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AI-driven analysis of ESG-linked financial determinants for sustainable growth in Thailand: A hybrid SEM framework

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ABSTRACT

This study examines sustainable growth among Thai listed firms using an AI-enhanced Structural Equation Modeling (AI-SEM) framework that integrates financial and ESG perspectives within contingency theory and stakeholder value maximization. The framework extends conventional SEM by incorporating anomaly detection, feature selection, and dimensionality reduction prior to estimation, followed by post-SEM time-series interpretability analysis to address multicollinearity, data noise, and firm-level heterogeneity. Using panel data from 147 firms listed on the Stock Exchange of Thailand during 2018–2022, fourteen hypotheses are tested across five financial and governance constructs: performance, internal control, economic profit, dividend policy, and market value added, with sustainable growth proxied by ESG outcomes. The results indicate that performance and internal control are key drivers of sustainable growth, both directly and indirectly through market value added. In contrast, economic profit exhibits a negative association with sustainability outcomes, while dividend policy is insignificant, reflecting Thailand's cyclical dividend behaviour. These findings underscore the context-dependent nature of sustainable growth and reinforce contingency theory by demonstrating how firm characteristics and market conditions jointly shape financial sustainability. The study further shows that integrating AI-enabled analytics into ESG–finance evaluation enhances decision precision and organisational adaptability, offering actionable insights for policymakers and regulators seeking to align data-driven financial strategies with long-term sustainability objectives and advance Sustainable Development Goals 8 and 9.

1. Introduction

The increasing complexity of global financial markets has accelerated the shift towards data-driven and adaptive corporate finance frameworks. Traditional financial indicators such as return on assets (ROA), debt-to-equity (D/E) ratios, and price-to-earnings (P/E) ratios remain widely used to assess corporate performance. However, they provide retrospective insights and fail to capture macroeconomic volatility, sector-specific risks, and long-term sustainability dimensions (Yadav et al., 2024). These limitations are particularly evident in the era of big data, where financial information is frequently incomplete, inconsistently disclosed, and inadequate for supporting real-time and multidimensional analysis.

In Thailand, sustainable growth and ESG adoption are shaped by concentrated ownership, evolving governance regulations, and uneven ESG disclosure maturity (Pongsaporamat, 2020; OECD, 2025). These institutional characteristics create a relevant context for analyzing how financial determinants translate into sustainability outcomes. Beyond Thailand, emerging economies such as Malaysia, Indonesia, and Vietnam are undergoing similar economic transformation and financial acceleration (Waqar et al., 2025).

At the same time, firms across the ASEAN region are increasingly adopting Environmental, Social, and Governance (ESG) principles to strengthen governance quality and align corporate practices with long-term sustainability objectives. This shift from shareholder-centric to stakeholder-inclusive governance (Jensen, 2010) has been shown to enhance market value added (MVA), investor confidence, and corporate resilience (Baumüller and Sopp, 2022; Chen et al., 2023; Correa-Mejía et al., 2024; Waqar et al., 2025). However, the financial mechanisms linking ESG integration with sustainable growth remain underexplored in these markets.

Despite growing attention to ESG–finance integration, modeling the relationship between short-term financial drivers and long-term sustainability outcomes remains challenging—particularly in emerging economies characterized by IFRS standardization, sectoral homogeneity, and concentrated ownership structures, which exacerbate

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multicollinearity and firm-level heterogeneity (Wattanawarangkoon et al., 2022; Ebiwonjumi et al., 2023). Conventional SEM approaches rely on static and linear assumptions, which limit their ability to capture nonlinear, dynamic, and time-varying relationships (Aras and Mutlu Yildirim, 2018; Saheb Ali Mondal et al., 2024).

Drawing upon sustainable growth, contingency, and open innovation perspectives, this study develops a hybrid analytical framework to address these conceptual and methodological gaps. Sustainable growth theory explains how firms sustain long-term performance through profitability, retention, leverage, and asset utilization (Higgins, 1977; Van Horne, 2001; Bagh et al., 2024), while contingency theory emphasizes the alignment of governance and strategic choices with contextual and environmental factors (Chen et al., 2023).

Complementing these, open innovation dynamics highlight cross-sector knowledge exchange and adaptive collaboration as enablers of ESG-oriented transformation (Yun et al., 2020; Wamba et al., 2020). Building on these foundations, this study introduces an AI-assisted Structural Equation Modeling (AI-SEM) framework designed as a two-stage analytical architecture, where feature selection, dimensionality reduction, and anomaly detection support SEM estimation, while temporal modeling is applied after estimation for interpretive purposes (Bakumenko and Elragal, 2022; Cappello et al., 2025; El-Sheikh et al., 2024). This framework enhances interpretability and predictive insight while preserving SEM as the core framework for theory-driven structural interpretation, addressing multicollinearity and time-varying ESG–finance linkages in Thailand's IFRS-standardized, concentrated-ownership market (Cherian and Seranmadevi, 2025; El-Sheikh et al., 2024).

1.1. Research question

How can an AI-SEM framework enhance the understanding of ESG-linked financial determinants of sustainable growth in Thai firms, and what insights does it provide for advancing sustainable financial governance in emerging markets?

Accordingly, this research aligns with the United Nations Sustainable Development Goals, specifically SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure), by promoting adaptive, transparent, and data-driven financial governance strategies in Thailand (UNDP, 2023). Ultimately, it provides policymakers, investors, and corporate leaders with insights on how to strengthen governance quality, enhance competitive advantage, and achieve sustainable growth through the application of advanced analytics and responsible financial practices.

2. Literature survey

This study integrates three theoretical perspectives: ESG-driven corporate responsibility, contingency theory, and open innovation dynamics. ESG provides a normative foundation for responsible governance and long-term value creation (Rezaee, 2025; Bagh et al., 2024). Contingency theory explains that the effectiveness of financial and governance mechanisms depends on firm and environmental contexts (Mahmud et al., 2021). Open innovation emphasizes knowledge exchange and collaboration as key elements of sustainability strategies. Together, these perspectives form the conceptual foundation of the AI-SEM framework and offer a dynamic view of ESG-linked financial determinants in emerging markets. By connecting ESG principles with contextual alignment and innovation-based adaptability, this framework presents sustainability as both a situational and collaborative process. The following subsections discuss firm-level ESG–finance dynamics in Section 2.1, open innovation mechanisms in Section 2.2, and methodological advances in AI-SEM in Sections 2.3 through 2.6.

2.1. Literature review on financial determinants of ESG-linked growth in Thai firms

Prior research on ESG-linked financial determinants in Thailand reveals that sustainable growth in emerging markets is often grounded in strategic and firm-level contingency perspectives, showing that the effectiveness of ESG drivers depends on firm-specific contexts, market structures, and stakeholder expectations (Lee and Suh, 2022; Cherian and Seranmadevi, 2025). Firm characteristics such as size, sector, and ownership concentration moderate ESG effectiveness, particularly in markets characterized by regulatory asymmetries (Mahmud et al., 2021; Alodat, Hao, 2025).

In Thailand, factors such as market scrutiny, concentrated ownership, and institutional gaps shape ESG adoption, particularly among SMEs with resource constraints (Rezaee, 2025). Traditional financial indicators including Return on Assets (ROA), Return on Equity (ROE), Debt-to-Equity Ratio (D/E), and Earnings per Share (EPS) remain widely used but provide limited predictive insights into sustainability-oriented outcomes (Aras and Mutlu Yildirim, 2018; Hair et al., 2021).

Contemporary scholarship increasingly highlights value-based indicators such as internal control (Huang et al., 2025), Economic Value Added (EVA) (Jankalová and Jankal, 2024), dividend policy (Peng and Li, 2025), and Market Value Added (MVA), each associated with ESG transparency and innovation-driven strategic value creation (Şerban et al., 2022; Zhou et al., 2022).

Empirical evidence further advances understanding of ESG–market value dynamics within specific institutional contexts. Dsouza et al. (2025) demonstrated that ESG outcomes significantly enhance market value in OECD countries through the mediating effects of profitability and operational performance. Complementing this, Gazi et al. (2024) examined the ECON–ESG framework across East Asia Pacific and South Asia (including Thailand), confirming long-run associations between ESG factors, GDP growth, and SDG achievement.

The 2025 OECD Economic Outlook for Thailand similarly emphasizes the importance of embedding ESG considerations within national growth strategies (OECD, 2025), underscoring the need for localized ESG frameworks aligned with domestic institutional conditions. These insights strongly align with contingency theory, illustrating that ESG–financial linkages are highly context-dependent, which reinforces this study's focus on Thai listed firms. Moreover, regional studies further highlight the role of institutional quality, governance frameworks, and investor awareness in shaping ESG outcomes across emerging markets.

For instance, Cherian and Seranmadevi (2025), show that the ESG–financial performance relationship in BRICS economies depends on industry structure, policy environment, and market maturity, underscoring the contextual logic of contingency theory. Together, these insights support the use of AI-enhanced SEM to capture country-specific dynamics of sustainable growth and stakeholder-driven value creation.

2.2. The role of open innovation dynamics in driving ESG-linked sustainable growth

As global sustainability commitments intensify, firms increasingly rely on external knowledge and complementary capabilities to advance ESG-linked innovation. Research on open and social innovation shows that digital platforms—such as delivery, mobility, fintech, and mobile payment ecosystems—enable collective intelligence and cross-sector value co-creation, consistent with open innovation perspectives emphasizing knowledge openness, collaboration, and ecosystem-based innovation (Yun et al., 2020).

Open innovation dynamics, defined as continuous interaction between internal capabilities and external knowledge ecosystems, function as a key enabler of ESG-driven sustainable growth (Yun et al., 2020). These dynamics enhance learning, stakeholder engagement, and adaptive capacity, while shaping inter-rationality among heterogeneous actors operating under different incentives, information constraints, and governance structures—conditions particularly salient for Thai SMEs facing evolving ESG expectations and limited resources (Wamba et al., 2020; Huang et al., 2025).

Platform-based collaboration, industry consortia, and public–private partnerships allow firms to embed regulatory standards, best practices, and stakeholder insights into ESG decision-making (Șerban et al., 2022; Zhou et al., 2022). Beyond cultural openness, these mechanisms influence the economics of open innovation by affecting business model design, coordination costs, and value capture, thereby determining whether ESG initiatives translate into sustained market value creation.

However, prior studies also emphasize constraints in open innovation systems, including bounded rationality, coordination complexity, governance costs, and resource limitations that may weaken long-term outcomes (Yun et al., 2020; Huang et al., 2025). These challenges highlight the need for governance structures and analytical tools that support efficient collaboration and informed strategic choices, especially among SMEs.

In this context, the proposed AI-SEM framework complements open innovation dynamics by improving the interpretability of ESG–financial relationships and supporting ecosystem-level coordination. By linking governance mechanisms and platform-based knowledge flows to ESG-linked value creation through Market Value Added (MVA), the framework provides an analytical foundation that aligns open innovation processes with measurable financial and sustainability outcomes. Sections 2.3–2.6 detail how this logic is operationalized through AI-assisted preprocessing and SEM-based structural analysis.

2.3. Definition and impact of multicollinearity

Multicollinearity, or a high linear relationship between independent variables, poses a significant threat to parameter estimation accuracy, particularly in large datasets and complex financial contexts (Chan et al., 2022). It inflates standard errors, destabilizes coefficients, and may cause relevant variables to appear insignificant. Overfitting is also more likely, reducing generalizability to new data. Common diagnostics include pairwise correlation ($\geq$0.8–0.9), Variance Inflation Factor (VIF $>$ 10), and Condition Index (CI $>$ 30), all of which help assess the severity of multicollinearity before applying corrective methods (Chan et al., 2022).

2.4. Multicollinearity in previous research and analytical gaps

Structural Equation Modeling (SEM) has long been a foundational tool for assessing structural relationships among latent constructs in financial research. However, prior studies reveal that SEM performance degrades when multicollinearity is present, as it obscures the contributions of individual predictors and inflates standard errors. Complex constructs such as ESG, Market Value Added (MVA), firm characteristics (CON), and financial performance indicators (PER) often exhibit nonlinear and overlapping interactions that traditional SEM struggles to represent (Wamba et al., 2020).

To overcome these challenges, researchers have developed several techniques to mitigate multicollinearity. Ridge regression penalizes all coefficients uniformly but fails to reflect variable importance (Chan et al., 2022). Principal Component Analysis (PCA) is commonly applied to reduce dimensionality, but it converts observed variables into abstract components, thereby compromising interpretability (Greenacre et al., 2022). Partial Least Squares (PLS) offers a more balanced alternative by preserving the relationship between predictors and outcome variables (Greenacre et al., 2022). Therefore, selecting the most appropriate method requires alignment between theoretical objectives and computational practicality.

Recent research points to the importance of contextual and institutional factors, such as financial transparency, which can moderate the relationships between key financial indicators, including dividend policy, and firm outcomes (Peng and Li, 2025). In standardized financial reporting environments, such as those using IFRS, indicators like ROA, ROE, and EVA tend to be highly correlated, especially in emerging markets (Liu et al., 2012). To address this, the literature increasingly points toward preprocessing techniques and feature selection strategies that are both robust and context-aware (Htun et al., 2023; Kuizinienė et al., 2024).

2.5. Multicollinearity challenges in SEM under IFRS in emerging financial markets

Multicollinearity remains a significant challenge in emerging markets, such as Thailand, where regulatory uniformity and IFRS-based reporting increase the interdependence among financial indicators. While researchers commonly use SEM for causal modeling, its validity declines when predictors are highly correlated, resulting in reduced accuracy and interpretive clarity (Chan et al., 2022). IFRS adoption, intended to enhance transparency and comparability, also reinforces structural similarity across firms. This standardization intensifies correlations among indicators, such as ROA and ROE, especially in capital-intensive and regulated sectors, including finance, energy, and banking (Hair et al., 2021; Sappor et al., 2023; Wattanawarangkoon et al., 2022).

Moreover, concentrated ownership and regulatory uniformity such as the oversight of the Bank of Thailand increase homogeneity in financial disclosures (Pongsaporamat, 2020). This convergence generates systemic collinearity, resulting in redundancy and reduced explanatory power. Traditional methods such as stepwise regression and VIF filtering can alleviate these issues but risk excluding theoretically essential variables (Meng et al., 2022). According to Helfaya and Aboud (2023), IFRS convergence and market concentration require more sophisticated modeling frameworks. To address these challenges, this study employs a standardized multi-year SETSMART dataset for SEM-based financial modeling in Thailand (Stock Exchange of Thailand, 2023).

2.6. Integrating artificial intelligence into structural equation modeling

Considering limitations found in prior research and Thailand's financial reporting context, recent studies propose Artificial Intelligence (AI) enhanced SEM as a robust alternative that addresses traditional SEM's constraints in scalability, static modeling, and high-dimensional collinearity while maintaining theoretical rigor. Hair et al. (2021) highlight scalability challenges in PLS-SEM, while Greenacre et al. (2022) and Meng et al. (2022) note interpretability trade-offs associated with PCA. To mitigate these issues, Htun et al. (2023) and Kuizinienė et al. (2024) recommend Recursive Feature Elimination (RFE) to enhance feature robustness in complex financial environments.

Recent developments further highlight the need for time-sensitive modeling tools. Qi et al. (2025) validates the effectiveness of the Temporal Fusion Transformer (TFT) in analyzing time-dependent financial data, enhancing both predictive accuracy and interpretability. In parallel, researchers have addressed methodological fragmentation in causal modeling by developing hybrid logic–statistical frameworks, such as those proposed by Hossain et al. (2025), who integrate fsQCA with SEM.

Kou and Lu (2025) highlight the importance of integrating diverse AI technologies within structured analytical frameworks for financial modeling. Drawing from this insight, the study introduces AI-enhanced SEM framework that integrates RFE, PCA, Isolation Forest, and TFT to address statistical, structural, and temporal challenges. This integration enhances interpretability, strengthens model robustness, and supports temporal dynamics, providing a scalable and adaptable approach for financial sustainability modeling in emerging markets. An overview of recent AI-SEM research contributions and methodological advancements is provided in Table 1.

In selecting the AI-SEM approach, we evaluated alternative modeling

Table 1
Literature review of AI–SEM research contributions and methodological advancements (2021–2025).

Author(s)	Key Focus	Methods	Identified Gap	Contribution to This Study
Kuizinienė et al. (2024)	Institutional context in SEM	SEM, PCA	PCA interpretability limits	Enhances contextualised PCA in AI-SEM
Htun et al. (2023)	Feature robustness	RFE, Boosting	High-dimensional collinearity	Informs feature screening in AI-SEM
Hossain et al. (2025)	Causal integration	PLS-SEM, fsQCA	Fragmented causal logic	Supports integrated AI-SEM design
Cappello et al. (2025)	Financial time-series	ML, Traditional models	Forecasting robustness	Motivates post-SEM temporal analysis
Liu et al. (2012)	Anomaly detection	Isolation Forest	Scalability issues	Enables robust outlier handling
Qi et al. (2025)	Temporal dynamics	TFT	Limited interpretability	Guides post-SEM interpretive layer
Dsouza et al. (2025)	ESG–value linkage	Panel econometrics	Emerging-market context gap	Grounds ESG–finance modelling
Gazi et al. (2024)	ESG–growth nexus	ARDL, VECM	Long-run ESG evidence	Supports ESG–macro integration
Cherian and Seranmadevi (2025)	ESG–performance	Systematic review	Fragmented ESG models	Strengthens construct selection
This Study (2025)	**Explainable AI-SEM**	**PLS-SEM + AI tools**	**No integrated AI-SEM**	**Proposes scalable, interpretable AI-SEM**

techniques such as Artificial Neural Networks (ANN) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) to ensure methodological alignment with the study's objectives and data structure. While Artificial Neural Networks (ANN) demonstrate superior predictive capability in capturing nonlinear patterns within financial data (Gupta and Jaiswal, 2025), their black-box nature limits causal interpretability compared to SEM-based approaches. Likewise, fsQCA is well suited for configurational analyzes and small-N case studies (Hossain et al., 2025). However, it is less appropriate for large panel datasets that necessitate path modeling and mediation analysis. In contrast, the AI-SEM framework enables causal modeling with latent constructs, supports rigorous hypothesis testing, and effectively accommodates large, multivariate panel data, rendering it a more suitable choice for elucidating the financial drivers of ESG-linked sustainable growth in Thai firms (Hair et al., 2021).

This comparative rationale reinforces the methodological appropriateness of the AI-SEM framework. By integrating Recursive Feature Elimination (RFE) (Htun et al., 2023), Principal Component Analysis (PCA) (Greenacre et al., 2022), Isolation Forest (Liu et al., 2012; Bakumenko and Elragal, 2022), and Temporal Fusion Transformer (TFT) (Qi et al., 2025) with PLS-SEM, the framework delivers both statistical rigor and theoretical coherence—addressing key limitations associated with ANN and fsQCA in this context. Given that ESG–financial linkages are dynamic and context-dependent (Dsouza et al., 2025; Cherian and Seranmadevi, 2025), the AI-SEM framework offers a transparent, adaptive model that advances ESG strategy development in emerging markets.

3. Research methodology

This framework integrates Contingency Theory (Mahmud et al., 2021), Stakeholder Value Maximization (Jensen, 2010), and the Sustainability Framework (UNDP, 2023) to align firm capabilities with stakeholder interests and ESG strategies. It bridges theoretical and empirical gaps and underpins hypotheses H1–H14. The study investigates financial determinants of sustainable growth among SET-listed firms using a hybrid PLS-SEM approach enhanced by AI-based preprocessing. Recursive Feature Elimination (RFE) and Temporal Fusion Transformer (TFT) are applied to capture nonlinear and temporal dynamics, improving both robustness and interpretability.

3.1. Sample design and data overview

This study analyses a five-year panel dataset (2018–2022) of 147 firms listed on the Stock Exchange of Thailand (SET), combining time-series and cross-sectional information. The sample was constructed exclusively from publicly available secondary sources. Financial data were obtained from SETSMART and firms' annual filings (Form 56–1), while ESG indicators were sourced from Settrade.com (2024), which provides standardised environmental, social, and governance disclosures at the firm level.

Firm inclusion was based on continuous listing status and data completeness over the study period to ensure longitudinal comparability. All variables were harmonised into an annual panel structure. No primary data collection involving human participants was conducted. A firm-level ESG integration index was constructed solely as a contextual moderating variable using aggregated, non-identifiable information and was not employed as an indicator within the SEM measurement model.

Building on the assembled dataset, ESG performance was measured using standardised indicators across environmental, social, and governance dimensions. Composite ESG scores were constructed to enhance comparability and transparency across firms. These measures ensure consistent representation of sustainability orientation in the SEM framework. Integrating AI-based feature selection with theory-driven SEM hypothesis testing further strengthens the framework's ability to generate robust and interpretable insights into ESG–financial relationships.

3.2. Conceptual model and hypothesis development

The conceptual model comprises six latent constructs: Performance (PER), Internal Control (INC), Economic Profit (POF), Dividend Policy (DEP), Market Value Added (MVA), and Sustainable Growth (SG). SG is defined as a firm's capacity to sustain revenue and earnings growth through profitability, retention, leverage, and asset utilization, consistent with classical finance theory (Higgins, 1977; Van Horne, 2001).

SG is driven by financial and governance factors, including PER, INC, POF, and DEP, operating through MVA, while environmental, social, and governance (ESG) conditions serve as contextual influences shaping investor confidence, risk perception, and capital allocation (Bagh et al., 2024; Naseer et al., 2024). ESG composite scores are used as a theoretically grounded proxy for sustainability outcomes due to incomplete firm-level PRAT data, supported by preprocessing refinements described in Section 3.4.

Two moderators, a disclosure-based ESG integration indicator reflecting firms' publicly reported ESG adoption and governance/sustainability practices, and business characteristics representing firm size and industry, address contextual heterogeneity. The ESG integration indicator is distinct from the market-based ESG composite used for SG, ensuring no overlap. Fourteen hypotheses (H1–H14) are developed to test direct, indirect, and moderated relationships among the constructs.

3.2.1. Firm performance and sustainable growth

Firm performance is a key driver of corporate value and long-term sustainability. Companies demonstrating strong financial and operational performance tend to achieve higher market value added (MVA) and sustainable growth, aligning with Thailand's economic development strategies that emphasize financial stability and competitiveness.

- **H1**: Performance positively influences market value added (MVA).
- **H2**: Performance positively influences sustainable growth (SG).
- **H3**: Performance indirectly influences sustainable growth through MVA.

3.2.2. Internal control and sustainable growth

Internal control mechanisms play a vital role in ensuring compliance, managing risk effectively, and maintaining financial transparency, which drive sustainable growth and strengthen investor confidence. Strong control systems also align with Thailand's national policies that promote good governance and economic stability.

- **H4**: Internal control positively influences MVA.
- **H5**: Internal control positively influences SG.
- **H6**: Internal control indirectly influences SG via MVA.

3.2.3. Economic profit and sustainable growth

Economic profit, which incorporates capital costs, is a key indicator of financial efficiency. Yet its role in driving sustainable growth is contested, especially in emerging markets shaped by volatile investments. This study examines how macroeconomic conditions and ESG integration moderate this relationship.

- **H7**: Economic profit influences MVA.
- **H8**: Economic profit influences SG.
- **H9**: Economic profit influences SG via MVA.

3.2.4. Dividend policy and sustainable growth

Dividend policy has a direct impact on investor sentiment, capital structure, and firm valuation. Its influence on sustainable growth varies across industries, particularly in emerging markets where firms prioritize financial resilience. This study employs sectoral risk analysis to examine the impact of dividend strategies on corporate sustainability.

- **H10**: Dividend policy positively influences MVA.
- **H11**: Dividend policy positively influences SG.
- **H12**: Dividend policy indirectly influences SG via MVA.

3.2.5. Market value added and sustainable growth

MVA is a key indicator of a firm's capacity to generate shareholder value and a strong predictor of sustainability, especially when analyzed in conjunction with ESG adoption and industry-specific financial risks.

- **H13**: MVA positively influences SG.
- **H14**: MVA influences SG with business characteristics and a disclosure-based ESG integration indicator as moderating factors.

The structural path diagram (Fig. 1) presents the conceptual model and hypothesized relationships. These are estimated using PLS-SEM within the AI-SEM framework. The model evaluates financial and governance effects on sustainable growth, including direct, indirect, and moderating influences.

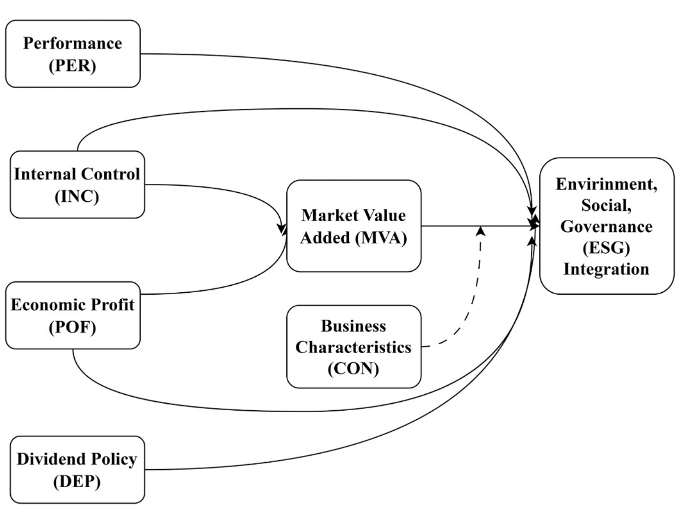

Fig. 1. The Conceptual model.

3.3. Latent constructs operationalization

To validate the conceptual model empirically, this study defines six latent constructs as core components representing financial strength, governance capability, and strategic direction toward sustainable growth. These constructs are modeled reflectively and measured using secondary data derived from audited financial statements, Form 56–1 annual filings, and firm-level ESG-related disclosures reported through publicly available sources.

Performance (PER) measures operational and financial effectiveness through key indicators, including Return on Assets (ROA), Return on Equity (ROE), Debt-to-Equity Ratio (D/E), and Price-to-Earnings Ratio (P/E). It reflects the firm's ability to utilize assets and generate shareholder value.

Internal Control (INC) represents governance quality and risk management, aligned with the COSO framework. It encompasses control environment, risk estimation, control activities, and monitoring, ensuring transparency and regulatory compliance.

Economic Profit (POF) is measured by Economic Value Added (EVA), which assesses the firm's ability to generate value exceeding capital costs and provides insight into financial efficiency from an investor's perspective.

Dividend Policy (DEP) captures the firm's approach to profit distribution and its implications for investor sentiment. This construct considers metrics such as Dividend Per Share (DPS) and the Dividend Yield (DIY), offering insight into how a firm balances reinvestment in growth with the need to deliver shareholder returns. Dividend strategy also signals financial discipline and confidence in future earnings.

Market Value Added (MVA) represents the market's valuation exceeding invested capital and reflects the combined influence of performance, control, profit, and dividend policy. As a mediating variable, it connects financial drivers to sustainable growth.

Sustainable Growth (SG) is represented as a second-order construct comprising Environmental, Social, and Governance dimensions. Due to incomplete firm-level PRAT components in the SETSMART dataset, a composite ESG score is employed as a proxy for sustainable growth rather than a direct financial growth measure. This operationalization does not equate ESG performance with growth outcomes but reflects firms' capacity for sustained value creation when conventional growth components are unavailable.

The use of ESG as a proxy is consistent with sustainable growth theory, which emphasizes long-term reinvestment capacity and governance discipline (Higgins, 1977), and aligns with recent emerging-market evidence (Bagh et al., 2024; Naseer et al., 2024). Similar approaches have been adopted in contexts where PRAT data are structurally constrained (Bagh et al., 2024).

SG is operationalized using a two-stage PLS-SEM approach, where latent scores for ESG dimensions are first estimated and then used to construct the higher-order SG variable. Firm-level ESG integration disclosures and business characteristics, including firm size and industry, are incorporated as moderators to capture contextual heterogeneity in the MVA–SG relationship.

3.4. AI-SEM framework development

This study develops an AI-enhanced SEM (AI-SEM) framework to improve robustness and interpretability in modelling ESG-linked financial determinants of sustainable growth. AI-SEM is conceptualised as an AI-augmented analytical architecture rather than an alternative estimator, in which artificial intelligence supports data conditioning and post-estimation diagnostics, while causal relationships are examined using theory-driven PLS-SEM. To safeguard temporal validity and prevent information leakage, all AI-assisted procedures adopt a time-aware data-splitting strategy in which model training and validation are strictly separated across time periods (Athey and Imbens, 2019; Pick and Timmermann, 2024). The detailed workflow, diagnostic procedures, and post-estimation temporal analysis are described in the following subsections.

3.4.1. AI -SEM workflow design

AI-based preprocessing is organised as a sequential workflow supporting SEM estimation, as illustrated in Fig. 2. The workflow clearly separates data conditioning, feature screening, and dimensionality control prior to structural modelling, while temporal analysis is conducted only after SEM to enhance interpretability without affecting theory-driven inference.

Fig. 2 illustrates the AI-SEM framework, where AI-based preprocessing supports SEM estimation and the Temporal Fusion Transformer (TFT) is applied only after SEM for interpretive analysis. A time-aware split is used, with 80 % of observations (2018–2021) for training and preprocessing and 20 % (2022) for walk-forward out-of-sample validation to preserve temporal order and avoid look-ahead bias (Athey and Imbens, 2019; Pick and Timmermann, 2024). Within the training window, Isolation Forest handles outlier detection, RFE is applied solely for predictive screening, and PCA orthogonalises collinear performance indicators (ROA, ROE) into PC1 and PC2 used in PLS-SEM (Table 4). PLS-SEM estimates theory-specified relationships, while TFT follows the same temporal protocol and provides post-estimation analysis of nonlinear and time-varying patterns without contributing inputs to the SEM model, ensuring temporal consistency and preventing data leakage (Caldeira and Neves, 2026; Hayat et al., 2026).

3.4.2. Multicollinearity Diagnostics and Stability Assessment

Multicollinearity among observed indicators is examined using Variance Inflation Factor (VIF) diagnostics in conjunction with outer loadings and weights from the measurement model to ensure estimation reliability. Indicators with VIF values exceeding the conventional threshold of 10 are flagged as problematic due to their potential to inflate standard errors and distort structural path estimates. The diagnostics indicate pronounced collinearity between Return on Assets (ROA) and Return on Equity (ROE), necessitating corrective action prior to SEM estimation. Detailed diagnostic outcomes are reported in Section 4.1 (Table 4).

3.4.3. Feature Refinement and Dimensionality Control

Building on the multicollinearity diagnostics in Section 3.4.2, this subsection addresses the technical treatment of correlated indicators prior to SEM estimation. Owing to pronounced collinearity between Return on Assets (ROA) and Return on Equity (ROE), Principal Component Analysis (PCA) is applied to orthogonalise this pair and stabilise parameter estimation. The resulting uncorrelated components (PC1 and PC2) replace the original indicators and serve as the final measures of the Performance (PER) construct in the PLS-SEM model, with loadings, explained variance, and post-PCA VIF values reported in Table 4. Recursive Feature Elimination (RFE) is used only for auxiliary predictive screening and does not define constructs, indicators, or structural paths, ensuring that dimensionality control improves statistical stability without altering the theory-driven SEM specification (Fig. 3).

3.4.4. SEM Integration and Post-Estimation Temporal Analysis

After feature refinement, the preprocessed dataset is integrated into the PLS-SEM framework to estimate theory-driven measurement and structural relationships. SEM estimation preserves the causal logic specified in the conceptual model. Subsequently, the Temporal Fusion Transformer (TFT) is applied exclusively as a post-estimation layer to examine nonlinear and time-varying dynamics among SEM-significant variables without modifying SEM results. TFT attention outputs, visualised as a heatmap (Fig. 5), reveal how the relative influence of key financial and ESG indicators evolves over time. These temporal insights support managerial interpretation, particularly by identifying periods in which profitability, governance, or sustainability factors exert stronger effects on Market Value Added (MVA), thereby enhancing decision relevance while maintaining methodological coherence.

3.5. Structural equation modeling (SEM) analysis

Fig. 3 presents the structural path diagram used to estimate the hypothesised relationships in the AI-SEM framework. This study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships among latent constructs using SmartPLS 4.0

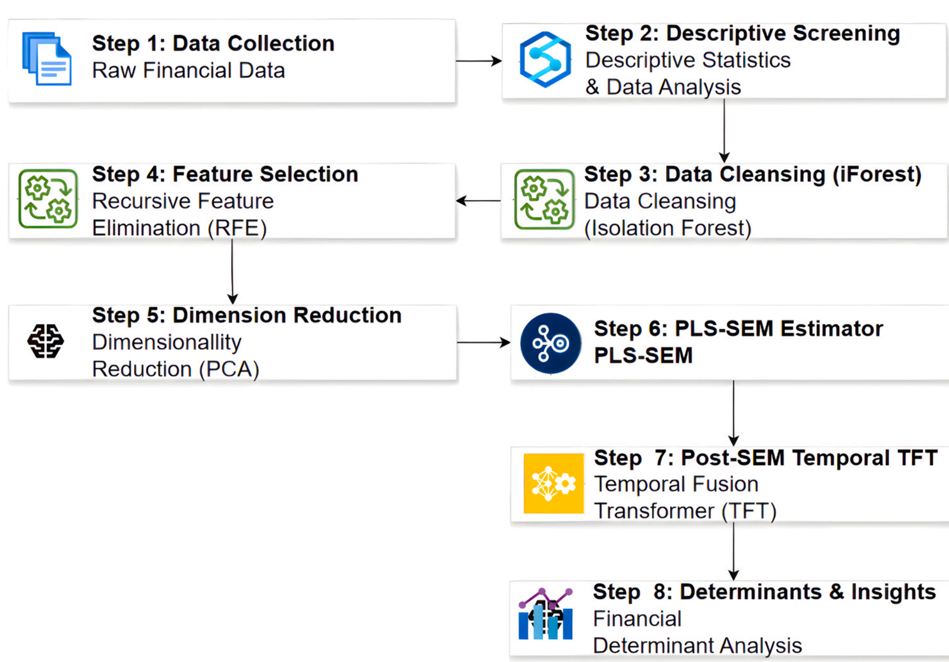

Fig. 2. AI-enhanced preprocessing pipeline for SEM analysis.

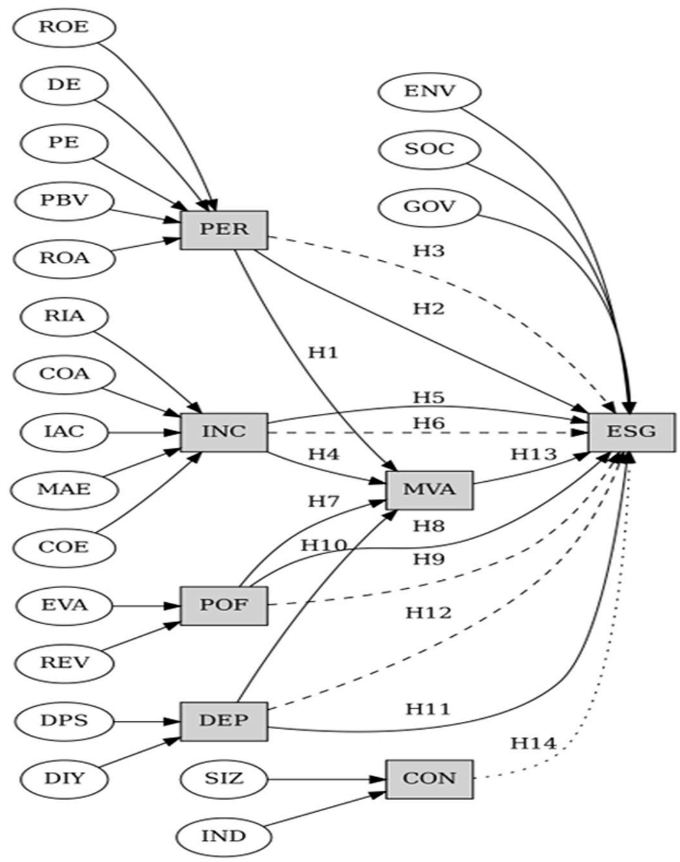

Fig. 3. Structural Path Diagram of the AI-SEM Model.

software. The analysis employs PLS-SEM because it effectively handles complex, high-dimensional models, particularly in exploratory research with non-normal data and moderate sample sizes. The procedure follows two stages: Measurement Model Validation and Structural Model Estimation. Traditional SEM approaches typically address high Variance Inflation Factor (VIF) values by removing variables. For instance, when ROA and ROE show strong correlations, stepwise regression often excludes ROA and retains ROE, even though both variables capture distinct aspects of financial performance.

3.5.1. Measurement model validation

To ensure construct reliability and validity, the measurement model was assessed through the following criteria: Cronbach's Alpha (CA) and Composite Reliability (CR) were used to evaluate internal consistency. All constructs exceeded the acceptable threshold of 0.70, indicating strong reliability. Average Variance Extracted (AVE) values were above the 0.50 benchmark, confirming convergent validity for each latent variable.

Discriminant validity was tested using the Fornell–Larcker criterion, which confirmed that the square root of each AVE exceeded inter-construct correlations. These results support the robustness of the reflective measurement model. A summary of these metrics is presented in Table 2, confirming that all constructs satisfy reliability and validity requirements for further structural analysis.

Table 2
Measurement model assessment summary.

Indicator	Acceptable Threshold	Observed Values
Cronbach's Alpha (CA)	≥ 0.70	0.80–0.89
Composite Reliability (CR)	≥ 0.70	0.85–0.93
Average Variance Extracted (AVE)	≥ 0.50	0.68–0.76
Fornell–Larcker	Must be met	All Constr. pass

3.5.2. Structural model estimation

The structural model was tested using bootstrapping (5000 resamples) to estimate the significance and robustness of the path coefficients. Key evaluation criteria include: Path Coefficients (β): These indicate the strength and direction of relationships among latent constructs.

Coefficient of Determination (R^2): R^2 values for Market Value Added (MVA) and Sustainable Growth (SG) were examined to assess the model's explanatory power. Predictive Relevance (Q^2): Blindfolding procedures confirmed that the model demonstrates predictive relevance, with Q^2 values exceeding zero for key endogenous variables.

3.6. Model evaluation and comparison

To assess the performance of the AI-SEM framework, we estimated a PLS-SEM model and compared it with a traditional SEM model using Predictive Accuracy, MSE, and R^2.

The Predictive Accuracy (PA) metric reflects the model's ability to correctly estimate sustainable growth outcomes from the selected financial and governance indicators. The AI-enhanced SEM outperformed the traditional SEM, exhibiting consistently higher PA scores across both endogenous constructs—Market Value Added (MVA) and Sustainable Growth (SG).

Based on Mean Squared Error (MSE) results, the AI-enhanced model achieved lower error margins, demonstrating better generalization and reduced overfitting. This improvement results from AI-driven preprocessing using Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and the Temporal Fusion Transformer (TFT), which collectively remove noise, address multicollinearity, and capture nonlinear temporal patterns in financial data.

The Coefficient of Determination (R^2) further confirmed the superior explanatory power of the AI-SEM. For Sustainable Growth, the R^2 value increased substantially when using the AI-enhanced framework, highlighting its improved capacity to model complex interactions between financial performance, governance variables, and ESG related outcomes.

4. Empirical results

The study employed an AI-SEM framework to investigate the influence of financial performance, internal control, and economic profit on Market Value Added (MVA) and Sustainable Growth (SG). The findings confirmed that financial performance and internal control significantly impact both MVA and SG, reinforcing their role in achieving ESG goals. The AI-SEM framework improves predictive accuracy and structural validity compared with a traditional SEM model. Additionally, firm size and industry type moderated the MVA-SG relationship, suggesting that larger or capital-intensive firms may face challenges in converting financial gains into sustainable growth. The results emphasize the need for ESG strategies tailored to firm characteristics.

4.1. Descriptive statistics of input variables

This section presents the preliminary statistical results of the financial and ESG-related variables used in the structural model. Prior to estimation, the dataset was assessed for distributional normality and multicollinearity—both of which are known to distort SEM performance if left unaddressed. Descriptive results revealed strong non-normality in variables such as Economic Value Added (EVA), Revenue Growth (REV), and Decision Making: Board (DMB), with extreme skewness ($|\text{Skewness}| > 2$) and kurtosis exceeding 20 (Table 3). EVA, for example, showed a skewness of –5.65 and kurtosis of 38.29, indicating high variability in capital efficiency.

These patterns indicate structural inconsistencies in financial reporting among Thai firms. To resolve this issue, Isolation Forest detected outliers, and RFE reduced redundancy while retaining key

Table 3
Descriptive statistics of financial and ESG variables.

Variable	$\bar{X}$	S.D.	Min	Max	Skewness	Kurtosis
ROE	0.66	0.12	–0.45	0.75	–0.90	2.34
ROA	0.34	0.08	–0.23	0.4	–0.67	0.7
DE	0.67	1.04	–3.85	3.67	–1.03	4.46
PE	9.83	29.79	–130.52	82.27	–1.45	4.49
PBV	27.4	40.39	0.88	247.2	**2.84**	9.16
COE	3.2	1.55	1	5	–0.40	–1.47
RIA	3.22	1.35	1	5	–0.47	–0.90
COA	3.17	1.37	1	5	–0.28	–1.22
IAC	2.9	1.61	1	5	–0.02	–1.63
MAE	3.27	1.41	1	5	–0.30	–1.25
EVA	–4.81E+ 12	2.04E+ 13	–1.54E+ 14	3.39E+ 13	**–5.65**	**38.29**
REV	–1.05E+ 24	3.91E+ 24	–2.92E+ 25	7.55E+ 24	**–4.94**	**27.24**
DPS	0.03	0.03	–0.15	0.22	0.84	15.02
DIY	56.67	60.09	–251.38	332.2	0.47	6.38
DMC	6.18E+ 10	1.27E+ 11	–1.01E+ 09	9.48E+ 11	**3.97**	19.66
DMB	5.53E+ 10	1.76E+ 11	–1.61E+ 10	1.27E+ 12	**5.42**	**32.43**
ENV	52.07	18.6	12.55	97.13	0.09	–0.50
SOC	52.2	19.89	16.56	93.31	0.19	–0.91
GOV	46.14	21.75	14.21	92.49	0.7	–0.81

Note: Bolded values indicate severe skewness (|skew| > 2) and kurtosis (kurtosis > 20), signaling the presence of extreme outliers that necessitate AI-based preprocessing steps.

predictors, thereby improving model stability and generalizability.

In terms of multicollinearity, VIF analysis revealed that ROA and ROE exceeded the standard threshold of 10 (see Table 4), indicating strong collinearity among performance indicators and risking biased SEM estimates.

To address this, Isolation Forest was first applied to detect outliers, followed by Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) to refine the predictor set and reduce redundancy.

Specifically, PCA converted the correlated ROA and ROE into two orthogonal components (PC1 and PC2), explaining approximately 82 % of the total variance. PC1 primarily captured profitability, while PC2 reflected asset efficiency. These components replaced ROA and ROE as indicators of the Performance (PER) construct in the PLS-SEM model, eliminating multicollinearity and enhancing estimation stability. Post-PCA diagnostics confirmed that all VIF values fell below 3, validating the effectiveness of the PCA-based preprocessing (Table 4).

4.2. Measurement model evaluation

The measurement model was evaluated using PLS-SEM in SmartPLS 4.0 following Hair et al. (2021). Sustainable Growth (SG) was modelled as a reflective second-order construct based on ESG dimensions using a two-stage approach. All constructs showed strong reliability and convergent validity (CA = 0.80–0.89; CR = 0.85–0.93; AVE = 0.68–0.76), and discriminant validity satisfied the Fornell–Larcker criterion. Although measurement invariance across years was not formally tested, annual re-estimation produced consistent structural patterns. AI-based preprocessing (RFE and PCA) further improved indicator parsimony and mitigated multicollinearity prior to SEM estimation.

Table 4
Multicollinearity diagnostics before and after PCA.

Variable	Loading	Outer Weight	VIF (Pre)	VIF (Post)
ROE	0.755	0.222	11.138	PC1 (2.3)
ROA	0.801	0.314	12.204	PC2 (2.1)
PC1 (ROE)	—	—	—	2.3
PC2 (ROA)	—	—	—	2.1
EVA	0.913	0.517	8.947	< 3.0
REV	0.929	0.568	8.947	< 3.0
RIA	0.61	0.109	7.633	< 3.0
DMB	0.894	0.581	6.492	< 3.0
DMC	0.88	0.546	6.492	< 3.0
MAE	0.774	0.323	5.539	< 3.0
COE	0.639	0.215	5.627	< 3.0
COA	0.727	0.326	5.347	< 3.0

Note: Grey cells indicate VIF > 10 before PCA, signalling multicollinearity. ROA and ROE were replaced by their orthogonal principal components (PC1 and PC2), whose post-PCA VIF values are reported for the Performance (PER) construct.

4.3. Structural model analysis

After validating the measurement model, the structural model was assessed using PLS-SEM in SmartPLS 4.0. Bootstrapping with 5000 subsamples was applied to test path significance. Following preprocessing, two core structural equations were derived from the SEM results.

$$\text{ESG (proxy for SG)} = 0.797 \cdot \text{MVA} + 0.205 \cdot \text{PER} + 0.233 \cdot \text{INC} - 0.141 \cdot \text{POF} + 0.098 \cdot \text{DEP} + \varepsilon \quad (1)$$

With mediation MVA modeled as:

$$\text{MVA} = 0.226 \cdot \text{PER} + 0.142 \cdot \text{INC} - 0.611 \cdot \text{POF} - 0.032 \cdot \text{DEP} + \zeta \quad (2)$$

Fig. 4 visualises the standardised path coefficients obtained from the AI-SEM estimation and summarises the structural relationships among the latent constructs.

4.3.1. Key structural model results

The AI-SEM model provides clear insights into the financial and organizational drivers of Sustainable Growth (SG), as summarized below.

(1) Performance (PER) and Internal Control (INC) as Key Drivers

PER and INC exert strong and statistically significant influences on both MVA and SG. Specifically: PER significantly predicts MVA ($\beta = 0.226$, $p \leq 0.001$; H1) and SG directly ($\beta = 0.205$, $p \leq 0.001$; H2), and indirectly through MVA ($\beta = 0.180$; H3), resulting in a total effect of 0.385. INC also shows significant direct effects on MVA ($\beta = 0.142$, $p \leq 0.001$; H4) and SG ($\beta = 0.233$, $p \leq 0.001$; H5), with an indirect effect through MVA ($\beta = 0.113$; H6), totaling 0.346. These results affirm that firms with strong operational performance and robust internal governance are more likely to enhance market value and achieve sustainable growth.

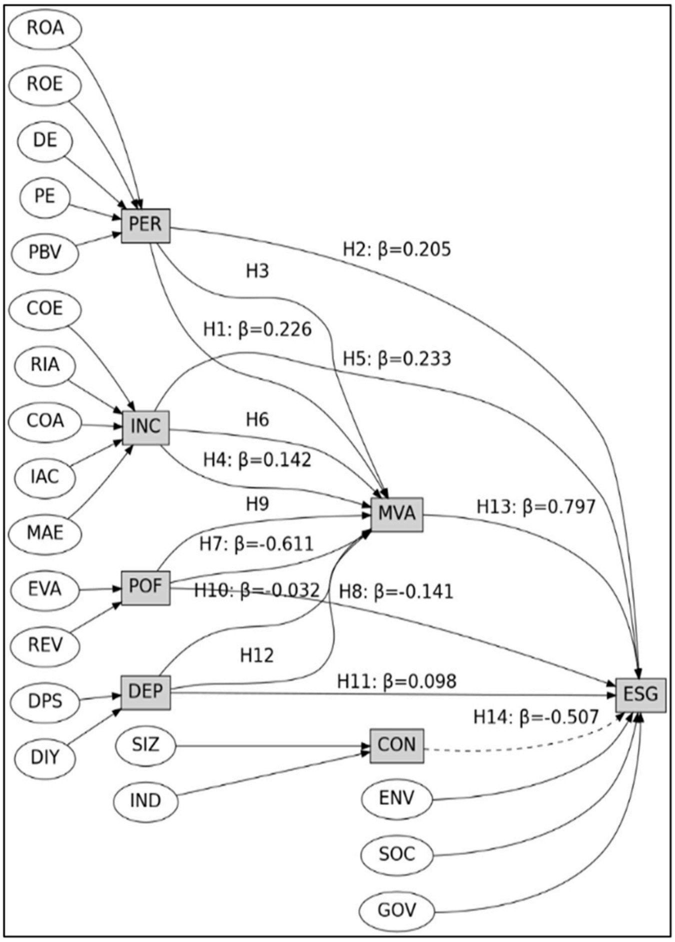

Fig. 4. AI-SEM Results with Standardized Path Coefficients (β).

(2) *Economic Profit (POF) and Its Negative Effects*

Contrary to expectations, Economic Profit (POF)—measured via EVA—negatively impacts both MVA and SG: Direct effects: POF → MVA (β = –0.611; H7), POF → SG (β = –0.141; H8). Indirect effect via MVA: –0.487 (H9) → Total effect = −0.628, the most negative in the model. This suggests that short-term profit orientation may hinder long-term sustainability outcomes.

(3) *Dividend Policy (DEP): Not Supported*

Dividend Policy (DEP), driven by one of its key indicators, Dividend Per Share (DPS), ranked first in the RFE results with a feature importance score of 0.94 (Table 6), indicating strong predictive relevance. However, DEP did not exhibit significant effects in the structural model (Table 5): DEP → MVA (β = –0.032, ns; H10), DEP → SG (β = 0.098, ns; H11), and the indirect path via MVA (β = –0.025; H12), and therefore is not supported. This discrepancy reflects both methodological and structural considerations. Methodologically, Recursive Feature Elimination (RFE) prioritizes out-of-sample predictive accuracy but does not account for stable structural relationships or residual multicollinearity within latent-variable models (Chan et al., 2022; Zhou et al., 2022). Even after PCA-based orthogonalization, the explanatory power of DEP is likely attenuated when modeled alongside stronger and more stable predictors such as Performance (PER), Internal Control (INC), and Economic Profit (POF).

Despite applying PCA and RFE, residual multicollinearity persisted among key financial indicators, likely suppressing DEP's unique contribution when modeled alongside stronger predictors such as Performance (PER), Internal Control (INC), and Economic Profit (POF). Contextually, dividend payouts in Thailand are often cyclical and discretion-based, reflecting sectoral cash-flow volatility and board-level smoothing policies, particularly in resource- and technology-intensive industries. As a result, DPS and dividend yield may exhibit temporal predictive relevance in specific periods, as captured by RFE and TFT attention patterns, yet fail to form a stable structural pathway to Market Value Added (MVA) or Sustainable Growth (SG) across the full panel window. This institutional and sectoral cyclicality explains why dividend policy remains structurally insignificant despite its short-term predictive prominence.

(4) *Market Value Added (MVA) as a Core Mediator*

MVA emerges as the strongest direct predictor of SG:

MVA → SG (β = 0.797, p ≤ 0.001; H13). This supports its role as a central mechanism through which financial and governance factors translate into sustainability outcomes.

(5) *Moderating Effect of Business Characteristics*

The interaction term for firm size and industry sector (CON) significantly moderates the MVA–SG relationship: CON × MVA → SG (β = –0.507, p ≤ 0.001; H14). This implies that firm specific characteristics may dampen the impact of market value on sustainability, particularly in large or capital-intensive organizations.

4.4. AI-SEM vs traditional SEM

The AI-SEM framework enhances predictive robustness, model stability, and interpretive depth compared with traditional Structural Equation Modeling (SEM), while retaining SEM as the core theory-

Table 5
Summary of hypothesis testing and path coefficients.

Hypothesis	Structural Path	Direct Effect	Indirect Effect	Total Effect	Result
H1	PER → MVA	0.226***	–	0.226***	Supported
H2	PER → ESG	0.205***	–	0.205***	Supported
H3	PER → MVA → ESG	0.226***	0.180***	0.385***	Supported
H4	INC → MVA	0.142***	–	0.142***	Supported
H5	INC → ESG	0.233***	–	0.233***	Supported
H6	INC → MVA → ESG	0.142***	0.113***	0.346***	Supported
H7	POF → MVA	–0.611***	–	–0.611***	Supported (Negative)
H8	POF → ESG	–0.141***	–	–0.141***	Supported (Negative)
H9	POF → MVA → ESG	–0.611***	–0.487***	–0.628***	Supported (Negative)
H10	DEP → MVA	–0.032 ns	–	–0.032 ns	Not Supported
H11	DEP → ESG	0.098 ns	–	0.098 ns	Not Supported
H12	DEP → MVA → ESG	–0.032 ns	–0.026 ns	0.073 ns	Not Supported
H13	MVA → ESG	0.797***	–	0.797***	Supported
H14	CON × MVA → ESG	–0.507***	–	–0.507***	Supported (Negative)

*** p ≤ 0.001 (highly significant); ns = not statistically significant (p > 0.05)
Note: ESG denotes the latent construct used as a proxy for Sustainable Growth (SG) due to incomplete PRAT data.

driven structural estimation and interpretation framework. By integrating AI-driven preprocessing techniques—Isolation Forest for outlier detection, Recursive Feature Elimination (RFE) for predictor screening, and Principal Component Analysis (PCA) for multicollinearity mitigation—AI-SEM improves data quality and indicator conditioning prior to SEM estimation.

Unlike traditional SEM, which relies on manually selected indicators and linear assumptions, AI-SEM incorporates systematic, data-adaptive preprocessing to address noise, redundancy, and indicator instability in high-dimensional financial datasets. In addition, the Temporal Fusion Transformer (TFT) is applied after SEM estimation as an auxiliary analytical layer to explore nonlinear and time-dependent patterns among SEM-validated predictors, without altering hypothesis testing or latent variable construction in the PLS-SEM model.

As shown in Table 6, the top ten Feature Importance Scores from Recursive Feature Elimination (RFE) represent each raw indicator's marginal contribution to predicting Sustainable Growth (SG). Following outlier removal using the Isolation Forest, RFE was performed prior to PCA to screen financially and governance-relevant predictors, ranging from Dividend per Share (DPS, 0.94), Return on Equity (ROE, 0.92), and Market Value Added (MVA, 0.89) to Internal Audit Control (IAC, 0.66).

Accordingly, ROA and ROE are reported as raw indicators for predictive relevance, while their orthogonal principal components (PC1 and PC2) replace them in the SEM estimation (Table 4). PCA is applied only to this collinear subset prior to PLS-SEM, whereas RFE-identified variables are examined post-SEM using the Temporal Fusion Transformer for auxiliary temporal interpretation. TFT outputs are not used as SEM indicators or weights, ensuring a clear separation between predictive analytics and theory-driven structural inference.

4.4.1. Interpretability of TFT Attention Outputs

To enhance model transparency and practical relevance, the TFT component generates attention-based outputs that visualize how the influence of key financial and ESG indicators evolves over time. These outputs were visualized as a heatmap (Fig. 5), aligned with RFE-ranked features, allowing stakeholders to observe dynamic patterns across annual periods (2018–2022). These attention outputs are interpretive and predictive in nature and do not constitute indicators, weights, or inputs in the SEM estimation.

For instance, DPS—despite being non-significant in SEM—exhibited high temporal attention during 2019 and 2020, suggesting short-term predictive relevance. Conversely, ROE and MVA consistently showed strong and stable attention weights, reinforcing their central role in driving sustainable outcomes. ROA and DE also exhibited meaningful but more stable patterns across years.

Such interpretability is valuable for both corporate and policy stakeholders. CFOs can monitor periods when profitability and capital structure metrics become more impactful, while ESG officers can identify optimal timing for sustainability interventions. This layer of insight bridges AI-driven modeling with actionable decision-making, while preserving SEM as the sole source of structural interpretation

Table 6
Top 10 Feature Importance Scores from RFE (Pre-PCA, Raw Indicators).

Feature	Score	Category	Role in SEM
DPS	0.94	Performance	Dividend signal
ROE	0.92	Profitability	Equity return
MVA	0.89	Value	Key mediator
ROA	0.87	Efficiency	Asset use
DE	0.83	Leverage	Financial risk
EVA	0.77	Profit	Economic return
COE	0.72	Capital Cost	Risk-adjusted cost
DIY	0.7	Payout	Yield signal
PE	0.68	Valuation	Market sentiment
IAC	0.66	Governance	Audit strength

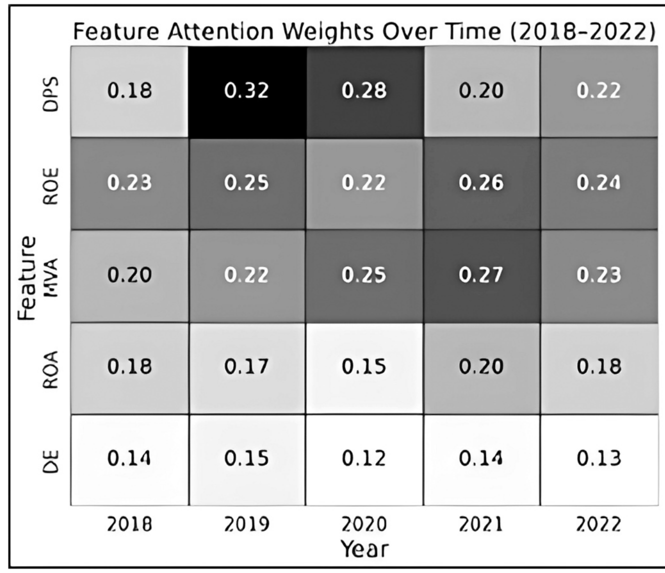

Fig. 5. Feature Attention Weights Over Time (2018–2022) derived from TFT-based post-SEM interpretability analysis. Note: *TFT Attention Heatmap Aligned with RFE top-ranked features DPS, ROE, MVA, ROA, DE.*

4.5. Model performance comparison

The AI-SEM outperformed traditional SEM across all evaluation metrics, as shown in Table 7. Predictive accuracy improved from 78.5 % to 92.3 %, model reliability rose from 80.2 % to 95.1 %, and explanatory power (R^2) increased from 0.65 to 0.82. Mean squared error (MSE) dropped significantly in both training (0.027 vs. 0.082) and validation (0.032 vs. 0.095), indicating enhanced generalizability. These improvements reflect the effectiveness of incorporating anomaly detection, feature selection, and dimensionality reduction into the SEM process.

Beyond summary metrics, hypothesis-level comparisons confirm the analytical advantage of AI-SEM. The AI-enhanced model yields stronger and clearer effects, with total effects increasing for key paths such as H6 (INC → MVA → ESG: 0.190–0.346) and H13 (MVA → ESG: 0.680–0.797). Mediation effects are also more clearly identified; for example, the negative impact in H9 weakens from −0.850 to −0.628, indicating a moderated but persistent trade-off between short-term profit focus and sustainability. In contrast, dividend policy remains insignificant across both models (H10–H12), confirming its limited structural role in emerging markets. Overall, the integration of AI-based preprocessing and temporal analysis enhances model precision, interpretability, and structural insight relative to traditional SEM.

4.6. The moderating role of business characteristics

The AI-SEM analysis revealed that Business Characteristics (CON)—particularly firm size and industry type—significantly moderate the relationship between Market Value Added (MVA) and Sustainable Growth (SG). These findings underscore the need for tailored sustainability strategies, as a "one size fits all" approach may be ineffective across diverse organizational contexts. Fig. 6 illustrates the moderating

Table 7
Model performance comparison: AI-SEM vs traditional SEM.

Evaluation criteria	Traditional SEM	AI-SEM	Improvement (%)
Predictive Accuracy (%)	78.5	92.3	+17.6
Model Reliability (%)	80.2	95.1	+18.6
Training Error (MSE)	0.082	0.027	↓ 67.1
Validation Error (MSE)	0.095	0.032	↓ 66.3
R-squared (R^2)	0.65	0.82	+26.2

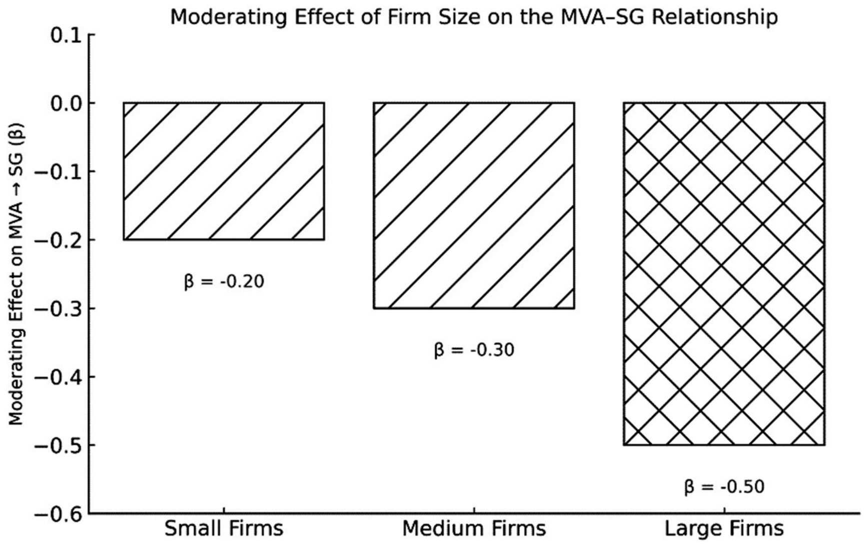

Fig. 6. Moderating effect of firm size on the MVA-SG relationship.

effect of firm size on the relationship between Market Value Added and Sustainable Growth.

Firm size, in particular, exerts a negative moderating effect on the MVA–SG relationship. As shown in the analysis, smaller firms exhibit a modest negative effect ($\beta \approx -0.20$), while medium-sized firms show a stronger effect ($\beta \approx -0.30$), and large firms the most pronounced ($\beta \approx -0.50$). This pattern suggests that organizational complexity and regulatory burdens in larger firms may hinder the translation of financial value into ESG outcomes. In contrast, smaller firms, with more agility and fewer constraints, tend to implement ESG initiatives more effectively.

The overall negative moderation ($\beta = -0.507$) reinforces the importance of considering firm specific characteristics when designing sustainability frameworks. These results highlight the structural and contextual barriers that larger firms may face in aligning market performance with long-term sustainable growth.

5. Discussion

The findings of this study provide a nuanced understanding of how ESG-related financial drivers shape firms' sustainability orientation, operationalised as a proxy for sustainable growth (SG) in the Thai capital market. Given the structural incompleteness of firm-level PRAT components, ESG composite scores are employed to capture sustainability orientation as a long-term value creation capability rather than a short-term growth outcome. In this context, ESG is not treated as a direct substitute for financial growth, but as an integrative indicator reflecting firms' capacity to sustain value creation through reinvestment discipline, governance quality, and strategic alignment. This interpretation is consistent with classical sustainable growth theory and emerging-market evidence, where ESG performance signals resilience and adaptability under institutional constraints (Higgins, 1977; Van Horne, 2001; Bagh et al., 2023; Naseer et al., 2024).

Within this framework, the empirical results confirm that operational performance and internal control are the most influential drivers of sustainability orientation. Firms with strong asset utilisation, earnings capacity, and robust governance mechanisms tend to generate higher market-recognised value and exhibit stronger ESG-linked sustainability outcomes. These findings reinforce prior evidence that sound financial fundamentals and effective internal control systems underpin investor confidence and long-term value creation, particularly in emerging markets characterised by regulatory standardisation and ownership concentration (Șerban et al., 2022; Zhou et al., 2022; Huang et al., 2025). Internal control, in particular, emerges as a critical governance conduit through which financial capability is translated into sustainable market value, aligning closely with the SDG 9 agenda.

However, not all financial indicators contribute uniformly to sustainable growth pathways. The consistently negative structural effect of economic profit (EVA) suggests that short-term efficiency-oriented metrics may conflict with sustainability-oriented strategies, especially in capital-intensive and cyclical industries. EVA may capture transient gains or deferred costs that do not translate into enduring stakeholder value, highlighting the limitations of efficiency-based measures when examined in isolation. This finding underscores the need to integrate profitability metrics with governance quality and ESG considerations, rather than prioritising short-term capital efficiency as a dominant strategic signal (Jankalová and Jankal, 2024).

The integration of artificial intelligence within the SEM framework is instrumental in revealing these differentiated effects without compromising theoretical coherence. In this study, SEM remains the primary vehicle for theory-driven structural interpretation and hypothesis testing, while AI components enhance data conditioning, feature screening, and post-estimation interpretability. PCA effectively mitigates multicollinearity among closely related performance indicators, and the Temporal Fusion Transformer captures time-dependent dynamics in ESG–financial relationships. This layered design enables complex, nonlinear patterns to be translated into interpretable managerial insights, while preserving SEM as the sole source of causal inference.

The divergence between the high predictive relevance of dividend per share (DPS) identified in the RFE stage and its lack of structural significance in SEM further illustrates the distinction between predictive salience and theory-consistent relationships. Dividend signals may attract short-term attention in specific periods, yet their effects dissipate once mediation through Market Value Added (MVA) and competing financial controls are accounted for. In emerging markets such as Thailand, dividend policy therefore functions as an episodic and time-contingent signal rather than a stable determinant of sustainable growth. This interpretation is consistent with dividend smoothing behaviour, where managers adjust payouts cautiously in response to earnings volatility and macroeconomic uncertainty, limiting the persistence of dividend policy as a structural driver of sustainability (Lintner, 1956; Jangphanish et al., 2025).

Market Value Added (MVA) emerges as the dominant mediating mechanism linking financial and governance drivers to sustainability orientation. Firms that successfully convert operational efficiency and internal control quality into market-recognised value gain stronger investor trust and more stable access to capital. The negative moderating effect of firm size indicates that this translation process is uneven: larger firms face higher coordination, governance, and compliance costs, whereas smaller firms exhibit greater agility in aligning financial performance with ESG outcomes. These results highlight the importance of context-specific sustainability strategies and reinforce the relevance of SDG 8 in emerging-market settings.

Finally, the findings reflect the role of open innovation dynamics in shaping ESG-linked sustainability outcomes. Firms increasingly rely on digital platforms, cross-sector collaboration, and knowledge-sharing ecosystems to co-create sustainability value. However, the ability to capture this value depends on governance capacity, business model design, and cost management within complex innovation networks. The results suggest that SME agility offers a comparative advantage in sustainability-oriented innovation systems, aligning with open innovation research that emphasises the interaction of organisational culture, engineering capability, and systemic complexity (Yun et al., 2020; Lee and Suh, 2022).

5.1. Practical and policy implications

At the policy level, the findings highlight clear opportunities to strengthen Thailand's financial governance and ESG regulatory framework. Key institutions, including the Securities and Exchange Commission of Thailand (SEC), the Stock Exchange of Thailand (SET), and the Bank of Thailand (BOT), can reduce short-termism and improve capital efficiency by embedding ESG performance indicators within financial reporting and evaluation systems. The observed disconnect between capital efficiency and sustainable growth underscores the need to align financial assessment with long-term sustainability outcomes, for which Market Value Added (MVA) serves as a practical proxy for policy monitoring and investor evaluation.

At the firm level, the results suggest that strengthening operating performance and internal control systems is essential for enhancing MVA, which emerges as the central mediator of sustainability outcomes. From an open-innovation economics perspective, ESG implementation entails coordination and governance costs that vary by firm size and industry; the negative moderation effect indicates that organisational complexity in larger firms can weaken the conversion of market value into sustainability outcomes. AI-driven time-attention tools, such as the Temporal Fusion Transformer (TFT), can support real-time managerial insight by identifying periods when profitability and governance factors exert the strongest influence. Balancing short-term efficiency measures (EVA) with long-term value metrics (MVA and ESG) is therefore critical to avoid value-dilutive short-termism.

Beyond firm-level strategies, SMEs often demonstrate greater agility in ESG adoption due to lower coordination costs and more flexible decision-making structures. Policymakers can leverage this advantage through green finance instruments, including green bonds, sustainability-linked loans (SLLs), and targeted incentives that promote innovation and inclusive growth aligned with SDG 8 and SDG 9. Finally, the development of standardised ESG assessment frameworks can improve data comparability and reporting consistency. At the regional level, alignment with ASEAN Taxonomy Version 4 strengthens cross-border sustainable finance classification and underscores the role of AI-driven analytics in supporting coordinated sustainability transitions and informed investment decisions across emerging markets.

6. Conclusions

This study develops and validates an AI-enhanced Structural Equation Modeling (AI-SEM) framework to examine ESG-linked financial determinants of sustainable growth among Thai listed firms. By integrating AI-assisted preprocessing and post-estimation interpretability with theory-driven SEM, the framework strengthens structural analysis under conditions of multicollinearity, firm heterogeneity, and temporal volatility.

The results show that financial performance and internal control are the most influential drivers of sustainable growth, exerting both direct effects and indirect effects through Market Value Added (MVA). In contrast, economic profit exhibits a consistently negative relationship, highlighting the limitations of short-term efficiency metrics in explaining sustainability-oriented outcomes. Dividend policy, although predictively salient, does not form a stable structural pathway, reflecting sectoral cyclicality and contextual dependence. The strong mediating role of MVA, together with moderation by firm size and industry, confirms that ESG–finance linkages are inherently context-specific, consistent with contingency theory.

Methodologically, the AI-SEM framework outperforms traditional SEM by improving predictive accuracy (92.3 %), enhancing explanatory power ($R^2 = 0.82$), and reducing estimation error. More importantly, it demonstrates how predictive analytics and AI-based interpretability can be integrated with theory-driven SEM without compromising causal clarity. The framework therefore offers a transparent and scalable approach for analysing sustainability-oriented financial governance in emerging markets.

7. Limitations and future research

This study has three main limitations. First, the focus on Thai listed firms may limit generalisability to other institutional contexts. Second, sustainable growth is proxied using ESG composite scores due to incomplete firm-level PRAT data, providing an indirect measure of growth dynamics. Third, formal measurement invariance across years was not tested because of limited annual subsample sizes, although year-by-year re-estimation produced consistent structural patterns.

Future research should incorporate full PRAT components, extend the framework to cross-country settings in ASEAN and other emerging economies, and integrate real-time ESG signals such as news sentiment and supply-chain data. Comparative studies using alternative structural and causal modeling approaches would further enhance methodological robustness and theoretical insight.

CRediT authorship contribution statement

Valida Phalalum: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kalyaporn Panmarerng:** Writing – review & editing, Validation, Supervision, Conceptualization.

Ethical statement

This research did not involve human participants or personal data. All information was collected from publicly accessible databases. In accordance with institutional and journal guidelines, ethical review and approval were not required.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used ChatGPT and Grammarly to improve language accuracy and manuscript structure. After using these tools, the authors reviewed and edited the content as necessary and take full responsibility for the integrity and accuracy of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data used in this study were obtained from publicly available sources, and are available from the corresponding author upon request.

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