should be perceived as moderators within the greater fraud ecosystem. Hence, application of the New Fraud Star Theory, which embraced nine fraud dimensions, interrelated in nature [9], is essential to bridge the gap between behavioral and technological views supported by findings such as capability drives fraud without system intervention [10] and CTAS moderates pressure but not all its determinants [11].

Recent advances in AI-driven fraud detection in public finance show that deployed anomaly detection algorithms, machine learning classification models, and network analytics successfully identify tax evasion patterns in real-time [ref]. In the Indonesian context, the CTAS embeds continuous data flows of e-invoice validation, taxpayer account reconciliations, and cross-agency data matching, offering unique digital signals to pinpoint fraudulent behaviors. Distinct from general digitalization reforms, these CTAS-specific features such as real-time integrations, anomaly detection rules, and system-level access controls directly alter the pathways by which fraud determinants influence detection outcomes. Consequently, the current study not only assesses whether digitalization "helps" but more importantly explores which CTAS mechanisms moderate behavioral and organizational fraud drivers.

Much of the literature regards digital tax systems as solutions in themselves, neglecting the behavioral, organizational, and systemic fraud determinants with which they interact. This either overstates technological capacity or understates non-technical drivers, and prior studies have remained fragmented, isolating single factors such as opportunity or rationalization rather than offering holistic analysis [12]. This paper tackles such gaps by repositioning the New Fraud Star Theory within digital governance to examine how AI-enabled CTAS moderates technological and organizational fraud determinants in Indonesia's reform context, so contributing theoretically by extending fraud research into digitalization and demonstrating the selective role of AI monitoring systems, and practically by providing actionable insights for policymakers seeking to strengthen compliance through CTAS design and directing reforms toward the most vulnerable fraud pathways.

Accordingly, the research is pursuing the following objectives: first, to analyze the effects of nine fraud determinants adapted from the New Fraud Star Theory on the digital fraud detection effectiveness; second, to examine the moderating role of AI-enabled CTAS features in shaping these relationships. By basing its research on the proposed framework, this study develops a total of sixteen hypotheses (H1–H16) that capture both the direct and moderating effects tested in the PLS-SEM model. The following hypotheses are proposed:

Direct Effects

- **H1:** System Pressure positively influences Digital Fraud Detection Effectiveness.
- **H2:** Digital Opportunity positively influences Digital Fraud Detection Effectiveness.
- **H3:** AI Rationalization positively influences Digital Fraud Detection Effectiveness.
- **H4:** Technological Capability negatively influences Digital Fraud Detection Effectiveness.

- **H5:** Cyber Arrogance positively influences Digital Fraud Detection Effectiveness.
- **H6:** Internal IT Governance positively influences Digital Fraud Detection Effectiveness.
- **H7:** External Digital Pressure positively influences Digital Fraud Detection Effectiveness.
- **H8:** Techno-Culture positively influences Digital Fraud Detection Effectiveness.

Moderation Effects of AI-enabled CTAS

- **H9:** AI-enabled CTAS moderates the relationship between System Pressure and Digital Fraud Detection Effectiveness.
- **H10:** AI-enabled CTAS moderates the relationship between Digital Opportunity and Digital Fraud Detection Effectiveness.
- **H11:** AI-enabled CTAS moderates the relationship between AI Rationalization and Digital Fraud Detection Effectiveness.
- **H12:** AI-enabled CTAS moderates the relationship between Technological Capability and Digital Fraud Detection Effectiveness.
- **H13:** AI-enabled CTAS moderates the relationship between Cyber Arrogance and Digital Fraud Detection Effectiveness.
- **H14:** AI-enabled CTAS moderates the relationship between Internal IT Governance and Digital Fraud Detection Effectiveness.
- **H15:** AI-enabled CTAS moderates the relationship between External Digital Pressure and Digital Fraud Detection Effectiveness.
- **H16:** AI-enabled CTAS moderates the relationship between Techno-Culture and Digital Fraud Detection Effectiveness.

2. Methods

2.1. Research Study Area

This study uses a quantitative and explanatory design to investigate the causal relationships of the technological and organizational determinants of digital tax fraud and to assess the moderation role of the AI-enabled Core Tax Administration System. The research model is based on the New Fraud Star Theory, adapted to a digital governance setting. The data are gathered via a structured Likert-scale questionnaire, which is administered to eligible corporate taxpayers. The use of primary data guarantees that the perceptions, experiences, and attitudes of the respondents are directly reflected in the measurement of the constructs.

2.2. Population and Sample

The population of this study includes corporate taxpayers registered and operating under the management of the Pratama Tax Office, Surabaya, which has implemented CTAS in its reporting and compliance. Since the total size is not exactly known, a non-probability purposive sampling method was used. Participants to be included in this research would include: (1) corporate taxpayers for at least two years under the Directorate General of Taxes, Regional Office I, and (2) having used CTAS for at least two years in its digital reporting and compliance.

Out of 150 questionnaires distributed, the total responses received were 112, and after screening, 107 were usable, thus giving a response rate of 71.3%. Nonresponse bias was checked by comparing early respondents with late respondents, using t-tests on key variables, which did not show any significant differences. Site selection, that is, Pratama Tax Office, Surabaya, was purposive since this office was among the first adopters of CTAS, making it an appropriate context within which to assess digital fraud detection. Although single-region sampling may limit external validity, it gives a focused lens to evaluate CTAS effectiveness in a setting representative of large corporate taxpayers.

2.3. Power Analysis

An a priori power analysis using G*Power 3.1 was conducted for a structural model with eight predictors and four interaction terms. This indicated a sample size of at least 89 would be needed to detect medium-sized effects ($f^2=0.15$) to achieve the desired power of 0.80 at $\alpha=0.05$. Therefore, the achieved sample size of 107 is appropriate for ensuring sufficient statistical power for both the main and moderating effects.

2.4. Data Collection and Variable Measurement

Data were collected through a five-point Likert scale questionnaire administered to the finance managers, directors, and tax officers within corporate taxpayers. The instrument was designed to measure constructs derived from the digital adaptation of the New Fraud Star Theory. Each construct was operationalized through the indicators that have been validated in prior studies.

- X1 – System Pressure: refers to digital pressures such as real-time monitoring requirements, profit target demands, and external stakeholder expectations. Indicators include compliance deadlines, performance-driven demands, and reporting obligations [13].
- X2 – Digital Opportunity: reflects weaknesses in IT controls, such as inadequate cybersecurity, poor segregation of system access, and insufficient monitoring mechanisms [14].
- X3 – AI Rationalization: denotes the psychological justification of non-compliance in digital systems, measured through beliefs that AI can bypass manual oversight, perceptions that automation reduces responsibility, and normalization of system manipulation [15].
- X4 – Technological Capability: represents technical expertise and access to exploit system weaknesses, including IT proficiency, insider knowledge, and the ability to manipulate digital reporting tools [16].
- X5 – Cyber Arrogance: measures overconfidence and ego-driven behavior in digital environments, such as excessive reliance on technological skills, autocratic decision-making, and resistance to system constraints [17].
- X6 – Internal IT Governance: reflects organizational weaknesses in digital control, such as lack of cybersecurity policies, ineffective SOPs, and absence of whistleblowing mechanisms [2], [18].
- X7 – External Digital Pressure: captures external drivers such as regulatory uncertainty in digital taxation, political or compliance pressure, and market-driven competition in the digital economy [19].
- X8 – Techno-Culture: refers to organizational culture toward digital adoption, measured through acceptance of manipulation, tolerance for unethical digital practices, and ethical orientation in system use [20].
- Z – AI-enabled CTAS (Moderator): operationalized as the digital tax system equipped with real-time data integration, system availability, cybersecurity safeguards, and AI-based fraud detection capabilities.
- Y – Digital Fraud Detection Effectiveness (Dependent Variable): measured by the effectiveness in reducing tax manipulation, detecting anomalies, improving compliance, and minimizing fraudulent reporting in digital systems

2.5. Procedures for Common Method Bias

To avoid common-method bias, several measures were taken. In terms of procedural separation, items were rotated in order and independent and dependent variable blocks were separated. The reduction of evaluation apprehension was guaranteed by anonymity and confidentiality. Also included was a marker variable unrelated to tax compliance as a means of detecting method variance. Using Harman's single-factor test, no single factor was found to account for more than 40% of the variance, which indicates that common-method bias is unlikely to be present. This study protocol was approved by the Institutional Review Board of the Faculty of Economics and Business, State University of Malang. Every participant gave informed consent before participation. The respondents were informed about confidentiality, and all data were anonymized and used for the research only.

2.6. *Method of Data Analysis*

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used through SmartPLS software to test the hypotheses [4]. The PLS-SEM was selected as a tool that can handle complex models with latent constructs and reflective indicators, and such a model was considered for this research. Reliability and validity were assessed through outer model evaluation, with convergent validity established by using outer loading values above 0.70 and AVE above 0.50. Discriminant validity was tested using cross-loading and the Heterotrait-Monotrait Ratio (HTMT) threshold < 0.90 [5].

Construct reliability was measured by CR and Cronbach's Alpha, for which values should be above 0.70. To evaluate the structural relationships, R-square values were examined using the described thresholds of substantial (0.75), moderate (0.50), or weak (0.25). Lastly, to determine the effect size, f^2 is calculated, using thresholds identified in small (0.02), medium (0.15), and large (0.35).

The significance of the path coefficients was tested by using bootstrapping with 5,000 resamples. Hypotheses were considered significant at $p < 0.05$ and t-statistics greater than 1.96. To examine whether AI-enabled CTAS influenced the relationship between the eight independent variables and digital fraud detection, a moderation analysis was conducted. Following Pandey et al. [4], significant interaction terms ($p < 0.05$) in the expected direction were taken as evidence of moderation effects.

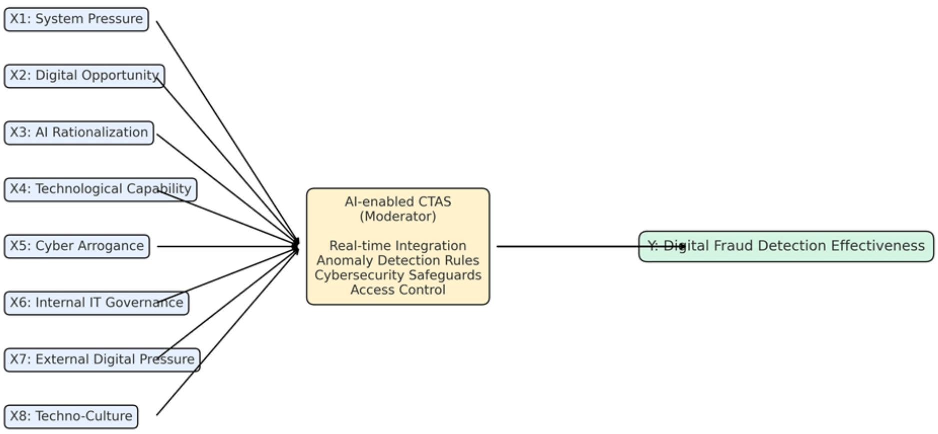

Figure 1. Conceptual Framework

Figure 1 depicts the conceptual framework for this study, integrating the New Fraud Star Theory and the AI-enabled Core Tax Administration System. In the meantime, eight dimensions of the New Fraud Star Theory, including System Pressure, Digital Opportunity, AI Rationalization, Technological Capability, Cyber Arrogance, Internal IT Governance, External Digital Pressure, and Techno-Culture, are independent variables that affect the digital fraud detection effectiveness. The AI-powered CTAS, with its real-time integrated, anomalous detection rules, cybersecurity safeguards, and access control, acts as the moderating variable that will weaken or change the relationships between fraud determinants and detection outcomes. The dependent variable is Digital Fraud Detection Effectiveness, or simply the capability of CTAS to improve compliance and reduce fraudulent practices. This framework thus underlines the dual role of technology in serving as both a structural safeguard and a contextual moderator in digital tax governance.

3. **Result and Discussion**

3.1. Outer Model

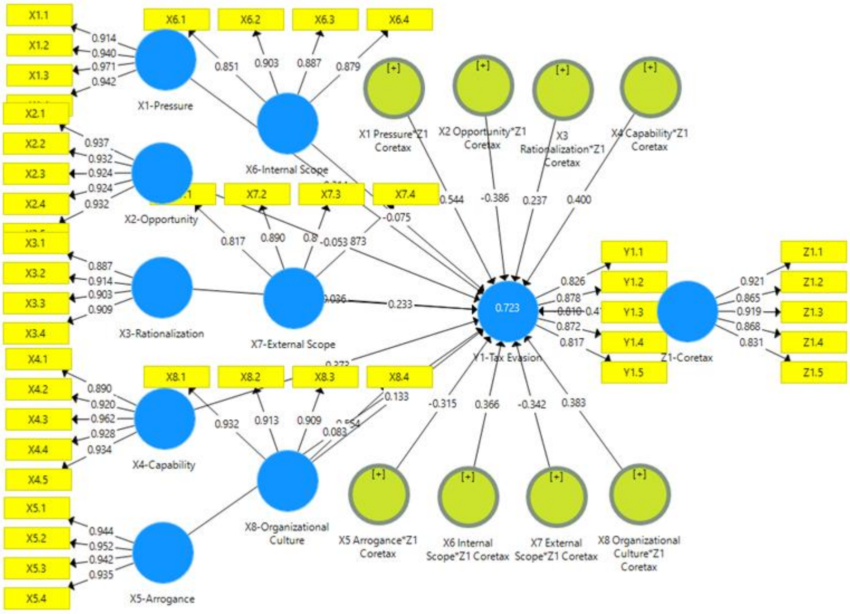

Figure 1. Outer Model

Source: SmartPLS 3.0

Figure 1 presents the convergent validity of the PLS-SEM model, the degree to which a latent construct explains its observed indicators' variance. The results of the analysis, with regard to convergent validity, indicate that AVE for all the constructs in the present study surpasses the 0.50 cut-off, thus providing good convergent validity. The following constructs also had a very good AVE score: System Pressure (0.816), Digital Opportunity (0.865), AI Rationalization (0.816), Technological Capability (0.859), and Cyber Arrogance (0.889). Other constructs, such as Internal IT Governance (0.774), External Digital Pressure (0.756), Techno-Culture (0.709), Digital Fraud Detection Effectiveness (0.708), and Core Tax Administration System (0.777), also showed adequate results. These results validate that all of the model constructs are properly measured by their indicators, again validating the use of the PLS-SEM approach, and serving as a solid basis for the following test of hypotheses.

Scores above 0.70 on Cronbach's Alpha are considered to constitute good internal construct reliability. The validation confirms that all constructs in the model attained Cronbach's Alpha well above this value, thus indicating a high degree of reliability. All the measures of System Pressure (0.957), Digital Opportunity (0.961), AI Rationalization (0.926), Technological Capability (0.959), Cyber Arrogance (0.959), Internal IT Governance (0.904), External Digital Pressure (0.896), Techno-Culture (0.849), Digital Fraud Detection Effectiveness (0.897), and Core Tax Administration System (0.928) indicate high internal consistency. Reliability provides stability to the constructs and further strength to the measurement model. Overall, high Cronbach's Alpha scores confirm the reliability of data applied in this study and further enhance the validity of model results.

3.2. *Inner Model*

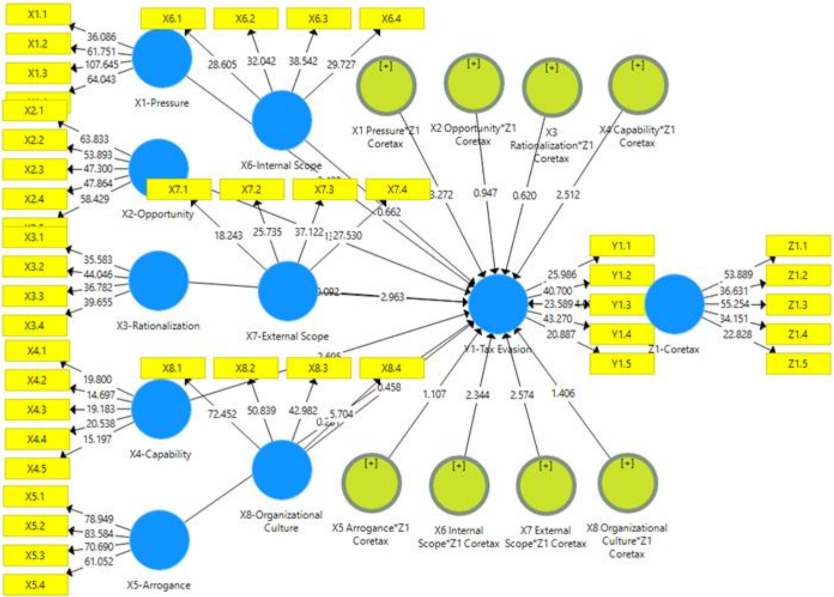

Figure 2. Inner Model
Source: SmartPLS 3.0

Figure 2 shows the dependent variable Y1, which is the Digital Fraud Detection Effectiveness with an R^2 value of 0.723, indicating that 72.3% of the variance in Digital Fraud Detection Effectiveness is explained by the independent variables in this model. This indicates the strength of explanation of the variables System Pressure, Digital Opportunity, AI Rationalization, Technological Capability, and others in predicting Digital Fraud Detection Effectiveness behavior. The R2 is 0.670 upon adjustment, showing that even after the effects of the number of variables have been accounted for, approximately 67% of Digital Fraud Detection Effectiveness variance is still explained. This, therefore, points to the performance of the model in determining the key factors of Digital Fraud Detection Effectiveness. Generally, it has been established that the model is valid and can make efficient predictions of Digital Fraud Detection Effectiveness activity.

f^2 test estimates the effect size of each independent variable on the dependent variable in the PLS-SEM model. The results indicate that the AI-ENABLED CTAS (Z1) possesses an effect size of large magnitude ($f^2 = 0.325$), which implies considerable contribution towards minimization of Digital Fraud Detection Effectiveness using electronic tax administration. Variables such as System Pressure (X1), Technological Capability (X4), and External Digital Pressure (X7) have small to moderate effect sizes ranging from 0.090 to 0.108, whereas other variables such as Digital Opportunity (X2), AI Rationalization (X3), and Cyber Arrogance (X5) exert virtually no influence. The results show that even though AI-ENABLED CTAS is indispensable, other variables such as System Pressure and Internal IT Governance tend to have quite limited impacts that are crucial in developing improved tax policy interventions.

Tabel 1. Hypothesis Testing – Direct Effects

Variable Path	Original Sample (O)	Standard Deviation (STDEV)	T Statistics	P Values	Interpretation
X1 System Pressure → Y1 Digital Fraud Detection Effectiveness	0.314	0.129	2.428	0.016	Significant
X2 Digital Opportunity → Y1 Digital Fraud Detection Effectiveness	-0.053	0.409	0.13	0.896	Not Significant
X3 AI Rationalization → Y1 Digital Fraud Detection Effectiveness	0.036	0.387	0.092	0.927	Not Significant
X4 Technological Capability → Y1 Digital Fraud Detection Effectiveness	-0.373	0.139	2.695	0.007	Significant
X5 Cyber Arrogance → Y1 Digital Fraud Detection Effectiveness	0.083	0.294	0.281	0.779	Not Significant
X6 Internal IT Governance → Y1 Digital Fraud Detection Effectiveness	-0.075	0.113	0.662	0.508	Not Significant
X7 External Digital Pressure → Y1 Digital Fraud Detection Effectiveness	0.233	0.079	2.963	0.003	Significant
X8 Techno-Culture → Y1 Digital Fraud Detection Effectiveness	0.133	0.292	0.458	0.647	Not Significant

The direct effect hypothesis test reveals that some of the independent variables have a statistically significant effect on Digital Fraud Detection Effectiveness. System Pressure (H1) shows a significant positive effect, as can be gauged from the 2.428 and 0.016 t-statistic and p-value, respectively, thereby indicating that performance-based System Pressure increases the probability for Digital Fraud Detection Effectiveness. Similarly, Technological Capability (H4) also has a significant negative correlation with Digital Fraud Detection Effectiveness (t-statistic = 2.695, p-value = 0.007), which indicates that the greater one's technical ability and access to information on taxes, the easier it is to evade. On the contrary, Digital Opportunity (H2), AI Rationalization (H3), Cyber Arrogance (H5), and Techno-Culture (H8) are insignificant, which is reflected in their respective p-values being above the 0.05 threshold, thereby leading to the rejection of these respective hypotheses.

Tabel 2. Hypothesis Testing – Moderation Effects

Variable Path	Original Sample (O)	Standard Deviation (STDEV)	T Statistics	P Values	Interpretation
X1 System Pressure * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	-0.544	0.166	3.272	0.001	Moderates
X2 Digital Opportunity * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	-0.386	0.407	0.947	0.344	Does Not Moderate
X3 Ai Rationalization * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	0.237	0.382	0.62	0.535	Does Not Moderate
X4 Technological Capability * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	0.4	0.159	2.512	0.012	Moderates
X5 Cyber Arrogance * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	-0.315	0.285	1.107	0.269	Does Not Moderate

X6 Internal It Governance * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	0.366	0.156	2.344	0.019	Moderates
X7 External Digital Pressure * Z1 Ai-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	-0.342	0.133	2.574	0.01	Moderates
X8 Techno-Culture * Z1 AI-Enabled Ctas → Y1 Digital Fraud Detection Effectiveness	0.383	0.272	1.406	0.16	Does Not Moderate

From the above, it is clear that moderation analysis indicates that AI-enabled CTAS is a significant moderating variable relative to several independent variables and Digital Fraud Detection Effectiveness. Most noticeably, AI-enabled CTAS significantly decreases the effects of System Pressure (H9), Technological Capability (H12), Internal IT Governance (H14), and External Digital Pressure (H15), which is indicated by p-values less than 0.05 and t-statistics larger than 1.96. Findings stress the ability of digital tax systems to neutralize the effect of certain fraud-related variables on Digital Fraud Detection Effectiveness. However, AI-enabled CTAS does not mediate between Digital Opportunity (H10), AI Rationalization (H11), Cyber Arrogance (H13), or Techno-Culture (H16), which justifies the fact that the system is possibly under-served to handle moral or cultural drivers of non-compliance. The results are in line with the optimal but selective role of AI-enabled CTAS in fostering tax compliance via intensified oversight and systematic control.

3.3. Discussion

3.3.1. System Pressure Has a Considerable Positive Impact on Digital Fraud Detection Effectiveness

The first hypothesis test confirms that System Pressure significantly influences Digital Fraud Detection Effectiveness with a t-statistic of 2.428 and p-value of 0.016, showing that external demands such as profit targets, operational continuity, and shareholder expectations increase fraudulent tendencies, consistent with the New Fraud Star Theory [20]. Respondents admitted experiencing financial and business pressures that heightened their risk of evading taxes, corroborating findings from Afjal et al [21] and Tsindeliani et al. [22] linking financial stress to non-compliance. These results highlight the importance of reducing compliance burdens and providing taxpayer support, echoing prior studies that stress alleviating excessive pressures as a deterrent to non-compliance [23]**.**

3.3.2. Digital Opportunity Does Not Make a Substantial Contribution to Digital Fraud Detection Effectiveness

The second hypothesis test shows that Digital Opportunity has no significant effect on Digital Fraud Detection Effectiveness (t-statistic = 0.130, p-value = 0.896), contradicting the New Fraud Star Theory's view that control weaknesses are prime enablers of fraud [20]. Although systemic vulnerabilities exist, respondents did not exploit them, suggesting that enhanced controls and monitoring reduce fraud likelihood. This aligns with Pandey et al [4] and Tsindeliani et al [22], who found that digital forensics reduce manipulation opportunities. The low impact of Digital Opportunity indicates that the AI-enabled CTAS effectively seals access points and deters abuse [24], reinforcing the idea that robust digital systems neutralize traditional fraud drivers through transparency and automation.

3.3.3. AI Rationalization does not have a significant impact on Digital Fraud Detection Effectiveness

The third hypothesis test reveals AI Rationalization does not significantly affect Digital Fraud Detection Effectiveness (t-statistic = 0.092, p-value = 0.927), challenging its assumed importance in fraudulent justification under the New Fraud Star Theory [20]. While past studies like Matute et al. [7] and Li et al. [25] showed that rationalization drives avoidance by portraying taxation as burdensome, respondents in this study did not morally justify fraudulent acts. Instead, systems like the AI-enabled CTAS, with real-time monitoring and transparency, appear to weaken rationalization motives. This finding suggests that systemic environments and governance frameworks play a stronger role in shaping compliance behavior than psychological justifications alone.

3.3.4. Technological Capability Exerts Strong Negative Influence on Digital Fraud Detection Effectiveness

The fourth hypothesis test demonstrates that Technological Capability strongly influences Digital Fraud Detection Effectiveness (t-statistic = 2.695, p-value = 0.007), indicating that individuals with advanced IT knowledge or access to insider systems are more prone to exploit loopholes. Respondents acknowledged that familiarity with regulations and system access enhances opportunities for manipulation, supporting findings from Bame-Aldred et al. [26] and Ajzen [24]. In line with the New Fraud Star Theory [20], technological proficiency provides the means to commit fraud if combined with pressure and opportunity. These results underline the need for stricter access controls, transparency, and oversight in high-risk areas to mitigate risks tied to technological skills.

3.3.5. Cyber Arrogance Does Not Have a Meaningful Impact on Digital Fraud Detection Effectiveness

The fifth hypothesis test shows that Cyber Arrogance does not significantly affect Digital Fraud Detection Effectiveness (t-statistic = 0.281, p-value = 0.779), contradicting the New Fraud Star Theory which views ego and superiority as drivers of fraud [20]. Respondents reported that ambition and egocentrism did not strongly influence their compliance decisions, contrasting with Sukmadilaga et al. [6] and Campbell [27], who suggested egocentric traits drive financial manipulation. The statistical insignificance here implies that psychological factors like Cyber Arrogance may only function as contextual or secondary influences, requiring further research into their relevance in specific compliance settings.

3.3.6. Internal IT Governance has no significant effect on Digital Fraud Detection Effectiveness

The sixth hypothesis test indicates Internal IT Governance does not significantly impact Digital Fraud Detection Effectiveness (t-statistic = 0.662, p-value = 0.508), despite respondents recognizing its general importance. Unlike Miao and Wen et al. [2] and Wenwu [28], who found weak governance increased fraud risks, the current findings suggest that organizational controls alone are insufficient without system-wide reinforcement. According to the New Fraud Star Theory [20], weak internal governance fosters fraud, but here systemic electronic monitoring, risk-based supervision, and strict enforcement appear to override internal weaknesses, aligning with recommendations from global policy frameworks.

3.3.7. External Digital Pressure Plays an Important Positive Role in Digital Fraud Detection Effectiveness

The seventh hypothesis test shows External Digital Pressure significantly impacts Digital Fraud Detection Effectiveness (t-statistic = 2.963, p-value = 0.003), with factors like regulatory ambiguity, market competition, and shareholder demands driving avoidance. Respondents reported feeling compelled to reduce tax costs to stay competitive, confirming the New Fraud Star Theory [20]. Supporting evidence comes from Koay et al. [29] and Indrayani and Li et al. [25], who linked political interference and competition with avoidance behaviors. These results highlight that systemic pressures, not just organizational ones, create conducive environments for fraud, requiring stronger regulatory stability, inter-agency transparency, and clearer fiscal guidelines at the policy level.

3.3.8. Social/Techno-Culture Has No Substantive Impact on Digital Fraud Detection Effectiveness

The eighth hypothesis test shows that Social/Techno-Culture does not significantly influence Digital Fraud Detection Effectiveness (t-statistic = 0.458, p-value = 0.647), contradicting the New Fraud Star Theory's view that permissive cultures fuel fraud [19], [20]. While some respondents admitted unethical practices were tolerated, these attitudes did not translate into actual fraudulent actions. This diverges from Nedopil [30], who argued that digitalization reshapes cultural norms toward avoidance. In this study, however, real-time monitoring through the AI-enabled CTAS mitigates cultural permissiveness, showing that technological oversight can neutralize behavioral norms by reinforcing systemic accountability.

3.3.9. AI-enabled CTAS Triggers System Pressure-Digital Fraud Detection Effectiveness Relationship

The ninth hypothesis test confirms that AI-enabled CTAS significantly moderates the relationship between System Pressure and Digital Fraud Detection Effectiveness (t-statistic = 3.272, p-value = 0.001), implying that stringent real-time monitoring reduces the impact of financial and operational pressures on fraudulent behavior. Respondents admitted that despite high performance demands, the presence of AI-enabled CTAS acted as a deterrent against evasion, aligning with Wenwu et al. [28] and Sánchez-Ballesta [31], who found electronic systems mitigate the effect of System Pressure on non-compliance. Consistent with the New Fraud Star Theory [20], open and closely monitored systems decrease opportunities for fraud even under intense pressure, since taxpayers perceive that transactions are continuously traced.

3.3.10. AI-enabled CTAS Does Not Moderate the Digital Opportunity–Digital Fraud Detection Effectiveness Relationship

The tenth hypothesis test shows AI-enabled CTAS does not significantly moderate the relationship between Digital Opportunity and Digital Fraud Detection Effectiveness (t-statistic = 0.947, p-value = 0.344), suggesting that system openness does not fully address weak internal controls or oversight. This contradicts Campbell et al. [27] and Wenwu et al [28], who argued that digital systems close loopholes, but instead supports the New Fraud Star Theory [20], which holds that Digital Opportunity persists unless reinforced by strong enforcement, policy clarity, and inter-agency coordination. While AI-enabled CTAS improves procedural transparency, it cannot alone eliminate structural weaknesses, highlighting the need for regulatory reforms and sanctions to complement digital monitoring.

3.3.11. AI-enabled CTAS Does Not Mediate between AI Rationalization and Digital Fraud Detection Effectiveness

The eleventh hypothesis test indicates that AI-enabled CTAS does not moderate the relationship between AI Rationalization and Digital Fraud Detection Effectiveness (t-statistic = 0.620, p-value = 0.535), showing that while respondents acknowledged rationalization beliefs such as taxation being burdensome, the system does not significantly alter such cognitive justifications. This finding contrasts with Campbell et al. [27] and Qi et al. 532], who suggested that electronic systems reduce rationalization. In line with the New Fraud Star Theory [20], rationalization is a psychological enabler separate from systemic controls, meaning that while AI-enabled CTAS constrains technical opportunities, it cannot fully neutralize entrenched normative beliefs that justify fraud.

3.3.12. AI-enabled CTAS Moderates the Technological Capability–Digital Fraud Detection Effectiveness Relationship

The twelfth hypothesis test confirms that AI-enabled CTAS significantly moderates the Technological Capability–Digital Fraud Detection Effectiveness relationship (t-statistic = 2.512, p-value = 0.012), reducing the influence of insider knowledge and technical proficiency on fraudulent acts. Respondents with high awareness of tax rules admitted that AI-enabled CTAS's real-time monitoring and system integration blocked attempts at exploitation, echoing findings by Koay et al [29] and Kryeziu et al. [33]. This aligns with the New Fraud Star Theory [20], which treats Technological Capability as a facilitator of fraud, but here demonstrates that strong administrative digital systems can effectively suppress fraud risks arising from technical expertise.

3.3.13. AI-enabled CTAS does not mediate the relationship between Digital Fraud Detection Effectiveness and Cyber Arrogance

The thirteenth hypothesis test shows AI-enabled CTAS does not moderate the Cyber Arrogance–Digital Fraud Detection Effectiveness relationship (t-statistic = 1.107, p-value = 0.269), indicating that ambition and ego-related motivations remain unaffected by monitoring systems. This deviates from the New Fraud Star Theory [20], which views ego as a fraud driver, and contrasts with Sukmadilaga et al. [6] and Cahyadini et al. [34], who emphasized egocentrism as a behavioral influence in weak control environments. The findings suggest that AI-enabled CTAS strengthens systemic oversight but cannot counter intrinsic traits like ambition, requiring cultural transformation, ethics education, and programs that instill integrity to complement technological solutions.

3.3.14. AI-enabled CTAS Moderates the Internal IT Governance–Digital Fraud Detection Effectiveness Relationship

The fourteenth hypothesis test demonstrates that AI-enabled CTAS significantly moderates the Internal IT Governance–Digital Fraud Detection Effectiveness relationship (t-statistic = 2.344, p-value = 0.019), compensating for organizational weaknesses such as missing SOPs or ineffective audits. Respondents acknowledged governance gaps but stressed that AI-enabled CTAS constrained manipulation by centralizing oversight and ensuring real-time traceability. This contradicts Hair et al [35], who emphasized internal governance as the primary control, but aligns with the New Fraud Star Theory [20], which notes governance weaknesses as fraud enablers unless supplemented by external safeguards. Here, AI-enabled CTAS functions as that safeguard, ensuring data quality and closing internal loopholes.

3.3.15. AI-ENABLED CTAS Moderates the External Digital Pressure and Digital Fraud Detection Effectiveness Relationship

The fifteenth hypothesis test indicates that AI-enabled CTAS significantly moderates the relationship between External Digital Pressure and Digital Fraud Detection Effectiveness (t-statistic = 2.574, p-value = 0.010), reducing the impact of market competition and fiscal uncertainty on evasion behaviors. Respondents confirmed experiencing strong external pressures but admitted that AI-enabled CTAS increased transparency and accountability, mitigating avoidance. These results align with Anirvinna et al. [36] who linked policy instability and competition with avoidance, and Koay et al. [29], who highlighted vague fiscal frameworks as enablers. According to the New Fraud Star Theory [205], external pressures foster fraud, but this study shows AI-enabled CTAS acts as a boundary mechanism that limits exploitability.

3.3.16. AI-ENABLED CTAS Does Not Moderate the Social/Techno-Culture and Digital Fraud Detection Effectiveness Relationship

The sixteenth hypothesis test reveals AI-enabled CTAS does not significantly moderate the Social/Techno-Culture–Digital Fraud Detection Effectiveness relationship (t-statistic = 1.406, p-value = 0.160), indicating that entrenched cultural tolerance of unethical practices cannot be altered by monitoring systems alone. Respondents in permissive organizations reported minimal compliance changes despite system transparency, contradicting Blaufus [37] who argued that digitalization can counter unethical culture. The New Fraud Star Theory [20] posits that culture is a strong determinant of fraud, and these findings affirm that while AI-enabled CTAS enforces systemic integrity, cultural permissiveness requires complementary interventions such as ethical leadership, integrity training, and fiscal incentives. In line with Qi et al. [32], well-designed tax incentives and social spending could reinforce compliance by shifting behavioral norms.

4. Conclusion

This study examined the determinants of digital tax fraud using the New Fraud Star Theory and evaluated the moderating role of AI-enabled CTAS. The findings show that system pressure, technological capability, and external digital pressure significantly shape fraud risks, while CTAS features such as real-time integration, anomaly detection, and access controls alter these pathways and enhance detection effectiveness. Theoretically, this extends fraud research by embedding behavioral determinants within digital governance, and methodologically, it demonstrates the value of moderated PLS-SEM with interaction effects. Practically, the results emphasize that strengthening specific CTAS controls is essential for improving compliance outcomes.

Nonetheless, the study is limited by its single-region sampling, reliance on self-reported data, and cross-sectional design. These constraints highlight the need for future work that incorporates multi-source and longitudinal data across diverse taxpayer groups. Despite these limitations, the research offers actionable contributions: it clarifies which determinants are most effectively mitigated by CTAS, provides insights for policymakers on AI-driven tax governance, and underscores the importance of aligning digital infrastructures with behavioral and organizational realities.

References

[1] Angeli A., Lattarulo P., Palmieri E., Pazienza M.G. Digital Fraud Detection Effectiveness and tax amnesties in regional taxation. *Econ Polit*. 2023. https://doi.org/10.1007/s40888-023-00297-9

[2] Miao S., Wen F. The impact of the organisational structure of tax authorities on tax and accounting fraud. *Accounting & Finance*. 2024;64(3):2735-2758. https://doi.org/10.1111/acfi.13232

[3] Jiang H., Hu W., Jiang P. Does ESG performance affect corporate tax avoidance? Evidence from China. *Finance Research Letters*. 2024;61:105056. https://doi.org/10.1016/j.frl.2024.105056

[4] Pandey K., Yadav S.S., Sharma S. Drivers of tax avoidance by MNEs in the developing countries under the digital economy: a modified-TISM approach. *Journal of Advances in Management Research*. 2023;20(5):896-919. https://doi.org/10.1108/JAMR-02-2023-0025

[5] Darmayasa I.N., Hardika N.S. Core tax administration system: the power and trust dimensions of slippery slope framework tax compliance model. *Cogent Business & Management*. 2024;11(1):2337358. https://doi.org/10.1080/23311975.2024.2337358

[6] Sukmadilaga C., Winarningsih S., Handayani T., Herianti E., Ghani E.K. Fraudulent financial reporting in ministerial and governmental institutions in Indonesia: An analysis using hexagon theory. *Economies*. 2022;10(4):86. https://doi.org/10.3390/economies10040086

[7] Matute J., Sánchez-Torelló J.L., Palau-Saumell R. The influence of organizations' tax avoidance practices on consumers' behavior: The role of moral reasoning strategies, political ideology, and brand identification. *Journal of Business Ethics*. 2021;174(2):369-386. https://doi.org/10.1007/s10551-020-04610-5

[8] Tsai P.H., Liu Y., Liu X. Collusion, political connection, and tax avoidance in China. *Kyklos*. 2021;74(3):417-441. https://doi.org/10.1111/kykl.12265

[9] Achmad T., Ghozali I., Pamungkas I.D. Detecting Fraudulent Financial Statements with Analysis Fraud Hexagon: Evidence from State-Owned Enterprises Indonesia. *WSEAS Transactions on Business and Economics*. 2024;21:2314-2323. https://doi.org/10.37394/23207.2024.21.190

[10] Monteverde V.H. New fraud star theory and behavioural sciences. *Journal of Financial Crime*. 2023;30(4):983-998. https://doi.org/10.1108/JFC-06-2020-0114

[11] Ajeigbe K.B., Ganda F., Enowkenwa R.O. Impact of sustainable tax revenue and expenditure on the achievement of sustainable development goals in some selected African countries. *Environment, Development and Sustainability*. 2024;26(10):26287-26311. https://doi.org/10.1007/s10668-023-03730-y

[12] Chami R., Darkey E., Williams O. A time to build: Does technical assistance matter for revenue mobilization?. *International Economics*. 2022;172:324-330. https://doi.org/10.1016/j.inteco.2021.11.003

[13] Barros V., Jalles J.T., Sarmento J.M. Drivers of the tax effort: evidence from a large panel. *Comparative Economic Studies*. 2023;65(1):96-136. https://doi.org/10.1057/s41294-022-00187-2

[14] Hesami S., Jenkins H., Jenkins G.P. Digital transformation of tax administration and compliance: A systematic literature review on E-Invoicing and prefilled returns. Digital Government: Research and Practice. 2024;5(3):1-20. https://doi.org/10.1145/3643687

[15] Sinaga S.T., Ekananda M., Gitaharie B.Y., Setyowati M. Tax Buoyancy in Indonesia: An Evaluation of Tax Structure and Policy Reforms. *Economies*. 2023;11(12):294. https://doi.org/10.3390/economies11120294
[16] Ponomareva K.A.R.I.N.A. Tax challenges arising from the digitalisation of the economy: The development of the OECD project and possible implementation in Russia. *BRICS Law Journal*. 2022;9(4):41-63. https://doi.org/10.21684/2412-2343-2022-9-4-41-63
[17] Chin Y.C., Zhao J. Governing cross-border data flows: International trade agreements and their limits. *Laws*. 2022;11(4):63. https://doi.org/10.3390/laws11040063
[18] Mohamad Ariff A., Kamarudin K.A., Musa A.Z., Mohamad N.A. Financial constraints, corporate tax avoidance and environmental, social and governance performance. *Corporate Governance: The International Journal of Business in Society*. 2024;24(7):1525-1546. https://doi.org/10.1108/CG-08-2023-0343
[19] Ratmono D., Frendy. Examining the fraud diamond theory through ethical culture variables: A study of regional development banks in Indonesia. *Cogent Business & Management*. 2022;9(1):2117161. https://doi.org/10.1080/23311975.2022.2117161
[20] F. Rasheed, J. Said, and N. I. Khan, "Evolution of fraud related theories: A theoretical review," *J. Nusantara Stud. (JONUS)*, vol. 8, no. 3, pp. 322–350, 2023, https://doi.org/10.24200/jonus.vol8iss3pp322-350
[21] Afjal M., Salamzadeh A., Dana L.P. Financial fraud and credit risk: Illicit practices and their impact on banking stability. *Journal of Risk and Financial Management*. 2023;16(9):386. https://doi.org/10.3390/jrfm16090386
[22] Tsindeliani I., Matyanova E., Razgildeev A., Vasilyeva E., Dudnik D., Mikhailova A. Tax optimization in the modern tax system under the influence of digitalization: Russian case study. *European Journal of Comparative Law and Governance*. 2021;8(4):429-452. https://doi.org/10.1163/22134514-bja10022
[23] I. N. Darmayasa, I. Arsana, and I. Putrayasa, "Reconstruction of the slippery slope framework tax compliance model," *ACRN J. Finance Risk Perspect.*, vol. 11, no. 1, pp. 19–32, 2022, https://doi.org/10.35944/jofrp.2022.11.1.002
[24] O. A. Gansser and C. S. Reich, "Influence of the new ecological paradigm (NEP) and environmental concerns on pro-environmental behavioral intention based on the theory of planned behavior (TPB)," *J. Cleaner Prod.*, vol. 382, p. 134629, 2023, https://doi.org/10.1016/j.jclepro.2022.134629
[25] Li Y., Al-Sulaiti K., Dongling W., Abbas J., Al-Sulaiti I. Tax avoidance culture and employees' behavior affect sustainable business performance: the moderating role of corporate social responsibility. *Frontiers in Environmental Science*. 2022;10:964410. https://doi.org/10.3389/fenvs.2022.964410
[26] T. Chung, P. N. Sharma, C. C. Lee, and J. Pinto, "National culture and occupational fraud magnitude: the moderating role of fraud type," *J. Forensic Account. Res.*, vol. 6, no. 1, pp. 406–435, 2021, https://doi.org/10.2308/JFAR-2020-025.
[27] L. Huang, "Quantifying taxation policy effectiveness: The mediating role of big data and the moderating influence of digitalization," *J. Internet Serv. Inf. Secur.*, vol. 14, no. 4, pp. 100–115, 2024, https://doi.org/10.58346/JISIS.2024.I4.009
[28] Wenwu X., Khurram M.U., Qing L., Rafiq A. Management equity incentives and corporate tax avoidance: Moderating role of the internal control. *Frontiers in psychology*. 2023;14:1096674. https://doi.org/10.3389/fpsyg.2023.1096674
[29] Koay G.Y., Sapiei N.S. The role of corporate governance on corporate tax avoidance: a developing country perspective. *Journal of Accounting in Emerging Economies*. 2025;15(1):84-105. https://doi.org/10.1108/JAEE-01-2023-0022
[30] Nedopil C. Integrating biodiversity into financial decision-making: Challenges and four principles. *Business Strategy and the Environment*. 2023;32(4):1619-1633.

https://doi.org/10.1002/bse.3208

[31] Sánchez-Ballesta J.P., Yagüe J. Does tax avoidance affect productivity in SMEs?. *Management Decision*. 2024;62(10):3261-3285. https://doi.org/10.1108/MD-07-2023-1159

[32] Qi Y., Che Azmi A. Factors affecting electronic invoice adoption and tax compliance process efficiency. *Transforming Government: People, Process and Policy*. 2021;15(1):150-168. https://doi.org/10.1108/TG-04-2020-0070

[33] Kryeziu L., Krasniqi B.A., Bağış M., Hajrullahu V., Zhushi G., Bytyçi D., Ismajli M. The effects of institutions, firm-level factors and rational decision-making on entrepreneurial behaviors of MSMEs: lessons and opportunities for transition communities. *Journal of Enterprising Communities: People and Places in the Global Economy*. 2024;18(4):771-797. https://doi.org/10.1108/JEC-05-2023-0075

[34] Cahyadini A., Hutagalung J.I.G., Muttaqin Z. The urgency of reforming Indonesia's tax Law in the face of economic digitalization. *Cogent Social Sciences*. 2023;9(2):2285242. https://doi.org/10.1080/23311886.2023.2285242

[35] E. Edeh, W. J. Lo, and J. Khojasteh, "Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) using R: A Workbook: By Joseph F. Hair Jr., G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt, Nicholas P. Danks, Soumya Ray," *Cham, Switzerland: Springer*, pp. 197, Open Access; €59.99, Hardcover Book, 2023, https://doi.org/10.1080/10705511.2022.2108813

[36] Anirvinna C., Goodwin R.D. An empirical assessment of technological advancements on supply chain management performance: a mixed-methods sem approach using smartpls. *Operations Management Research*. 2025;1-25. https://doi.org/10.1007/s12063-025-00556-x

[37] Blaufus K., Jarzembski J.K., Reineke J., Trenn I. Public disclosure of tax strategies and firm's actual tax policy. *Journal of Accounting, Auditing & Finance*. 2025;40(3):863-887. https://doi.org/10.1177/0148558X231200913