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# From AI Policy to Financial Reporting Outcomes: AI Ecosystem, AI Investment, and Accrual Quality in Leading ASEAN-6 Banking Firm (2020 - 2024)

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**ABSTRACT**

This study examines the relationship between national AI ecosystem factors and accrual quality in leading ASEAN-6 banking firms over the period 2020–2024. Using a balanced panel dataset of 140 firm-year observations from 28 banks, accrual quality is measured through the loan loss provision (LLP) model. The study employs a panel fixed effects regression with Driscoll-Kraay standard errors to control for cross-sectional dependence and serial correlation. The model demonstrates a strong explanatory power with a within $R^2$ of 0.3405 and is jointly significant ($F(3,132) = 22.71$, $p < 0.001$). The results show that regulatory sandbox existence significantly reduces accrual quality scores (Coef. = −0.0343; t = −5.5493; $p < 0.001$), indicating improved reporting quality. In contrast, AI governance readiness has a significant but opposite effect (Coef. = 0.0094; t = 2.3585; p = 0.0183), suggesting increased accrual deviation. AI investment intensity is found to be statistically insignificant (Coef. = −10.8135; p = 0.4381). Overall, the findings highlight that regulatory sandbox serves as the most robust institutional mechanism linking AI ecosystem development to improved financial reporting quality in ASEAN banking systems.

**Keywords:** Accrual Quality; Regulatory Sandbox; AI Governance; AI Investment; Loan Loss Provision Model

## INTRODUCTION

The banking industry has undergone significant evolution. (King, 2018) conceptualizes and correlates this evolution likened to the steps of industrial revolution, in which Banking 1.0 marked as the genesis of banking system with its traditional paper and pen business operation; Banking 2.0 with its landmark technological adoption and subsequent birth of financial technology; Banking 3.0 with its transformation towards digitalized practices; and the ubiquitous Banking 4.0, that is a bank with an interconnected ecosystem between human-machine computing power leveraged to improve business processes efficiency. One such technology of Banking 4.0 is Artificial Intelligence (AI), which has proven to be capable of facilitating the reduction of cost of doing business via automation, a more satisfactory service delivery via AI-powered services, and higher quality of risk management and fraud mitigation via AI-based banking management and oversight system. AI fits within the category of Banking 4.0 as one of the hallmarks of advanced technologies in enabling and driving socio-economic transformation. AI advancement in the banking industry is expected to generate value up to USD$1 trillion each year (Noreen et al., 2023).

While this evolution was already underway, the COVID-19 pandemic serves as its catalyst. During this period, most banks struggled to maintain operational effectiveness in the face of social and physical limitations of the pandemic. As (Sabihaini et al., 2024) has noted, the chaotic environment gave rise to the needs for information processing. These facts justify the increase of AI innovation, which may not solely be for profitability, but also survivability (Mishrif & Khan, 2023). As the reality of COVID-19 was, banking firms around the globe encountered the challenges of transformation toward digitalization to fulfill business process needs, while at the same time, facing a call for austerity due to the weakened revenues and pessimistic economic outlook (Anderson et al., 2021). During which, firms were faced with a challenging environment and multifaceted dilemmas in actuating their innovation capability (Yiming & Manansala, 2024).

Beyond COVID-19, AI innovation continues to grow and shape the landscape of the banking sector and so too are the demands for transparency and integrity in financial information. As financial reporting serves as one of the forms of accountability to its stakeholders, it necessitates a reliable and credible reporting system. As users of financial information demands accuracy and reliability for the information presented (Pradnyawati et al., 2024). In which, AI innovations are also expected to contribute towards this end. Within this context, accrual quality represents a critical and measurable dimension of financial reporting quality. In the banking sector specifically, accrual quality is most directly observable through the Loan Loss Provision (LLP) process, whereby banks exercise discretion in forecasting and estimating the expected credit losses faced. Discretionary manipulation of LLP is a well-documented phenomenon, in which banks can utilize it to obscure true financial performance. The (Beatty & Liao, 2014) model operationalizes accrual quality through this channel: the lower the residual scores from the model, the higher adherence to faithful representation and thus inferred to be less affected to managerial discretion in estimation and forecasting processes, thereby reflecting higher accrual quality.

Despite these expectations, AI innovation faces fundamental challenges due to the complex interplay of institutional and financial barriers. This challenges manifests due to the fact that effective AI adoption hinges on the contribution of government as the strategic enablers of AI.

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AI innovations are expected to contribute in producing a better accrual quality, but it cannot stand alone. For AI innovations to succeed, it requires support to overcome the structural barriers faced, mainly through institutional channels, such as: policies, financial assistance, technological support, and government intervention (Bangguiyac & Castañeda, 2025). The aforementioned support is conceptualized as: First, regulatory sandbox programmes, to create a controlled environment in which banks can experiment with AI-based credit risk modelling, LLP estimation tools, and other implements which may assist in estimation and forecasting processes. As it was expected that countries with a more mature regulatory sandbox framework expected to host a banking sector with lower discretionary accrual quality score, reflecting a higher accrual quality. Second, national AI governance, it encompasses institutional capacity, and regulatory coherence to sustain an AI ecosystem. Higher governance readiness is expected to translate into an environment more friendly to AI innovations, thus would boost its growth and usage. Third, the intensity of AI investment at national level. It measures the venture capital investment of AI in the financial sector to a country's Gross Domestic Product (GDP). It reflects the depth of which the broader AI ecosystem from which banks are expected to draw technological resources and be competitively innovative. Higher AI investment intensity is expected to accelerate the diffusion of AI-based estimation and forecasting processes, further predicted to reduce the scope of discretionary accrual behavior.

Current literature on AI ecosystems remains largely fragmented across public administration and information systems research, with minimal integration into the accounting and banking disciplines (Chichernea et al., 2015; Han & Chen, 2021; Madan & Ashok, 2023; Taeihagh, 2021; Xie et al., 2026). While AI governance studies identify institutional enablers of technology diffusion, they rarely quantify how these conditions translate into micro-level financial reporting outcomes. Conversely, the banking literature on accrual quality focuses on managerial discretion and prudential supervision, omitting AI-assisted forecasting and estimation as determinants of reporting quality. Evidence linking regulatory innovation, specifically regulatory sandboxes and AI investment intensity, to accounting outcomes remains particularly scarce.

The ASEAN region constitutes a uniquely appropriate empirical context for testing these relationships. The six economies chosen (ASEAN-6): Indonesia, Singapore, Malaysia, Thailand, the Philippines, and Viet Nam, represents a deliberate heterogeneous set of financial systems spanning and differing in stages of AI support, governmental readiness, and intensity of AI-focused investment. Regardless, the accommodation of the expected variation is through a balanced panel of the top five banks per country over the span of 2020-2024, estimated with panel regression with country fixed effects (Country FE) and Driscoll-Kraay standard errors (DK – SE). It allows the analysis to isolate country-level changes in accrual quality score across banking systems.

The novelty of this research is threefold. First, it introduces specific institutional-level determinants as predictors of bank-level accrual quality, which are directly operationalised through the LLP framework. Second, the utilization of a multi-country ASEAN-6 panel dataset (2020-2024) is unique in presenting comparative evidence from both advanced and emerging financial systems during a period of accelerated digitalization and AI adoption. Third, by linking macro-level AI ecosystem development to micro-level accrual quality consequences, the study demonstrates how innovation policy can result in a "trickle-down" effect which benefits in improving the accuracy of financial information produced at micro-level institutions, in this case, banks.

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## LITERATURE REVIEW

### AI Ecosystem

AI Ecosystem explains that AI as a technology that cannot quite be described as a singular process, but rather as a web of systems across multiple layers of infrastructure and actors in which each provide contribution to formulate an interdependent ecosystem. Its fundamentals lie in the concept of National Innovation System Theory, which posits that innovation arises from the dynamic interaction between firms, universities, government, and other institutions that collectively shape and influence one and another (Clarke et al., 2017).

Building on the National Innovation System, the AI ecosystem can be conceptualized as a specialized environment in which its actors interact in striving the common goal of enabling the development and diffusion of AI technology.

### AI Implementation in Financial Institution

The integration of AI into financial institutions is the systematic processes of AI inclusivity into banking and financial operation. It involves embedding data-driven algorithms into core business processes (e.g., service delivery, credit scoring, fraud detection, forecasting and estimation, and supervisory capacity). Contemporary research highlights that this inclusion enables banks to process significantly more complex data with higher volume (Goyal et al., 2025). This has the express benefit of improving the accuracy and timeliness of its forecasting and estimation processes.

### Accrual Quality

Accrual quality refers to the degree to which accruals are subsequently confirmed by realized cash flows, it reflects the accrual of forecasting and estimation done by an entity, that are embedded and reflected in the financial reporting. (Dechow & Dichev, 2002) conceptualized accrual quality as the ability of working capital accruals to reverse into future cash flow with minimal estimation error, thus implies that lower unexplained accrual variation reflects a financial statement that faithfully represents underlying economic performance. This theorem further developed by (Francis et al., 2004), which found a significant relationship between accrual quality and cost of capital, which describes that a firm with higher accrual quality is more likely to attract capital at lower costs, as stakeholders may perceive less risks in their reported earnings. Within this framework, accrual quality captures the credibility and informativeness of accounting numbers as is, rather than what the managerial intent is.

In the banking sector, accrual quality is predominantly shaped by the estimation of LLP, which represent the primary discretionary accrual. (Beatty & Liao, 2014) demonstrate that variation in LLP reflects both economic fundamentals and managerial discretion. Accordingly, accrual quality in banks can be operationalized through the precision of LLP estimation, where lower residual or discretionary components indicate more faithful representation of underlying credit risk and, therefore, higher financial reporting quality.

### Regulatory Sandbox

The regulatory sandbox concept is a financial governance instrument that offers firms a time-bound, supervised environment in which novel technologies and business models may be tested under a controlled and relaxed regulatory constraint without full statutory liability (Bromberg et al., 2017). (Arner et al., 2015) identifies the regulatory sandbox as a transitional governance mechanism which enables a robust policy calibration, which is particularly relevant in jurisdictions where policy framework is inadequate or otherwise insufficient to adapt to technological changes. Regulatory sandbox provides a relaxed and controlled environment whilst at the same time enforces a heightened regulatory monitoring and reporting obligations. This serves as the institutional disciplining mechanism on participating firms. This supervisory pressure is theorized to improve the quality of managerial forecasting and estimation processes, in the banking sectors, this materialized mainly in LLP.

Within the ASEAN context, the adoption of regulatory sandboxes has been heterogeneous, notably in its inception date, producing meaningful multi-country variation. This study operationalizes regulatory sandbox as a dummy variable based on the existence of regulatory sandbox. Thus, a country with established regulatory sandbox practices has the inferred benefit that materializes in a more entrenched supervisory norms and compliance culture.

Under the LLP accrual quality model, the lower score reflects reduced discretionary provisioning and thus improved accrual quality. Accordingly, the hypothesis is formulated as such.

*H1: Regulatory Sandbox existence significantly reduces accrual quality scores, reflecting improved accrual quality.*

**AI Governance**

The governance of AI at national level is the foundational determinant on how institutional environments shape technological innovation and adoption and its subsequent “trickle down” to organizational outcomes. Effective AI governance encompasses not merely regulatory prohibition, but also the structured capacity of institutions to enable, monitor, and foster AI-driver innovation across economic sectors (OECD, 2025).

When applied to the banking sector, the linkage between national Governance Capacity and firm-level accounting behavior has been demonstrated and shown as a significant predictor of informational transparency, in which stronger governance correlates with a reduced earnings manipulation and higher quality of financial disclosures (Liao et al., 2024).

This study operationalizes national AI governance using Oxford Insights’ Government AI Readiness Index, which captures a country’s institutional preparedness to govern, regulate, and deploy AI (Hankins et al., 2023). The index is then z-score standardized to facilitate multi-country comparability within the ASEAN-6 panel. Countries with higher AI governance readiness are expected to provide an institutional environment with a more structured oversight and discipline. Of which in the context of LLP estimation, translates to lower accrual quality scores reflecting improved quality.

*H2: Higher national AI Governance scores significantly reduces accrual quality scores, reflecting improved accrual quality.*

**AI Investment**

AI Investments functions as the stimulus of technological advancements by the means of directly enabling and facilitating the events of AI innovations to materialize at the organizational level. (Brynjolfsson & McAfee, 2014) establish that economic capital commitment to innovations expands technological infrastructure, the result of which is lower adoption threshold and cost for firms operating within that national ecosystem. Within the banking sector specifically, the availability of AI-capable infrastructure expands banks access to AI-assisted forecasting and estimation tools, including those applicable to credit loss provisioning. This mechanism is particularly salient for LLP estimation, where the AI-assisted model has demonstrated superior predictive accuracy

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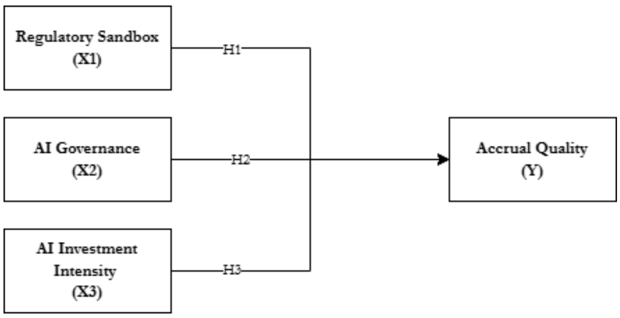
in relative to purely judgmental approaches, thus reducing the discretionary component of accruals.

This study operationalizes AI investment intensity as venture capital investment of AI in the financial sector to a country's GDP, transformed using natural log to normalize distribution and prevent skewness. The data of which sourced from OECD's AI Policy Observatory. The use of venture capital to GDP as a proxy is consistent with contemporary literature that treats capital flows as prospective indicators of technological capacity building within an economy (Kortum & Lerner, 2000). Cross-country heterogeneity in this measure within the ASEAN-6 context provides the empirical variation necessary to identify its effect on firm-level accrual behavior. Within the LLP model, the lower scores denote improved accrual quality.

*H3: Higher national AI Investment intensity significantly reduces accrual scores, reflecting improved accrual quality.*

**Conceptual Framework**
The framework of which the research is based upon is depicted in **Figure 1**.

**Figure 1.** Research Framework




Thus, the hypothesis could be formulated as shown in **Table 1**.

**Table 1.** Hypothesis Formulation

| Hypothesis | Operationalization |
|---|---|
| Regulatory Sandbox existence significantly reduces accrual quality scores, reflecting improved accrual quality. | H1 |
| Higher national AI Governance scores significantly reduce accrual quality scores, reflecting improved accrual quality. | H2 |
| Higher national AI Investment Intensity significantly reduces accrual scores, reflecting improved accrual quality. | H3 |

## RESEARCH METHOD

The population of this study is commercial banks operating within the ASEAN-6 countries, comprising: Indonesia, Singapore, Malaysia, Vietnam, the Philippines, and Thailand. These banking institutions operate under heterogeneous conditions, spanning national AI governance, regulatory frameworks, and diverse level of AI investments. The selection of ASEAN-6 as opposed to the entire ASEAN countries was based on accounting alignment to International Financial Reporting Standards (IFRS), as well as data availability and reliability.

**Table 2.** Sample Mapping

| Criterion | Amount |
|---|---|
| Top 5 banks based on market capitalization in ASEAN-6 countries and that publishes an audited financial report for FY 2020 - 2024. | 30 |
| Banks provide general and non-specialized financial services typically expected for commercial banks. | (2) |
| Amounts of sample | 28 |
| **Total of Observation Data (5 Years * 28 Samples)** | **140** |

As presented in **Table 2**, purposive sampling method is applied by selecting banks of each ASEAN-6 countries that meet the following criteria: (1) the firm is among the top 5 banks based on market capitalization and publishes an audited financial report throughout 2020 – 2024 period, and (2) Bank provide general and non-specialized financial services typically expected for commercial bank. The final sample size of 140 satisfies these criteria and thus were used.

To assess the correlation between each variable examined in this research, the study employs a quantitative panel data regression with country FE and DK – SE as the primary research methodology.

The research method was chosen based on three considerations. First, panel data regression is most appropriate by the nature of the population, sample, and time frame, as well as the research objectives of comparison. Second, country FE control to account the time-invariant heterogeneity that exists within the sample. Third, DK - SE, as correction forces for cross-sectional and serial errors that are structurally induced by country-level regressors in a multi-country panel. Of which, neither OLS nor cluster-robust alternatives can adequately address given the population of six countries.

$$Y_{it} = a + \beta_1 X1_{it} + \beta_2 X2_{it} + \beta_3 X3_{it} + \mu_i + \varepsilon_{it}$$

| | |
|---|---|
| $Y_{it}$ | : Accrual Quality of bank i in year t |
| $a$ | : Intercept |
| $X1_{it}$ | : Regulatory Sandbox |
| $X2_{it}$ | : AI Governance |
| $X3_{it}$ | : AI Investment Intensity |
| $\mu_i$ | : Country fixed effect |
| $\varepsilon_{it}$ | : Error term |

X1 represents the availability of regulatory sandboxes in which the banking sector could leverage. It is measured using a dummy variable based on the existence of a regulatory sandbox framework.

| | |
|---|---|
| *0* | : No existence of regulatory sandbox framework |
| *1* | : Confirmed existence of regulatory sandbox framework |

X2 reflects the institutional quality and policy readiness of a country in institutional preparedness to govern, regulate, and deploy AI innovation. The z-standardization was done to allow for sound interpretation and comparability within the ASEAN-6 banking sample.

$$Z_{X2} = \frac{X - \mu}{\sigma}$$

| | |
|---|---|
| *X* | : Governance Index score for each country-year |
| *μ* | : Mean Governance Index score of the sample |
| *σ* | : Standard deviation of Governance Index score of the sample |

X3 reflects the relative scale of financial commitment towards AI development. It captures the depth of AI ecosystem funding by measuring venture capital allocation to AI activities in the financial sector relative to overall economic size, then transformed using natural log to normalize distribution and prevent skewness.

$$X3_{it} = ln\left(\frac{VC.X3_{it}}{GDP_{it}} + 1\right)$$

| | |
|---|---|
| *ln* | : Natural log |
| $VC.X3_{it}$ | : Total venture capital investment in AI in country *i* during year *t* |
| $GDP_{it}$ | : GDP of country *i* during year *t* |

Y reflects the precision and reliability of accrual-based accounting estimates and forecasting in representing the bank's underlying economic performance. Accrual quality primarily relates to the accuracy of discretionary components embedded, in this context, the LLP, which are subject to managerial judgment.

Y is measured using the LLP model, which estimates LLP based on fundamental credit risk determinants, where all variables are scaled by total assets at the beginning of the period to ensure comparability.

$$LLP_{it} = \beta_o + \beta_1 \Delta NPL_{it} + \beta_2 NCO + \beta_3 \Delta LOANS_{it} + \beta_4 SIZE_{it} + \varepsilon_{it}$$

$$AQ_{it} = |\varepsilon_{it}|$$

| | |
|---|---|
| $LLP_{it}$ | : Loan Loss Provision/$TA_{t-1}$ |
| $\Delta NPL_{it}$ | : Change in Non-performing Loans/$TA_{t-1}$ |
| $NCO_{it}$ | : Net Charge-offs/$TA_{t-1}$ |
| $\Delta LOANS_{it}$ | : Change in Total Loans/$TA_{t-1}$ |
| $SIZE_{it}$ | : Natural Logarithm of Total Assets:s ln($TA_t$) |

## RESULTS

**Table 3.** Descriptive Statistics (N = 140)

| Variable | Min. | Mean | Max. | Skewness |
|---|---|---|---|---|
| Y | 0.0082 | 0.0312 | 0.0895 | 0.793 |
| X1 | 0.0000 | 0.3929 | 1.0000 | 0.434 |
| X2 | -1.4705 | 0.1647 | 2.8924 | 0.581 |
| X3 | 0.0000 | 0.0002 | 0.0013 | 2.663 |

**Table 3** presents statistics for all study variables across 140 observations.

**Table 4.** Panel FE Regression Result (DK-SE; Lag = 2)

| Variable | Coef. | DK - SE | T-stat | P-value |
|---|---|---|---|---|
| X1 | -0.0343 | 0.0061 | -5.5493 | < 0.0010 |
| X2 | -0.0094 | 0.0040 | 2.3585 | 0.0183 |
| X3 | -10.8135 | 13.9463 | -0.7754 | 0.4381 |
| **Model Stats** | **N = 140** | **$R^2$ = 0.3405** | | |

*Note. DK-SE* = Driscoll-Kraay Standard Errors.

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In **Table 4**, $R^2$ is inherently more conservative than total $R^2$ because the fixed effects absorb all country variations before the model is even tested for fitness. Within $R^2$ of 34.05%, the variables of the research when applied to the banking sector, is a meaningful and respectable fit. It is consistent with comparable panel studies in accounting and banking literature. The model explains 34.05% of the within-country variation in bank-level accrual quality across the sample, whilst the remaining 65.95% is attributable to firm-level factor (e.g., bank size, loan composition, and management discretion) that are not included as regressors in this country-level policy model.

For X1, it is the strongest and most precisely estimated effect in the model. The P-value of < 0.0010 far below the significance threshold of 0.05. The DK – SE of 0.0061 is a tight relative to the coefficient, this indicates that the result is robust and survives the nonparametric SE correction of Driscoll-Kraay for cross-country and serial dependence. A country transitioning from X1 = 0 (no sandbox) to X1 = 1 (active sandbox) is associated with a 3.43 percentage point reduction in accrual quality score. This proves that the existence of regulatory sandbox improves accrual quality.

Assessing H1, the findings (Coef. = -0.0343; DK – SE = 0.0061; T-stat = -5.5493; P-value = <0.0010), provides evidence that X1 strongly and unambiguously supports H1.

For X2, it is proven to be statistically significant at 95% confidence threshold, proven by P-value = 0.0183. The DK – SE of 0.0040 is likewise well-estimated and it too proven to be robust and survives the nonparametric SE correction of Driscoll-Kraay. The finding indicates that with one-standard-deviation increase in X2 is associated with 0.94 percentage point increase in accrual quality score, all fact leads to the conclusion that this is not a trivial positive effect. The coefficient (+0.0094) is proven to be a contradiction of H2, as H2 predicts a negative coefficient (higher governance results in lower accrual score, with an effect of improved accrual quality).

Assessing H2, the findings (Coef. = -0.0094; DK – SE = 0.0040; T-stat = 2.3585; P-value = 0.0183) suggest that higher AI Governance Index actually increases accrual quality score in a significant manner. Thus, H2 is not supported.

For X3, it is statistically insignificant at all conventional thresholds ($t = -0.7754$, $p = 0.4381$), failing to reject $H_0$: $\beta_3 = 0$. Though, it is important to note that this is far from any rejection region and constitutes a categorically non-significant result, not a borderline miss. The raw coefficient magnitude of −10.8135 must not be read in isolation. X3 is constructed as ln((VC AI investment in Finance and Insurance / Country GDP) + 1), and its observed values across the sample are very small in absolute scale, ranging from approximately 0 to a maximum of 0.0013, with a sample mean of 0.0002. The negative sign of the coefficient is directionally consistent with H3, which predicts that higher AI investment intensity reduces accrual deviation.

However, given the statistical insignificance of the result and the fundamental imprecision of the estimate, means that this directional consistency carries no inferential weight. The evidence is insufficient to establish any statistically or economically reliable relationship between AI investment intensity and bank-level accrual quality within this sample, and the result should be interpreted as inconclusive rather than as evidence of no effect, given that the limited time horizon of t = 5 years constrains the within-country variation available to identify this coefficient reliably. Nevertheless, the findings (Coef. = -10.8135; DK – SE = 13.9463; T-stat = -0.7754; P-value = 0.4381) indicate that H3 is not supported.

**Table 5.** Two Sample T-Test: Accrual Quality by Sandbox Status

| Group | N | Mean | Std. Dev. |
|---|---|---|---|
| X1 = 0 (No Sandbox Existence) | 85 | 0.0369 | 0.0256 |
| X1 = 1 (Sandbox Existence) | 55 | 0.0222 | 0.0164 |
| **T-stat** | **t = 3.8120** | **P < 0.0010** | **df = 138** |

The two-sample T-test shown in **Table 5** confirms (t(138) = 3.8120; P-value < 0.0010) that banks in countries with an active regulatory sandbox (N = 55; mean Y = 0.0222, and Std. Dev. = 0.0164) exhibit significantly lower accrual score than banks in non-sandbox countries (N = 85; mean Y = 0.0369; SD = 0.0256). The sandbox group shows not only a lower mean, but also lower variance in accrual quality scores, suggesting sandbox adoption is associated with both level improvement on provisioning behaviour across firms. This bivariate result provides corroborating directional evidence for H1 in an unconditional setting, as the mean difference of 0.0147 confounds the sandbox effect with all systematic between-country differences.

**Table 6.** F-test Result

| Variable | df1 | df2 | F-stat | P-value |
|---|---|---|---|---|
| Joint: X1 X2 X3 | 3 | 132 | 22.71 | <0.0010 |
| Joint: Country Fixed Effect | 5 | 132 | Absorbed | <0.0010 |

*Note: df2 = N – k – (G-1) = 140 – 3 – (6 – 1) = 132; k = X1, X2, X3 and G - 1 = 5 country FE dummies absorbed.*

The Joint X1, X2, and X3 tests of **Table 6** return a F-stat of 22.71 evaluated at df(3, 132). The overall model is shown to be jointly significant at P-value < 0.0010, validating that AI policy variable as a system, explain within-country variation in accrual quality. This indicates a strong model signal.

The Joint Country FE reported F-stat of "Absorbed", this due to the elimination of country dummies from the estimation matrix rather than explicitly estimated as coefficients. The absorption of country FE means the model controls for all time-invariant, country-specific characteristics (e.g., financial regulatory quality, institutional development, and culture of provisioning conservatism, etc). This is an appropriate and necessary specification given that X1, X2, and X3 are country level-variables with obvious cross-country heterogeneity. Without these country FE, the estimates would be confounded by these systematic country differences, which could materially affect the research outputs. The P-value posted at <0.0010 means the country FE are jointly highly significant. The test result confirms that at least one country's mean accrual quality differs significantly from the other country after controlling for X1, X2, and X3. This validates FE specification as a necessity and is appropriate for the research design. And lastly, the non-significance of X3 individually doesn't undermine the overall model's validity, as the joint tests confirm that the model's inferential foundation is sound.

## DISCUSSION

### H1: Regulatory Sandbox Existence Significantly Reduces Accrual Quality Scores, Reflecting Improved Accrual Quality

H1 posits that the existence of a regulatory sandbox is associated with a statistically significant reduction in accrual quality scores, in which in accordance to (Beatty & Liao, 2014) model, denote reduced discretionary deviation in LLP, indicating improved accrual quality.

The result of the test as shown in **Table 4** and **Table 5**, shows that X1 produces a coefficient of −0.0343 with a DK SE of 0.0061, yielding T-stat = −5.5497, and P-value <

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0.0010. This result is significant at all conventional thresholds (α = 0.10, 0.05, and 0.01) and survives the nonparametric Driscoll-Kraay correction for heteroskedasticity, serial autocorrelation up to lag 2, and cross-sectional spatial dependence simultaneously.

Thus, it is confirmed that H1 is supported. The regulatory sandbox is associated with a statistically significant, precisely estimated, and economically large reduction in accrual quality scores within ASEAN-6 countries, consistent with the hypothesis that institutional AI governance frameworks enabling controlled experimentation facilitate more disciplined LLP in banking.

**H2: Higher National AI Governance Index Scores Significantly Reduces Accrual Quality Scores, Reflecting Improved Accrual Quality**

H2 opines that higher national AI governance readiness, as measured by the z-standardized AI Governance Readiness Index (X2), is associated with a statistically significant reduction in accrual quality scores, reflecting improved LLP discipline.

The result shown in **Table 4** and **Table 5** shows that X2 yields a coefficient of +0.0094 with DK - SE of 0.0040, T-stat = +2.3585, and P-value = 0.0183. As mentioned prior, the statement that one-standard-deviation increase in X2 is associated with 0.94 percentage point increase in accrual quality score, remains. The P-value of 0.0183 shows that this result is statistically significant at α = 0.05. It shows an increase in accrual quality score, which indicates that higher X2 resulted in lower accrual quality within a country. This is not a statistical artifact as DK correction accounts for cross-country and serial dependence. The contradiction is substantive and must be addressed through theoretical reasoning rather than statistical dismissal.

Two possible explanations could be given to explain this phenomenon. One of it is transitional mechanism, in which countries with higher governance readiness scores may be at earlier stages of operationalizing AI in banking, where the regulatory sophistication reflected in the index precedes the actual deployment of AI-driven provisioning tools, temporarily leaving accrual quality unimproved or even more variable during the preparatory phase. The other explanation would be that an environment with both high AI Governance Readiness and financial sector environment (e.g., greater market depth, more active supervisory scrutiny, etc) independently sustains accrual variability regardless of AI Governance Quality.

Thus, it is confirmed that H2 is not supported. The AI Governance Index has a statistically significant effect on accrual quality at α = 0.05 (Coef. = -0.0094; DK – SE = 0.0040; T-stat = 2.3585; P-value = 0.0183), but the direction of this effect is positive, in which higher governance readiness is associated with higher accrual deviation, which a direct opposite of H2's prediction. The null hypothesis of no effect is rejected, but the directional hypothesis is contradicted.

**H3: Higher National AI Investment Intensity Significantly Reduces Accrual Quality Scores, Reflecting Improved Accrual Quality**

H3 theorize that greater national AI investment intensity is associated with a statistically significant reduction in accrual quality scores, reflecting more accurate and precise LLP driven by AI adoption funded through private capital markets.

In **Table 4** and **Table 5**, X3 yields a Coef. of −10.8135; DK - SE of 13.9463; T-stat = −0.7754, and P-value = 0.4381. The result fails to reach significance at α = 0.01, α = 0.05, or α = 0.010.

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With this finding, the statistical evidence provided fails to support H3 at any conventional significance threshold, though the direction of the point estimate is consistent with the hypothesis. The imprecision of X3 could be explained by the sparse and dominated by year-to-year fluctuations in AI VC investment, which are volatile and concentrated. The concentration of AI VC investment in a small number of ASEAN countries, specifically Singapore, means that within-country variation in X3 after demeaning is driven by a small number of extreme year-observations in a few countries, producing an inherently unstable estimate with t = 5 annual observations per country.

Thus, H3 is confirmed to not be supported. It fails to reach statistical significance at any conventional threshol. The result captures two related but distinct problems with the X3 estimate. The DK - SE exceeding the coefficient in absolute magnitude means the uncertainty around X3 is larger than the estimate itself, producing a T-statistic of only −0.7754. The resulting 95% confidence interval crosses zero and spans a range of both strongly negative and moderately positive values. This means the data is compatible with H3 being directionally correct, directionally wrong, and with no effect at all. Thus, suffice to sa that the result is insufficient to establish any statistically or economically reliable relationship between the variable at play. The limited time horizon of the research is identified (t = 5 annual observation per country) and the concentration of venture capital distribution marked as the factors explaining this occurence.

## CONCLUSION

This study examines whether institutional support and AI investment intensity are correlated with accrual quality among leading ASEAN-6 banking firms over the period 2020 – 2024, employing a panel fixed effects regression with DK – SE across 140 firm-year observations from 28 banks in six countries. The results yield a differentiated set of findings across the three hypotheses. H1 is supported: the existence of a regulatory sandbox is associated with a statistically significant and economically large reduction in accrual quality scores (Coef. = -0.0343; DK – SE = 0.0061; T-stat = -5.5493; P-value = <0.0010), with the effect surviving nonparametric correction for cross-sectional and serial dependence, indicating that operational regulatory sandbox play a significant part in providing a meaningful infrastructure for a supportive AI Ecosystem, with the express benefit of improving LLP discipline within ASEAN-6 countries. H2 is not supported in its hypothesized direction: the AI Governance Index exerts a statistically significant but positive effect on accrual quality scores (Coef. = -0.0094; DK – SE = 0.0040; T-stat = 2.3585; P-value = 0.0183), suggesting that higher governance readiness, during the 2020–2024 window, is associated with greater rather than lower accrual deviation. The explanation given for this could be attributed to transitional mechanism phenomenon and/or external factor at play which independently sustains accrual variability regardless of AI Governance Quality. H3 is not supported: AI investment intensity produces a statistically indeterminate coefficient (Coef. = -10.8135; DK – SE = 13.9463; T-stat = -0.7754; P-value = 0.4381), with a DK – SE exceeding the coefficient in absolute magnitude, a result attributable to the severe distributional concentration of AI venture capital across ASEAN-6 and the structural constraints of a five-year panel. Collectively, the model achieves a within-country $R^2$ of 0.3405 and an overall $F(3, 132) = 22.71$ ($p < 0.0010$), establishing that AI environment variables as a system explain a significant share of within-country accrual quality variation, with the regulatory sandbox emerging as the dominant and most robust institutional channel through which AI policy translates into a creation of favourable AI Ecosystem which provides measurable improvements in bank accrual quality across ASEAN-6 countries.

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## DECLARATION OF CONFLICTING INTERESTS

The author declares that no potential conflict of interest concerning the study, authorship, and/or publication of this article.

## REFERENCES

Anderson, J., Bholat, D., Gharbawi, M., & Thew, O. (2021). The impact of COVID-19 on artificial intelligence in banking. *Bruegel Blogs*. https://go.gale.com/ps/i.do?p=AONE&sw=w&issn=&v=2.1&it=r&id=GALE%7CA659197095&sid=googleScholar&linkaccess=fulltext

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2015). The evolution of fintech: A new post-crisis paradigm? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2676553

Bangguiyac, G. D., & Castañeda, M. O. (2025). Entrepreneurial leadership and business performance of MSMEs: The mediating role of government support. *International Journal of Applied Business and International Management, 10*(2), 313–329. https://doi.org/10.32535/ijabim.v10i2.4079

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics, 58*(2–3), 339–383. https://doi.org/10.1016/j.jacceco.2014.08.009

Bromberg, L., Godwin, A., & Ramsay, I. (2017). Fintech sandboxes: Achieving a balance between regulation and innovation.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Chichernea, D. C., Holder, A. D., & Petkevich, A. (2015). Does return dispersion explain the accrual and investment anomalies? *Journal of Accounting and Economics, 60*(1), 133–148. https://doi.org/10.1016/j.jacceco.2014.08.001

Clarke, T., Chelliah, J., & Pattinson, E. (2017). National innovation systems in the Asia Pacific: A comparative analysis. In *Innovation in the Asia Pacific: From manufacturing to the knowledge economy* (pp. 119–143). https://doi.org/10.1007/978-981-10-5895-0_6

Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review, 77*(s-1), 35–59. https://doi.org/10.2308/accr.2002.77.s-1.35

Francis, J., LaFond, R., Olsson, P. M., & Schipper, K. (2004). Costs of equity and earnings attributes. *The Accounting Review, 79*(4), 967–1010. https://doi.org/10.2308/accr.2004.79.4.967

Goyal, K., Garg, M., & Malik, S. (2025). Adoption of artificial intelligence-based credit risk assessment and fraud detection in the banking services: A hybrid approach (SEM-ANN). *Future Business Journal, 11*(1), Article 44. https://doi.org/10.1186/s43093-025-00464-3

Han, M. S., & Chen, W. (2021). Determinants of eco-innovation adoption of small and medium enterprises: An empirical analysis in Myanmar. *Technological Forecasting and Social Change, 173*, 121146. https://doi.org/10.1016/j.techfore.2021.121146

Hankins, E., Fuentes, P., Livia, N., Grau, M. G., & Rahim, S. (2023). *Oxford Insights*.

King, B. (2018). *Bank 4.0: Banking everywhere, never at a bank*. Marshall Cavendish Business.

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics, 31*(4), 674–692. https://doi.org/10.2307/2696354

Liao, C. H., San, Z., & Tsang, A. (2024). Corporate governance reforms and voluntary disclosure: International evidence on management earnings forecasts. *Journal of International Accounting, Auditing and Taxation, 54*, 100602. https://doi.org/10.1016/j.intaccaudtax.2024.100602

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly, 40*(1), 101774. https://doi.org/10.1016/j.giq.2022.101774

Mishrif, A., & Khan, A. (2023). Technology adoption as survival strategy for small and medium enterprises during COVID-19. *Journal of Innovation and Entrepreneurship, 12*(1), Article 53. https://doi.org/10.1186/s13731-023-00317-9

Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial intelligence (AI) in banking industry & consumer's perspective. *Sustainability, 15*(4). https://doi.org/10.3390/su15043682

OECD. (2025). *Governing with artificial intelligence: The state of play and way forward in core government functions*. OECD Publishing. https://doi.org/10.1787/795de142-en

Pradnyawati, S. O., Yuliantari, N. K. A., Wedayanti, N. M. E., & Yunita, N. L. P. (2024). The analysis of financial ratios, good corporate governance, reward, and asymmetric information in earnings management of manufacturing companies in Indonesia. *International Journal of Applied Business and International Management, 9*(3), 416–432. https://doi.org/10.32535/ijabim.v9i3.3466

Sabihaini, Kurniawan, A., Prasetio, J. E., & Rusdiyanto. (2024). Environmental analysis and impact on green business strategy and performance in SMEs post the COVID-19 pandemic. *Cogent Economics & Finance, 12*(1). https://doi.org/10.1080/23322039.2024.2330428

Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and Society, 40*(2), 137–157. https://doi.org/10.1080/14494035.2021.1928377

Xie, L., Peng, Z., & Tong, X. (2026). AI strategy, earnings management, and corporate fraud: Evidence from listed firms in China. *Economic Modelling, 156*, 107460. https://doi.org/10.1016/j.econmod.2025.107460

Yiming, Z., & Manansala, L. (2024). The impact of digital transformation on the innovation capacity of Chinese-listed firms: The role of government subsidies. *International Journal of Applied Business and International Management, 9*(2), 31–46. https://doi.org/10.32535/ijabim.v9i2.3393

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