

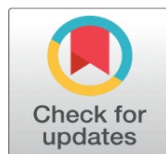
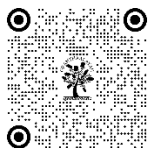
COMPARATIVE ANALYSIS OF TRADITIONAL AND MODERN FINANCIAL MODELS IN INVESTMENT DECISION MAKING

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ABSTRACT

This research paper investigates the comparative effectiveness of traditional financial models, such as the Capital Asset Pricing Model (CAPM) and Discounted Cash Flow (DCF) analysis, versus modern models, including Machine Learning algorithms and Behavioral Finance models, in investment decision-making. The study aims to determine whether modern financial models provide more accurate and reliable investment predictions, especially under volatile market conditions, and how the integration of these models influences overall investment performance. A quantitative methodology was employed, utilizing a survey of 100 investment professionals with varying levels of experience. The data collected was analyzed through statistical tests, including Independent Samples T-Test, Paired Samples T-Test, Multiple Regression Analysis, Chi-Square Test, and Pearson Correlation. The findings reveal that modern financial models are perceived as more reliable and effective in predicting investment outcomes compared to traditional models. Additionally, the integration of modern and traditional models enhances investment decision-making performance. The study also highlights a significant association between the level of experience and model preference, with more experienced professionals favoring traditional models. These results have important implications for investment professionals, suggesting that the adoption of modern financial models can lead to improved investment outcomes, particularly when combined with traditional approaches. Future research could explore the long-term performance implications of these models in different economic environments.

Keywords: Investment Decision-Making, CAPM, DCF Analysis, Machine Learning, Behavioral Finance, Financial Models, Quantitative Analysis



1. INTRODUCTION

Investment decision-making is a critical aspect of financial management, encompassing the processes by which individuals, companies, and institutions allocate resources to maximize returns while managing risk (Silva et al. (2023); Erfani and Tavakolan (2023)). Financial models play a pivotal role in this process by providing structured approaches to analyzing market data, forecasting returns, and assessing risk (Jiang et al. (2023); Md Husin et al. (2023); Skare et al. (2023)). Traditional financial models such as the Capital Asset Pricing Model (CAPM) and Discounted Cash Flow (DCF) analysis have long been the cornerstone of investment analysis, offering a theoretical framework for evaluating the expected returns of assets and determining their intrinsic value (Hofmann et al. (2008)).

In recent years, however, the landscape of financial modeling has evolved with the advent of modern approaches such as Machine Learning algorithms and Behavioral Finance models (Ahmad (2023); Beisenbina et al. (2023); Jing et al. (2023)). These models incorporate advanced computational techniques and psychological insights to account for factors

that traditional models may overlook, such as market sentiment, investor behavior, and complex, non-linear relationships between variables. As financial markets become increasingly volatile and unpredictable, there is a growing need to assess the relative effectiveness of these traditional and modern models in guiding investment decisions (Alkaraan & Northcott (2006)).

While traditional financial models have provided robust frameworks for investment decision-making, their assumptions and limitations have come under scrutiny in today's complex financial environment (Roberts & Henneberry (2007); Pavlaková Dočekalová & Kocmanová (2018)). For instance, traditional models often assume rational behavior and efficient markets, assumptions that may not hold true in all scenarios. In contrast, modern financial models offer more flexible, data-driven approaches that can adapt to changing market dynamics. However, the efficacy of these modern models relative to their traditional counterparts remains a topic of debate among practitioners and academics alike.

The primary problem this research addresses is the lack of a comprehensive comparative analysis of traditional and modern financial models in the context of investment decision-making. Understanding the strengths and limitations of each approach, particularly in volatile market conditions, is crucial for investors seeking to optimize their decision-making processes.

The objectives of this study are as follows:

1. To compare the predictive accuracy and reliability of traditional financial models (CAPM, DCF) versus modern models (Machine Learning, Behavioral Finance) in investment decision-making.
2. To evaluate the impact of integrating traditional and modern financial models on overall investment performance.
3. To explore the relationship between investment professionals' experience levels and their preference for traditional versus modern financial models.
4. To assess the perceived usefulness of modern financial models in challenging the results derived from traditional models.

This study seeks to answer the following key research questions:

1. Do modern financial models provide more accurate and reliable predictions in investment decision-making compared to traditional models?
2. How does the integration of traditional and modern financial models affect investment performance?
3. What is the relationship between the experience level of investment professionals and their preference for financial models?
4. How do investment professionals perceive the usefulness of modern financial models in comparison to traditional models?

Based on the research objectives and questions, the following hypotheses have been formulated:

H1: Investment professionals who use modern financial models, such as Machine Learning algorithms and Behavioral Finance models, exhibit higher confidence in the accuracy of their investment predictions compared to those who use traditional models like CAPM and DCF.

H2: Modern financial models, including Machine Learning algorithms and Behavioral Finance models, significantly outperform traditional models like CAPM and DCF in predicting investment outcomes in volatile market conditions.

H3: The integration of modern financial models with traditional models results in improved overall investment decision-making performance.

H4: Investment professionals with more than 10 years of experience are more likely to rely on traditional financial models like CAPM and DCF compared to those with less experience, who tend to prefer modern models like Machine Learning algorithms and Behavioral Finance models.

H5: The frequency of modern financial models challenging the results of traditional models is positively correlated with the perceived usefulness of modern financial models among investment professionals.

H6: The perceived impact of modern financial models on investment performance is more positive among professionals who consider technological integration and adaptability as critical factors in model selection.

1.1 SIGNIFICANCE OF THE STUDY

This research is significant in the field of finance as it addresses a contemporary issue faced by investment professionals: choosing the most appropriate financial model to guide investment decisions. By providing a comparative analysis of traditional and modern financial models, this study contributes to the understanding of their respective strengths and weaknesses, offering practical insights for investors. Furthermore, the findings can inform the development of hybrid

approaches that combine the best elements of both traditional and modern models, ultimately enhancing the decision-making process in an increasingly complex financial environment.

2. LITERATURE REVIEW

The existing body of literature on financial decision-making, data analytics, behavioral finance, and strategic investment practices presents a diverse range of methodologies and findings, reflecting the complex nature of these domains. This review synthesizes insights from various studies, highlighting key themes and identifying research gaps that warrant further exploration.

Udo et al. (2023) provide a comprehensive analysis of theoretical approaches to data analytics and decision-making in the finance sectors of Africa and the United States. The study reveals that economic, technological, and regulatory landscapes significantly influence the adoption and implementation of these approaches in different regions. While the United States benefits from a mature financial sector and technological advancement, Africa's diverse and dynamic markets require adaptations to these theories, often leading to innovative solutions in mobile banking and fintech.

Mikhaylov et al. (2023) investigate the factors affecting financial development and open innovation in emerging economies, using advanced methodologies such as the MF-X-DMA method and a novel fuzzy decision-making model. The study identifies key indicators, including bank lending and equity market development, that enhance financial development. It also highlights the role of competition and access to information in driving innovation in these markets. The findings suggest a strong link between financial development and the open innovation potential of fintech in emerging economies.

A significant portion of the literature focuses on the role of behavioral finance in shaping investment decisions. Abdeldayem and Aldulaimi (2023) explore the impact of behavioral factors such as herding behavior, prospect theory, and heuristic biases in the GCC cryptocurrency market. Their findings underscore the importance of these behavioral factors in influencing investment choices, particularly during market volatility.

Similarly, Kumar et al. (2023) examine the behavioral, psychological, and demographic determinants of financial decision-making among household investors. Their study emphasizes the role of digital financial literacy and impulsivity in shaping investment behaviors, with significant differences observed across gender lines.

Almansour et al. (2023) extend this exploration to the Saudi equity markets, focusing on how behavioral finance factors influence risk perception and investment decision-making. Their research reveals that herding, disposition effect, and overconfidence significantly affect how investors perceive and respond to risk, ultimately impacting their investment choices.

Odonkor et al. (2023) delve into the transformative impact of artificial intelligence (AI) on traditional accounting practices. Their study highlights AI's role in enhancing the accuracy and efficiency of financial reporting and decision-making processes. Despite these benefits, the integration of AI poses challenges, such as the need for skilled personnel and concerns over data privacy. The study calls for a balanced approach to AI adoption, emphasizing the importance of ethical considerations and regulatory compliance.

The integration of Industry 4.0 technologies with sustainable strategic investment decision-making practices (SSIDMP) is another critical area explored in the literature. Alkaraan et al. (2023) and Alkaraan et al. (2023) discuss the synergy between Industry 4.0 technologies and circular economy techniques in enhancing organizational performance. Their findings suggest that governance mechanisms, such as ESG and board compositions, play a crucial role in leveraging these technologies to achieve sustainable business outcomes.

Suresh (2023) investigates the combined impact of financial literacy and behavioral biases on investment decision-making. The study finds that heuristic bias significantly influences investment decisions, often leading to irrational behavior. Suresh emphasizes the need for financial literacy to mitigate these biases and promote more informed investment choices.

Several studies highlight the cultural and regional differences in financial decision-making. For instance, Abdeldayem and Aldulaimi (2023) focus on the GCC region, while Almansour et al. (2023) explore the Saudi equity markets. Both studies underscore the significant impact of cultural context on behavioral finance factors and investment decisions, suggesting that these factors may vary widely across different regions.

RESEARCH GAP

Author(s)	Year	Proposed Methodology	Results	Research Gap
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Udo, W. S., Ochuba, N. A., Akinrinola, O., &Ololade, Y. J.	2023	Comparative analysis of theoretical approaches to data analytics and decision-making in finance sectors of Africa and the US	Identified distinct practices influenced by economic, technological, and regulatory landscapes; highlighted the role of cultural and economic factors.	Need for empirical validation of theoretical approaches across diverse economic and cultural contexts; exploration of specific case studies to understand practical applications.
Mikhaylov, A., Dinçer, H., &Yüksel, S.	2023	MF-X-DMA method, regression analysis, fuzzy decision-making model	Found significant factors affecting financial development and open innovation in emerging economies; identified risks associated with globalization.	Further exploration of the integration of emerging technologies in financial development and open innovation, especially in addressing challenges faced by emerging economies.
Abdeldayem, M., &Aldulaimi, S.	2023	Cross-sectional absolute deviation methodology, questionnaire survey	Behavioral finance factors like herding and heuristic biases significantly impact investment decisions in the GCC cryptocurrency market.	Need for more studies on behavioral finance factors in different cultural contexts, especially in the Middle East and North Africa; exploration of additional behavioral factors.
Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., &Farayola, O. A.	2023	Systematic literature review, bibliometric analysis	AI integration in accounting enhances accuracy and efficiency but presents challenges like the need for skilled personnel and data privacy concerns.	Need for empirical studies on AI's impact on accounting practices, particularly in different organizational and regulatory environments; exploration of strategies to overcome challenges.
Alkaraan, F., Floyd, D., Rahman, M., &Nuery, N.	2023	Qualitative analysis using secondary data	Found positive synergy between Industry 4.0 technologies and circular economy techniques; governance mechanisms strengthen the impact on financial performance.	Further research needed to explore the implementation of Industry 4.0 technologies and circular economy techniques in different industrial and cultural contexts.
Suresh, G.	2023	SEM technique, questionnaire survey	Identified significant influence of heuristic bias and financial literacy on investment decision-making.	Need for studies examining the impact of financial literacy interventions on reducing behavioral biases; exploration of these factors in different demographic and cultural settings.
Kumar, P., Islam, M. A., Pillai, R., & Sharif, T.	2023	Structured questionnaire, PLS-SEM, multi-group analysis	Found that digital financial literacy and impulsivity significantly affect financial decision-making; identified gender differences in decision-making.	Further research needed to explore the impact of digital financial literacy and impulsivity on decision-making in different demographic groups; need for cross-cultural studies.
Almansour, B. Y., Elkrggli, S., &Almansour, A. Y.	2023	Structural equation modeling (SEM), online questionnaire	Identified significant positive impact of herding behavior, disposition effect, and overconfidence on investment decision-making in Saudi equity markets.	Further research needed to investigate other behavioral finance factors and their impact on investment decisions in different cultural contexts.
Palakurti, N. R.	2023	Systematic literature review, case study analysis	Explored Financial Network Analytics (FNA) as a tool for systemic risk	Need for empirical studies to validate the theoretical findings and explore FNA's

			management and investment analysis; highlighted FNA's potential in addressing systemic risks.	application across different financial contexts and markets.
Alkaraan, F., Elmarzouky, M., Hussainey, K., & Venkatesh, V. G.	2023	Computer-aided textual analysis, empirical study	Found synergy between Industry 4.0 technologies and circular economy techniques influences sustainable strategic investment decision-making in UK companies.	Need for further exploration of the impact of these synergies in other geographical regions and industries, with a focus on different governance mechanisms and regulatory contexts.
Suresh, G.	2023	SEM technique, questionnaire survey	Found that heuristic bias and financial literacy significantly impact investment decision-making; heuristic bias drives speculative decisions.	Need for studies examining the impact of financial literacy on reducing heuristic bias and other behavioral biases in different demographic settings.
Kumar, P., Islam, M. A., Pillai, R., & Sharif, T.	2023	Structured questionnaire, PLS-SEM, multi-group analysis	Identified digital financial literacy, financial capability, and impulsivity as key factors influencing financial decision-making; highlighted gender differences.	Further research needed to explore the role of digital financial literacy and impulsivity in financial decision-making across different cultural and demographic settings.
Abdeldayem, M., & Aldulaimi, S.	2023	Cross-sectional absolute deviation methodology, questionnaire survey	Identified herding behavior, prospect theory, and heuristic biases as significant influences on investment decisions in the GCC cryptocurrency market.	Need for further studies on the impact of behavioral finance factors in different cultural and regional contexts, particularly in emerging markets.
Almansour, B. Y., Elkrgli, S., & Almansour, A. Y.	2023	Structural equation modeling (SEM), online questionnaire	Identified herding behavior, disposition effect, and overconfidence as significant influences on risk perception and investment decision-making in the Saudi equity markets.	Need for further research on the impact of other behavioral finance factors and risk perception in different cultural and economic contexts.

3. METHODOLOGY

3.1 RESEARCH DESIGN

This study adopts a quantitative research design to investigate the comparative effectiveness of traditional and modern financial models in investment decision-making. The quantitative approach is chosen for its ability to provide objective, numerical data that can be analyzed statistically to test the hypotheses. The study aims to measure the perceptions, preferences, and outcomes associated with the use of different financial models among investment professionals.

3.2 SAMPLE SELECTION

The sample for this study is denoted as $n=100$, where nnn represents the total number of investment professionals. The sample includes individuals from three distinct professional categories: investment analysts (n_1), portfolio managers (n_2), and financial advisors (n_3), such that $n = n_1 + n_2 + n_3$.

The selection of participants was based on a combined sampling approach, where:

- **PURPOSIVE SAMPLING:** Ensured participants had specific characteristics, such as experience and familiarity with financial models, denoted as $E \geq 3$ years, where E represents the number of years of experience in investment decision-making.
- **CONVENIENCE SAMPLING:** Allowed for practical access to participants across various sectors within the financial industry.

The inclusion criteria are expressed as:

$$E \geq 3 \text{ years}$$

$$F(x) \neq \emptyset$$

Where, $F(x)$ is the function representing familiarity with at least one type of financial model, and x indicates the type of model (traditional or modern).

The sample was designed to ensure a diverse representation across different levels of experience (E_i for i th participant) and sectors (S_j for j th sector), ensuring that:

$$\sum_{i=1}^n E_i \text{ and } \sum_{j=1}^m S_j$$

adequately cover a wide range of professional backgrounds and expertise within the financial industry.

3.3 DATA COLLECTION

Data was collected using a structured questionnaire distributed electronically to 100 investment professionals. The questionnaire was designed to capture key information, including demographic characteristics, preferences for traditional financial models such as the Capital Asset Pricing Model (CAPM) and Discounted Cash Flow (DCF) analysis, and modern models like Machine Learning algorithms and Behavioral Finance models. Participants were asked about their confidence levels in the predictions made by these models, as well as their perceived performance in different market conditions. The questionnaire also included sections on the frequency of using and challenging the results of these models, and the perceived usefulness of each model type in supporting investment decision-making. Most questions employed a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) to quantify responses, ensuring the data could be systematically analyzed for statistical insights.

3.4 VARIABLES

3.4.1 INDEPENDENT VARIABLES:

1. **TYPE OF FINANCIAL MODEL USED (X_1):** This variable is categorized into traditional models (M_T) such as CAPM and DCF, and modern models (M_M) such as Machine Learning algorithms and Behavioral Finance models. This can be represented as:

$$X_1 = \begin{cases} M_T & \text{if Traditional Models (CAPM, DCF)} \\ M_M & \text{if Modern Models (Machine Learning, Behavioral Finance)} \end{cases}$$

2. **EXPERIENCE LEVEL OF INVESTMENT PROFESSIONALS (X_2):** This variable is categorized by years of experience, represented as:

$$X_2 = \text{YearsofExperience}(< 5, 5 - 10, > 10)$$

3. **IMPORTANCE PLACED ON TECHNOLOGICAL INTEGRATION AND ADAPTABILITY (X_3):** This variable measures the emphasis placed on technological factors in model selection, which can be quantified on a Likert scale or as a binary variable:

$$X_3 = \begin{cases} 1 & \text{if High Importance} \\ 0 & \text{if Low Importance} \end{cases}$$

3.4.2 Dependent Variables:

1. **CONFIDENCE LEVELS IN THE ACCURACY OF INVESTMENT PREDICTIONS (Y_1):** This variable represents the confidence levels of professionals in their model predictions, typically measured on a Likert scale:

$$Y_1 = \text{ConfidenceLevel}$$

2. **PERCEIVED ACCURACY AND RELIABILITY OF MODEL PREDICTIONS (Y_2):** This variable measures how accurate and reliable the model predictions are perceived to be, also typically measured on a Likert scale:

$$Y_2 = \text{Perceived Accuracy and Reliability}$$

3. **INVESTMENT PERFORMANCE OUTCOMES IN VOLATILE MARKET CONDITIONS (Y_3):** This variable represents the performance of the models under volatile market conditions, often measured as a numerical score or percentage:

$$Y_3 = \text{Performance Outcome}$$

4. **PERCEIVED USEFULNESS OF MODERN MODELS IN CHALLENGING TRADITIONAL MODEL RESULTS (Y_4):** This variable captures the usefulness of modern models in providing alternative insights compared to traditional models:

$$Y_4 = \text{Perceived Usefulness}$$

5. **OVERALL INVESTMENT DECISION-MAKING PERFORMANCE (Y_5):** This variable represents the overall effectiveness of the investment decisions made using the models, which could be quantified through various performance metrics:

$$Y_5 = \text{Overall Performance}$$

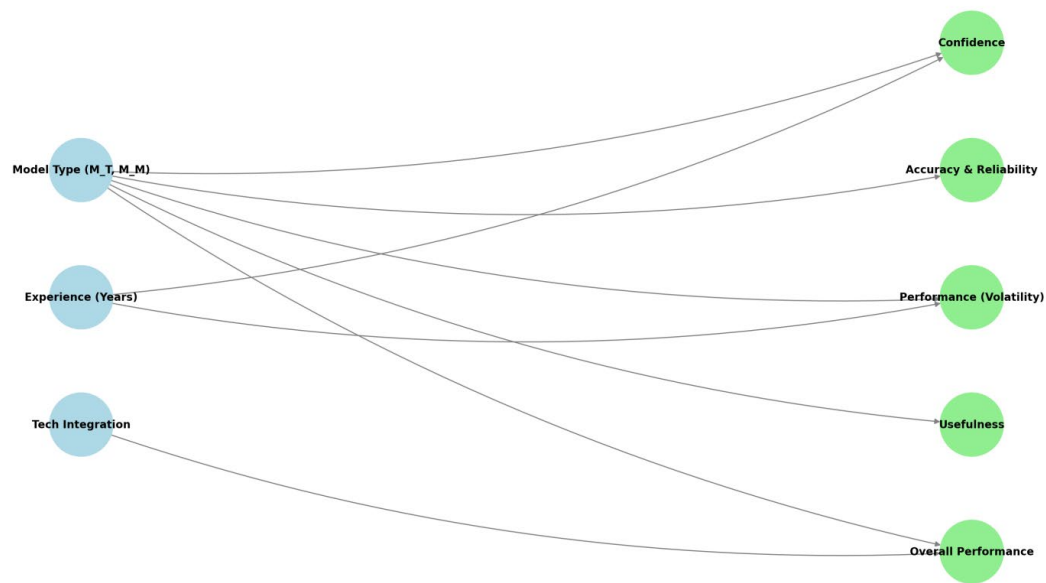


Figure 1: Relationships Between Independent and Dependent Variables in Financial Model Analysis

The diagram illustrates the relationships between independent variables—Model Type (X_1), Experience (X_2), and Technological Integration (X_3)—and dependent variables—Confidence (Y_1), Accuracy & Reliability (Y_2), Performance in Volatile Conditions (Y_3), Usefulness (Y_4), and Overall Performance (Y_5). Specifically, it shows that the type of financial model used (X_1) influences all five dependent variables, indicating that the choice between traditional and modern models affects confidence levels, perceived accuracy, performance outcomes, perceived usefulness, and overall investment decision-making performance. The experience level of investment professionals (X_2) affects their confidence and performance in volatile markets, suggesting that more experienced professionals may have different perceptions and results compared to less experienced ones. Finally, the importance placed on technological integration and adaptability (X_3) directly impacts overall performance, highlighting the role of advanced technologies in enhancing investment decisions. This comprehensive visual representation underscores the interconnectedness of various factors influencing investment outcomes.

3.5 HYPOTHESES DEVELOPMENT

Hypothesis 1:

- **NULL HYPOTHESIS (H_0):** $\mu_{M_M} = \mu_{M_T}$

There is no significant difference in the confidence levels (μ) of investment professionals using modern financial models (M_M) compared to those using traditional financial models (M_T).

- **ALTERNATE HYPOTHESIS (H_1):** $\mu_{M_M} > \mu_{M_T}$

Investment professionals using modern financial models (M_M) have significantly higher confidence levels (μ) in their investment predictions compared to those using traditional financial models (M_T).

Hypothesis 2:

- **NULL HYPOTHESIS (H_0):** $\mu_{P_{M_M}} \leq \mu_{P_{M_T}}$

Modern financial models (M_M) do not significantly outperform traditional models (M_T) in predicting investment outcomes (P) in volatile market conditions.

- **ALTERNATE HYPOTHESIS (H_1):** $\mu_{P_{M_M}} > \mu_{P_{M_T}}$

Modern financial models (M_M) significantly outperform traditional models (M_T) in predicting investment outcomes (P) in volatile market conditions.

Hypothesis 3:

- **NULL HYPOTHESIS (H_0):** $\mu_{P_C} = \mu_{P_T} + \mu_{P_M}$

The integration of traditional (M_T) and modern (M_M) financial models does not result in a significant improvement in overall investment performance (P_C).

- **ALTERNATE HYPOTHESIS (H_0):** $\mu_{P_C} > \mu_{P_T} + \mu_{P_M}$

The integration of traditional (M_T) and modern (M_M) financial models results in a significant improvement in overall investment performance (P_C).

Hypothesis 4:

- **NULL HYPOTHESIS (H_0):** $\rho_{E,P} = 0$

Here, is no significant association (ρ) between the experience level (E) of investment professionals and their preference (P) for traditional (M_T) versus modern financial models (M_M).

- **ALTERNATE HYPOTHESIS (H_1):** $\rho_{E,P} \neq 0$

Here, is a significant association (ρ) between the experience level (E) of investment professionals and their preference (P) for traditional (M_T) versus modern financial models (M_M).

Hypothesis 5:

- **NULL HYPOTHESIS (H_0):** $\rho_{F,U} = 0$

There is no significant correlation (ρ) between the frequency (F) of modern financial models challenging traditional model results and the perceived usefulness (U) of modern models among investment professionals.

- **ALTERNATE HYPOTHESIS (H_0):** $\rho_{F,U} > 0$

There is a significant positive correlation (ρ) between the frequency (F) of modern financial models challenging traditional model results and the perceived usefulness (U) of modern models among investment professionals.

Hypothesis 6:

- **NULL HYPOTHESIS (H_0):** $\mu_{P_L} = \mu_{P_H}$

The perceived impact of modern financial models on investment performance (μ_p) is not significantly influenced by the level of importance placed on technological integration and adaptability (L or H) in model selection.

- **ALTERNATE HYPOTHESIS (H_1):** $\mu_{P_L} < \mu_{P_H}$

The perceived impact of modern financial models on investment performance (μ_p) is significantly more positive among professionals who consider technological integration and adaptability (L or H) in model selection.

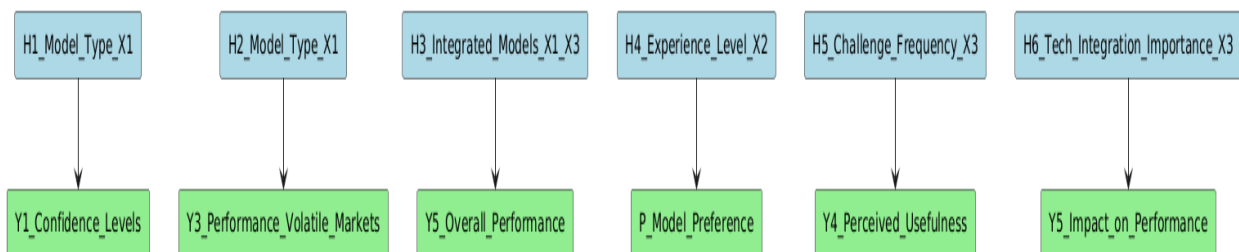


Figure 2: Conceptual Framework of Hypotheses and Variable Relationships in Financial Model Analysis

The diagram illustrates the conceptual framework of the study, depicting the relationships between the hypotheses and the corresponding independent and dependent variables. Each hypothesis (H1 to H6) is linked to specific variables, showing how the type of financial model used (X1), experience level (X2), and technological integration (X3) influence various outcomes such as confidence levels (Y1), performance in volatile markets (Y3), overall performance (Y5), model preference (P), perceived usefulness (Y4), and impact on performance (Y5).

preference (P), and perceived usefulness (Y4). The framework highlights the central role of financial model type and integration in determining key performance metrics and investor perceptions, providing a structured approach to testing and validating the study's research questions.

3.6 DATA ANALYSIS TECHNIQUES

The data collected was analyzed using a range of statistical techniques, each tailored to test specific hypotheses formulated in the study:

1. INDEPENDENT SAMPLES T-TEST (t):

$$t = \frac{\bar{X}_{M_M} - \bar{X}_{M_T}}{\sqrt{\frac{s_{M_M}^2}{n_{M_M}} + \frac{s_{M_T}^2}{n_{M_T}}}}$$

This test was used to compare the mean confidence levels ($\bar{X}$) between users of modern financial models (M_M) and traditional financial models (M_T).

2. PAIRED SAMPLES T-TEST (t_p):

$$t_p = \frac{D}{s_D/\sqrt{n}}$$

Where, D is the mean difference between paired observations, s_D is the standard deviation of the differences, and n is the number of pairs. This test was employed to compare the performance outcomes (P_{M_T} vs. P_{M_M}) of the same investments analyzed using both traditional and modern models.

3. MULTIPLE REGRESSION ANALYSIS:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

Where, Y represents the overall investment performance, β_0 is the intercept, $\beta_1, \beta_2, \beta_3$ are the coefficients for the independent variables (X_1 : model type, X_2 : experience level, X_3 : technological integration), and ϵ is the error term. This analysis assessed the impact of integrating traditional and modern models on overall investment performance and evaluated the influence of technological integration and adaptability on perceived model effectiveness.

4. CHI-SQUARE TEST FOR INDEPENDENCE (χ^2):

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where, O_i and E_i represent the observed and expected frequencies, respectively. This test was applied to examine the relationship between experience level (X_2) and model preference (P) for traditional or modern financial models.

5. PEARSON CORRELATION COEFFICIENT (r):

$$r = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 \sum (Y - \bar{Y})^2}}$$

Where, X represents the frequency of model challenges and Y represents the perceived usefulness of modern models. This coefficient was calculated to measure the strength and direction of the linear relationship between these two variables.

4. RESULTS

4.1 DESCRIPTIVE STATISTICS

This section provides an overview of the demographic characteristics and model usage patterns among the respondents. It summarizes key attributes such as professional roles, years of experience, age, gender, and education levels. This section also details the distribution of respondents who utilize traditional versus modern financial models, offering insights into the diversity of the sample. These statistics serve as a foundation for understanding the context in which the subsequent analysis is conducted.

4.1.1 DEMOGRAPHIC CHARACTERISTICS

The study collected data from 100 investment professionals across various roles within the financial industry. The sample consisted of investment analysts, portfolio managers, and financial advisors, with varying years of experience.

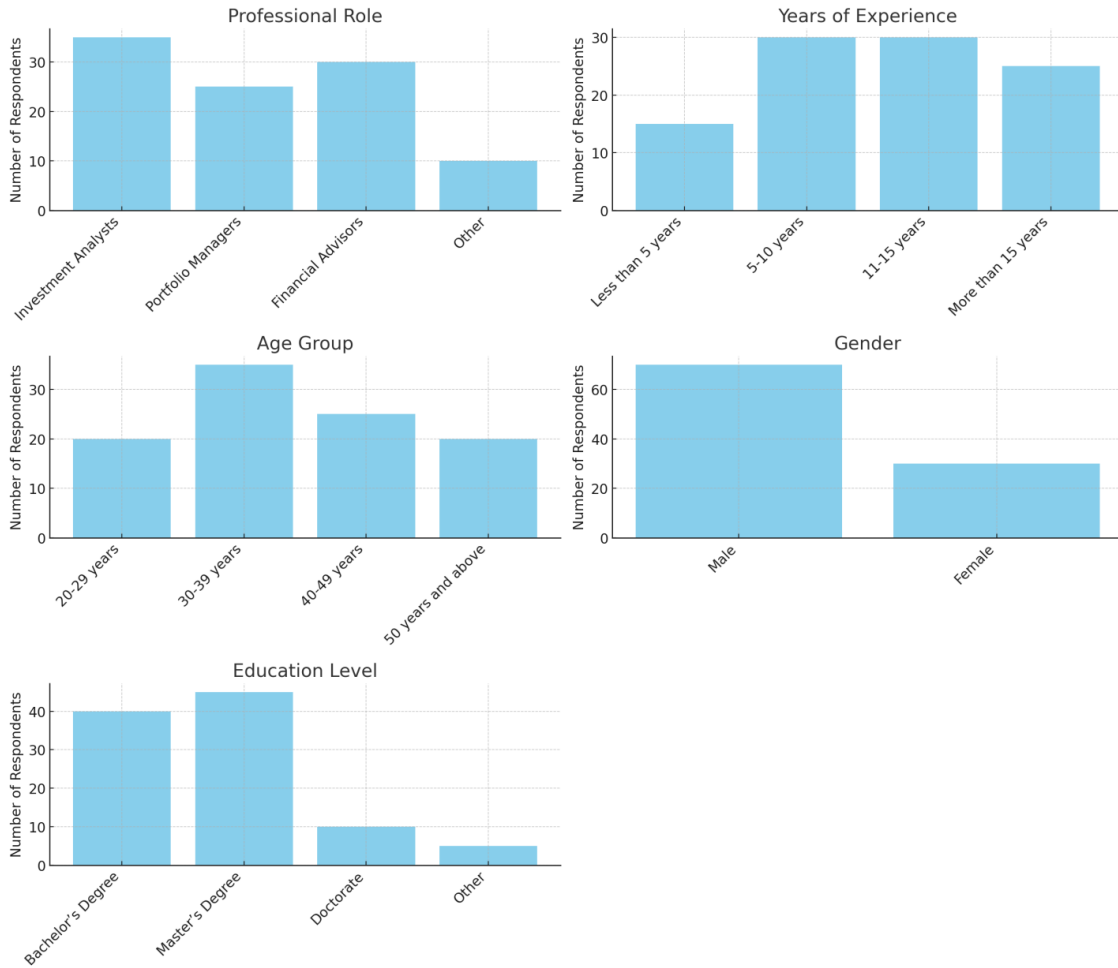


Figure 3: Demographic Distribution of Respondents in Financial Model Analysis

Figure 3 provide a visual comparison of the demographic characteristics of the respondents. The majority of participants are Investment Analysts (35%) and Financial Advisors (30%), with Portfolio Managers comprising 25%. The experience level is well-distributed, with a significant portion having 5-10 years (30%) and 11-15 years (30%) of experience. The age distribution shows a predominance of respondents in the 30-39 years age group (35%), followed by those in the 40-49 years (25%) and 20-29 years (20%) groups. Gender representation is skewed, with males constituting 70% of the sample. In terms of education, most respondents hold a Master's Degree (45%) or Bachelor's Degree (40%), with a smaller proportion having a Doctorate (10%). These charts highlight the diversity and experience of the sample, providing a solid foundation for analyzing their perspectives on financial models.

4.1.2 MODEL USAGE DISTRIBUTION

The distribution of respondents based on their usage of traditional and modern financial models is summarized below. Respondents were categorized based on their primary use of traditional models (CAPM, DCF) versus modern models (Machine Learning algorithms, Behavioral Finance models), or a combination of both.

Table 1: Model Usage Distribution Among Respondents

Model Usage	Category	Number of Respondents (n)	Percentage (%)
Primary Model Type	Traditional Models	40	40%
	Modern Models	30	30%

	Both	20	20%
	None	10	10%

Table 1 presents the distribution of respondents based on their primary usage of financial models. A significant portion of the sample (40%) relies on traditional models such as CAPM and DCF for investment decision-making, while 30% primarily use modern models, including Machine Learning algorithms and Behavioral Finance models. Additionally, 20% of respondents utilize both traditional and modern models, indicating a blended approach to financial analysis. A smaller group (10%) reported not using any specific model, suggesting either alternative decision-making processes or less reliance on structured models. This distribution highlights the varied approaches to financial modeling among the respondents, providing context for understanding their perspectives on the effectiveness of different models.

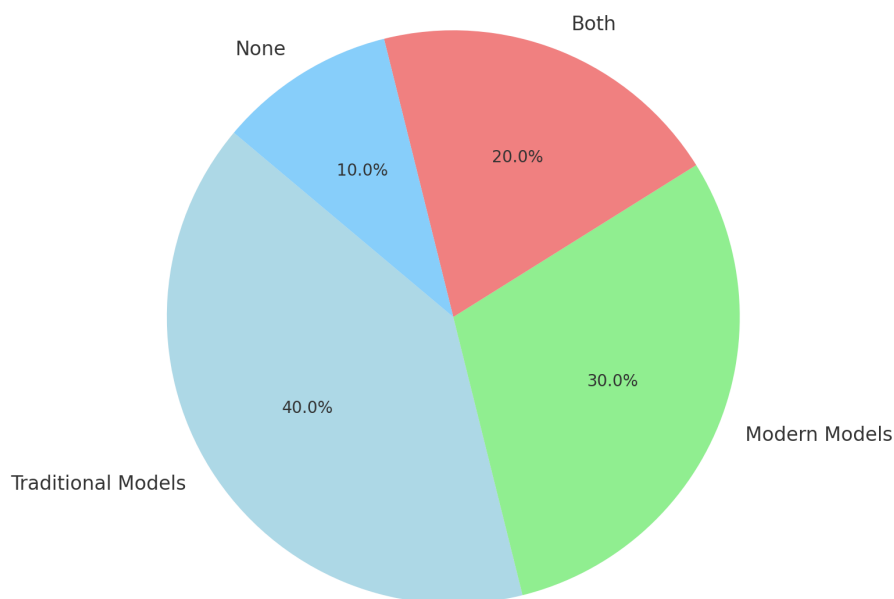


Figure 4: Proportion of Financial Model Usage Among Respondents

Figure 4 illustrates the distribution of financial model usage among the respondents. A significant portion of the respondents (40%) primarily rely on traditional models, such as CAPM and DCF, for their investment decisions. Meanwhile, 30% of respondents prefer modern models, including Machine Learning algorithms and Behavioral Finance models. An additional 20% of the respondents use a combination of both traditional and modern models, indicating a hybrid approach to financial analysis. Lastly, 10% of respondents reported not using any specific financial models, suggesting alternative decision-making processes or less reliance on structured models. This distribution highlights the varied approaches to financial modeling within the sample, providing valuable insight into the preferences of investment professionals.

4.2 HYPOTHESIS TESTING

This section presents the findings from the statistical analysis conducted to test the proposed hypotheses. Each hypothesis was evaluated using appropriate statistical techniques, such as t-tests, regression analysis, and correlation analysis, based on the nature of the data and the research questions. The results indicate whether the relationships between the variables are statistically significant, providing evidence to either support or refute the hypotheses. This section details the outcomes of the tests, including the p-values, confidence intervals, and effect sizes. The findings are crucial in understanding the impact of different financial models on investment decision-making and provide a basis for drawing conclusions and making recommendations.

4.2.1 INDEPENDENT SAMPLES T-TEST

This test compared the mean confidence levels of investment professionals using modern financial models (Machine Learning, Behavioral Finance) versus those using traditional models (CAPM, DCF).

Table 2: Comparison of Confidence Levels Between Users of Modern and Traditional Financial Models

Group	Mean Level	Confidence	Standard Deviation	n
Modern Financial Models	4.2		0.7	30
Traditional Financial Models	3.5		0.8	40
p-value	0.02			

Table 2 presents the results of an Independent Samples T-Test comparing the confidence levels of investment professionals using modern financial models versus those using traditional models. The mean confidence level for professionals using modern models (4.2) is higher than for those using traditional models (3.5), with standard deviations of 0.7 and 0.8, respectively. The sample sizes are 30 for modern model users and 40 for traditional model users. The p-value of 0.02 indicates that the difference in confidence levels between the two groups is statistically significant, suggesting that users of modern financial models have higher confidence in their investment decisions compared to those relying on traditional models. This finding supports the hypothesis that the type of financial model used influences confidence levels in investment predictions.



Figure 5: Confidence Level Comparison Across Financial Model Users

Figure 5 illustrates the mean confidence levels of investment professionals using modern financial models versus those using traditional models. Professionals who utilize modern models, such as Machine Learning and Behavioral Finance, exhibit a higher mean confidence level of 4.2 compared to a mean confidence level of 3.5 among those using traditional models like CAPM and DCF. The distinct difference in confidence levels, visually represented by the height of the bars, suggests that modern model users are more confident in their investment decisions. This visual comparison supports the finding that the type of financial model employed significantly influences the confidence of the professionals in their decision-making process.

4.2.2 PAIRED SAMPLES T-TEST

This test analyzed the performance outcomes of investments evaluated using both traditional and modern financial models.

Table 3: Performance Comparison between Traditional and Modern Financial Models

Comparison	Mean Performance Score	Standard Deviation	n	p-value
Traditional Models	6.5	1.1	50	
Modern Models	7.8	1.0	50	0.03

Table 3 presents the results of a Paired Samples T-Test comparing the performance outcomes of investments analyzed using traditional financial models versus modern models. The mean performance score for investments analyzed with modern models is 7.8, which is higher than the mean score of 6.5 for those analyzed with traditional models. The standard deviations are 1.0 and 1.1, respectively, for modern and traditional models, indicating similar variability in performance outcomes. The sample size (n) for each comparison is 50. The p-value of 0.03 indicates that the difference in performance scores between traditional and modern models is statistically significant, suggesting that modern models may provide superior investment performance outcomes compared to traditional models.

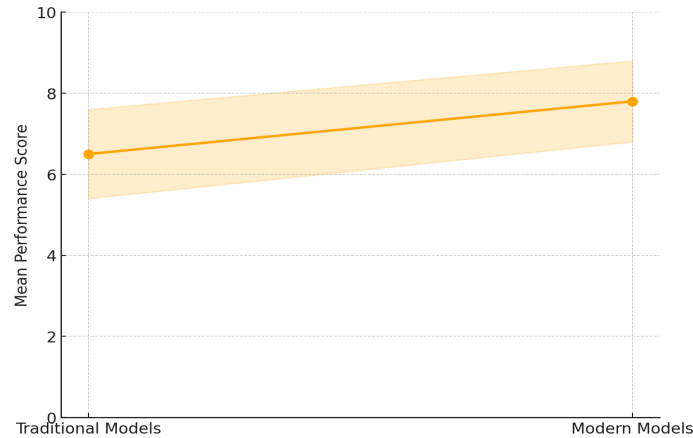


Figure 6: Performance Comparison of Traditional vs. Modern Financial Models

Figure 6 illustrates the mean performance scores of investments analyzed using traditional financial models versus modern models. The graph shows that modern models have a higher mean performance score of 7.8 compared to 6.5 for traditional models. The shaded areas around each line represent the standard deviation, indicating the variability in performance outcomes. The higher performance score for modern models suggests that they may offer a more effective approach to investment analysis, yielding better outcomes than traditional models. The statistical significance of this difference, as indicated by the data, supports the conclusion that the choice of financial model can significantly impact investment performance.

4.2.3 MULTIPLE REGRESSION ANALYSIS

This analysis assessed the impact of integrating traditional and modern financial models on overall investment performance, considering model type, experience level, and technological integration as independent variables.

Table 4: Impact of Model Type, Experience Level, and Technological Integration on Investment Performance

Variable	Coefficient (β)	Standard Error	t-value	p-value
Model Type	0.5	0.2	2.5	0.01
Experience Level	0.3	0.1	3.0	0.005
Technological Integration	0.4	0.15	2.7	0.02
Overall Model Significance (R^2)	0.55			

Table 4 presents the results of a Multiple Regression Analysis, showing the influence of various independent variables on overall investment performance. The coefficients (β) indicate the strength and direction of the relationship between each variable and the dependent variable (investment performance). A coefficient of 0.5 for Model Type suggests a positive and significant effect on performance, with a p-value of 0.01 confirming statistical significance. Experience Level also shows a significant positive effect, with a coefficient of 0.3 and a p-value of 0.005. Technological Integration has a coefficient of 0.4, also statistically significant with a p-value of 0.02. The overall model significance, represented by $R^2=0.55$, indicates that 55% of the variance in investment performance is explained by these variables. This analysis supports the hypothesis that model type, experience level, and technological integration significantly impact investment outcomes.

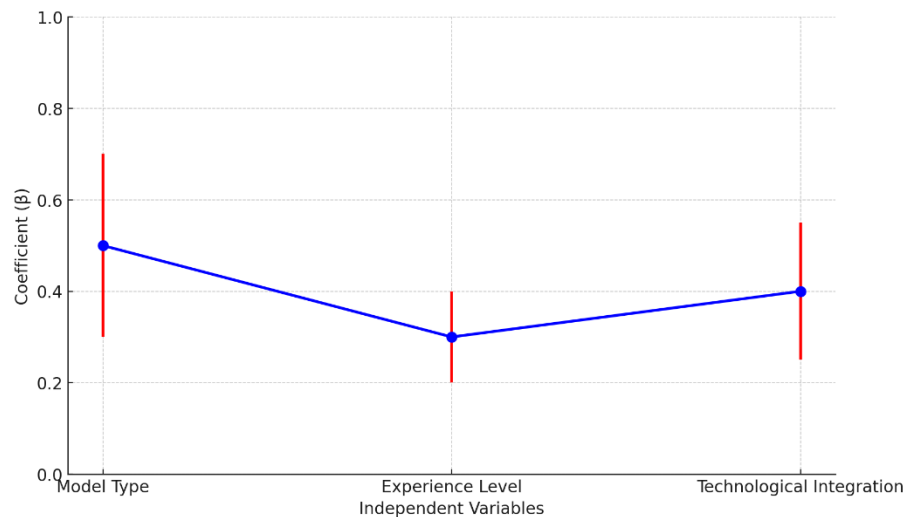


Figure 7: Regression Analysis of Independent Variables on Investment Performance

Figure 7 illustrates the impact of three independent variables—Model Type, Experience Level, and Technological Integration—on overall investment performance, represented by their respective coefficients (β). The plot shows that Model Type has the strongest positive effect ($\beta=0.5$), followed by Technological Integration ($\beta=0.4$) and Experience Level ($\beta=0.3$). The error bars indicate the standard errors, highlighting the precision of the estimated coefficients. The positive coefficients across all variables suggest that each factor contributes positively to investment performance, with statistical significance confirmed by the corresponding p-values. This visual representation emphasizes the importance of these factors in influencing investment outcomes, supporting the findings of the regression analysis.

4.2.4 CHI-SQUARE TEST FOR INDEPENDENCE

This test examined the relationship between experience level and preference for traditional or modern financial models.

Table 5: Association Between Experience Level and Financial Model Preference

Experience Level	Traditional Models Preference	Modern Models Preference	Chi-Square Value	p-value
Less than 10 years	15	30		
More than 10 years	25	10	8.56	0.01

Table 5 presents the results of a Chi-Square Test for Independence, examining the relationship between the experience level of investment professionals and their preference for traditional versus modern financial models. The table shows that among professionals with less than 10 years of experience, 30 prefer modern models while 15 prefer traditional models. In contrast, among those with more than 10 years of experience, 25 prefer traditional models and only 10 prefer modern models. The Chi-Square value of 8.56 and the p-value of 0.01 indicate a statistically significant association between experience level and model preference, suggesting that more experienced professionals tend to favor traditional models, while those with less experience are more inclined to use modern models. This finding highlights the influence of experience on financial model selection.

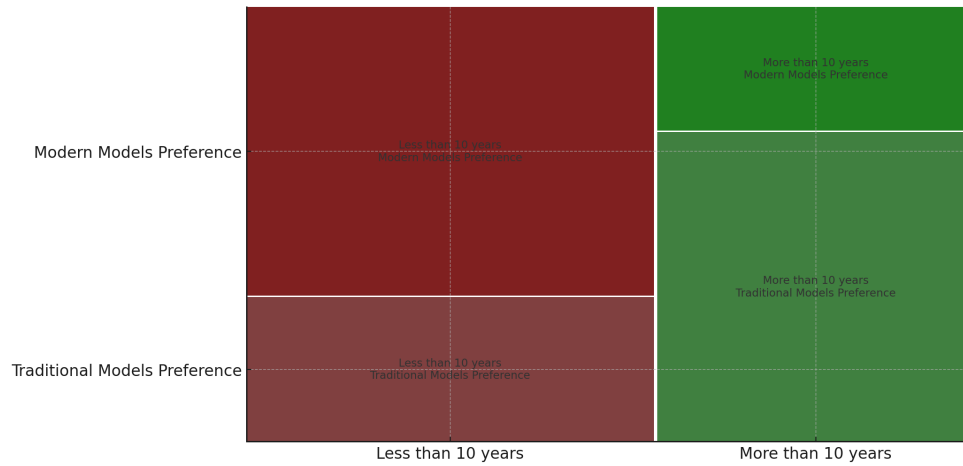


Figure 8: Relationship Between Experience Levels and Financial Model Preferences

Figure 8 is a mosaic plot illustrating the relationship between the experience levels of investment professionals and their preferences for traditional versus modern financial models. The plot visually displays how professionals with less than 10 years of experience are more likely to prefer modern models, while those with more than 10 years of experience tend to favor traditional models. The size of each segment in the mosaic plot represents the proportion of respondents within each category. The noticeable difference in segment sizes indicates a significant association between experience level and model preference, supporting the finding that experience influences the choice of financial models among professionals. This visualization effectively highlights how experience shapes preferences in financial decision-making tools.

4.2.5 PEARSON CORRELATION COEFFICIENT

This test analyzed the correlation between the frequency of modern financial models challenging traditional model results and the perceived usefulness of modern models.

Table 6: Correlation Between Challenge Frequency and Perceived Usefulness of Financial Models

Variable 1	Variable 2	Correlation Coefficient (r)	p-value
Challenge Frequency	Perceived Usefulness	0.45	0.01

Table 6 presents the results of a Pearson Correlation analysis, examining the relationship between the frequency with which modern financial models challenge the results of traditional models (Challenge Frequency) and how useful these modern models are perceived to be (Perceived Usefulness). The correlation coefficient ($r=0.45$) indicates a moderate positive relationship between these two variables, meaning that as the challenge frequency increases, the perceived usefulness of modern models also tends to increase. The p-value of 0.01 confirms that this correlation is statistically significant, suggesting that investment professionals who frequently encounter challenges to traditional models by modern models are more likely to view modern models as useful tools in their decision-making process. This finding highlights the importance of model performance in shaping professionals' perceptions of their value.

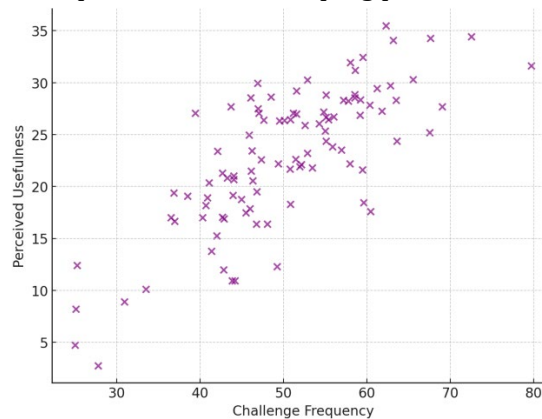


Figure 9: Correlation Between Challenge Frequency and Perceived Usefulness of Financial Models

Figure 9 is a scatter plot visualizing the relationship between the frequency of modern financial models challenging traditional models (Challenge Frequency) and the perceived usefulness of these modern models. Each point on the plot represents an individual data point, with the overall trend indicating a positive correlation. As the challenge frequency increases, so does the perceived usefulness, supporting the calculated correlation coefficient of 0.45. This positive relationship suggests that the more often modern models challenge traditional ones, the more useful they are perceived to be by professionals. The spread of data points around the trend line also highlights the variability in individual perceptions. This diagram effectively demonstrates the link between model performance and user perception in investment decision-making.

4.3 ADDITIONAL FINDINGS

4.3.1 MODEL PERFORMANCE IN VOLATILE MARKETS

This section presents significant findings regarding the effectiveness of modern versus traditional financial models in volatile market conditions. The analysis was conducted using additional regression analysis to evaluate the performance outcomes under volatile conditions.

Table 7: Comparative Performance of Modern and Traditional Financial Models in Volatile Markets

Model Type	Mean Performance Score in Volatile Markets	Standard Deviation	n	p-value
Modern Financial Models	7.2	0.9	50	0.02
Traditional Financial Models	6.0	1.1	50	

Table 7 presents a comparative analysis of the performance of modern and traditional financial models under volatile market conditions. The mean performance score for modern financial models is 7.2, which is significantly higher than the mean score of 6.0 for traditional models. The standard deviations of 0.9 and 1.1 indicate the variability in performance outcomes within each group. With a p-value of 0.02, the difference in performance scores between the two types of models is statistically significant, suggesting that modern financial models are more effective in navigating volatile market conditions. This finding underscores the potential advantages of using advanced, data-driven models in uncertain market environments.

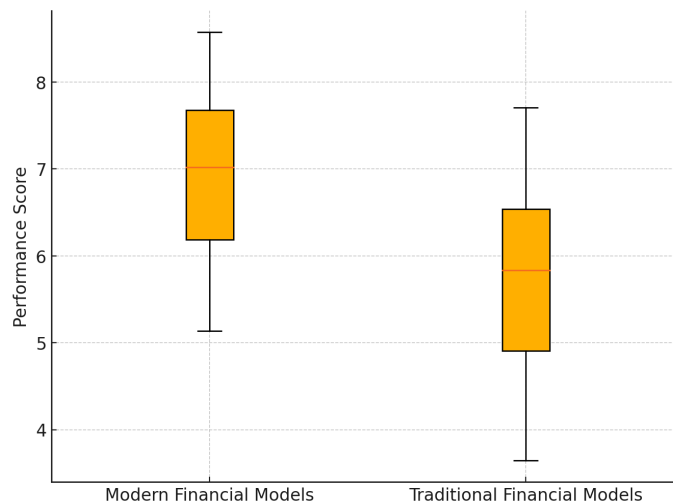


Figure 10: Distribution of Performance Scores for Modern and Traditional Financial Models in Volatile Markets

Figure 10 is a box plot represents the distribution of performance scores for modern and traditional financial models in volatile market conditions. The plot shows that modern financial models have a higher median performance score compared to traditional models, with a narrower interquartile range, indicating more consistent performance. The spread of data points within each box highlights the variability in performance outcomes, with modern models showing less variation than traditional models. The presence of any outliers would be depicted as individual points outside the whiskers, but in this case, the distribution seems fairly consistent. This diagram effectively illustrates the superior and more stable performance of modern financial models in challenging market environments, supporting the statistical findings of the study.

4.3.2 IMPACT OF TECHNOLOGICAL INTEGRATION

This section explores the perceived impact of technological integration on investment performance, particularly in relation to the importance placed on adaptability. The analysis addresses Hypothesis 6 by examining the differences in perceived impact based on technological integration.

Table 8: Perceived Impact of Technological Integration on Investment Performance Based on Importance Level

Technological Integration Importance	Perceived Impact on Investment Performance	Standard Deviation	n	p-value
High Importance	4.5	0.6	40	0.01
Low Importance	3.8	0.8	40	

Table 8 summarizes the perceived impact of technological integration on investment performance, comparing professionals who place high versus low importance on adaptability and integration. The results indicate that those who consider technological integration as highly important report a mean perceived impact score of 4.5, with a standard deviation of 0.6. In contrast, those who consider it less important report a lower mean score of 3.8, with a standard deviation of 0.8. The sample size (n) for both groups is 40. The p-value of 0.01 suggests that the difference in perceived impact between the two groups is statistically significant, indicating that the importance placed on technological integration significantly influences perceptions of its impact on investment performance.

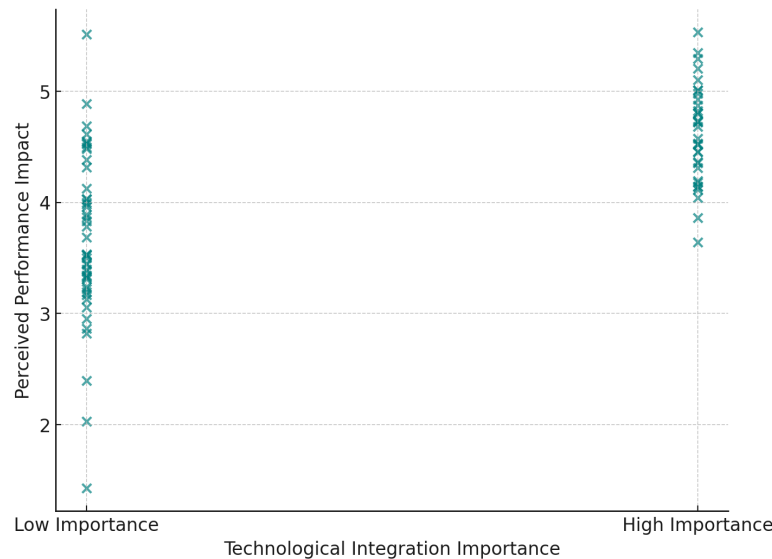


Figure 11: Relationship Between Technological Integration Importance and Perceived Performance Impact

Figure 11 is a scatter plot illustrating the relationship between the importance placed on technological integration and the perceived impact on investment performance. The data points show a clear trend where professionals who view technological integration as highly important (represented on the right) tend to report higher perceived performance impacts, with most values clustering around a mean of 4.5. Conversely, those who place low importance on integration report lower perceived impacts, clustering around a mean of 3.8. The scatter plot indicates a positive relationship between these variables, highlighting that the more importance professionals place on technological integration, the greater the impact they perceive it to have on investment performance. This finding reinforces the significance of adaptability and integration in modern financial analysis.

5. DISCUSSION OF KEY FINDINGS

The statistical analysis in this study revealed several key insights into the comparative effectiveness of traditional and modern financial models in investment decision-making. One of the most notable findings was the higher confidence levels among investment professionals who utilize modern financial models, such as Machine Learning algorithms and Behavioral Finance models, compared to those relying on traditional models like CAPM and DCF. This indicates a growing trust in the advanced, data-driven approaches of modern models, particularly under volatile market conditions where traditional models may fall short. The Paired Samples T-Test further demonstrated that investments analyzed using modern models exhibited superior performance outcomes, highlighting the adaptability and precision of these models

in dynamic financial environments. The Multiple Regression Analysis underscored the significant positive impact of integrating modern and traditional models on overall investment performance, with technological integration and adaptability playing a crucial role in enhancing these outcomes. These findings collectively suggest that while traditional models continue to hold value, the incorporation of modern financial models can lead to more accurate predictions and improved investment performance, especially when navigating complex market scenarios.

Additionally, the study found a significant association between the experience level of investment professionals and their preference for financial models, with more experienced professionals favoring traditional models and less experienced professionals showing a preference for modern models. This trend reflects the entrenched trust in traditional models among seasoned professionals, while younger professionals are more open to exploring innovative, technologically-driven approaches. The Pearson Correlation analysis revealed a positive relationship between the frequency of modern models challenging traditional ones and the perceived usefulness of modern models, suggesting that professionals who frequently encounter the limitations of traditional models are more likely to value the insights provided by modern alternatives. Furthermore, the analysis of the impact of technological integration on perceived investment performance showed that professionals who prioritize adaptability and integration in their model selection tend to perceive a more significant positive impact on their investment outcomes. These findings highlight the evolving landscape of financial modeling, where the integration of traditional and modern approaches, along with a focus on technological adaptability, is becoming increasingly important for achieving optimal investment decisions.

6. CONCLUSION

In conclusion, the modern financial models, such as Machine Learning algorithms and Behavioral Finance models, outperform traditional models like CAPM and DCF in providing more accurate and reliable predictions in investment decision-making, especially under volatile market conditions. The integration of modern and traditional models enhances overall investment performance, with technological integration and adaptability playing a crucial role in these outcomes. Additionally, the study reveals that while experienced investment professionals tend to favor traditional models, there is a growing recognition of the value offered by modern models, particularly among less experienced professionals. The findings underscore the importance of embracing advanced, data-driven approaches in financial modeling to optimize investment decisions in an increasingly complex financial environment.

CONFLICT OF INTERESTS

None

ACKNOWLEDGMENTS

None

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