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Artificial Intelligence Applications in Stock Investment: The Impact of Machine Learning and Big Data on Investment Performance

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ABSTRACT: The present study investigated the impact of Artificial Intelligence (AI) applications, in terms of the Machine Learning Integration (MLI) and the Big Data Analytics Utilization (BDAU), on stock investment performance in Small and Medium Enterprises (SMEs). The study adopts a broad perspective, focusing not only on algorithmic correctness but also on Dynamic Capability Theory (Teece, 2007) and the Technology-Organization-Environment (TOE) model (Tornatzky and Fleischer, 1990). In this view, the performance of investment is seen as a multidimensional process which is determined not only by technological tools, but also by the organizational capability and human preparedness.

A purposive and stratified survey of 612 SME managers and investors in Vietnam, Malaysia, and Indonesia was undertaken to determine and collect data, and 385 valid responses were selected to proceed with the analysis. The regression outcomes revealed that Machine Learning Integration corresponded to the most powerful contributor of the enhanced investment performance (β = 0.736, $p < 0.05$), with Big Data Analytics Utilization also performing significantly (β = 0.714, $p < 0.05$). Moreover, Investor Technological Readiness (ITR) was identified to mediate the association between BDAU and investment performance (β = 0.520, $p < 0.05$), which highlights the significance of human capability and belief in transforming data-driven information to profitable investment policies.

The results are theoretical as they reveal that digital technologies do not necessarily lead to success; their advantages are determined by the extent of their integration in the organizational processes and the investor's willingness to handle the implementation. Pragmatically, the research proposes that SMEs ought to integrate the adoption of technology with training and capacity-building interventions, whereas policymakers ought to establish enabling ecosystems with low-cost digital infrastructure and human capital development.

However, the study's weaknesses, including cross-sectional and self-reported data, as well as regional boundaries, limit the extrapolation of the findings. Future studies need to be longitudinal and cross-country to include the institutional and dynamic differences.

KEYWORDS: Artificial Intelligence, Machine Learning, Big Data Analytics, Investor technological Readiness, SME Investment performance, Dynamic Capability Theory, TOE Framework.

1. INTRODUCTION

Questions must be raised about the actual effectiveness of Artificial Intelligence (AI) as stock investment methods become increasingly integrated, especially among Small and Medium Enterprises (SMEs), which often have limited resources and technological infrastructure. Although the increased accuracy of investments and the reduction of behavioral biases are singled out as the most common virtues of Machine Learning (ML) and Big Data Analytics (BDA), SMEs often face a range of barriers to implementation, such as limited technical knowledge and a low level of data quality in some cases (Tawil et al., 2024). As the research stipulates that AI-powered tools prove superior to the traditional models in terms of stock volatility and returns forecasts (Ramos-P319), their success in the SME environment still relies largely on how well the organization will be able to adapt such technologies and how ready the digital leads themselves will be. Also, many ML models are highly complex and inscrutable because they are labeled as the black-box, which will affect the level of trust among investors and the decision-making procedural step (Nakashima et al., 2022). Such issues are more crucial even in SMEs, where financial decisions are generally more susceptible to constraints on resources. The current research, thus, will seek to understand how the adoption of AI does indeed improve the performance of investment within SMEs, or as a matter of over-hyped expectations of new technologies.

Pilot studies in the past have delved into great detail in discussing the potential of Artificial Intelligence (AI), particularly Machine Learning and Big Data Analytics in enhancing stock market predictions and portfolio management (Leung et al., 2023). Although these technologies have proven to be effective when applied by large corporations, most of the available literature fails to capture the applicability and viability of the technologies when implemented in the Small and Medium Enterprises (SMEs) environment, in which financial resources and an ineffective technological base are usually challenges (Akter et al., 2021). Moreover, research on the topic mostly focuses on the accuracy of the algorithm, rather than its practical use, completely ignoring the context, i.e., the willingness and ability of investors to use it, as well as the fact that an organization is not ready and will not be able to adopt AI (Kgakatsi et al., 2024). Such gaps shed light on the necessity of more multidimensional research that would not be limited to technical performance only and would be oriented toward how AI can support strategic needs and operative realities of SMEs. This paper is a reaction to this; as far as the moderating effect of investor technological readiness on the influence of AI-enabled investment tools on investment outcomes in SMEs is concerned, the perspective is more contextual and less represented in the available body of current studies.

In this research, the authors seek to explore three central investigative questions:

1. To what extent does the integration of Machine Learning impact investment performance in SMEs?
2. How does the utilization of Big Data Analytics influence the investment performance of SMEs?
3. How does investor technological readiness moderate the relationship between Big Data Analytics utilization and investment performance in SMEs?

The present study aims at researching the applicability of AI technologies, namely Machine Learning and Big Data, to enhance investment results in the particular situation in SMEs, where the availability and technical capability are largely lacking. Contrary to the past research, which leans towards good or bad performance of the AI in big financial firms, this research will examine a little bit more the effectiveness of these tools in small businesses that may have inferior data systems. Important about this study is the fact that investor technological readiness is included as a moderating variable or introducing the human-organizational dimension, not generally included in most of the technology-oriented research. This research will be aimed at two things in equal measure: to quantify the magnitude of the effect that AI tools may have on the performance of investments in SMEs, and to determine whether this effect is related in any way to the level of preparation and willingness to employ the technology on the part of investors. Through this, the study will not only fill a void in the existing body of research on AI-finance but also provide informative solutions to SMEs that want to make better and more strategic decisions regarding their investments.

2. LITERATURE REVIEW

2.1 Investment Performance at SMEs

The performance of stock investments within the SMEs is the extent to which the businesses make a profit on their way through their stock investments of financial and capital assets regarding profitability, risk-adjusted performance, and increase (Serrasqueiro et al., 2023). In the current digital economy, measurement has become more complex due to limited capital sources, increased competition, and the influence of digital transformation. Stock Investment decisions and their correctness are no longer based only on the content of the usual financial indicators; a greater role is increasingly being played by the successful application of technology and data-driven decision-making (Tawil et al., 2024).

Good stock investment returns are crucial in ensuring SMEs remain competitive and develop sustainably in the long term, this is crucial considering most SMEs do not have as much financial stability as the larger companies do. According to the latest research, SMEs operating with the help of digital analytics and machine learning are more likely to allocate their resources more efficiently and predict the returns more precisely (Li et al., 2024). For instance, those utilizing AI to forecast market flows have reported significant improvements in stock investment efficiency compared to traditional methods (Ugbebor et al., 2024).

With these trends, it is easy to realize that the best way to develop more intelligent, technology-oriented stock investment strategies is to gain insight into the performance of the stock investment.

2.2 Anchoring Theoretical Framework

2.2.1 Technology-Organization-Environment (TOE) Framework

The Technology Organisation Environment (TOE) framework presented by Tornatzky and Fleischer (1990) provides a balanced approach to the analysis of the way small and medium-sized enterprises (SMEs) implement the use of new technology such as Machine Learning and Big Data Analytics. Based on this framework, the adoption of technology is not merely the quality of sophistication or the power of the tool, but also the internal capacity or the externality of a company that can redefine the success of the adoption of technology.

The technological context in this study is considered as the way the SMEs view the usefulness and complexity of the AI tools. Organizational context involves the presence of factors such as company structure, decision-making procedure, and the level of familiarity with digital technology among the investors or decision-makers. Environmental context entails market trends, competition, and governmental regulations (Baker, 2012).

Another aspect that makes TOE particularly convenient is that it can examine both the internal preparedness and external forces that determine the extent and possibility of a firm implementing AI. As a matter of fact, in practice, SMEs can find it easier to apply successfully to the application of AI in its investment strategies only after aligning all three domains to take place: seeing AI as advantageous and uncomplicated to implement (technology), possessing talented individuals who know how to deploy it (organization), and competing in an environment where sharper, evidence-based decisions are favored (environment) (Badghish & Soomro, 2024). Due to this, the TOE framework can serve as an effective means in exploring the process whereby the unique reality of SMEs influences the connection between the capabilities of AI and the rate at which it enhances its returns in terms of investment performance.

The TOE framework postulates that the decision to adopt new technology made by a business is influenced by three strongly interrelated factors, namely the perception of the benefit and the challenge of the available technology, the available resources and the organizational structure of the organization, and the degree of pressure it is exposed to by the external markets and regulations. This view softens things by acknowledging that firms do not make choices in nothingness: businesses are affected by a broader system, otherwise constituted by technological trends, internal constraints, and external pressures such as competition and changes in policies. It is due to this reason that the process of embracing new technology is not only simple or reasoned. Rather, it is an intelligent choice that companies take based on how they view a tripartite situation that is continuing to evolve on an ongoing basis (Tornatzky & Fleischer, 1990; Baker, 2012).

2.2.2 Dynamic Capability Theory (DCT)

Dynamic Capability Theory (DCT) is a theory that was developed by Teece, Pisano, and Shuen (1997), which places its emphasis on the capacity of a firm to adjust by combining, creating, and reconstituting both internal and external resources so that it may remain competitive in dynamic environments. This theory is particularly applicable in the case of AI used by SMEs in investment strategies because it explains how technologies such as Machine Learning or Big Data can be converted to actual performance improvements.

In contrast to fixed skills, dynamic capabilities have flexibility and change due to market reactions, emerging technologies, as well as firm-specific learning (Teece, 2014). In this regard, Cai & Chen (2024) again illustrate a firm in real-life scenarios: it takes the machine learning algorithm to time-sensitive portfolio decisions, and the use of Big Data within the analysis of investor sentiment to take advantage of when there is an opportunity and change accordingly. The Investor’s technological readiness is also in line with DCT in that it puts emphasis on the ability of the firm to transform its knowledge absorption capacity into practical action involving the creation of value through investments. The stock market is very dynamic and unpredictable, and the SMEs that develop a high competency in such areas as data literacy, algorithm building, and predictive analysis become faster and more successful in such markets (Protogerou et al., 2012). On the whole, DCT provides a practical model to bridge the gap between the AI tools and strategic investment behavior, as the competency of firms and SMEs to remain flexible and competitive.

Dynamic Capability Theory implies that the long-term competitive advantage of the company does not correlate to its stable resource base, but to its capacity for consistent realignment and updating of its core capabilities in connection with shifts in technology and the business environment. It considers successful companies as the ones that can establish routines and use them to identify new opportunities, act on these opportunities, and reshape their current resource base to suit new situations. Instead of using the one-size-fits-all approach to strategy, this theory focuses on how well a business can develop and renew its capabilities as the key to long-term success in markets that are fast-moving and not uncertain, where innovation is continuous (Teece et al., 1997; Teece, 2014).

2.3. Impact of Machine Learning Integration on Investment Performance at SMEs

Machine Learning Integration (MLI) in small or medium-sized enterprises (SMEs) is defined as a respectful application of machine learning algorithms and techniques to improve business decision-making and forecasting, and recognizing patterns (Jordan & Mitchell, 2015). In the case of SMEs, it usually involves automating the knowledge extracted from data to make stock investment decisions, portfolio management, and risk evaluation. As reported by Wang & Aviles (2023), ML is also reshaping the economy of prediction by making it even cheaper to make accurate predictions, which enables businesses to be efficient. This incorporation includes technical infrastructure, algorithm insertion, training data, and business strategy linkage, a conglomeration that brings forth competitive advantage by intelligent automation (Shrestha et al., 2021).

Economically, in terms of labor and capital, the integration of ML can bring on capital intensification and increase their productivity. According to the endogenous growth theory of Romer (1990), the use of technology in business operations is very crucial to long-term growth, as it is particularly essential to SMEs with limited resources. Schumpeterian thinking views MLI as a discontinuous innovation that allows smaller companies to break down the traditional obstacles to innovation by providing the ability to achieve scalable analytics (Grashof & Kopka, 2022).

Nowadays, the utilization of Machine Learning Integration (MLI) in business use has been on the rise as companies seek to optimally use the increasing databases. Among SMEs, this change is more than just a technological upgrade; it is also strategic. The article by Wamba-Taguimdje et al. (2020) proposes that the ML-adopting SMEs are in a better position to anticipate the trends of the market, customize financial practices, and mitigate the risks of their stock investments. Nevertheless, not all SMEs can implement them quickly due to low digital literacy, small budgets, and poor IT infrastructure (Restrepo-Morales et al., 2024). In spite of these challenges, corporations in such a range of industries as fintech, e-commerce, and manufacturing are slowly incorporating ML technologies into stock investment planning, credit scoring, and dynamic price tools. Philosophically, the change indicates a utilitarian attitude that ML is applied to enhance general business performance, and a pragmatic approach that to adaptable and results-oriented knowledge systems (Starke et al., 2021). In such a manner, MLI is made to align with moral principles and very much practical thinking that confirms wise progressive approaches to decisions.

Machine Learning Integration (MLI) can be a big benefit in enhancing the performance of the SMEs involved in their investing endeavors when implemented efficiently. ML assists businesses in predictive analytics and helps businesses in predicting financial risks, making better decisions in portfolios, as well as identifying areas with high returns. A study by Kraus et al. (2019) reveals that the firms that apply predictive algorithms to data are more likely to have great ROI and capital utilization. As an example, SME stock trading platforms support real-time ML tools, which have made the prediction of the trend more accurate and minimized the possible losses by recognizing trends fast (Lv et al., 2019).

Dynamic capability theory supports the positive effect of MLI on the results of stock investment outcomes. This theory explicates that the success of a firm to adjust to emerging conditions is dependent on its capability to rearrange, renovate, and cultivate the internal and external aptitudes (Teece, 2007). According to this perspective, MLI provides evidence-based information to SMEs promptly, and it assists in decision-making in the event of uncertainty when stock investment decisions are made. Nonetheless, the degree to which this impact is strong has varied opinions among the researchers. On the one hand, there is an opinion that MLI has a direct and significant impact on the results of stock investment of SMEs. According to Duan et al. (2020), ML can make businesses change their strategies in real time, increase profits, and reduce risk. This school of thought is not founded on the technological determinism idea that technology is a force that drives business performance. Conversely, other studies claim that MLI benefits are determined by other aspects. According to the research by Wamba et al. (2021), MLIs alone are insufficient unless they are adequately prepared, which is best done through effective leadership as well as data systems and highly qualified personnel. This is in line with the resource-based view (Barney, 1991), according to which technology has to be accompanied by company resources and capabilities that would enable it to make a meaningful difference.

Meanwhile, MLI has a lot of potential, but in practice, it only works when the right conditions are provided. These are managerial support, modern digital systems, and a change-friendly culture. Once such conditions are satisfied, the companies are more capable of internalizing and utilizing technology, which can be converted into valuable financial returns (Zhai et al., 2018).

Drawing upon the combined theoretical foundations previously discussed, the initial hypothesis can be expressed as follows:

H1: Machine Learning Integration positively impacts Stock Investment Performance in SMEs

2.1 Impact of Big Data Analytics Utilization on Investment Performance at SMEs

Big Data Analytics Utilization (BDAU) is described as the implementation of advanced tools in organizations as a strategic and operationally oriented deployment that provides practical insights based on large and diverse datasets, allowing new processes and the ability to make superior decisions and forecasts (Wamba et al., 2017). With the small and medium-sized enterprises (SMEs), BDAU supports the collection, processing, and interpretation of structured and unstructured data to reveal the stock investment opportunities, maximization of resource utilization, and financial risk management (Akter et al., 2016).

Theoretically, BDAU is based on the resource-Based View (RBV), according to which the data and analytics capabilities are regarded as strategic means- and specifically the means that are rare, valuable, and inimitable (Barney, 1991). It also falls under the Dynamic Capability Theory (Teece, 2007), which focuses on a firm’s capacity to re-align and alter analytics resources in line with changing market conditions- a very important aspect when one starts with agile SMEs. Economically, an economic analysis of BDAU would be that BDAU would increase allocative efficiency because firms would make stock investment decisions using objective information, rather than gut feeling, as economic assumptions within the neoclassical approach to economics are that decisions are made on a rational basis. Philosophically, it is a sign of epistemological pragmatism, which is an ideology that posits that knowledge is verified by its application in practice and usefulness (Feenberg, 2002). In that sense, BDAU is between technological instrumentalism and rational judgment.

As digital technologies and more readily available data tools are on the rise, BDAU has turned out to be an essential ingredient of the competitive strategy of SMEs. Instead of being an exclusive prerogative of big organisations, BDAU now helps SMEs to determine financial risks, monitor dynamics within the market, and simulate the stock investment cases (Babalghaith & Aljarallah, 2024). This is of essence considering the low financial reserves of SMEs, wherein the informed decision takes the business either to greater heights or to extinction. According to Wang and Byrd (2017), the more companies engage in the use of BDA, the higher the strategic alignment and the better the results in stock investments. Connection is still uneven despite the potential of the BDAU. Though many SMEs have already improved because of the limited digital skills, a lack of infrastructure, as well as the perception of the costs of implementing it (Shujahat et al., 2019). Consequently, the rate of adoption varies demographically and across industries, with tech-savvy industries such as fintech and logistics being the first to implement it. Realistically, SMEs are starting to take BDA not only as a technical improvement, but also as a way of taking over the decision-making process; adopting a culture of data-informed judgment rather than instinctive management.

Based on the integrated theoretical frameworks outlined earlier, the second hypothesis is formulated as follows:

H2: The importance of the Utilization of Big Data Analytics positively affects Stock Investment Performance in SMEs.

2.2 The Moderating Role of Investor Technological Readiness

The concept of Investor Technological Readiness (ITR) is the level to which investors are psychologically and practically ready to implement and utilize emerging digital technologies, such as big data analytics, artificial intelligence tools, and algorithm platforms, in their stock investment activities (Parasuraman, 2000; Fan, 2021). It entails two different sides, namely the psychological side, which entails the level of trust that one has towards these digital tools, and the functional side, which entails the capabilities that these digital tools have with the individual. With a great deal of technological readiness by investors, investors can more easily grasp and utilize the knowledge of these technologies. This not only aids in enabling them to make their stock investment decisions more accurately but also minimizes uncertainty

It is based on the observations made by Parasuraman (2000), who came up with the Technology Readiness Index (TRI), which observes how individuals embrace technology. It is also corroborated by the Diffusion of Innovation Theory (Alhammadi et al., 2023), according to which an individual adopts a new technology depending on how they perceive the benefits of the same, along with their willingness to embrace new things. Economically, ITR belongs to the more general framework of behavioral finance, proposing the following idea: psychological biases and digital literacy levels also determine the behavior of investors and the efficiency of the market due to them (Barber & Odean, 2001). The environment in which SMEs operate, characterized by extreme adaptability and data-driven decision-making as the main factors in survival, places a significant emphasis on how willing investors are to employ the use of technology, which, in turn, determines the success of their stock investments. With more SMEs approaching Big Data Analytics (BDA) to identify possible ventures to invest in, and utilizing capital in a better manner, the involvement of investors in such digital analysis is getting more significant than ever. However, as Li et al. (2021) note, the effectiveness of BDA tools depends essentially on the ability of the users to make sense of the data provided and use it strategically. These are capabilities which again depend on the technological readiness that an investor has. In line with this finding, the recent research by Tawil et al. (2024) indicates that such investors as SME, who are not digitally skilled and not confident, find it far easier to obtain insights into data but fail to transform this data information into real stock investment decisions.

In a theoretical perspective, Investor Technological Readiness (ITR) represents an informal outlook on knowledge, i.e., that knowledge gains its significance only when it is put into practice with direct dealing with technology. It is also based on the notion of technological instrumentalism (Feenberg, 2002) that views technology as a set of tools whose usefulness ought to be determined by how it is utilized by humans. In this way, investors are not passive consumers of technology but rather, they are the creators of the consequences and value that are produced by the even more digital stock investment spaces.

Investor Technological Readiness (ITR) is highly important to define the level of effectiveness of turning Small and Medium Enterprises (SMEs) Big Data Analytics (BDA) into practical stock investment profits. Although BDA tools can be used as an effective method of predicting trends, evaluating risks, and predicting possible returns, these benefits will never result in any performance enhancement in case the investor feels insecure about using the tool in question and is unable to do so (Akter et al., 2016). High ITR investors tend to rely more on data-driven knowledge, correctly interpret sophisticated models, and respond faster to market stimuli, and such investors will have more successful stock investment results (Wamba et al., 2020). Cognitive Fit Theory (Vessey, 1991) supports the existence of this relationship by positing that a decision-making situation is enhanced when the format and complexity of the data are adjusted with the cognitive preferences and skills of the person who has to make the decision. In layman's terms, when an investor is acquainted with and comfortable using analytical tools, then sifting out unprocessed information into wisened stock investment decisions is much simpler and enhances returns.

Some scholars, however, do not all agree as to the strength of this moderating role. Others, such as Fosso Wamba et al. (2017), stress that the absence of investor readiness can result in the underutilization or even misuse of digital tools, which in turn is likely to cause confusion or a condition called decision paralysis. They find out in their studies that companies with high-tech maturity in their decision-makers have systematically outperformed other companies characterized by low readiness. This opinion is corroborative of the Capability-Based View of the firm (Teece, 2007), according to which human capabilities have to be combined with technology in order to realize value.

Conversely, other scholars, such as Wahab & Radmehr (2024), claim that the impact of ITR does not appear in all cases. They indicate that the advantages of technological readiness may be mitigated by such factors as the company culture or the fluctuations in the external market. As a case in point, in markets that are highly unpredictable, even those investors who are tech savvy might resort to instinct or a quick set of rules rather than choosing to only use data. Behavioral economics editors look at this debate as an extension of a greater tension in which, although we, as prepared stock investors, assume that an investor rationally bases their decisions on preset data, the human mind has difficulty-imposed limits, biases, and emotions. The latter can still distort judgment even when sophisticated tools are involved, and thus the moderating effect of ITR may not necessarily be as robust as theory would propose.

Drawing upon the combined theoretical foundations previously discussed, the third hypothesis can be expressed as follows:

H3: Technological readiness of investors moderatess the correlation between big data analytics use and stock investment performance in SMEs.

Anchored in well-established theoretical underpinnings, this study advances its scholarly contribution through the presentation of the following conceptual framework:

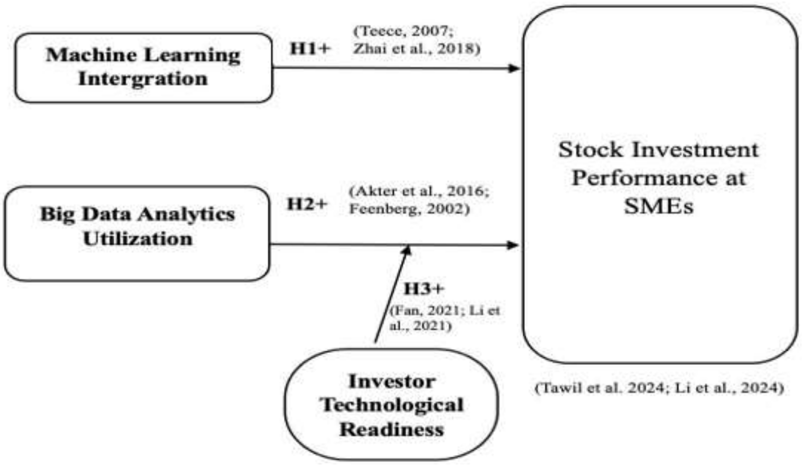

Figure 1: The Paper's Conceptual Framework

3. METHOD

This study aims to examine the relationship between machine learning integration, big data analytics utilization, and stock investment performance in SMEs, while also assessing the moderating role of investor technological readiness. It employs a quantitative methodological framework, utilizing purposive sampling to balance empirical rigor with representational accuracy (Creswell & Creswell, 2017). Participants were purposively chosen based on their active involvement in financial decision-making within SMEs, with variation in digital literacy levels, industry sector, and investment exposure to ensure diversity in technological adoption contexts.

The sample was stratified into four groups. The first included SME managers and investors in Vietnam with limited financial and technological resources, whose investment decisions reflect constraints in data availability and reliance on traditional approaches. The second group consisted of SMEs from emerging Asian economies such as Malaysia and Indonesia, where digital transformation is gradually progressing, and investment decisions combine both traditional financial practices and AI-enabled tools. The third group comprised technology-oriented SMEs in sectors such as fintech, logistics, and e-commerce across Southeast Asia, whose high exposure to Machine Learning and Big Data applications reflects advanced adaptation to AI-driven investment strategies. Finally, the fourth group included international SMEs and investment professionals operating in cross-border environments, whose practices reveal diverse approaches to integrating AI tools with global investment strategies.

Eligibility criteria required participants to have engaged in stock investment-related decision-making within the past six months, either directly as investors or indirectly as financial managers in SMEs. Stratification factors included firm size, country of operation, technological readiness, and degree of exposure to AI-enabled platforms. Data collection relied on an online survey distributed through professional associations, university communication channels, LinkedIn investor groups, and SME networks across Southeast Asia.

After applying thorough data validation procedures, 385 responses were deemed complete and consistent, forming the final dataset out of an initial 612 entries. The questionnaire utilized a 5-point Likert scale (from 1, "strongly disagree," to 5, "strongly agree") to capture participants' perspectives on Machine Learning integration, Big Data Analytics utilization, investor readiness, and investment performance. This participant structure enables comprehensive analysis of how AI-enabled tools influence SME investment performance across varying levels of technological capacity.

4. RESULTS

4.1. Reliability analysis

Table 1: Reliability analysis of "Stock Investment Performance". Source: (The authors, 2025)

Reliability Statistics

Cronbach's Alpha	N of Items
.813	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SIP1	9.339	7.542	.678	.807
SIP2	8.500	7.908	.668	.696
SIP3	8.762	7.575	.768	.787
SIP4	8.746	6.319	.651	.669

Where survey items SIP1 through SIP4 corresponded to questions 1–4 measuring Stock Investment Performance. As shown in Table 1, each dependent sub-variable achieved an adjusted item–total correlation of at least 0.3. The overall Cronbach's alpha was 0.813 surpassing the accepted minimum of 0.6 and remaining higher than the values that would have resulted from the exclusion of any single item. In addition, every dependent sub-variable displayed a Cronbach's alpha above its respective adjusted item–total correlation, even under item deletion scenarios. Consequently, all items were retained for subsequent analysis, with similar consistency patterns confirmed across the other variables.

4.2. Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix. Source: (The authors, 2025)

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
SIP1 .609	MLI1 .639	BDAU1 .630	ITR1 .629
SIP2 .545	MLI2 .646	BDAU2 .704	ITR2 .579
SIP3 .632	MLI3 .744	BDAU3 .643	ITR3 .699
SIP4 .648	MLI4 .644	BDAU4 .674	ITR4 .601
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Where survey items MLI1–MLI4, BDAU1–BDAU4, and ITR1–ITR4 were used to measure the two independent variables and the moderator respectively. As shown in Table 2, the rotated component matrix grouped all 16 sub-variables into four distinct factors, corresponding to the dependent variable, the two independent variables, and the moderator. Each sub-variable exhibited factor loadings above the 0.5 threshold, and no items were eliminated during factor analysis.

4.3. Multiple linear regression model

Table 3: Coefficients[a]. Source: (The authors, 2025)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.798	.601		4.882	.000
	MLI	.737	.802	.736	3.635	.000
	BDAU	.752	.677	.714	3.730	.000

a. Dependent Variable: SIP

Where **SIP**: mean of SIP1-SIP4; **MLI**: mean of MLI1–MLI4;
BDAU: mean of BDAU1–BDAU4

Table 3 indicates that the t-test significance (Sig.) values of .0.00 fall below the conventional alpha level of 0.05. This finding demonstrates that the independent variables have a statistically significant influence on the dependent variable. Consequently, both hypotheses are validated.

4.4. Moderator analysis

Table 4: Results analysis of "Investor Technological Readiness". Source: (The authors, 2025)

Model : 1
Y : SIP
X : BDAU
W : ITR
Sample Size: 385

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OUTCOME VARIABLE:
SIP
Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.795	.632	.713	5.906	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	7.806	.993	60.710	.000	7.191	7.174
BDAU	.703	.787	4.336	.000	.600	.586
ITR	.587	.981	4.933	.000	.596	.581
Int_1	.520	.852	4.844	.000	.615	.605

Where **ITR**: mean of ITR1 to ITR4

Table 4 reveals that the p-value for the interaction term (Int_1) is 0.000, well below the 0.05 threshold, indicating a statistically significant moderating effect of investor technological readiness on the relationship between big data analytics utilization and investment performance in SMEs. The interaction coefficient of 0.580 further suggests that stronger investor technological readiness amplify the positive influence of big data analytics utilization on investment performance in SMEs. Accordingly, hypothesis H3 is supported.

5. DISCUSSION

5.1. Result summary

The regression analysis reveals that the integration of Machine Learning exerts the most substantial effect on the effectiveness of socialization programs for children with autism, with a coefficient of 0.736. the utilization of Big Data Analytics also demonstrates a meaningful influence, though to a lesser degree, reflected in its coefficient of 0.714. Moreover, investor technological readiness acts as a moderating factor, shaping the link between the utilization of Big Data Analytics and investment performance in SMEs with a moderate effect size (0.520). This analytical approach was employed to thoroughly address the research questions and to illuminate the relationships among the principal variables.

5.2. Theoretical implication

The findings demonstrate that the positive impact of Machine Learning Integration (MLI) on SME stock investment performance is strong. This is in line with Dynamic Capability Theory (Teece, 2007; Kraus et al., 2019), which argues that predictive algorithms can assist firms in restructuring resources and responding to market uncertainty. It is also in line with Duan et al. (2020), who put stress on the fact that ML can alter strategies in real-time. But it is somewhat counterintuitive to the Resource-Based View, which states that technology itself is inadequate, that there must be leadership and other complementary resources (Wamba et al., 2021). In this respect, the results annoy a strict technological determinist perspective and incline towards a rather contextual view, in which internal preparedness is critical to the realization of actual performance returns. In theory, though, MLI cannot be viewed as a driver on its own but as an ability that needs to be integrated into SME eco-systems. This adds to the TOE model by demonstrating that organizational configurations and managerial practices only magnify the advantages of ML, and not eliminate them.

In the same way, the fact that the use of Big Data Analytics (BDAU) enhances the investment performance of SMEs confirms the Resource-Based Theory, as data analytics could be a scarce and uncopyable resource (Barney, 1991; Akter et al., 2016). This is in line with Wang and Byrd (2017), who discovered that analytics enhances alignment of the strategies and quality of decisions. However, there are studies saying that BDAU has its benefits restricted by skills gaps and infrastructure difficulties (Shujahat et al., 2019). This concern is partly supported by our findings, thus indicating that BDAU cannot be unconditionally effective. Rather, as with the Dynamic Capability Theory (Teece, 2014), analytics, along with its combination with organizational routines, should be continuously integrated to produce long-term benefit. By doing this, the research also backs up a pragmatic perception of knowledge by demonstrating that data can truly only be valuable when converted to actionable, context-specific investment practices for SMEs.

Lastly, the mediating influence of the Investor Technological Readiness (ITR) emphasizes the human and behavioral aspect, which is usually ignored in the technology-adoption theory. Based on the constructs of readiness used by Parasuraman (2000) and Cognitive Fit Theory (Vessey, 1991), the results support the BDAU effect by showing that skills of investors and investor confidence are the determinants of the ability to transform data into decisions. This is consistent with Wamba et al. (2020) demonstrating that readiness enhances market responsiveness, but differs from Wahab and Radmehr (2024), who believe that external market shocks may overwhelm the benefits of readiness. Therefore, ITR is to be regarded as a conditional amplifier, contrary to the universal moderator. In theory, this represents an extension of Dynamic Capability Theory in that there is not only organizational adaptability but also cognitive and psychological. Consequently, investor preparedness becomes a key human capital skill that has a positive effect on the bridge between analytics and actual performance of investment in SMEs.

5.3. Practical implication

The fact that Machine Learning Integration (MLI) enhances the performance of SME stock investment, which has been confirmed in Hypothesis 1, provides a number of practical lessons. To the managers and owners, the findings suggest that predictive algorithms are not only considered as accuracy tools but also aid adaptive decision making when operating in uncertain markets (Kraus et al., 2019). Nevertheless, the technology, as such, is not bound to produce better results. To reap maximum gains, SMEs will have to invest in training and digital infrastructure, as well as make sure that personnel understand how to apply ML to its full potential (Wamba et al., 2021). On the policy front, this implies that digital literacy should be subsidized and that more affordable and SME-decent solutions to ML that lower barriers of entry should be encouraged (Restrepo-Morales et al., 2024).

The results on Hypothesis 2 highlight the importance of Big Data Analytics Utilization (BDAU) to enhance investment decisions. Organizing analytics as part of their business strategy will enable SMEs to predict risks and resources more effectively by allocating them and enhancing resilience in competitive markets (Akter et al., 2016; Wang and Byrod, 2017). However, the process of BDAU does not just involve the acquisition of software. Analytics capabilities need to be aligned with organizational processes in order to be effective. This involves educating financial managers to make the right interpretation of data and correlating data knowledge directly to investment portfolios. This way, the use of data becomes more than symbolic; it becomes a real improvement of outcomes. It can be contributed to by policymakers and industry associations assisting with providing affordable cloud-based services and shared data platforms that large firms can access without the need to deal with cost and access challenges (Babalghaith & Aljarallah, 2024).

In the case of Hypothesis 3, the moderating factor of Investor Technological Readiness (ITR) refers to an important aspect of human capital. The most sophisticated data systems cannot be used to deliver value without the ability, trust, and desire to do so (Parasuraman, 2000; Li et al., 2021). In the case of SMEs, this implies giving capacity-building priority. Technological upgrades should be accompanied by continuous training, mentoring, and development in data literacy. This demands combined initiatives with investments in technology, being accompanied by upskilling initiatives (Tawil et al., 2024). Partnerships between fintech providers and SMEs can also be promoted by policymakers, and the platforms should not be easily accessible to users, but rather integrated with knowledge-transfer systems.

Combined, these implications emphasize that technology, infrastructure, and human preparedness should all change in tandem. By considering readiness as a key factor that is just as important as machine learning and hardware, SMEs will be able to translate analytics and machine learning into tangible, quantifiable benefits of stock investment returns.

5.4. Limitation

The research is limited in a number of ways. To start with, it is not based on longitudinal survey data, which can fail to determine definite causality - investment results change over time, and a single observation can miss these changes (Kraus et al., 2019). Second, the sample only included SMEs in Southeast Asia; thus, the results might not apply to other regions with other financial systems or regulatory environments (Tawil et al., 2024). Third, self-reported perceptions were used to measure technological preparedness and might increase bias and do not adequately capture structural constraints, including infrastructure or financing scales (Li et al., 2021). Lastly, as much as the study identifies the digital adoption, it fails to appreciate cultural or psychological issues that may impact the use of technology in financial decision-making, and thus, the complexity of behavior is not highly explored.

5.5. Future direction for Research

Longitudinal designs should be applied in future research to monitor the way in which Machine Learning and Big Data Analytics determine investment performance in the long-term, particularly in unstable market environments (Wamba et al., 2020). It also requires cross-country comparisons in order to reveal the effects of various institutional and regulatory settings on the results of adoption. Other than survey means, the researchers may incorporate quantitative data together with qualitative interviews to understand cultural and contextual obstacles to using the technology (Shujahat et al., 2019). A better picture would also be taken by measuring investor preparedness with self-reports as well as objective digital literacy tests. Last but not least, looking at the interaction of organizational culture and investor readiness might help show how social and psychological factors mediate the relationship between analytics adoption and investment performance.

5.6. Conclusion

The paper presents the idea that both Machine Learning Integration (MLI) and Big Data Analytics Utilization (BDAU) can help enhance stock investment in SMEs to a significant degree. Meanwhile, these are reinforced by Investor Technological Readiness (ITR), which links technical tools and actual decision-making. Putting the results into the context of the Dynamic Capability Theory and the TOE model, the research points out that technology alone is ineffective, organizational readiness and investor expertise are needed to convert the digital potential into the tangible results (Teece, 2014; Barney, 1991). To practice, SMEs should combine the use of technology with training and supportive infrastructure, and policymakers need to offer cheap digital solutions and learning opportunities. Combined, these results emphasize the fact that the combination of technology, organizational capacity, and human readiness is the key to sustainable performance in SMEs.

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APPENDIX: Survey

Table 5. Survey Questionnaire

Background information

1	**What is your current role in the SME?**	Owner/Founder	Manager/Director	Financial/Investment Officer	Other (please specify)	
2	**How many employees does your SME currently have?**	Fewer than 10 (Micro enterprise)	10–49 (Small enterprise)	50–249 (Medium enterprise)	250 or more	
3	**In which country is your SME primarily operating?**	Vietnam	Malaysia	Indonesia	Other (please specify)	
4	**How would you describe your level of technological readiness in adopting AI-driven tools for investment decisions?**	Very Low	Low	Moderate	High	Very High

No.	Variables	Coded Sub-variables	Content
1.	**Stock Investment Performance at SMEs**	**SIP1**	SME has achieved higher profitability in stock investments when adopting digital technologies (Serrasqueiro et al., 2023).
		SIP2	AI-driven approaches have improved the accuracy of forecasting stock returns compared to traditional methods (Ugbebor et al., 2024).
		SIP3	The use of digital analytics has enabled more efficient allocation of financial resources in stock investment (Li et al., 2024).
		SIP4	Integrating machine learning and data analytics has reduced investment risks and enhanced long-term competitiveness (Tawil et al., 2024).
2.	**Machine Learning Integration**	**MLI1**	Machine Learning integration has improved the ability to recognize stock market patterns and trends (Jordan & Mitchell, 2015).

		MLI2	Applying predictive algorithms has enhanced return on investment (ROI) and capital utilization in SMEs (Kraus et al., 2019).
		MLI3	Machine Learning enables real-time adjustments of investment strategies, leading to higher profitability (Duan et al., 2020).
		MLI4	Effective leadership and internal resources are essential for Machine Learning integration to positively impact stock performance (Wamba et al., 2021).
3.	**Big Data Analytics Utilization**	**BDAU1**	Using Big Data Analytics has improved decision-making effectiveness in stock investments (Akter et al., 2016).
		BDAU2	Big Data capabilities enhance strategic alignment and lead to better investment outcomes in SMEs (Wang & Byrd, 2017).
		BDAU3	Big Data adoption helps SMEs determine financial risks and monitor market dynamics more effectively (Babalghaith & Aljarallah, 2024).
		BDAU4	The adoption of Big Data Analytics supports more objective, data-driven investment decisions rather than instinct-based ones (Feenberg, 2002).
4.	**Investor Technological Readiness**	**ITR1**	Investors with higher technological readiness can better interpret digital tools for investment decision-making (Parasuraman, 2000).
		ITR2	Technological readiness increases confidence in adopting Big Data and AI tools for stock investments (Fan, 2021).
		ITR3	Investors with strong digital skills are more successful in transforming data insights into profitable stock investment decisions (Li et al., 2021).
		ITR4	High technological readiness among investors reduces uncertainty and enhances trust in AI-driven investment processes (Tawil et al., 2024)

Survey link:
https://docs.google.com/forms/d/e/1FAIpQLSfBI3PN-dkrSvpJl9JcPlS-Fd6H9tJrpKvpbYkz0pizmyVSiA/viewform?usp=header