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Investment Analytics, Fintech, Risk Perception, and Diversification

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Abstract
Purpose: This study examines how investment analytics capability influences portfolio diversification effectiveness through financial technology integration and strategic risk perception in Indonesia's emerging capital market.
Research Methodology: A quantitative cross-sectional design was applied using purposive sampling of 150 investors, advisors, asset managers, and fund managers. Data were collected through a Likert-scale questionnaire and analyzed using PLS-SEM with SmartPLS 4.
Results: Investment analytics capability positively influences financial technology integration ($\beta = 0.642$, $p < 0.001$) and strategic risk perception ($\beta = 0.591$, $p < 0.001$). Financial technology integration improves diversification effectiveness ($\beta = 0.483$, $p < 0.001$), while strategic risk perception has a negative effect ($\beta = -0.324$, $p < 0.001$).
Conclusion: Investment analytics capability enhances diversification through technology adoption but may also increase risk awareness that limits portfolio expansion.
Limitations: This study is limited by its cross-sectional design, sample size, and focus on Indonesian investors, which may affect broader applicability.
Contributions: This study contributes an integrated model linking analytical capability, fintech adoption, and risk perception, while providing insights for investors and financial institutions to improve investment strategies.

Keywords: *Capital Markets, Diversification, Financial Technology, Investment Analytics, Risk Perception*

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1. Introduction

Capital markets worldwide have undergone major transformation driven by rapid developments in data processing, artificial intelligence, cloud computing, and digital financial infrastructure (Chen et al., 2021). These developments have fundamentally reshaped how financial information is collected, verified, analyzed, and utilized for investment decision-making processes across all market segments

(Ozili, 2021). Traditional approaches based primarily on fundamental analysis and technical chart patterns are now complemented, and in many cases enhanced, by advanced data-driven methods that allow deeper insight into market dynamics, more precise risk measurement, and formulation of dynamic investment strategies (Markowitz, 1952). In emerging economies such as Indonesia, the rapid growth of digital investment platforms, automated advisory services, algorithmic trading systems, big data applications, and mobile-based financial services has significantly expanded market reach, lowered transaction barriers, and improved operational efficiency, yet also revealed substantial gaps in analytical readiness, technological literacy, and data governance maturity among market participants (Indonesian Capital Market Review, 2024).

Portfolio diversification remains the central principle and foundational strategy of modern investment practice, designed explicitly to minimize exposure to unsystematic risk through careful combination of assets whose returns demonstrate imperfect correlation patterns (Markowitz, 1952). However, the actual effectiveness of such diversification strategies in practice depends heavily upon several interrelated factors: quality, completeness, and timeliness of available information; depth and sophistication of analytical capacity; extent and quality of technological support infrastructure; and cognitive frameworks through which investment professionals and individual investors perceive, interpret, and respond to different dimensions of risk (Li & Wang, 2022). Agarwal and Zhang (2025) note that in emerging markets, structural limitations related to transparency, liquidity, regulatory frameworks, and information availability further complicate diversification efforts and increase the value of robust analytical capabilities.

Investment analytics capability represents a strategic resource that determines how effectively market participants can identify, acquire, process, interpret, and ultimately utilize available information and technology resources to support decision-making (Akhtar & Das, 2024). It encompasses competencies ranging from basic data management and statistical processing to advanced modeling, forecasting, and strategic interpretation skills. Meanwhile, behavioral finance research emphasizes that risk perception especially regarding long-term systemic vulnerabilities, regulatory changes, and macroeconomic instability significantly shapes allocation choices, risk tolerance, and overall portfolio structure (Al-Shammari & Al-Fares, 2023). Despite growing literature examining these aspects individually, empirical evidence regarding their integrated relationships and combined effects remains relatively limited, particularly within specific emerging market environments characterized by unique institutional, economic, and behavioral conditions (Henriques & Sadorsky, 2025).

In the Indonesian context specifically, rapid expansion of the investor base alongside deepening digital transformation creates an urgent need to understand how analytical competencies interact with technology adoption and risk perceptions to shape actual investment outcomes. Recent market developments indicate that while digital tools are increasingly available, many participants struggle to translate them into improved performance or better risk management due to insufficient analytical readiness. Furthermore, heightened awareness of systemic risks in emerging markets often leads to overly conservative or concentrated positions that undermine potential diversification benefits.

This research addresses these identified gaps by examining systematically how investment analytics capability influences the extent and quality of financial technology integration and the formation of strategic risk perception, and how these intermediate factors in turn affect portfolio diversification effectiveness. The findings are expected to provide valuable theoretical insights as well as practical guidance for investment practitioners, financial institutions, technology providers, educational institutions, and regulatory authorities operating within and beyond the Indonesian capital market environment (Candy, Robin, Sativa, Septiana, Can, & Alice, 2022).

2. Literature Review and Hypotheses Development

2.1 Theoretical Foundation

This research is grounded in four complementary theoretical frameworks that collectively provide a comprehensive multi-dimensional lens through which to understand how capability technology risk perception and investment outcomes interact within the context of emerging capital markets. Each framework contributes distinct yet mutually reinforcing insights and together they form a robust conceptual foundation capable of explaining both rational resource-driven dynamics and behavioral psychology-based influences observed in investment practice.

The resource-based view of the firm originally developed by Barney (1991) serves as the core theoretical anchor for understanding investment analytics capability as a strategic asset. This perspective posits that sustained competitive advantage derives from valuable rare inimitable and non-substitutable resources and capabilities. In the investment domain information processing skills analytical expertise and the ability to derive actionable insights from complex data represent precisely such capabilities. They are valuable because they improve decision-making quality rare because they require specialized knowledge and experience difficult to imitate because they are embedded in human capital and organizational processes and not easily substituted by generic tools or systems. This framework emphasizes that capabilities do not exist in isolation. Rather they determine how effectively other resources including financial technology platforms market data feeds and research resources are deployed and utilized. This perspective is particularly relevant to this study as it frames investment analytics capability not merely as a technical skill set but as a foundational driver that shapes the extent and quality of technology adoption the depth of risk assessment and ultimately the effectiveness of portfolio construction strategies. Extensions to dynamic environments such as the dynamic capabilities framework proposed by Teece Pisano and Shuen 1997 further reinforce this logic. In rapidly evolving digital markets the capacity to continuously adapt analytical approaches and integrate new technologies becomes even more critical to maintaining performance and resilience (Chatterjee, 2025).

Modern Portfolio Theory first formalized by Markowitz (1952) provides the fundamental normative framework for understanding portfolio diversification effectiveness and the core objective of risk-return optimization. This theory establishes that diversification works not simply by holding many assets but by combining assets whose returns are not perfectly correlated thereby reducing unsystematic risk, the risk specific to individual securities or sectors without necessarily lowering expected returns. The theory mathematically demonstrates that the efficiency of a diversified portfolio depends heavily on the quality of inputs including accurate estimates of expected returns variances and especially covariance structures across asset classes. This creates a direct conceptual link to the variables examined in this study. Investment analytics capability determines the precision and comprehensiveness of these estimates. Financial technology integration expands the scope timeliness and sophistication of data available and modeling capacity. Risk perception influences how investors interpret and apply these quantitative insights in practice. In emerging markets like Indonesia where information transparency is lower liquidity varies widely and structural shifts occur frequently the assumptions of Modern Portfolio Theory are not automatically satisfied. This makes the role of analytics and technology even more vital for achieving meaningful diversification benefits. Subsequent extensions including the Capital Asset Pricing Model by Sharpe 1964 and Arbitrage Pricing Theory by Ross 1976 further elaborate risk dimensions yet all rest on the premise that effective risk measurement and management are essential to successful portfolio construction precisely the functions enhanced by analytics and technology (Eling & Schuhmacher, 2021).

Technology acceptance and extension frameworks centered on the Technology Acceptance Model introduced by Davis (1989) and extended through models such as Technology Acceptance Model 3 by Venkatesh and Bala (2008) the Unified Theory of Acceptance and Use of Technology and the Task-Technology Fit perspective provide the theoretical basis for understanding how capability shapes the adoption integration and effective utilization of digital financial tools. Davis original formulation identifies perceived usefulness and perceived ease of use as the primary determinants of technology adoption and usage behavior. However later extensions particularly Technology Acceptance Model 3 emphasize that individual capabilities experience and task characteristics are critical antecedents that influence these perceptions and determine whether technology is merely used superficially or deeply integrated into core workflows. Task-Technology Fit theory by Goodhue and Thompson 1995 further clarifies that technology delivers value only when its functional characteristics match the requirements of the task being performed. In the investment context this means that digital platforms data analytics tools and algorithmic systems will only deliver their full potential when users possess the analytical capability required to configure interpret and apply outputs effectively. These frameworks explain why availability of technology alone does not guarantee improved outcomes. Capability is the essential enabler that transforms technical potential into practical performance. Furthermore they highlight that deep operational integration going beyond basic usage to embedding systems into decision-making processes is what drives meaningful improvements in efficiency and effectiveness.

Behavioral finance perspectives originating largely from the seminal work of Kahneman and Tversky (1979) on Prospect Theory provide the necessary framework to account for cognitive and psychological influences that deviate from fully rational decision-making assumptions underlying traditional finance models. Behavioral finance recognizes that investors do not always process information objectively or optimize choices according to expected utility theory. Instead they rely on mental heuristics are influenced by cognitive biases and are sensitive to how information is framed and perceived. Risk perception particularly long-term systemic risk perception is not simply an objective reflection of measurable volatility but a subjective cognitive construct shaped by information availability processing capacity experience and emotional factors. This perspective is central to this study because it explains how enhanced analytical capability does not merely improve technical accuracy but fundamentally transforms how risks are perceived interpreted and prioritized. It also illuminates the mechanisms through which heightened awareness of systemic vulnerabilities even when accurate, can lead to conservative risk-avoidant behaviors that may reduce diversification scope. Concepts such as ambiguity aversion loss aversion overconfidence and home bias extensively documented in behavioral finance literature are especially relevant in emerging markets where uncertainty is higher and institutional frameworks are less mature. Together these theories explain why two investors with similar resources and market access may adopt very different diversification strategies depending on their analytical readiness and risk perception profiles(Hesniati, Ogawa, Clarence, Topher, & Engelina, 2022).

When integrated these four theoretical perspectives form a unified conceptual model that bridges rational-resource technological and behavioral dimensions. The resource-based view and dynamic capabilities explain the role of investment analytics capability as a foundational strategic resource(Chatterjee, 2025). Modern Portfolio Theory defines the normative objectives and mechanisms of diversification effectiveness. Technology acceptance and fit frameworks describe how capability enables effective integration of digital tools. Behavioral finance accounts for how capability shapes risk perception and decision-making patterns. This multi-theory foundation allows this research to capture both the enabling and conditioning effects of analytics capability providing a far more complete understanding of investment behavior and outcomes than could be achieved through any single theoretical lens alone(Maulana, Chandra, & Muhammad, 2026).

2.2 Investment Analytics Capability

Investment analytics capability represents a comprehensive multi-dimensional construct that refers to the systematic capacity to acquire process transform interpret and derive actionable insights from diverse financial economic market and alternative data sources to support high-quality investment decision-making as outlined by Chen, Liu, and Zhang (2021) and Chen and Wang (2022). It encompasses a spectrum of competencies ranging from fundamental data management and descriptive statistics to advanced econometric modeling machine learning applications predictive forecasting risk decomposition valuation modeling and strategic synthesis of complex multi-source information. Unlike general financial literacy or basic numeracy investment analytics capability is specifically oriented toward the unique requirements of investment analysis. It includes skills in market data management time-series analysis correlation and causal modeling performance attribution stress testing scenario analysis and translating quantitative findings into coherent strategy-relevant conclusions. It also involves the ability to integrate information across asset classes sectors geographic regions and time horizons as well as to assess data quality reliability and limitations an especially critical skill in emerging market environments where data availability and consistency vary substantially.

According toLi and Wang (2022) investment analytics capability directly and significantly improves core dimensions of investment analysis. These include forecasting accuracy for asset prices returns and macroeconomic trends precision in valuation models for equities fixed income instruments and alternative assets effectiveness in identifying measuring and decomposing different types of risk and the ability to recognize structural shifts market anomalies and emerging opportunities. Strong analytical capability allows investors to move beyond simple price-based or rule-of-thumb approaches toward evidence-based rigorous and forward-looking analysis. Furthermore research byFeng and Li (2024) demonstrates that analytics capability functions as a critical complement to technological resources. Users with higher analytical maturity are better able to configure systems select appropriate models interpret outputs correctly identify limitations and extract substantially greater value from available data and technology infrastructure. Without sufficient analytical capability even the most sophisticated data platforms remain underutilized misapplied or limited to superficial usage patterns.

Beyond operational efficiency and accuracy investment analytics capability fundamentally shapes how risks are understood and evaluated. Research by Datta and Singh (2025) shows that enhanced analytical readiness enables investors to conduct deeper broader and more nuanced risk assessments that go beyond short-term price volatility to identify structural vulnerabilities macroeconomic exposures regulatory risks liquidity constraints and long-term systemic threats. It transforms risk perception from subjective intuition or simplified indicators toward systematic evidence-based evaluation. This is particularly relevant in emerging economies such as Indonesia where market conditions are dynamic institutional frameworks are evolving and risks are often more complex and less transparent than in developed markets.

Building on these established findings and theoretical foundations this study proposes that investment analytics capability exerts two primary complementary influences central to the research model. First it enables and supports deeper more effective and more strategic integration of financial technology tools and systems throughout investment workflows. Capability provides the knowledge base required to select appropriate technologies adapt them to specific analytical needs align them with decision-making processes and fully leverage their functionalities. Second investment analytics capability enhances the depth comprehensiveness and accuracy of risk assessment leading to stronger more informed strategic risk perception. Therefore the following hypotheses are formally proposed:

H_1: Investment analytics capability has a significant positive influence on financial technology integration.

H_2: Investment analytics capability has a significant positive influence on strategic risk perception.

These hypotheses establish the foundational role of analytics capability as the primary driver shaping both technological adoption patterns and cognitive risk assessment frameworks within the investment environment.

2.3 Financial Technology Integration

Financial technology integration is defined here not merely as the adoption or usage of digital tools but as the extent to which digital systems algorithms data platforms automated workflows and supporting infrastructure are embedded aligned and operationally interoperable within core investment processes and decision-making systems according to Ozili (2021) and Sia and Ngai (2022). It represents a continuum ranging from isolated superficial usage of individual tools to deep seamless integration where technology forms an integral part of every stage of the investment cycle. These stages include data gathering cleaning and validation analysis modeling valuation and risk assessment portfolio construction execution monitoring rebalancing and reporting. Effective integration implies alignment between technological capabilities organizational or individual investment processes and strategic objectives as well as high levels of interoperability data consistency and workflow automation.

The benefits of deep financial technology integration are well-documented in literature. Fang and Lin (2023) demonstrate that comprehensive integration significantly expands the accessible investment universe allowing investors to access broader ranges of asset classes sectors geographic markets and investment products that were previously impractical or impossible to monitor and analyze thoroughly. It substantially improves data quality completeness timeliness and consistency reducing information asymmetry and processing errors. Integration also enables sophisticated analytical capabilities including advanced correlation modeling factor analysis risk decomposition scenario simulation optimization algorithms and real-time monitoring which are essential for constructing truly efficient well-diversified portfolios. Furthermore it supports systematic portfolio rebalancing enhances trade execution quality substantially lowers transaction costs and reduces operational frictions and inefficiencies across the investment process chain.

For emerging capital markets the role of financial technology integration is especially transformative. Huang and Wu (2025) highlight that deep integration helps overcome many structural limitations typical of developing markets. These include limited information transparency fragmented trading systems manual processes liquidity constraints and restricted access to research and analysis. In the Indonesian market specifically digital integration has expanded investor participation improved price discovery and supported development of new investment products and services. By standardizing and automating data processing and analysis technology integration creates conditions where effective comprehensive diversification becomes feasible and practical for a much broader range of market participants.

However literature consistently emphasizes that these benefits are realized only when integration is deep aligned and supported by adequate analytical capability. Superficial or fragmented adoption produces limited or even misleading outcomes. Building on these perspectives and the core principles of Modern Portfolio Theory it is hypothesized that:

> H_3: Financial technology integration has a significant positive influence on portfolio diversification effectiveness.

This hypothesis captures the central expectation that deep well-aligned technology integration directly improves the quality breadth and efficiency of portfolio diversification outcomes.

2.4 Strategic Risk Perception

Strategic risk perception is defined as the cognitive evaluation understanding and awareness of long-term systemic structural and fundamental vulnerabilities and uncertainties within the broader investment environment following (Wang, Li, & Zhang, 2020). Unlike short-term risk perception which focuses primarily on price volatility daily fluctuations or immediate event-driven risks strategic risk perception centers on conditions and factors that influence market functioning asset valuations and investment viability over medium-to-long-term horizons. Key dimensions include macroeconomic instability such as inflation trends interest rate cycles currency volatility fiscal sustainability and economic growth patterns regulatory and policy shifts institutional framework strengths and weaknesses political stability and governance quality market structure and liquidity conditions and broader systemic risks affecting the financial system.

Strategic risk perception is not simply an objective assessment derived from data. It is fundamentally a subjective cognitive construct shaped by information availability processing capacity analytical frameworks experience and behavioral factors. Research by Datta and Singh (2025) shows that investment analytics capability is a primary determinant of how comprehensively and accurately strategic risks are perceived. Stronger analytical readiness enables investors to detect understand and evaluate structural vulnerabilities that remain invisible or poorly understood by less sophisticated participants. Consequently analytics capability does not reduce risk awareness it deepens and sharpens it transforming it from vague concern into structured informed assessment.

However literature from behavioral finance and emerging market investment research demonstrates that high strategic risk perception has predictable effects on investment behavior. Al-Shammari and

Al-Fares (2023) andHarianto and Suciati (2026) find that heightened awareness of systemic vulnerabilities tends to promote conservative risk-avoidant behaviors. Investors narrow their investment scope reduce exposure to perceived high-risk sectors or markets increase concentration in assets or regions viewed as safer or more familiar and exhibit stronger home bias. In environments characterized by greater uncertainty and institutional incompleteness these tendencies are often amplified. While accurate risk assessment is essential for sound management excessive or overly defensive responses can undermine diversification benefits and long-term performance potential.

These dynamics are particularly relevant to the Indonesian capital market where investors face unique combinations of economic regulatory and political risks. Building on theoretical foundations from behavioral finance and empirical evidence this study proposes:

> H_4: Strategic risk perception has a significant negative influence on portfolio diversification effectiveness.

This hypothesis formalizes the expectation that while enhanced risk awareness is valuable heightened strategic risk perception tends to restrict diversification scope and effectiveness.

2.5 Mediation Mechanisms

Beyond direct relationships between variables this research proposes that financial technology integration and strategic risk perception function as significant mediating mechanisms that explain how investment analytics capability influences portfolio diversification outcomes. These dual pathways represent complementary yet partially opposing mechanisms that together produce complex nuanced effects reconciling seemingly conflicting findings observed in prior literature.

Through the technological pathway investment analytics capability enables and supports deeper more effective and more strategic financial technology integration. Capability shapes technology adoption by determining how systems are selected configured adapted and utilized transforming potential technological resources into operational assets that expand investment reach improve information quality and enable advanced modeling and optimization. In turn deep integration directly enhances diversification effectiveness by removing structural barriers improving analytical precision and supporting systematic efficient portfolio construction. This pathway represents the positive enabling mechanism through which analytics capability delivers value.

Through the cognitive pathway investment analytics capability simultaneously deepens and sharpens strategic risk perception. Enhanced analytical capacity reveals and highlights vulnerabilities and structural risks that otherwise remain unnoticed or underestimated. While this awareness improves risk management quality it also tends to generate more conservative positioning narrower investment scope and greater concentration effects that constrain diversification breadth and effectiveness. This pathway represents the conditioning restraining mechanism that accompanies capability development.

Guo and Chen (2023)emphasize that these dual mediating pathways explain why direct relationships between analytics capability and performance are often weak or inconsistent. The positive technological effects and negative risk-related effects partially offset each other. Only by explicitly modeling both pathways can the true nature and impact of investment analytics capability be fully understood. This study therefore hypothesizes:

> H_5: Financial technology integration significantly mediates the positive relationship between investment analytics capability and portfolio diversification effectiveness.

> H_6: Strategic risk perception significantly mediates the negative relationship between investment analytics capability and portfolio diversification effectiveness.

Together these mediation hypotheses capture the full complexity of how analytics capability operates through complementary technological and cognitive channels to shape diversification outcomes. Expanded theoretical and empirical context

To further strengthen this literature review it is valuable to elaborate on the broader context and empirical patterns that motivate the proposed relationships. In recent years capital markets globally including Indonesia have experienced rapid digital transformation driven by advancements in data availability computing power cloud infrastructure and algorithmic capabilities. While these developments have created unprecedented opportunities to improve investment analysis and diversification they have also created significant gaps between technological potential and actual outcomes. Research across emerging economies consistently shows that the benefits of digital transformation are not evenly distributed. They are concentrated among participants with strong analytical readiness and capability to make effective use of available tools.

For Indonesia specifically the Indonesian Capital Market Review 2024 highlights that while investor numbers have grown rapidly and digital platforms have proliferated many participants especially retail investors and smaller institutions face significant challenges in translating access to technology into improved investment outcomes. Key barriers identified include limited analytical skills insufficient understanding of data quality and limitations inability to interpret complex outputs and behavioral tendencies toward conservatism or excessive risk-taking. These observations align closely with the theoretical framework and hypotheses proposed here emphasizing the central role of investment analytics capability as the critical factor determining how technology and risk perceptions translate into portfolio performance.

Furthermore the unique characteristics of emerging markets such as higher volatility lower liquidity weaker information transparency and evolving regulatory environments amplify the importance of both analytics capability and risk perception. In developed markets more standardized conditions may reduce the relative impact of capability differences. In contrast in environments like Indonesia capability differences become far more consequential creating substantial gaps between investors with strong analytical readiness and those without.

Empirical evidence from similar emerging market contexts supports the relationships proposed. Studies from India Brazil Southeast Asia and Eastern Europe consistently demonstrate that analytics capability is positively associated with technology adoption and usage depth that technology integration improves portfolio outcomes and that heightened risk awareness in uncertain environments leads to more conservative allocation patterns. These findings provide external validation for the conceptual model and strengthen the relevance of this research within the Indonesian setting.

Finally the integration of multiple theoretical perspectives in this study addresses an important limitation observed in much prior research which tends to focus narrowly on either technological adoption or behavioral factors in isolation. By simultaneously modeling capability technology risk perception and outcomes this research offers a more holistic balanced and practically relevant explanation of investment dynamics in digitally transforming emerging capital markets.

3. Research Methodology

3.1 Research Design and Population

This study adopts a quantitative cross-sectional research design, which is appropriate for analyzing hypothesized relationships among variables at a specific point in time (Hair et al., 2019). The target population comprises active individual investors, investment advisors, asset managers, and fund managers operating within the Indonesian capital market. The sample size was set at 150 respondents, satisfying the statistical requirement of a minimum of ten observations per structural path in the model a widely accepted guideline for PLS-SEM analysis (Sarstedt et al., 2022). Purposive sampling was employed with clearly defined inclusion criteria: respondents must have a minimum of two years of active investment experience and must be directly involved in portfolio construction or investment management decisions. These criteria were established to ensure that respondents possessed meaningful decision-making experience and could provide informed, experience-based responses rather than general perceptions. Data collection was conducted from January to March 2026 through online questionnaires distributed via professional capital market associations, securities trading platforms, university alumni networks, and financial professional communities. All participants provided informed consent prior to participation, and all responses were processed anonymously to ensure confidentiality and compliance with research ethics standards.

3.2 Measurement Instrument — Questionnaire Development and Validation

3.2.1 Questionnaire Development and Item Format

The research instrument was developed systematically through multiple stages to ensure quality, clarity, and contextual relevance. First, all questionnaire items were adapted from established and published measurement scales in peer-reviewed literature, ensuring that every statement possessed a solid theoretical and empirical foundation. All items were formulated as closed-ended statements measured using a five-point Likert scale, with response options ranging from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, to 5 = Strongly Agree. This format was selected because it represents the standard approach in finance and management research, is easily understood by respondents, and produces data consistent with the assumptions of PLS-SEM analysis.

The complete questionnaire consists of two main sections. The first section collects respondent demographic information including: gender, age group, educational background, years of investment experience, and primary type of investment instrument. The second section constitutes the core of the instrument, comprising four sets of statements corresponding to the research variables, with the following details. Investment Analytics Capability (7 items): Adapted from Chen et al. (2021) and Li & Wang (2022). Items were designed to measure respondents' ability to gather financial and market data, perform statistical processing, conduct econometric modeling, identify and decompose risks, and formulate evidence-based investment strategies. Sample statement: "I am able to process market data to identify patterns and trends in asset price movements". Financial Technology Integration (6 items): Adapted from Ozili (2021) and Sia et al. (2022). This scale measures not merely the usage of digital tools, but the depth of integration, the extent to which technology is embedded throughout every stage of the investment decision-making workflow, from data collection and analysis through execution, monitoring, and rebalancing. Sample statement: "I use digital platforms in an integrated manner for the entire process of portfolio analysis and management". Strategic Risk Perception (5 items): Adapted from Wang et al. (2020). Items focus on long-term systemic risks rather than short-term price volatility, including macroeconomic instability, regulatory and policy changes, political and institutional risks, market liquidity conditions, and broader financial system vulnerabilities. Sample statement: "I consider risks related to government policy changes and market regulations in every investment decision I make". Portfolio Diversification Effectiveness (6 items): Adapted from (Markowitz, 1952). Items measure the extent to which respondents construct portfolios with low inter-asset correlation, reduce unsystematic risk, and balance risk and return in accordance with Modern Portfolio Theory principles. Sample statement: "I construct portfolios using assets whose prices do not move in the same direction to reduce the risk of losses."

3.2.2 Translation and Content Validation Procedure

To ensure the instrument functioned accurately in the Indonesian context, a standard back-translation procedure was conducted: first, all items were translated from English into Indonesian by a finance professional proficient in both languages and familiar with capital market terminology; second, the Indonesian version was translated back into English by an independent linguist who was unaware of the original instrument; third, the original and back-translated English versions were compared for semantic equivalence, and any discrepancies were discussed and resolved through iterative refinement until full conceptual equivalence was achieved.

Subsequently, a pretest was administered to 15 respondents matching the target profile, investors and financial professionals with at least two years of experience. They were asked to provide feedback on language clarity, term appropriateness, comprehension, and time required to complete the questionnaire. Based on this feedback, minor refinements were made to wording and technical terminology to improve clarity without altering the underlying conceptual meaning. No items were removed at this stage.

3.2.3 Rationale for Scale Selection
The decision to adopt specific scales from the literature was based on the following considerations: The Investment Analytics Capability scale was selected because it comprehensively spans competencies from basic data management through advanced modeling and strategic interpretation, rather than measuring general financial literacy, the Financial Technology Integration scale was chosen because it distinguishes superficial usage from deep operational embedding within workflows, which is central to this study's theoretical argument, The Strategic Risk Perception scale was selected because it focuses specifically on long-term systemic risks, unlike short-term volatility perception which has been extensively studied and the Portfolio Diversification Effectiveness scale was adopted because it directly operationalizes the risk-reduction and optimization principles of Modern Portfolio Theory, which forms the normative foundation of this research.

3.2.4 Reliability and Validity Assessment Procedures Prior to Structural Model Evaluation
Before testing the hypotheses through the structural model, the measurement model was evaluated sequentially following the two-stage protocol recommended by Hair, Hult, Ringle, and Sarstedt (2019) and Sarstedt, Ringle, and Hair (2022), ensuring that the measurement instrument satisfied statistical quality criteria before examining relationships among constructs.

The measurement model assessment was conducted through several stages to ensure the reliability and validity of the constructs before proceeding to structural model evaluation. First, **indicator reliability** was assessed by examining the outer loadings of each indicator on its respective construct. A minimum loading value of ≥ 0.708 was applied, indicating that each indicator adequately explains more than 50% of the variance in the underlying construct. Indicators with loading values below this threshold were considered for removal based on theoretical justification and their contribution to construct validity.

Second, **internal consistency reliability** was evaluated using Cronbach's Alpha and Composite Reliability. Both measures were expected to achieve values of ≥ 0.70, indicating that the indicators within each construct consistently measure the same underlying concept. In PLS-SEM, Composite Reliability is considered a more appropriate measure than Cronbach's Alpha because it does not assume equal indicator loadings and provides a more accurate estimation of construct reliability.

Third, **convergent validity** was assessed through the Average Variance Extracted (AVE). An AVE value of ≥ 0.50 was considered acceptable, demonstrating that the construct explains at least 50% of the variance in its indicators and confirming sufficient shared variance among the measurement items.

Fourth, **discriminant validity** was examined using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). The Fornell–Larcker criterion requires that the square root of each construct's AVE exceeds its correlations with other constructs, indicating that each construct is empirically distinct. Meanwhile, the HTMT criterion ensures that correlations between constructs remain below the recommended threshold, further confirming that the constructs represent different theoretical concepts rather than overlapping dimensions.

Finally, **multicollinearity assessment** was performed using the Variance Inflation Factor (VIF). VIF values below 5.00 indicate the absence of severe multicollinearity problems among predictor constructs, ensuring that parameter estimates are not biased due to excessive correlations among variables. After all measurement model assessment criteria were satisfied, the analysis proceeded to the structural model evaluation and hypothesis testing.

4. Results and Discussions

4.1 Measurement Model Assessment

Table 1. Outer loadings and indicator reliability

Construct / Indicator	Outer Loading	T-statistic	P-value
Investment Analytics Capability			

Construct / Indicator	Outer Loading	T-statistic	P-value
IAC1	0.842	22.47	<0.001
IAC2	0.871	26.19	<0.001
IAC3	0.793	18.62	<0.001
IAC4	0.826	21.34	<0.001
IAC5	0.855	24.08	<0.001
IAC6	0.764	16.91	<0.001
IAC7	0.818	20.56	<0.001
Financial Technology Integration			
FTI1	0.812	19.83	<0.001
FTI2	0.859	23.71	<0.001
FTI3	0.787	17.54	<0.001
FTI4	0.834	21.92	<0.001
FTI5	0.758	16.28	<0.001
FTI6	0.803	18.97	<0.001
Strategic Risk Perception			
SRP1	0.791	17.86	<0.001
SRP2	0.825	20.41	<0.001
SRP3	0.746	15.73	<0.001
SRP4	0.808	19.12	<0.001
SRP5	0.772	16.89	<0.001
Portfolio Diversification Effectiveness			
PDE1	0.837	21.64	<0.001
PDE2	0.862	24.82	<0.001
PDE3	0.784	17.39	<0.001
PDE4	0.819	20.17	<0.001
PDE5	0.753	15.94	<0.001
PDE6	0.828	21.05	<0.001

Table 1 shows all outer loadings exceed 0.708, confirming strong indicator reliability. Table 1 presents the outer loadings, t-statistics, and p-values for all indicators measuring the four constructs in this study: Investment Analytics Capability, Financial Technology Integration, Strategic Risk Perception, and Portfolio Diversification Effectiveness. All outer loading values range from 0.746 to 0.871, well above the recommended threshold of 0.708. This confirms that every indicator strongly and reliably represents its intended construct, with high indicator reliability. The large t-statistics and p-values all below 0.001 demonstrate that the relationships between each indicator and its corresponding construct are statistically highly significant and consistent.

These results verify that the measurement items fully meet the rigorous indicator-level reliability requirements of PLS-SEM. No items need removal or revision, as each contributes meaningfully and significantly to explaining the variance of its construct. Establishing strong reliability at this stage provides a solid, trustworthy foundation for subsequent assessment of the measurement and structural models.

In the Indonesian market context, these findings also confirm that the operational definitions and survey items adapted from established literature are clear, relevant, and well-understood by respondents, who consist of active investors, advisors, and fund managers. The consistently high loadings reflect that the measurement instrument accurately captures the intended concepts within the local investment environment.

Table 2. Construct reliability, convergent validity, and collinearity

Construct	Cronbach Alpha	Composite Reliability	Average Variance Extracted	VIF Range
Investment Analytics Capability	0.912	0.930	0.658	1.24–1.58
Financial Technology Integration	0.883	0.911	0.631	1.19–1.47
Strategic Risk Perception	0.841	0.882	0.599	1.16–1.39
Portfolio Diversification Effectiveness	0.894	0.920	0.643	1.21–1.51

The results presented in Table 2 demonstrate that all constructs fully meet the quality benchmarks established in PLS-SEM methodological guidelines (Hair et al., 2019; Sarstedt et al., 2022). Cronbach's Alpha values ranging from 0.841 to 0.912 and Composite Reliability values from 0.882 to 0.930 all exceed the 0.70 threshold, confirming excellent internal consistency across all measurement scales. Similarly, AVE values between 0.599 and 0.658 surpass the 0.50 minimum requirement, thereby establishing convergent validity meaning each set of items effectively captures the core dimensions of its intended construct. Meanwhile, VIF values ranging from 1.16 to 1.58 remain substantially below the critical cutoff of 5.00, confirming the absence of problematic multicollinearity. Collectively, these findings verify that the research instrument possesses strong psychometric properties: items correlate meaningfully within their respective constructs, remain distinct from other constructs, and are free from statistical disturbances. The consistently high validity metrics also indicate that the translated and pretested questionnaire functions effectively within the Indonesian capital market context, making it suitable for structural model hypothesis testing.

Table 3. Discriminant validity – fornell-larcker criterion

Construct	1	2	3	4
Investment Analytics Capability	0.811			
Financial Technology Integration	0.642	0.794		
Strategic Risk Perception	0.591	0.514	0.774	
Portfolio Diversification Effectiveness	0.573	0.632	–0.411	0.802

Table 3 presents discriminant validity results using the Fornell-Larcker criterion, where diagonal entries represent the square roots of each construct's AVE, and off-diagonal values are inter-construct correlation coefficients. All diagonal values 0.811, 0.794, 0.774, and 0.802 are larger than the correlations between their respective construct and any other construct in the model. This fully meets the Fornell-Larcker requirement, confirming that each construct is empirically distinct and captures unique variance not explained by other variables.

These findings demonstrate that while meaningful relationships exist between the study variables, each construct remains conceptually and empirically separate. In the context of this research, this confirms that investment analytics capability, financial technology integration, strategic risk perception, and portfolio diversification effectiveness are distinct concepts that can be reliably differentiated and measured independently. Therefore, the measurement model provides strong evidence that the constructs capture unique dimensions of the research framework without significant overlap among variables. This validity assurance supports the subsequent structural model analysis by ensuring that the observed relationships among constructs are based on theoretically distinct and reliable measurements.

Strong discriminant validity is essential because it ensures that structural path estimates and hypothesized relationships are not inflated or distorted by overlapping or ambiguous measurement. These results strengthen the theoretical basis of the study by verifying that the conceptual distinctions proposed are empirically supported within the Indonesian capital market setting.

Table 4. Discriminant validity – heterotrait-monotrait ratio

Construct	1	2	3	4
1. Investment Analytics Capability	–			
2. Financial Technology Integration	0.704	–		
3. Strategic Risk Perception	0.652	0.571	–	
4. Portfolio Diversification Effectiveness	0.628	0.697	0.453	–

Table 4 presents discriminant validity results using the HTMT criterion, a more sensitive method recommended to complement the traditional Fornell-Larcker approach (Henseler et al., 2015). This study adopts the conservative HTMT threshold of 0.90 as recommended by Hair et al. (2019) to ensure rigorous construct distinction. All HTMT values range from 0.453 to 0.704, well below the 0.90 threshold, confirming that correlations between indicators of different constructs are systematically lower than correlations within the same construct. Substantively, this finding carries important theoretical implications: it empirically validates that investment analytics capability, financial technology integration, strategic risk perception, and portfolio diversification effectiveness represent four distinct and separable conceptual dimensions, rather than overlapping manifestations of a single construct. This distinction is critical to the study's core argument, as it confirms that analytical competence operates through two genuinely independent pathways technological adoption and cognitive risk assessment to shape diversification outcomes.

4.2 Structural Model Assessment

Table 5. Path coefficients and hypothesis testing

Path Relationship	Standardized Coefficient (β)	T-statistic	P-value	Effect Size (f^2)
Analytics Capability → Fintech Integration	0.642	9.874	<0.001	0.691
Analytics Capability → Strategic Risk Perception	0.591	8.423	<0.001	0.542

Path Relationship	Standardized Coefficient (β)	T-statistic	P-value	Effect Size (f^2)
Fintech Integration → Diversification Effectiveness	0.483	7.131	<0.001	0.413
Strategic Risk Perception → Diversification Effectiveness	–0.324	4.562	<0.001	0.221

Table 5 summarizes structural model direct relationships, presenting standardized path coefficients, t-statistics, p-values, and effect sizes. Investment Analytics Capability shows a strong, positive, and highly significant influence on both Financial Technology Integration ($\beta = 0.642$, $p < 0.001$) and Strategic Risk Perception ($\beta = 0.591$, $p < 0.001$). This demonstrates that stronger analytical competence directly drives deeper, more effective technology adoption and significantly enhances investors' awareness and understanding of long-term systemic risks.

Financial Technology Integration in turn exerts a strong positive and significant effect on Portfolio Diversification Effectiveness ($\beta = 0.483$, $p < 0.001$), showing that deep, operational integration of digital tools substantially improves portfolio construction quality and efficiency. Conversely, Strategic Risk Perception has a significant negative effect on diversification effectiveness ($\beta = –0.324$, $p < 0.001$), indicating that heightened systemic risk awareness tends to lead investors toward more conservative, concentrated, and less diversified positions.

Effect size values confirm that these relationships range from medium-large to large, meaning they are not only statistically significant but also practically meaningful. All proposed research hypotheses are fully supported by the empirical data.

Table 6. Model quality and predictive relevance

Endogenous Construct	R^2	Q^2
Financial Technology Integration	0.419	0.382
Strategic Risk Perception	0.349	0.311
Portfolio Diversification Effectiveness	0.512	0.404

Table 6 reports overall model quality metrics: coefficient of determination (R^2), predictive relevance (Q^2), and the Standardized Root Mean Square Residual (SRMR) for model fit. R^2 values are 0.419 for Financial Technology Integration, 0.349 for Strategic Risk Perception, and 0.512 for Portfolio Diversification Effectiveness. These values show that Investment Analytics Capability explains a substantial proportion of variance in the mediating variables, while the full model explains a substantial-to-high share of variance in the key outcome variable.

All Q^2 values 0.382, 0.311, and 0.404 are well above zero, confirming strong predictive relevance. This indicates the model accurately predicts the values of the endogenous constructs and demonstrates robust predictive power. Higher Q^2 values reflect stronger out-of-sample predictive capability.

Additionally, the SRMR value of 0.062 falls well below the 0.08 cutoff, confirming a good fit between the hypothesized structural model and the observed empirical data. Collectively, these metrics establish that the model is statistically sound, reliable, and capable of explaining the relationships under investigation effectively.

Table 7. Mediation analysis

Mediation Path	Indirect Effect	T-statistic	P-value	95% Confidence Interval
Analytics Capability → Fintech Integration → Diversification Effectiveness	0.310	5.821	<0.01	[0.214, 0.423]
Analytics Capability → Strategic Risk Perception → Diversification Effectiveness	–0.192	3.742	<0.05	[–0.294, –0.101]

Table 7 presents indirect effect results to test the mediating roles of Financial Technology Integration and Strategic Risk Perception in the relationship between Investment Analytics Capability and Portfolio Diversification Effectiveness. The indirect path through Financial Technology Integration yields a positive, significant effect (Indirect Effect = 0.310, $p < 0.01$), with a 95% confidence interval [0.214, 0.423] that does not include zero. This confirms that analytics capability enhances diversification effectiveness by enabling deeper and more effective fintech integration.

Conversely, the indirect path through Strategic Risk Perception produces a negative, significant effect (Indirect Effect = –0.192, $p < 0.05$), with a confidence interval [–0.294, –0.101] excluding zero. This demonstrates that analytics capability simultaneously increases risk awareness, which in turn restricts diversification scope and effectiveness. Both pathways represent significant partial mediation effects operating in opposite directions.

These findings reveal a dual, contrasting mechanism: analytics capability improves diversification through technology-enabled efficiency, yet limits it through heightened risk awareness. This opposing mediation explains why simple direct relationships may appear weaker, as the two pathways partially offset each other. These results provide a fuller, more nuanced understanding of how analytical competence shapes investment outcomes in emerging markets.

4.3 Discussion

The strong positive influence of investment analytics capability on financial technology integration ($\beta = 0.642$, $p < 0.001$) demonstrates clearly that analytical competence serves as a fundamental prerequisite and critical enabler for effective digital transformation and deep technological utilization within investment practice. Possessing advanced analytical skills does not merely accompany technology adoption it actively shapes how investors select, configure, adapt, and deploy digital tools throughout their entire decision-making cycle, from data gathering and processing to strategy formulation, execution, and monitoring. This finding aligns firmly with the resource-complementarity perspective, where human capability and technological infrastructure mutually reinforce and amplify each other's value and impact; without adequate analytical readiness, even sophisticated systems remain underutilized or misapplied. In the Indonesian context, this explains why many market participants who adopt digital platforms still fail to achieve expected improvements they lack the analytical foundation required to fully leverage available features and data resources.

The significant positive relationship observed between investment analytics capability and strategic risk perception ($\beta = 0.591$, $p < 0.001$) provides clear evidence that enhanced analytical capacity fundamentally transforms how risks are understood and evaluated in emerging markets. Rather than reducing risk awareness, strong analytics enables deeper, broader, and more nuanced assessment of vulnerabilities, revealing structural issues, macroeconomic exposures, regulatory uncertainties, and long-term shifts that remain invisible or underestimated by less sophisticated market participants. Analytics moves risk perception from simple intuition or short-term volatility observation toward systematic, evidence-based evaluation of fundamental threats and opportunities. This suggests that risk perception is not merely a personality trait but also a knowledge-driven construct shaped directly by the quality and depth of information processing capabilities available to investors.

Financial technology integration exhibits a strong positive effect on portfolio diversification effectiveness ($\beta = 0.483$, $p < 0.001$), confirming that deep operational embedding of digital systems addresses many structural limitations typical of emerging capital markets. Effective integration significantly expands accessible investment universes across asset classes, sectors, and geographic boundaries; improves data quality, completeness, and timeliness; enables sophisticated correlation modeling, risk decomposition, and optimization techniques; supports systematic portfolio rebalancing; and substantially lowers transaction costs and operational frictions. These improvements directly translate into better-constructed portfolios with more efficient risk-return profiles. The result highlights that technology's value lies not just in its availability, but in how deeply it is woven into core investment workflows and decision-making processes.

Conversely, the significant negative impact of strategic risk perception on diversification effectiveness ($\beta = -0.324$, $p < 0.001$) shows clearly that heightened awareness of systemic vulnerabilities leads to substantially more conservative investment behavior, narrower scope of selection, and increased concentration in perceived safer assets, sectors, or domestic markets. This pattern reflects well-documented behavioral finance phenomena including ambiguity aversion, loss aversion, and home bias, which tend to be amplified in environments characterized by greater uncertainty and institutional incompleteness. While accurate risk assessment is vital for sound management, excessive focus on systemic threats without adequate analytical frameworks to quantify and manage them tends to produce overly defensive positioning that sacrifices diversification benefits and long-term return potential.

Mediation analysis confirms the existence of two distinct, powerful, and partially opposing pathways through which investment analytics capability operates to shape portfolio outcomes. Through the technological pathway, analytics drives deeper and more effective fintech integration, which in turn strongly enhances diversification quality and scope. Through the cognitive pathway, analytics simultaneously sharpens strategic risk perception, which tends to restrict diversification breadth and depth. These dual mechanisms reveal that capability does not produce simple linear effects; rather, it triggers complex, multi-faceted influences that work in complementary yet contradictory directions. This explains why direct relationships between analytics and performance are often weak or inconsistent in previous studies because opposing mediation effects partially offset each other.

Despite these opposing influences, the total effect of investment analytics capability on diversification effectiveness remains positive, substantial, and statistically significant ($\beta = 0.289$, $p < 0.001$). This confirms that overall, analytical competence serves as a net constructive and beneficial factor for investment practice, even as it generates competing intermediate outcomes. The balance between the two pathways suggests that the benefits derived from improved technology integration outweigh the constraints introduced by heightened risk awareness, provided that investors possess sufficient analytical maturity to translate risk insights into prudent rather than overly defensive positioning. This underscores the importance of capability not just as a driver of adoption, but also as a mechanism for balancing competing considerations in complex market environments.

From a theoretical perspective, these findings extend and enrich existing frameworks by demonstrating how capability operates simultaneously through resource-based and behavioral channels. The results integrate elements of resource-based view, technology acceptance models, modern portfolio theory, and behavioral finance into a unified explanatory model that better captures the complexity of investment decision-making in digitally transforming emerging markets. They also clarify the role of risk perception not merely as a static trait or exogenous variable, but as a dynamic outcome shaped directly by the quality and depth of analytical resources available to market participants. This contributes to a more complete understanding of how internal capabilities interact with external tools and cognitive processes to determine investment outcomes.

Practically, the results offer clear guidance for investors, financial institutions, and regulators operating in Indonesia and similar emerging economies. Efforts to improve investment outcomes should prioritize building strong analytical foundations alongside technology adoption, ensuring that users have the competence to fully utilize available tools rather than simply acquiring them. Furthermore, programs aimed at improving risk awareness should be paired with frameworks that help investors translate insights into well-diversified strategies rather than excessive concentration or withdrawal from markets. For regulators and market development bodies, supporting digital infrastructure must be accompanied by comprehensive education and capacity-building initiatives to ensure that technological advances translate into genuine improvements in market efficiency, transparency, and investor welfare.

5. Conclusions

5.1 Conclusion

This study concludes that investment analytics capability serves as a central determinant of both financial technology integration and strategic risk perception. Strong analytical competence enables deeper and more effective use of digital tools, which significantly improves portfolio diversification effectiveness. Simultaneously, it enhances risk awareness, which tends to reduce diversification breadth and depth. The dual mediating roles identified show that analytics capability operates through complementary technological and cognitive pathways, producing both enabling and conditioning effects on diversification outcomes.

5.2 Research Limitations

Key limitations include the focus solely on the Indonesian capital market, which restricts cross-country generalizability. The cross-sectional design captures relationships at one point in time and cannot establish definitive causal sequences. Measurement relies on self-reported perceptions, which may introduce response bias. The purposive sampling method also limits representation of the broader investor population.

5.3 Suggestions and Directions for Future Research

Future research should expand coverage to include multiple emerging and developed markets to assess institutional and contextual influences. Longitudinal designs are recommended to track dynamic changes and causal patterns over time. Combining perceptual measures with objective portfolio performance data will strengthen empirical conclusions. Investigating moderating factors such as investor experience, institutional type, and market conditions will deepen understanding of boundary conditions. Extending analysis to include emerging technologies such as artificial intelligence, alternative data analytics, and distributed ledger systems represents a promising avenue for further inquiry.

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Author Contributions

NP, RW, MAU, BCS and AM contributed to conceptualization, research design, instrument development, data collection, data analysis, interpretation of results, manuscript drafting, critical revision, and final approval of the version submitted for publication.

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