CRUNCHING PROFITS AND CODE: THE AI-ENHANCED PATH TO SME INVESTABILITY

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ABSTRACT

Small and Medium Enterprises (SMEs) are the backbone country's economic development. However, a gap exists in the market for these firms to obtain investments due to a lack of adequate framework to assess the risk profile of these firms adding to the investor sentiment towards these SMEs'. Despite that, traditional methods such as financial indicators have often been used to evaluate firm performance and aiding in investors investment decisions. However, the adoption of AI model such as logistic regression further enhances the risk assessment process.

Keywords: *SME, AI, Firm Performance*

INTRODUCTION

Small and Medium Enterprises (SMEs) play a pivotal role in driving economic resilience, innovation, and employment across emerging markets. In Malaysia, SMEs represent over one-third of the national GDP and are integral to inclusive economic development (Yusoff et al., 2018). Despite their strategic importance, Annamalah et al. (2022) also believes that SMEs continue to face persistent challenges in attracting external investment, largely due to issues of scale, inconsistent financial disclosures, and the perceived opacity of their business models. These barriers contribute to a fundamental problem of information asymmetry, where investors are unable to fully gauge the viability or risk profile of potential investee firms.

Historically, firm-level financial indicators have served as a key mechanism for evaluating business performance and guiding investment decisions (Kotane & Kuzmina-Merlino, 2012). These metrics offer insights into a firm's operational efficiency, profitability, and long-term sustainability. However, conventional evaluation methods often relying on multiple ratios and linear regression frameworks (Crutzen & Peters, 2023). This may not adequately capture the underlying patterns or complexity of SME financial behavior. This limitation is particularly pronounced in under-researched contexts such as Malaysia, where firms operate within heterogeneous regulatory, cultural, and technological environments.

Recent advancements in machine learning (ML) and artificial intelligence (AI) have opened new avenues for developing data-driven, high-accuracy models capable of enhancing financial decision-making. These techniques, particularly supervised learning algorithms, have demonstrated strong predictive performance in classification tasks, including default risk assessment, credit scoring, and investment screening (Chang et al., 2024). Nevertheless, most existing AI-based models rely on expansive sets of variables, which, while improving accuracy, often and increase the cost of data collection which is especially detrimental when applied to SMEs (Tulli, 2020).

This study seeks to address this gap by developing a streamlined AI-driven model that classifies SMEs as investable or non-investable using a minimal set of financial performance indicators. By focusing on parsimony without compromising predictive validity, the research explores whether simplified financial models can deliver actionable insights for investors and financing institutions. The analysis employs a binary classification approach, using historical SME financial data within a logistic regression framework to assess the model's performance.

This paper contributes to the literature in three significant ways. First, it provides empirical evidence on the sufficiency of key financial indicators in determining firm investability within an emerging market setting. Second, it integrates AI-based methods into the SME evaluation process, offering a methodological bridge between traditional financial analysis and modern predictive analytics. Third, it addresses the practical need for lightweight, replicable investment assessment tools that can be adopted by financial intermediaries working with resource-constrained or early-stage enterprises.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on SME investment evaluation and the use of financial indicators in predictive modeling. Section 3 outlines the theoretical arguments while Section 4 highlights the research gap. Section 5 highlights methodology. Finally, Section 6 concludes the study with results and discussion.

LITERATURE REVIEW

The evaluation of SME investability has received increasing attention in both academic and practitioner circles, driven by the vital role of SMEs in economic development and the challenges they face in accessing funding. While traditional approaches emphasize multi-ratio assessments and subjective credit scoring, recent studies have highlighted the potential of machine learning to enhance accuracy and objectivity. This section presents the theoretical underpinnings and empirical findings related to SME investability, financial performance indicators, and AI-enhanced evaluation models. It concludes by identifying gaps that motivate the current research.

Theoretical Arguments

Profitability is often viewed as a fundamental measure of business performance, but its influence on a firm's investability particularly among small and medium enterprises (SMEs) warrants deeper theoretical examination. From the Resource-Based View, profitability reflects a firm's capacity to utilize internal strengths for sustained advantage (Mailani et al., 2024). Drawing upon the Resource-Based View (RBV), profitability can be seen as the financial reflection of a firm's ability to leverage internal competencies and scarce resources to achieve sustained advantage. Concurrently, Stakeholder Theory suggests that profitable firms are more likely to meet the expectations of diverse interest groups, such as investors, creditors, and regulators, enhancing their legitimacy and perceived stability. Stakeholder Theory adds that profitable firms better satisfy the expectations of stakeholders, boosting legitimacy and perceived stability (Mahajan et al., 2023). Finally, from the lens of Pecking Order Theory, firms with strong internal profitability are better positioned to finance operations without depending heavily on external debt or equity, sending strong signals of financial independence and lower investment risk. The Pecking Order Theory implies that profitable firms rely less on external financing, signaling financial independence (Yıldırım & Çelik, 2020).Together, these perspectives frame profitability not merely as an accounting outcome, but as a dynamic signal of investability, especially within capital-constrained SME ecosystems."

Profitability Ratios and SME Investability

Profitability has traditionally served as a central dimension of firm performance and a key signal to potential investors, particularly in the SME context where financial transparency may be limited. Among the many financial ratios employed, Return on Equity (ROE) and Return on Assets (ROA) have emerged as prominent indicators of operational efficiency and shareholder value creation. These measures are not only widely accessible but also directly linked to a firm's ability to generate earnings from internal resources an important attribute in early-stage or cash-constrained enterprises.

Empirical studies by Arbelo et al. (2020) suggest that firms with strong profitability metrics are more likely to be deemed investable due to efficient resource utilization and earnings generation.. However, Theiri et al. (2023) also suggests that high profits without reinvestment deter long-term interest. This indicates that the predictive utility of ROE and ROA varies by context and requires analytical support.

However, profitability is not a universally reliable predictor. Some studies suggest a non-linear or even negative association, particularly in different models and industries. For example Moussu and Petit-Romec (2018) observed that exceptionally high ROE values may stem from disproportionately high risk taken especially inn the banking industry thereby misleading investors. Thus, while ROE and ROA are valuable indicators, their predictive power for investability is neither absolute nor uniform. Their influence may depend on how the data is interpreted, processed, or enhanced by analytical tools such as machine learning.

AI Model as a Moderator

Recent developments in artificial intelligence (AI) have introduced new possibilities for improving the predictive accuracy and interpretability of financial models. AI-based classification tools, including logistic regression models embedded within intelligent platforms such as Orange, allow for the automatic learning of complex patterns in financial data. In this context, AI acts not only as a predictive engine but also as a moderating mechanism which is enhancing or reshaping the relationship between profitability ratios and SME investability.

Several studies support the positive moderating role of AI models. By automating feature weighting, AI-based models could detect nuanced interactions between financial indicators and correct for outliers or noise, thereby amplifying the predictive contribution of profitability ratios AI not only predicts outcomes but moderates the link between financial ratios including profitability and investability (Ali, 2025). Studies show that AI-enhanced logistic regression increases the predictive impact of ROE and ROA, by refining decision thresholds and reducing noise (Yaiprasert & Hidayanto, 2023).

In the current study, the logistic regression model powered by Orange Data Mining is posited to moderate the relationship between ROE, ROA and SME investability by optimizing the mapping of profitability thresholds to binary classification outcomes. Its role is not merely computational, but analytical that potentially strengthens the association between financial performance and investment viability.

Research Gap

While numerous studies have integrated financial ratios into predictive models for creditworthiness and firm failure, few have exclusively focused on profitability ratios for predicting investability especially in the context of Malaysian SMEs. Moreover, the majority of AI-based applications rely on large sets of financial variables, making them complex, resource-intensive, and difficult to apply in real-time scenarios for under-resourced financial institutions. There is a notable absence of models that are both parsimonious and empirically robust, using profitability indicators alone to predict investability through an AI-powered framework.

METHODOLOGY

This study employs a structured approach to ensure the reliability and validity of results while addressing the complexities associated with integrating AI into financial decision-making. This chapter presents the methods used to examine the relationships between risk assessment, investment performance, and moderating factor such as artificial intelligence.

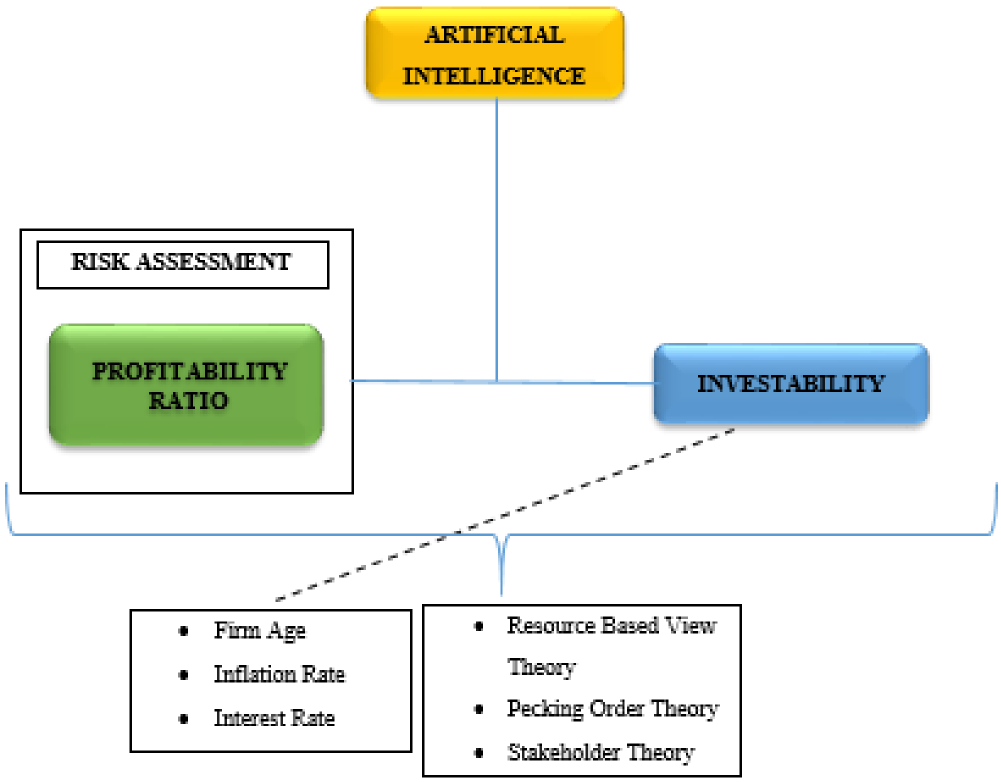

Figure 1: Conceptual & Theoretical Framework

The conceptual framework provides a structured foundation for examining the relationships between the study variables, offering a clear representation of how financial ratios as independent variable influence investment performance, which is the dependent variable. Central to this framework is the moderating role of AI adoption, which acts as an enabler that amplifies the impact of the independent variables on the dependent variable.

Data

This study uses secondary data to examine the effects of AI-driven risk assessment on the investability of SMEs in Malaysia. The population for the study consists of all SMEs in Malaysia, across all industries. Secondary data will be sourced from publicly available databases, reports, and records, such as SME Corp Malaysia, the Department of Statistics Malaysia (DOSM), Orbis and industry-specific financial datasets. These sources provide reliable data on financial ratios.

To ensure a representative sample, stratified random sampling is employed. The SME population is divided into strata based on industry type (e.g., manufacturing, retail, services) and geographic location (e.g., urban vs. rural SMEs). Proportional sampling is then conducted within each stratum to achieve fair representation.

The sample size determination follows Krejcie and Morgan’s (1970) formula, which ensures statistical adequacy. Based on this approach, approximately 250 SMEs are selected over the last 9 years from 2015 to 2023 for analysis, ensuring sufficient statistical power to generalize findings. By focusing on secondary data, this approach minimizes data collection bias and allows the study to leverage existing, validated datasets for comprehensive analysis.

Prior to data analysis, a total of 3000 dummy data is constructed and collected based on the benchmarks as stated below. These dummy data are constructed to build an AI risk assessment model using Orange Data Mining and fed into in to train the Logistic Regression model. A total of 3000 dummy data is required to ensure the model is benchmark-compliant.

Specification of Model

The full model for the study aims to quantify the relationship between profitability ratio, liquidity ratio, efficiency ratio and leverage ratio and investability, with AI acting as a moderator. Investability, as the dependent variable, is measured through key financial metrics, such as return on assets (ROA), return on equity (ROE) which are the independent variables in the model. These variables are considered the primary drivers of investability. The moderating role of AI is captured by interaction terms, where AI moderates the relationship between the independent variables and investability. AI enhances financial decision-making by providing predictive analytics, improving operational efficiencies through automation, and offering more accurate assessments of creditworthiness, thus potentially improving investment outcomes. The model incorporates several controlled variables such as firm age, interest rate and inflation rate to control for external factors that may influence investability.

The model is mathematically expressed as:

$$\boldsymbol{INVPER_{i,t}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\ \boldsymbol{PROFRTI_{i,t}} + \boldsymbol{\beta_2 AGE_{i,t}} + \boldsymbol{\beta_3 INT_{i,t}} + \boldsymbol{\beta_4 INF_{i,t}} + \boldsymbol{\varepsilon_{i,t}}$$

Where:
INVPERF = Investability
PROF = Profitability Ratio
AGE = Firm Size
INT= Interest Rate
INF= Inflation Rate
β0 = Constant
β1, β2, β3, β4, β5, β6, β7= Parameters to be estimated
t = Time dimension of the data
ε = Error or disturbance term

This full model provides a comprehensive framework for assessing how AI-driven risk assessment influences SME investability, while accounting for important contextual variables that could affect the results. By using secondary data, such as financial reports and industry databases, the model allows for empirical testing and analysis of AI’s role in optimizing investment decisions for SMEs.

Measures

Risk Assessment as Independent Variable

Risk assessment in investment contexts often hinges on a firm’s ability to generate consistent returns while maintaining financial stability. Within this framework, Return on Equity (ROE) and Return on Assets (ROA) emerge as two of the most informative profitability indicators.

$$RETURN\ ON\ ASSETS = \frac{NET\ PROFIT}{TOTAL\ ASSETS}\ X\ 100$$

$$RETURN\ ON\ EQUITY = \frac{NET\ PROFIT}{TOTAL\ SHAREHOLDER'S\ EQUITY}\ X\ 100$$

Investability as Dependent Variable

Investability, as the dependent variable in this study, represents a firm's perceived attractiveness to investors based on financial viability, operational stability, and growth potential.In this study, Investability is employed as the dependent variable, representing the target outcome that the artificial intelligence (AI) model is designed to predict. It is operationalised as a binary variable, where:

- 1 indicates that a small and medium-sized enterprise (SME) is investable, and
- 0 indicates that the SME is not investable.

The classification is based on the financial health and performance indicators of the firms under study. The investability status is determined either through expert labelling or pre-established thresholds derived from investment viability criteria in existing literature or professional practice.

The study utilises a machine learning-based AI model to predict investability, which the logistics regression replacing conventional econometric methods with a data-driven predictive framework. The AI model is trained using historical financial data from SMEs, enabling it to learn complex and potentially non-linear relationships between various financial indicators and the corresponding investability outcome.

AI Model as Moderator

This study introduces Artificial Intelligence (AI) as a moderating variable to explore its influence on the relationship between profitability and investability. As firms increasingly incorporate AI-driven tools into financial evaluation and decision-making processes, the role of AI in shaping investment outcomes becomes increasingly relevant. By leveraging machine learning algorithms trained on historical financial data, AI enhances the ability to identify patterns, assess risk, and forecast firm performance with greater precision. In this study, AI moderation is modelled to assess whether the presence of AI-based financial evaluation systems alters the strength or direction of the relationship between profitability indicators specifically ROE and ROA and a firm's investability. This approach allows for the integration of modern computational techniques into traditional financial assessment frameworks, offering new insights into how technological adoption may influence investment decisions in practice.

Control Variables

Investment decisions are rarely made in a vacuum. Beyond firm-level profitability, a range of underlying contextual factors often exerts quiet yet consequential influence on whether a firm is deemed investable. To address this, the present study integrates three control variables which are firm age, inflation rate, and interest rate into the model. Firm age is used to reflect organizational maturity, under the premise that older firms may possess more stable operational histories and investor familiarity. Inflation rate is included to account for purchasing power fluctuations and macroeconomic uncertainty, both of which may affect perceived investment risk. Likewise, interest rate fluctuations shape the cost of capital and broader investment sentiment. Controlling for these variables enables the analysis to more accurately isolate the relationship between profitability and investability, while accounting for structural and economic noise that may otherwise confound interpretation.

RESULTS

Descriptive Statistics

Table 1: Summary Statistics

Variables	Mean	Std. Dev.	Min	Median	Max
Investability	0.5002	0.5001	0.0000	1.0000	1.0000
AI_Model	0.0763	0.2655	0.0000	0.0000	1.0000
ROE	12.7937	27.7355	-446.054	10.7980	403.717
ROA	5.8549	8.5199	-50.085	4.5540	95.081
Firm Age	28.7751	11.9640	1.0000	29.0000	86.0000
Inflation Rate	1.8689	1.4385	-1.1387	2.1044	3.8712
Interest Rate	2.6313	3.0792	-2.3453	3.3070	7.3268

Table 1 presents the descriptive statistics of all variables used in the study, covering both firm-level and macroeconomic indicators. The dependent variable, Investability, is binary in nature, with a mean of 0.5002, indicating a relatively balanced distribution between investable and non-investable firms across the panel. The moderating variable, AI_Model, also binary, shows limited adoption with a low mean of 0.0763, suggesting that only a small proportion of firms in the sample have implemented AI in their risk assessment or financial processes.

For the independent variables, profitability metrics ROE and ROA exhibit high variability, as evidenced by standard deviations of 27.74 and 8.52, respectively. Extreme values (e.g., a minimum ROE of -446.05 and maximum of 403.72) reflect the diverse performance outcomes of firms in the sample, likely capturing distressed and high-growth entities alike. Control variables such as Firm Age show a reasonably normal spread (mean = 28.78), while Inflation Rate and Interest Rate capture Malaysia's fluctuating macroeconomic environment over the study period. Their distributions suggest some negative outliers but are centred around economically plausible ranges. This descriptive overview validates the inclusion of all selected variables and highlights the empirical richness of the dataset, forming a strong foundation for subsequent panel regression analyses.

Table 2: Cross Tabulation

Group	Not Investable (0)	Investable (1)	Total
Low ROA + AI-Adopted Firms	1.3%	98.8%	100.0%
Medium ROA + AI-Adopted Firms	92.5%	7.5%	100.0%
High ROA + AI-Adopted Firms	62.8%	37.3%	100.0%
Low ROE + AI-Adopted Firms	0.0%	100.0%	100.0%

Medium ROE + AI-Adopted Firms	100.0%	0.0%	100.0%
High ROE + AI-Adopted Firms	57.4%	42.6%	100.0%

Note:
ROA and ROE were split into high and low categories based on their respective median values. Firms with values above the median are categorized as high ROA and high ROE, while those equal to or below the median are categorized as low ROA and low ROE. A similar thresholding method was applied to distinguish between low and high spillover groups, where applicable. This binary segmentation facilitates interaction analysis between firm profitability and AI-generated investability outcomes.

The interaction between profitability and the AI-driven risk assessment model presents a profound disruption to traditional financial inference. Conventional frameworks assume that firms with stronger profitability metrics such as high ROA or ROE are inherently more investable.

Contrary to traditional financial reasoning, which assumes that firms with higher profitability ratios such as ROA and ROE are more likely to attract investment, the AI-driven investability assessment reveals a profound inversion of this assumption. The model classifies 98.75% of firms in the lowest ROA group and 100% of firms in the lowest ROE group as investable. In contrast, medium-profit firms are overwhelmingly flagged as not investable, and even high-profit firms receive significantly lower investability predictions, only 37.25% for high ROA and 42.59% for high ROE.

This counterintuitive pattern suggests that the AI model does not rely solely on profitability as a primary investment signal. Instead, it may capture underlying factors such as growth potential, reinvestment strategy, market agility, or strategic innovation, which often characterize firms with temporarily suppressed profits. The model’s tendency to favor low-profit firms could reflect an advanced understanding of risk-return asymmetry, where low current profitability may coexist with high future value potential particularly in asset-light, tech-driven, or fast-scaling enterprises.

Ultimately, this demonstrates that the AI model functions not as a mirror of traditional heuristics but as a disruptive evaluator of firm potential. By consistently classifying low-ROA and low-ROE firms as investable, the model introduces a new paradigm of financial signal interpretation that emphasizes contextual, forward-looking, and possibly non-financial indicators of value. For investors and analysts, this underscores the power of AI to uncover investability profiles that conventional ratio analysis might overlook or misclassify.

Table 3: Correlation matrix

Variables	ROE	ROA	Firm Age	INF	INT
ROE	1.0000				
ROA	0.5978*	1.0000			
Firm Age	-0.0999*	-0.0562*	1.0000		
INF	0.0640*	0.0631*	-0.0000	1.0000	
INT	-0.0206	-0.0270	0.0000	-0.5450*	1.0000

The correlation matrix offers valuable insights into the bivariate relationships among the study's key variables. Notably, ROE and ROA exhibit a moderately strong positive correlation ($r = 0.5978$, $p < 0.01$), indicating that firms with higher returns on assets also tend to report higher returns on equity. This relationship is consistent with financial theory, as both metrics reflect profitability, albeit from different accounting perspectives.

The remaining correlations are weak and statistically significant, suggesting nuanced relationships. For example, Firm Age is negatively correlated with both ROE ($r = -0.0999$, $p < 0.01$) and ROA ($r = -0.0562$, $p < 0.01$), implying that older firms in the sample tend to report slightly lower profitability. This may reflect lifecycle effects or diminishing returns to scale over time.

Interestingly, Inflation Rate is weakly positively correlated with ROE ($r = 0.0640$, $p < 0.01$) and ROA ($r = 0.0631$, $p < 0.01$), suggesting that mild inflationary conditions might be associated with improved profitability, potentially due to pricing power or revenue adjustments. However, Interest Rate is negatively correlated with Inflation ($r = -0.5450$, $p < 0.01$), a theoretically consistent outcome as central banks often raise interest rates in response to rising inflation.

Importantly, no pairwise correlations exceed the critical threshold of $|0.8|$, confirming the absence of multicollinearity among the explanatory variables. This ensures the robustness of subsequent regression estimations, as independent variable relationships are not overly redundant.

Regression Results

The regression analysis from Table 4 investigates the impact of firm-specific financial indicators on investability, accounting for potential heteroskedasticity and within-cluster correlation through White heteroskedastic-robust and double-clustered standard errors. The models are evaluated across various clustering strategies to ensure robustness.

Return on Assets (ROA) and Return on Equity (ROE):

Across all specifications, both ROA and ROE are positively and significantly associated with firm investability. Specifically, the coefficients for ROA range from 0.027 to 0.028, and for ROE from 0.0037 to 0.0039, consistently across White and double-clustered estimates. This suggests that firms with better profitability performance whether measured through asset efficiency or shareholder returns are more likely to be deemed investable.

Firm Age

Firm Age exhibits a negative and statistically significant relationship with investability (coefficients ranging from −0.0059 to −0.0060). This indicates that younger firms are more likely to be considered investable, possibly due to higher growth potential, innovation, or agility in adapting to market needs, as opposed to older firms which may face legacy constraints.

Inflation Rate and Interest Rate

Inflation and interest rates are found to be statistically insignificant in most models, and in the fixed effects model they were dropped due to collinearity with the year fixed effects. This suggests that macroeconomic volatility may already be captured within year-level controls or does not exhibit strong firm-level heterogeneity in this context.

Model Fit and Robustness

The models demonstrate strong explanatory power, with R-squared values around 0.42–0.43, indicating that the selected variables explain approximately 42% to 43% of the variation in investability. The F-statistics are highly significant, confirming overall model validity. Consistency in coefficient magnitude and direction across White and double-clustered standard errors confirms robustness against heteroscedasticity and within-firm or within-year correlations.

Robustness Check: Endogeneity Of Profitability Measures

Given the potential for endogeneity in the relationship between profitability and investability particularly due to measurement error, or simultaneity, this study implements robustness checks using both instrumental variables two-stage least squares (2SLS) and system GMM estimators. The AI_Model variable is used as an instrument for profitability proxies (ROA and ROE), based on its role as a technological driver that influences firm performance without being directly affected by SME investability.

The 2SLS results, shown in Table 5, indicate that the coefficient for ROA remains statistically insignificant under the endogeneity correction ($p = 0.289$), and the Durbin-Wu-Hausman test fails to reject the null hypothesis of exogeneity ($p = 0.218$). This suggests that OLS estimates of ROA can be considered consistent. Likewise, ROE remains statistically insignificant even after endogeneity correction ($p = 0.138$), reinforcing its weak influence in earlier models.

To further validate these findings, a dynamic panel data model using system GMM is employed. The results indicate that ROA remains positive and statistically significant (coefficient = 0.023, $p < 0.001$), while ROE continues to show no significant effect ($p = 0.120$). The Hansen and Sargan tests confirm the validity of the instruments (Hansen $p = 0.127$; Sargan $p = 0.483$), and the Arellano-Bond test for AR(2) yields a p-value greater than 0.05, confirming no second-order autocorrelation.

Taken together, these results suggest that ROA is a robust predictor of investability and is not significantly influenced by endogeneity, while ROE remains a less consistent indicator, even after accounting for potential endogeneity biases.

Robustness Check: Alternative Specification af AI Model As Instrument

To test the robustness of our instrumental variable approach, we assess the model's sensitivity to the use of AI_Model as an instrument for ROE instead of ROA. This approach allows us to verify whether the findings hold under a different specification of instrument assignment.

Table 5 also presents results from both the 2SLS and system GMM estimations using this alternate setup. When AI_Model is used to instrument for ROE, the results remain largely consistent: ROE continues to be statistically insignificant in the 2SLS model ($p = 0.138$), and also in the GMM specification ($p = 0.120$). Moreover, diagnostic statistics from the GMM estimation including the Hansen overidentification test ($p = 0.171$) and the Arellano-Bond AR(2) test ($p = 0.076$) support the validity of the instrument set and model specification.

These robustness tests affirm that the main findings are not sensitive to changes in the instrumented profitability variable, and further strengthen the argument that ROA is a more reliable profitability measure than ROE in explaining SME investability. The AI_Model instrument remains valid across specifications, but only ROA yields consistent and statistically significant results under both exogenous and endogenous frameworks.

Table 4: Regression Result

VARIABLE	ROA		ROE	
	White	Double -Clustered	White	Double-Clustered
ROA	0.02745***	0.02746***	—	—
	(0.00253)	(0.00342)		
ROE	—	—	0.00385***	0.00378***
			(0.00081)	(0.00088)
FIRM_AGE	-0.00591***	-0.00593***	-0.00591***	-0.00593***
	(0.00067)	(0.00093)	(0.00067)	(0.00093)
INFLATION_RATE	0.01099	omitted	0.01099	omitted
	(0.00643)		(0.00643)	
INTEREST_RATE	-0.00297	omitted	-0.00297	omitted
	(0.00313)		(0.00313)	
CONSTANT	0.44756***	0.46159***	0.44756***	0.46159***
	(0.03073)	(0.03501)	(0.03073)	(0.03501)
F-STATISTIC	119.47	85.18	119.47	85.18
R-SQUARED	0.4226	0.4302	0.4226	0.4302
ADJ R-SQUARED	—	0.4274	—	0.4274
OBSERVATIONS	2,241	2,241	2,241	2,241

Table 5: Endogenity Test Results

VARIABLE	ROA		ROE	
	GMM	CIV (2SLS)	GMM	CIV (2SLS)
COEFFICIENT	0.0231***	0.0126	0.0028	0.0177
STD. ERROR	(0.0050)	(0.0119)	(0.0018)	(0.0119)
Z / T-STATISTIC	z = 4.65	z = 1.06	z = 1.55	z = 1.48
P-VALUE	p = 0.000	p = 0.289	p = 0.120	p = 0.138
ENDOGENEITY TEST	χ^2 = 1.52 (p = 0.218)	χ^2 = 1.52 (p = 0.218)	χ^2 = 1.52 (p = 0.218)	χ^2 = 1.52 (p = 0.218)
GMM AR(2) TEST	p = 0.086	—	p = 0.076	—
SARGAN P-VALUE	0.483	—	0.386	—
HANSEN P-VALUE	0.127	—	0.171	—

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