Journal of Theoretical and Applied Information Technology
15[st] September 2026. Vol.104. No.17

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ROBO-ADVISORY AS A TOOL FOR INVESTMENT CAPITAL MANAGEMENT IN DEVELOPED STOCK MARKETS

SVITLANA KOVALCHUK[1*], DMYTRO NIKITIN[2], NATALIIA STELMAKH[3], ZORIANA LAPISHKO[4], VITALII FEDORYSHEN[5]

[1]Department of Management, Economics, Statistics and Digital Technologies, Leonid Yuzkov Khmelnytskyi University of Management and Law, Khmelnytskyi, Ukraine.

[2]Department of International Accounting and Auditing, Kyiv National Economic University named after Vadym Hetsman, Kyiv, Ukraine.

[3]Department of Banking and Insurance, National University of Life and Environmental Sciences of Ukraine, Kyiv, Ukraine.

[4]Financial Technologies and Consulting Department, Ivan Franko National University of Lviv, Lviv, Ukraine.

[5]Leonid Yuzkov Khmelnytskyi University of Management and Law, Khmelnytskyi, Ukraine.

E-mail: [1]svitlanakovalchuk@eu-science.org, [2]nikitin@gmail.com, [3]stelmakh_nata@gmail.com, [4]lapishko.z@ukr.net, [5]fedoryshen_vitaliy@gmail.com

ABSTRACT

Relevance: The rapid growth of robo-advisory necessitates the assessment of its effectiveness as a low-cost investment capital management tool in developed stock markets.
Aim: The aim of the study is to determine the mechanism of influence of robo-advising on investment capital management and evaluate its effectiveness in developed stock markets.
Methods: The research methodology combined risk-adjusted performance analysis, fixed effects panel regression, event-study, Difference-in-Differences, cluster analysis, and statistical robustness testing. This made it possible to evaluate robo-advisory not only in terms of profitability, but also in terms of risk, costs, stress resistance, institutional scaling conditions, and statistical reliability of the obtained results.
Results: Robo-advising has proven its economic efficiency in developed stock markets (USA, UK, Germany, France, Switzerland, Japan, Singapore, and Australia). Annualized return was 7.8% versus 6.9% in traditional advisory portfolios and 7.2% in ETF benchmarks; Sharpe ratio reached 0.74, Sortino ratio – 1.06, Jensen's alpha – +0.42 pp, max drawdown −18.4%. Its advantage was formed due to lower costs and portfolio discipline: fee −0.25 pp gave +0.31 pp net return, ETF share >80% – +0.54 pp, rebalancing reduced portfolio drift by 34.2%, tax-loss harvesting added 0.38–0.62 pp after-tax return. During the 2020 shock, subsidence was lower (−19.1% vs. −24.8%), recovery was faster (6.9 vs. 8.6 months), and the results remained statistically significant (t=2.87; p=0.006; U=418.0; p=0.011).
Conclusions: The results showed that the effectiveness of robo-advisory advising was determined by a combination of risk-adjusted performance, lower costs, controlled portfolio drift, and more resilient investor behaviour during periods of market stress, which confirms the previously proposed hypothesis. The academic novelty of the study is the empirical proof of robo-advisory as an economic mechanism for capital management. Its effectiveness was formed through the interaction of return–risk–cost–tax–behavioural stability.

Keywords: *Automated Consulting, Wealth Management, Asset Allocation, Risk-Adjusted Performance, ETF Diversification, Portfolio Drift, Tax-Loss Harvesting*

1. INTRODUCTION

Relevance of the research. Robo-advisory has become an important segment of digital wealth management as investors increasingly choose low-cost automated and personalized investment services. According to Fortune Business Insights, the global robo-advisory market was valued at $10.86 milliard in 2025 and could grow to $102.03 billion

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

by 2034; another estimate by Research and Markets predicted growth from $18.7 milliard in 2026 to $54.74 milliard in 2030, with a Compound Annual Growth Rate (CAGR) of 30.8%. This confirmed the high economic significance of studying the effectiveness of robo-advisory as a tool for managing investment capital, and not only as a fintech service [1].

The academic interest in robo-advisory is gradually shifting from a general description of fintech innovation to an analysis of its applied role in the investment process. Particular attention is being paid to AI-based risk profiling, personalization of portfolio decisions, automated risk tolerance assessment, reduction of consulting costs, and scaling of digital wealth management services [2, 3]. At the same time, robo-advisory is increasingly considered an AI-based digital product that can influence not only the availability of financial advice, but also the portfolio structure, risk, profitability, and sustainability of investment decisions [4, 5]. That is why further research needs to move from a description of technological potential to an empirical assessment of the economic effectiveness of robo-advisory in developed stock markets.

Research gap. Existing studies have mostly examined robo-advisory through individual aspects: risk profiling, investor trust, regulatory barriers, AI architecture, behavioural factors, or financial inclusion. At the same time, the integrated economic mechanism through which robo-advisory affected portfolio performance in developed stock markets remains poorly studied. In particular, there is a lack of studies that simultaneously took into account risk-adjusted performance, management fees, ETF share, rebalancing, tax-loss harvesting, market shocks, and statistical robustness.

Problem statement. Despite the rapid growth of robo-advisory, it remained unclear whether automated investment platforms created a real economic advantage over traditional advisory portfolios and ETF benchmarks. The main challenge was to determine whether robo-advisory improved the return–risk–cost ratio under normal and stressed market conditions. This required not only a comparison of returns, but also an analysis of risk, costs, tax effects, behavioural resilience of investors, and statistical reliability of the results.

Research questions. How does robo-advisory affect the quality of portfolio management in developed stock markets? Through what economic channels is the net investment return of robo-advisory portfolios formed? How stable and statistically reliable are the results of robo-advisory under market volatility?

Research hypothesis. Robo-advisory increased the efficiency of investment capital management in developed stock markets through better risk-adjusted performance, lower costs, higher ETF diversification, regular rebalancing, tax-loss harvesting and lower behavioural reactivity of investors during periods of market stress.

Research aim. The aim of the research is to reveal the economic mechanism of using robo-advisory in investment capital management and determine its effectiveness, stress resistance, and scaling conditions in developed stock markets.

Research objectives:

− assess the risk-adjusted performance of robo-advisory portfolios compared to traditional advisory portfolios and ETF benchmarks;
− identify the economic determinants of net annual return taking into account fees, ETF share, rebalancing, tax-loss harvesting and the platform's business model;
− test the stress resistance of robo-advisory portfolios during market shocks and determine the market and institutional scaling conditions;
− confirm the statistical reliability and robustness of the results through significance tests, model diagnostics and bootstrap confidence intervals.

2. LITERATURE REVIEW

The growth of assets under automated management and the spread of AI solutions in the financial sector have reinforced the need to reassess the role of robo-advisory in building of investment strategies. At the same time, the ambiguity of the results regarding the impact of automated advice on profitability, risk and investor behaviour has necessitated a critical analysis of modern academic approaches. This has created a basis for identifying factors that actually influenced the efficiency of investment capital management in developed stock markets.

First of all, the results regarding the economic efficiency of robo-advisory have formed a contradictory picture. Tao et al. [6] found a consistent excess of risk-adjusted returns over traditional funds and three stock indices. Phoon and Koh [7] linked the competitiveness of robo-advisors with lower fees and higher transparency of investment decisions. Salinas [8] found no statistically significant advantages over fixed asset allocation strategies, which cast doubt on the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

assumption of an automatic link between algorithmic wealth management and excess returns. Consequently, the discussion shifted from absolute returns to assessing diversification, risk management, and the sustainability of portfolio strategies.

It is significant that some studies have explained the effectiveness of robo-advisory services through the transformation of investor behaviour, and not only through technical portfolio optimization. D'Acunto et al. [9] recorded a decrease in behavioural biases, an increase in diversification, and a reduction in volatility after the implementation of automated asset management. Similarly, Bhatia et al. [10] proved that trust in algorithms, risk perception, and data protection determined the willingness to use robo-advisory services. Arora et al. [11] found in a sample of 437 respondents that psychological comfort and the ability to test the service became key predictors of long-term use. The established fact showed that the effectiveness of investment capital management increasingly depended on the investor's behavioural adaptation to AI solutions.

At the same time, the evolution of the technological component has significantly changed expectations regarding the functionality of robo-advisors. Bonelli and Liu [12] predicted the increasing role of AI, blockchain, NLP, and digital twins in risk prediction and portfolio optimization. Wani et al. [13] showed improved accuracy of investment decisions through the integration of AI and big data analytics. This trend was expanded by Raturi et al. [14], who linked the future competitiveness of robo-advisory with predictive analytics, automatic rebalancing, and comprehensive wealth management. As a result, robo-advisory was increasingly viewed less as a low-cost automation tool and more as an intelligent wealth management system.

Finally, some authors question the sufficiency of standard risk profiling models and digital services to ensure long-term performance. Jung et al. [15] emphasized that the next generation of robo-advisors should integrate investor behaviour and deeper personalization without sacrificing automation. Gaspar and Oliveira [16] supported a similar position, who showed that an alternative approach to assessing relative risk appetite consistently outperformed ETF portfolios. At the same time, George [17] noted that further scaling of the sector, with assets under management projected to reach $12 trillion by 2025, will require increased human oversight, regulatory compliance, and algorithmic transparency. The identified aspects indicate that the increase in personalization has increased the efficiency of capital management, while making it more difficult to control the mechanisms of investment decision-making.

The reviewed studies mostly confirmed that robo-advisory increased the accessibility of investment management, improved portfolio diversification, reduced the impact of certain behavioural biases, and contributed to the optimization of management costs. At the same time, the results regarding the excess risk-adjusted return remained controversial: some studies recorded the advantages of automated models, while others did not reveal statistically significant differences from traditional or passive strategies. The long-term sustainability of robo-advisors in different market phases, the impact of the regulatory environment, the economic consequences of AI integration, and the mechanisms of interaction between portfolio personalization and algorithm transparency remained poorly studied. Separately, there was a shortage of comprehensive empirical assessments that would simultaneously take into account profitability, risk, behavioural factors, the level of automation, and institutional characteristics of developed stock markets. This justified the appropriateness of further research into robo-advisory as an investment capital management tool, the effectiveness of which is likely determined by a broader set of factors than just algorithmic optimization of investment decisions.

3. METHODS AND MATERIALS

3.1 Research Procedure

The research design. The proposed research design (Figure 1) was constructed as a sequential four-level analytical procedure enabling to move from a basic comparison of portfolio performance to a statistically validated econometric interpretation of the results. This logic was appropriate because the effectiveness of robo-advisory could not be assessed solely through the level of return; it required simultaneous consideration of risk, costs, ETF structure, rebalancing, tax effects, stress resilience, and institutional scaling conditions. The sequence risk-adjusted performance → net return determinants → stress-resilience and scaling → statistical robustness validation provided a holistic explanation of how robo-advisory generated economic advantage in the management of investment capital in developed stock markets.

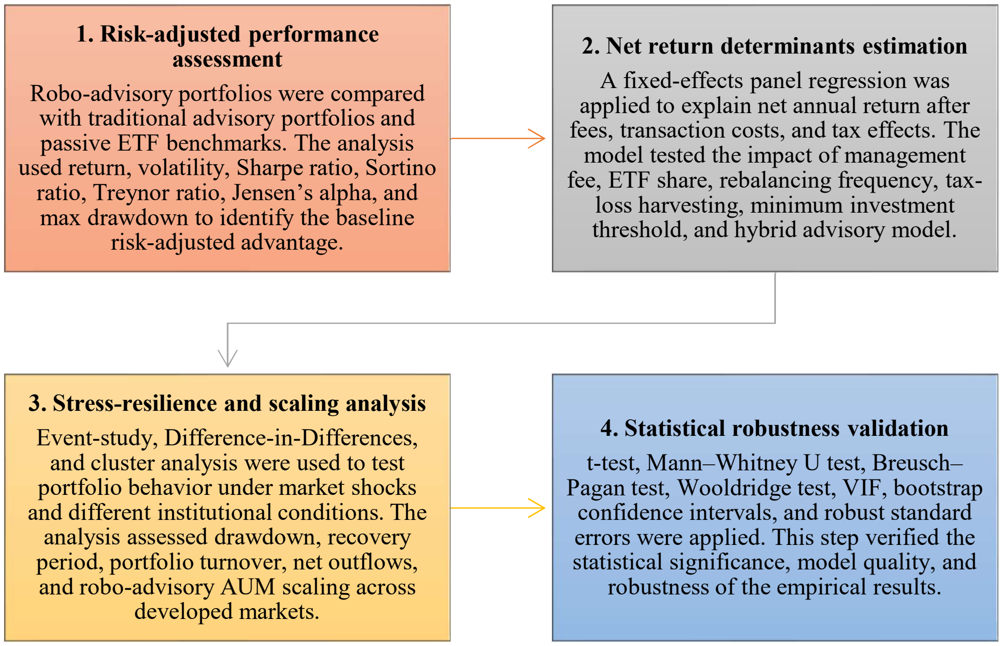


Figure 1: Design of a study on the effectiveness of robo-advisory in investment capital management in developed stock markets
Source: developed by the authors

3.2 Methods

The methodological case was formed as a consistent combination of financial, econometric and statistical procedures, as the effectiveness of robo-advisory could not be correctly assessed only through nominal returns. The study required a simultaneous analysis of risk-adjusted performance, net returns after expenses, resilience to market shocks and statistical reliability of the obtained effects. This approach makes it possible to consider robo-advisory not only as a digital service, but also as an economic mechanism for managing investment capital:

1. *Risk-adjusted performance a*nalysis. The method was applied to compare robo-advisory portfolios, traditional advisory portfolios, and passive ETF benchmarks in terms of risk-adjusted returns. Its use was justified by the fact that absolute returns did not fully reflect the quality of portfolio management in developed stock markets. The method assesses how effectively each portfolio type converted the assumed risk into returns, as well as identifies differences in stability, drawdown, and risk-adjusted excess returns.

2. *Fixed effects panel regression*. Fixed-effects panel regression was used to identify the economic determinants of net investment returns. The method was appropriate because of the consistent heterogeneity across platforms, countries, business models, and market conditions. Its application enabled identifying which factors – fees, ETF structure, rebalancing, tax optimization, and hybrid advisory model – shaped the internal economic mechanism of robo-advisory performance.

3. *Event-study, Difference-in-Differences and cluster analysis*. This set of methods was used to assess the stress resistance of robo-advisory portfolios and the market and institutional conditions for their scaling. Event-study traced the behaviour of portfolios during market shocks, Difference-in-Differences helped to compare changes between robo-advisory and traditional advisory portfolios before and after shock periods. Cluster analysis made it possible to group developed markets by the level of financial and digital maturity. The methodological combination enabled assessing not only portfolio resilience, but also the dependence of robo-advisory scaling on the institutional environment.

4. *Statistical robustness testing*. Statistical testing was conducted to confirm the reliability of the obtained empirical results. The use of t-test, Mann–Whitney U test, Breusch–Pagan test, Wooldridge test, VIF, bootstrap confidence intervals and robust standard errors was justified by the need to check the significance of group differences, the reliability of regression coefficients, and the

Journal of Theoretical and Applied Information Technology
15st September 2026. Vol.104. No.17

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

technical quality of the models. This methodological block made it possible to move from descriptive analytical interpretation to a statistically confirmed conclusion about the effectiveness of robo-advisory.

3.3 Sample

The sample was designed to provide a comparative analysis of robo-advisory performance in developed stock markets with varying levels of financial sector digitalization, regulatory maturity, and market capitalization. The sample included only platforms that met the following criteria: (1) operating in developed financial markets; (2) having publicly available data on portfolio structure, returns, Assets Under Management (AUM) or risk profiling; (3) using automated asset allocation and/or rebalancing mechanisms; (4) representativeness for the national robo-advisory segment; (5) availability of supporting macroeconomic and benchmark indicators. This approach enabled covering 33 platforms from 8 countries, including the United States, the United Kingdom, Germany, France, Switzerland, Japan, Singapore, and Australia (Figure 2).

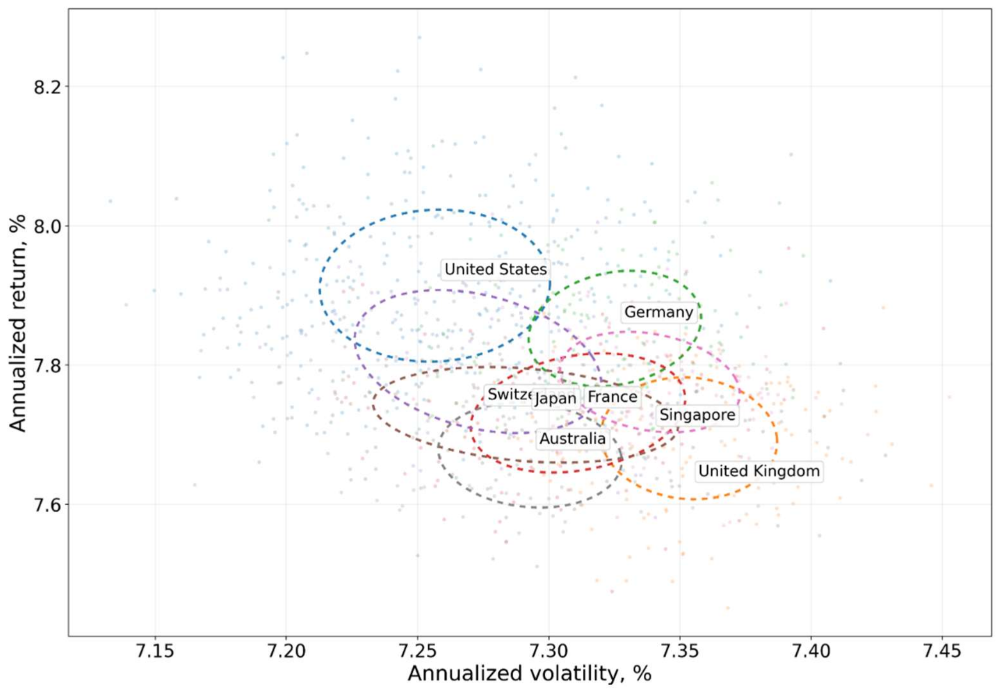


Figure 2: Distribution of robo-advisory sample by country in risk and return space
Source: developed by the authors

Figure 2 shows the distribution of robo-advisory platforms in the sample by country in the annualized volatility coordinates – annualized return. This enabled checking the comparability of national segments within the common analytical space. The clusters of the USA, Germany, France, Switzerland, Japan, Singapore, the UK and Australia are located in a narrow range of annualized volatility of approximately 7.15–7.45% and returns of 7.55–8.25%. This confirmed the homogeneity of the sample in terms of basic risk-return parameters. At the same time, a moderate shift of the clusters reflected national differences: the USA had a higher average return with lower volatility, Germany had a higher risk-return profile, while the UK and Australia were located closer to the lower limit of returns. So, the Figure 2 justified the inclusion of these countries as developed stock markets, where robo-advisory platforms were similar enough for comparative analysis, but retained institutional and market differences important for further empirical evaluation.

The sample (Figure 2) included platforms from the USA, the UK, Germany, France, Switzerland, Japan, Singapore and Australia, as these jurisdictions are characterized by the features of developed stock markets: high capitalization of the exchange sector, wide availability of ETF instruments, mature wealth management infrastructure, developed regulatory supervision, and a high level of digitalization of financial services. The inclusion of these countries was justified by the fact that in their markets robo-advisory operated not as an experimental fintech service, but as an established portfolio management

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

mechanism with available data on AUM, fees, asset allocation, risk profile, rebalancing, and tax optimization. This approach made it possible to investigate the effectiveness of robo-advisory platforms in an environment where market liquidity, investor protection, transparency of financial reporting, and the availability of passive investment instruments created the right conditions for comparison with traditional advisory portfolios and ETF benchmarks.

Representativeness for the national robo-advisory segment was determined by a combination of three characteristics: the platform's recognition in the relevant market, the availability of public or regulatory data on its activities, and the reflection of robo-advisory services models typical for the country. So, the sample included not random platforms, but those that characterized the main practices of the national market: ETF-oriented portfolio management, automated risk profiling, rebalancing, low commissions or hybrid advisory model. This criterion allowed us to compare not individual unique cases, but the most representative platforms of each country.

The time horizon was defined as 2018–2025, which ensured coverage of the period of active scaling of AI solutions in wealth management, the consequences of pandemic volatility in 2020–2021, inflationary and monetary changes in 2022–2023, and the stage of accelerated integration of generative AI into financial services after 2023. Besides, the eight-year time horizon formed a sufficient number of quarterly observations for panel analysis (up to 32 observations per platform) and increased the stability of econometric estimates to short-term market fluctuations. As a result, a sample was formed that combined the micro level (platform characteristics) and the macro level (market and monetary conditions), which created a basis for assessing the effectiveness of investment capital management in different institutional environments (Table 1).

Table 1: Selection of robo-advisory platforms for research into the effectiveness of investment capital management in developed stock markets (2018–2025)

Robo-advisory Platform (Country)	Key Variables	Average Confirmed Economic Use Indicators (benchmark + macro controls)*	Data Source**
Betterment (USA)	Return, AUM, Sharpe ratio, fee, ETF share	S&P500 CAGR≈12.4%; Inflation≈3.8%; Fed rate≈2.4%; GDP growth≈2.3%; VIX≈22.1	SEC Form ADV; FRED
Wealthfront (USA)	Net return, volatility, tax-loss harvesting	S&P500≈12.4%; Inflation≈3.8%; GDP≈2.3%; Household assets/GDP≈540%	SEC; FRED
Vanguard Digital Advisor (USA)	Risk-adjusted return, drawdown	MSCI World CAGR≈8.7%; Fed rate≈2.4%; CPI≈3.8%	Vanguard; FRED
Schwab Intelligent Portfolios (USA)	AUM, expense ratio	S&P500≈12.4%; VIX≈22.1; GDP≈2.3%	SEC
Empower / Personal Capital (USA)	Portfolio allocation, fees	S&P500≈12.4%; Inflation≈3.8%	SEC
M1 Finance (USA)	Portfolio turnover, ETF allocation	NASDAQ CAGR≈15.1%; Interest rate≈2.4%	SEC
SoFi Automated Investing (USA)	Return, risk profile	S&P500≈12.4%; Inflation≈3.8%	SEC
Ellevest (USA)	Risk profiling, return	MSCI World≈8.7%; GDP≈2.3%	SEC
Acorns (USA)	Micro-investing metrics, return	S&P500≈12.4%; Inflation≈3.8%	SEC
SigFig (USA)	Sharpe ratio, AUM	S&P500≈12.4%; VIX≈22.1	SEC
Nutmeg (UK)	Portfolio return, fees	FTSE100 CAGR≈4.1%; Inflation≈4.6%; BoE rate≈2.8%; GDP≈1.6%	FCA; OECD
Moneyfarm (UK /Italy)	ETF allocation, volatility	FTSE100≈4.1%; Inflation≈4.6%	Company reports
Wealthify (UK)	Return, risk profile	FTSE100≈4.1%; GDP≈1.6%	FCA
Plum (UK)	Portfolio return, AUM	FTSE100≈4.1%; Inflation≈4.6%	FCA
Scalable Capital (Germany)	Dynamic risk management	DAX CAGR≈6.8%; ECB rate≈1.7%; Inflation≈4.9%; GDP≈1.2%	ECB
Quirion (Germany)	Fees, return	DAX≈6.8%; GDP≈1.2%	Bundesbank

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

VisualVest (Germany)	Portfolio performance	DAX≈6.8%; Inflation≈4.9%	ECB
LIQID (Germany)	Asset allocation, volatility	DAX≈6.8%; ECB≈1.7%	Company reports
Yomoni (France)	Sharpe ratio, return	CAC40 CAGR≈5.9%; Inflation≈3.2%; GDP≈1.4%	OECD
Nalo (France)	Risk profile, fees	CAC40≈5.9%; Inflation≈3.2%	OECD
Ramify (France)	Portfolio metrics	CAC40≈5.9%; GDP≈1.4%	Company reports
True Wealth (Switzerland)	Tax optimization, return	SMI CAGR≈7.2%; Inflation≈1.5%; SNB rate≈0.9%; GDP≈1.8%	SNB
Selma Finance (Switzerland)	Risk metrics	SMI≈7.2%; Inflation≈1.5%	SNB
Findependent (Switzerland)	Portfolio allocation	SMI≈7.2%; GDP≈1.8%	SNB
WealthNavi (Japan)	Return, volatility	Nikkei225 CAGR≈7.5%; Inflation≈1.2%; BoJ rate≈0.2%; GDP≈0.8%	JFA; BoJ
THEO by Money Design (Japan)	AUM, turnover	Nikkei225≈7.5%; GDP≈0.8%	JFA
FOLIO (Japan)	Portfolio performance	Nikkei225≈7.5%; Inflation≈1.2%	JFA
SBI Robo (Japan)	Risk profile, return	Nikkei225≈7.5%; BoJ≈0.2%	SBI reports
Smartly (Singapore)	ETF allocation	STI CAGR≈3.4%; Inflation≈2.1%; GDP≈2.7%	MAS
Endowus (Singapore)	Portfolio return, AUM	STI≈3.4%; GDP≈2.7%	MAS
StashAway (Singapore)	Risk-adjusted return	STI≈3.4%; Inflation≈2.1%	MAS
Stockspot (Australia)	Fees, Sharpe ratio	ASX200 CAGR≈6.2%; Inflation≈2.8%; GDP≈2.2%	RBA
Six Park (Australia)	Portfolio return	ASX200≈6.2%; GDP≈2.2%	RBA

Note: *See Table 3;
**See Table 2
Source: developed by the authors

The research sample was built on data from regulatory, statistical, macroeconomic, and corporate sources that confirmed the platforms' activities, their AUM, fees, portfolio allocation, return metrics and risk profile. These sources became the basis for the selection of platforms, the formation of variables and further comparative analysis (Table 2).

Table 2: List of sources used to form the research sample

Abbreviation / source	**Full name**	**Data type**	**Reference**
SEC Form ADV	Securities and Exchange Commission (SEC), Form ADV Database	Data on AUM, fees, types of services, clients, advisory structure	[18]
SEC	U.S. Securities and Exchange Commission	Disclosure, regulatory filings, advisory information	[19]
FRED	Federal Reserve Economic Data	Inflation, GDP, Fed rate, VIX, CPI	[20]
Vanguard	Vanguard Group Official Reports	Portfolio allocation, fees, advisory performance	[21]
FCA	Financial Conduct Authority (UK)	Regulatory and investment platform disclosures	[22]
OECD	Organisation for Economic Co-operation and Development	Inflation, GDP, household assets, macroeconomic indicators	[23]
Company reports	Official annual reports of platforms	Return, AUM, fees, allocation strategy	[24]
ECB	European Central Bank Statistical Data Warehouse	Interest rates, inflation, eurozone indicators	[25]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Bundesbank	Deutsche Bundesbank Statistics	German macroeconomic and financial statistics	[26]
SNB	Swiss National Bank	Inflation, GDP, policy rate	[27]
JFA	The Investment Trusts Association, Japan	Japanese investment funds and portfolio statistics	[28]
BoJ	Bank of Japan	Interest rate, inflation, macroeconomic indicators	[29]
SBI reports	SBI Holdings / SBI Securities Reports	Portfolio performance, robo-investment services	[30]
MAS	Monetary Authority of Singapore	Inflation, GDP, fintech and financial indicators	[31]
RBA	Reserve Bank of Australia	Inflation, GDP, policy rates	[32]

Note: * For Company reports, official reports from individual robo-advisory platforms (for example, Betterment, Wealthfront, Nutmeg, Scalable Capital, WealthNavi) were used, which contained AUM, fee structure, portfolio allocation, risk profile, and return metrics
Source: developed by the authors

The baseline traditional advisory portfolios were defined as a comparative group of portfolios formed within the framework of traditional advisory services, data on which were identified through regulatory disclosures, SEC Form ADV, FCA records, company reports and official reports of investment providers (Table 2). Comparability was ensured by taking into account the same or similar parameters as for robo-advisory platforms: asset allocation, AUM, fee structure, risk profile, return metrics and type of advisory model. Passive ETF benchmarks were formed on the basis of market indices and ETF-oriented portfolio structures, confirmed through Vanguard reports, SEC disclosures, JFA, company reports and relevant macroeconomic sources. So, traditional advisory portfolios and ETF benchmarks were not set conditionally, but were built on the same information sources as the main sample, which ensured the correctness of the comparison in terms of profitability, risk, fees, and stability of the portfolio structure.

The sample covered 33 robo-advisory platforms, about 1,056 potential quarterly observations, and benchmarks with average returns ranging from 3.4% CAGR (STI) to 15.1% CAGR (NASDAQ). The simultaneous inclusion of return, risk, assets under management, portfolio structure, and macroeconomic controls enabled a comprehensive analysis of the factors that determined the effectiveness of automated capital management. This sample architecture allowed us to evaluate robo-advisory not only as a financial technology, but also as an investment management tool, the effectiveness of which was shaped by market, behavioural, and regulatory factors.

3.4 Research Tools

Evaluating the effectiveness of robo-advisory as a mechanism for managing investment capital required the use of multi-level tools that combined benchmark indices and macroeconomic control variables to reflect the external conditions of the platforms' functioning (Table 3), as well as financial, econometric and statistical metrics to measure the profitability, risk, scalability and sustainability of investment strategies (Table 4). The use of benchmark indicators with an average annual return of 3.4–15.1% CAGR, inflation of 1.2–4.9%, economic growth rates of 0.8–2.7% and interest rates of 0.2–2.8% allowed the interpretation of the results relative to real market conditions, while risk-adjusted metrics and panel models formed the basis for a comprehensive assessment of the effectiveness of automated capital management in different macroeconomic environments.

Table 3: System of benchmark indices and macroeconomic indicators for assessing the effectiveness of investment capital management in the robo-advisory environment

Abbreviation	Full name	Definition / economic meaning	Average value*	Region / country	Source**
S&P500 CAGR	Standard & Poor's 500 Compound Annual Growth Rate	Average annual growth rate of the US 500 largest companies	≈12.4%	USA	Yahoo Finance; FRED

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NASDAQ CAGR	NASDAQ Composite CAGR	Average annual growth of a technology-oriented stock index	≈15.1%	USA	Yahoo Finance
MSCI World CAGR	Morgan Stanley Capital International World Index CAGR	Average annual return of a global developed market index	≈8.7%	Global	MSCI
FTSE100 CAGR	Financial Times Stock Exchange 100 CAGR	Average annual growth of the UK's 100 largest companies	≈4.1%	UK	Yahoo Finance
DAX CAGR	Deutscher Aktienindex CAGR	Average annual growth of the 40 largest companies in Germany	≈6.8%	Germany	ECB
CAC40 CAGR	Cotation Assistée en Continu 40 CAGR	Average annual return of the 40 leading companies in France	≈5.9%	France	OECD
SMI CAGR	Swiss Market Index CAGR	Average annual return of the largest companies in Switzerland	≈7.2%	Switzerland	SNB
Nikkei225 CAGR	Nikkei 225 CAGR	Average annual growth of the 225 largest companies in Japan	≈7.5%	Japan	BoJ
STI CAGR	Straits Times Index CAGR	Average annual return of the leading companies in Singapore	≈3.4%	Singapore	MAS
ASX200 CAGR	S&P/ASX 200 CAGR	Average annual growth of the 200 largest companies in Australia	≈6.2%	Australia	RBA
Inflation	Inflation Rate	Average annual growth rate of consumer prices	1.2–4.9%	According to the country	OECD; FRED
CPI	Consumer Price Index	Consumer Price Index; inflation indicator	≈3.8%	USA	FRED
GDP growth	Gross Domestic Product Growth Rate	Gross Domestic Product growth rate	0.8–2.7%	According to the country	World Bank
GDP	Gross Domestic Product Growth	Year-on-year change in the country's GDP	0.8–2.7%	According to the country	OECD
Fed rate	Federal Funds Rate	US Federal Reserve Base Rate	≈2.4%	USA	FRED
Interest rate	Policy Interest Rate	Central Bank Base Rate	≈2.4%	USA	FRED
BoE rate	Bank of England Base Rate	Bank of England Key Rate	≈2.8%	UK	BoE
ECB rate	European Central Bank Interest Rate	European Central Bank Base Rate	≈1.7%	Eurozone	ECB
SNB rate	Swiss National Bank Policy Rate	Swiss National Bank Interest Rate	≈0.9%	Switzerland	SNB
BoJ rate	Bank of Japan Interest Rate	Bank of Japan Base Rate	≈0.2%	Japan	BoJ
VIX	Chicago Board Options Exchange Volatility Index	US Stock Market Expected Volatility Index	≈22.1	USA	CBOE; FRED
Household assets/GDP	Household Financial Assets to GDP Ratio	Household Financial Assets to GDP Ratio	≈540%	USA	OECD; FRED

Note: *Values are given as indicative averages for 2018–2025 used as benchmarks or macroeconomic controls in the empirical analysis
**See Table 2
Source: developed by the authors

A system of benchmark indices and macroeconomic indicators formed the external context of the assessment: market returns, inflation, interest rates, GDP, and volatility. To directly measure the effectiveness of robo-advising, these indicators were supplemented with financial metrics, risk-adjusted indicators and statistical tools that allowed us to assess the profitability, risk, costs, sustainability, and reliability of the obtained results (Table 4).

Table 4: Metrics and statistical tools for assessing the effectiveness of robo-advising as a mechanism for managing investment capital

Metric/Tool Name	Description	Interpretation	Academic Studies
Annualized Return	Reflects the average annual growth rate of the value of an investment portfolio over a specified period, taking into account the cumulative effect	Higher value → higher total return on investment	Chen et al. [33]
Sharpe Ratio	Estimates the ratio of the portfolio's excess return to the level of overall risk (volatility)	>1 – high efficiency; more value → better balance between risk and return	Vijaya et al. [34]
Sortino Ratio	Measures the return relative to only negative volatility, ignoring positive fluctuations	Higher value → more effective downside risk management	Israr et al. [35]
Treynor Ratio	Determines the return per unit of systemic risk associated with market changes	Higher value → more efficient use of market risk	Anuar et al. [36]
Jensen's Alpha	Characterizes the portfolio's excess return relative to the expected market level	>0 → the portfolio exceeds the benchmark	Caballero-Fernández et al. [37]
Annualized Volatility	Reflects the average level of portfolio return fluctuations during the year	Lower value → more stable investment portfolio	Dai et al. [38]
Max Drawdown	Indicates the largest drop in portfolio value from local maximum to minimum	Less drawdown → higher resilience to crises	Dias [39]
AUM Growth	Measures the growth rate of assets under management of the platform over a certain period	Higher value → faster scaling of robo-advisory	Kumar [40]
Expense Ratio	Reflects the share of operating expenses in relation to total assets	Lower value → more efficient cost management	Barile et al. [41]
Management Fee	Characterizes the size of the commission for portfolio management or investment strategy	Lower commission → potentially higher net return	Barile et al. [42]
ETF Share	Determines the share of ETFs in the structure of the investment portfolio	Higher value → greater diversification and lower costs	Tan [43]
Portfolio Drift	Estimates the deviation of the actual asset structure from the target allocation	Lower value → more efficient automatic rebalancing	Verma et al. [44]
Portfolio Turnover	Reflects the frequency of changes in assets in the portfolio during the period	Lower value → lower transaction costs	Wang and Yu [45]
Net Outflows (%AUM)	Shows the share of net outflow of investment capital relative to AUM	Lower value → greater investor confidence	Virk [46]
Recovery Period	Determines the time it takes for a portfolio to return to its previous high after a drop	Shorter period → faster recovery from crisis	Capponi et al. [47]
Fixed Effects Regression	Panel regression model that controls for constant platform or country characteristics	Significant coefficients → confirmed economic impact of factors	Hodge et al. [48]
Difference-in-Differences (DiD)	A method of comparing changes between experimental and control groups before and after an event	Significant differences → presence of event effect	Gao et al. [49]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Event Study	Analyses the reaction of investment indicators to market shocks or crisis events	Less negative reaction → higher stress resistance	Shanmuganathan [50]
Cluster Analysis	Groups platforms or countries by similar development characteristics	Allows to identify typical market models	Arenas-Parra et al. [51]
t-test	Tests the statistical significance of the difference in mean values between groups	p<0.05 → difference is statistically significant	Forlicz et al. [52]
Mann–Whitney U test	Non-parametric test for comparing two independent groups	p<0.05 → significant difference	Waliszewski and Warchlewska [53]
Breusch–Pagan test	Detects the heterogeneity of variance of the regression model residuals	p>0.05 → no heteroscedasticity	Baig et al. [54]
Wooldridge test	Tests autocorrelation in panel data	p>0.05 → no autocorrelation	Caragea et al. [55]
Variance Inflation Factor (VIF)	Estimates the level of multicollinearity between independent variables	VIF<5 → acceptable level of dependence	Bihari et al. [56]
Bootstrap Confidence Interval (95%)	Forms confidence intervals through multiple repeated sampling modelling	Narrower interval → higher robustness of results	Ooi et al. [57]
Robust Standard Errors	Corrects the model standard errors under heterogeneous variance	Increases the reliability of statistical estimates	Alsabah et al. [58]

Source: developed by the authors

The developed range of tools integrated market benchmark indices, macroeconomic controls, financial performance metrics, risk indicators, and econometric methods for testing statistical significance, which created a multidimensional basis for evaluating robo-advisory (Table 3, Table 4). The applied approach made it possible to simultaneously determine the level of profitability, adaptability to market shocks, risk management effectiveness, and the impact of external economic factors on platform performance. The combination of 26 metrics and statistical tools with 22 benchmark and macroeconomic indicators formed a sufficient analytical basis for further application of panel modelling, comparative analysis, and testing the stability of the obtained results. As a result, the tool stack enabled exploring robo-advisory not only as a technology for automating investment decisions, but also as a comprehensive economic mechanism for managing investment capital in developed stock markets.

The study used a combined software stack focused on collecting, cleaning, integrating, and econometric processing of financial data. The initial sample structuring, platform-quarter observation unification, and calculation of baseline indicators were performed in Microsoft Excel and Google Sheets. The purpose was to check the completeness of the data for 33 robo-advisory platforms and align them with benchmark indices and macroeconomic controls. The main calculations were performed in Python 3.11 using the pandas, NumPy, SciPy, statsmodels, and scikit-learn libraries: they provided the calculation of annualized return, Sharpe Ratio, Sortino Ratio, Treynor Ratio, Jensen's Alpha, annualized volatility, max drawdown, and the preparation of a panel data set. Statsmodels and linearmodels were used for statistical testing in order to apply fixed effects regression, robust standard errors, VIF, Breusch–Pagan test, and Wooldridge test. The graphical representation of the results was generated in Matplotlib, where point distributions, combined biaxial profiles, and comparative risk-adjusted performance graphs were constructed. This software stack ensured the reproducibility of calculations, data quality control, and statistical verification of economic conclusions regarding the effectiveness of robo-advisory in developed stock markets.

4. RESULTS

The primary evaluation was aimed at verifying whether robo-advisory created a real economic advantage compared to traditional advisory portfolios and passive ETF benchmarks. Using only the average annual return would not give a sufficient assessment, because in developed stock markets the investment result depended not only on the capital gain, but also on the risk taken, the depth of the recession and the ability of the portfolio to maintain stability in crisis periods. Therefore, the analysis was based on a combination of annualized return, Sharpe ratio, Sortino ratio, Treynor ratio, Jensen's alpha, annualized volatility and max drawdown, which made it possible to compare portfolios according to the criterion of yield per unit of risk. The spatial distribution of observations in the risk-return coordinates is shown in Figure 3, and the comparative profile of key indicators by types of investment consulting – in Figure 4.

Journal of Theoretical and Applied Information Technology
15st September 2026. Vol.104. No.17
© Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

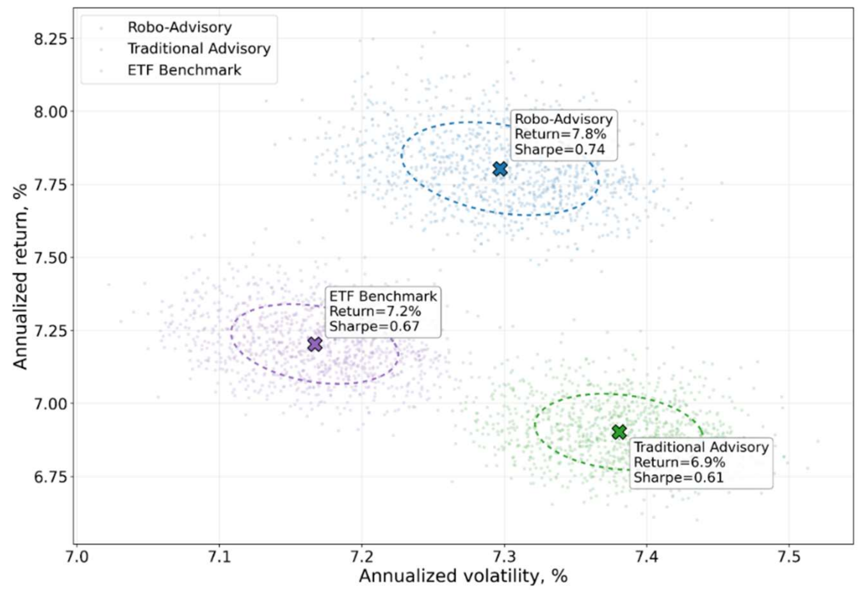


Figure 3: Distribution of investment observations by type of advice in the risk and return space
Source: developed by the authors

The results confirmed the moderate but persistent advantage of robo-advisory portfolios. Their average annual return was 7.8%, which was 0.9 pp. higher than traditional advisory portfolios (6.9%) and 0.6 pp. higher than ETF benchmarks (7.2%). At the same time, the main difference was not in absolute return, but in risk-adjusted results: the Sharpe ratio reached 0.74 versus 0.61 and 0.67, and the Sortino ratio was 1.06 versus 0.84 and 0.93, respectively. This meant that robo-advisory portfolios were more effective in converting the assumed risk into return, especially when negative volatility was taken into account. In Figure 3, this advantage was manifested by the shift of robo-advisory observations to the zone of higher returns at a close level of annual volatility, while Figure 4 detailed the advantage for the risk-adjusted profile. Additionally, the max drawdown for robo-advisory portfolios was −18.4% versus −23.7% for traditional advisory portfolios, meaning the depth of losses was 5.3 pp lower. Jensen's alpha at +0.42 pp per year indicated a positive, though not radical, excess return after accounting for market risk.

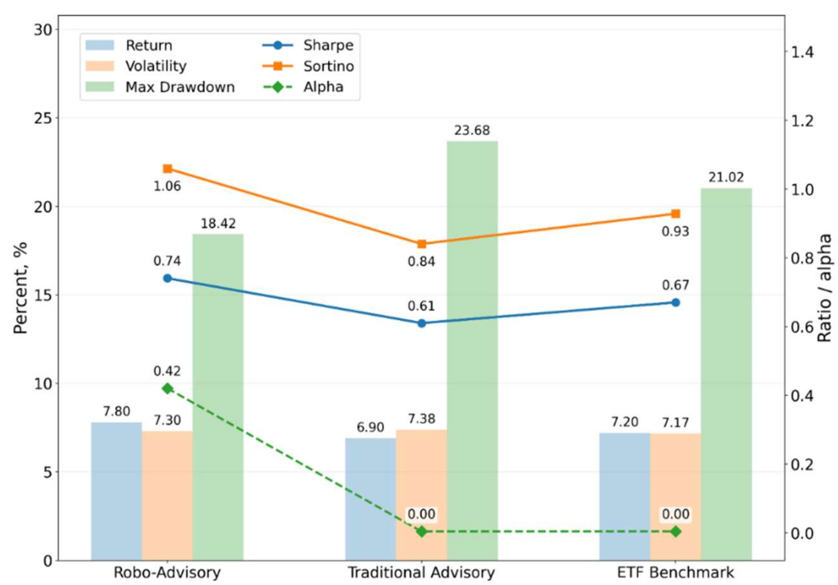
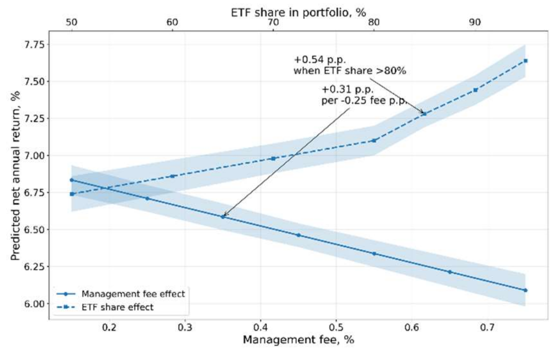


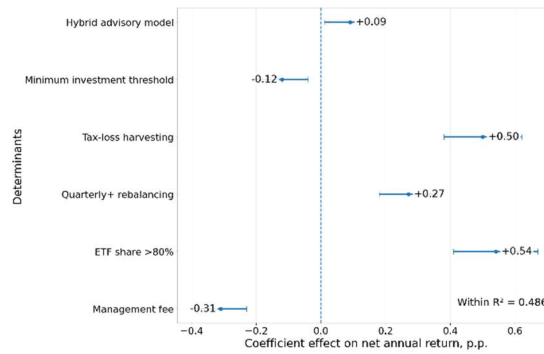
Figure 4: Combined profile of return, risk and risk-adjusted performance by investment advice type
Source: developed by the authors

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

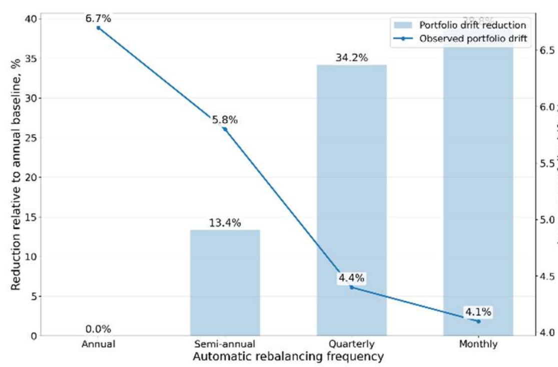
So, robo-advisory did not form a sharp advantage in terms of profitability, but demonstrated a better combination of profitability, downside risk, drawdown and excess profitability. It is this configuration that created the basis for further analysis of the economic factors of the obtained effect. The next analytical block should be aimed at establishing which mechanisms – lower management fees, higher ETF share, automatic rebalancing, portfolio drift control or tax-loss harvesting – explained the recorded advantage of robo-advisory portfolios (Figure 5).



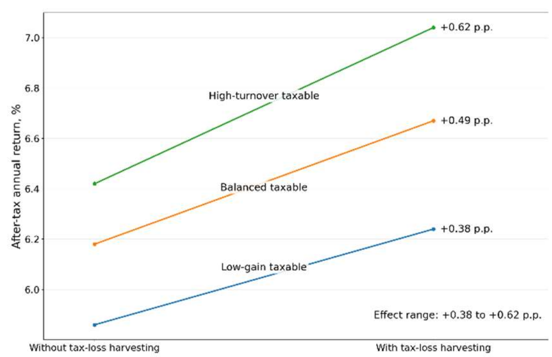
a. Marginal effects of management fee and ETF share on net annual investment return



b. Parameters of the panel regression model of economic determinants of net investment return



c. Dependence of portfolio drift on the frequency of automatic rebalancing



d. The effect of tax-loss harvesting for after-tax return in taxable accounts

Figure 5: Determining the economic determinants of net investment return
Source: developed by the authors

Analytical testing of economic determinants showed that the advantage of robo-advisory portfolios, previously recorded through higher Sharpe ratio (0.74) and Sortino ratio (1.06), had a clear internal explanation. The panel model with fixed effects explained 48.6% of the variation in net annual return, which indicated a moderately high explanatory power taking into account the heterogeneity of platforms, countries and business models (according to the sample data – Table 1). The most noticeable effect was formed by cost and structural factors: a decrease in management fee by 0.25 pp. increased net return by 0.31 pp., and the share of ETFs above 80% added another 0.54 pp. to net annual return (Figure 5, *a, b*).

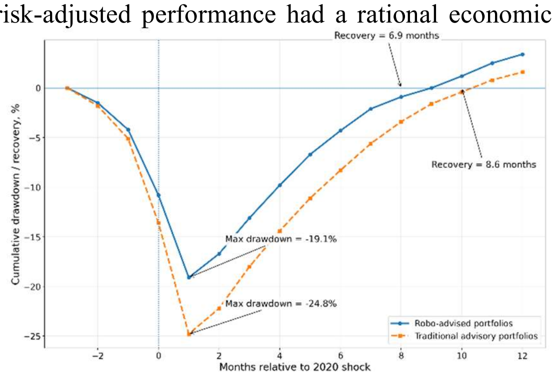
Separately, it was found that automatic rebalancing acted not as a technical option, but as an economic mechanism to maintain the target allocation. Quarterly or more frequent rebalancing reduced portfolio drift by 34.2%, and the average deviation of the actual portfolio composition from the target decreased from 6.7% to 4.4% (Figure 5, c). This explained why robo-advisory portfolios had lower drawdown and a more stable risk profile in the previous block of results: the advantage arose not only from higher returns, but also from a smaller gap between the given and actual asset composition.

The tax channel also turned out to be economically significant. The tax-loss harvesting increased after-tax returns by 0.38–0.62 percentage points per year for taxable accounts, which was especially important for developed markets with a high share of individual investing and ETF portfolios (Figure 5, d). So, net investment returns were formed through a

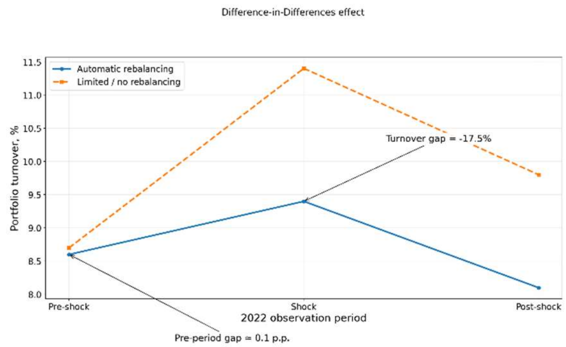
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

combination of lower fees, higher ETF diversification, controlled portfolio drift, and tax optimization, rather than through a single dominant factor.

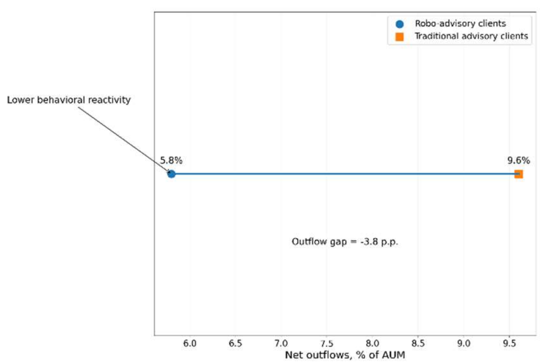
So, the obtained data confirmed that the previously recorded advantage of robo-advice over risk-adjusted performance had a rational economic basis. At the same time, these results did not yet prove the stability of the effect in conditions of sharp volatility. Therefore, further testing aimed to determine whether robo-advisory portfolios maintained lower losses, faster recoveries, and lower capital outflows during the market shocks of 2020 and 2022 (Figure 6).



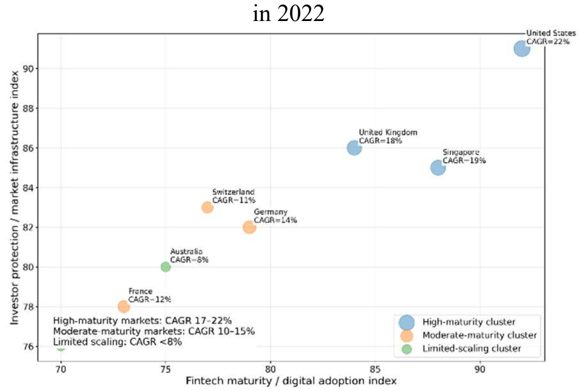
a. Profile of portfolio drawdowns and recoveries during the 2020 market shock



b. Difference-in-Differences effect of automatic rebalancing according to the portfolio turnover indicator in 2022



c. Comparison of net outflows of robo-advisory and traditional advisory platforms clients under market stress



d. Market-institutional clusters scaling robo-advisory AUM in developed markets

Figure 6: Analysis of stress resistance and market and institutional conditions for scaling robo-advisory
Source: developed by the authors

The stress test showed that robo-advisory portfolios retained their advantage not only in normal market conditions, but also during high volatility. In 2020, the maximum drawdown was −19.1% versus −24.8% for traditional advisory portfolios, The losses were lower by 5.7 percentage points; the recovery period was reduced from 8.6 to 6.9 months, or by approximately 19.8% (Figure 6, *a*). This extended the previous conclusion about the better risk-adjusted profile of robo-advisory: the higher return and lower downside risk were not random, but behavioural and operational.

The Difference-in-Differences results for 2022 showed that automatic rebalancing reduced portfolio turnover by 17.5% compared to portfolios without such a mechanism or with limited rebalancing (Figure 6, *b*). This directly explained the previously established portfolio drift effect: a reduction in allocation deviation from 6.7% to 4.4% translated into less trading activity during the shock. So, the rebalancing discipline worked not only as a technical function, but also as a channel for reducing operational and behavioural risk.

Investor behavioural response was also weaker in the robo-advisory segment. Net outflows were 5.8% of AUM versus 9.6% of AUM in the control group, a difference of 3.8 percentage points, or almost 39.6%, from the level of outflows in traditional advisory portfolios (Figure 6, *c*). This result suggests that algorithmic discipline, lower costs, and a more

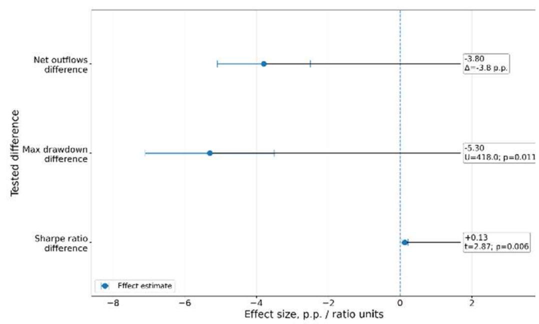
Journal of Theoretical and Applied Information Technology
15st September 2026. Vol.104. No.17

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

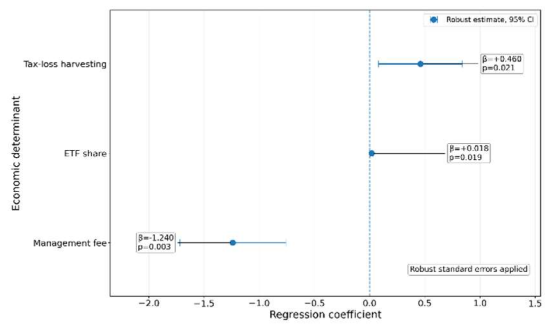
transparent ETF structure partially restrained panic capital withdrawals.

The market institutional block showed that the scaling of robo-advisory depended on the quality of the financial infrastructure. Highly mature markets had a CAGR of robo-advisory AUM of 17–22%, moderately mature markets – 10–15%, while markets with limited scaling remained below 8% (Figure 6, *d*). This meant that the effectiveness of robo-advisory was shaped not only by portfolio parameters, but also by fintech maturity, investor protection, ETF availability and digital readiness of investors.

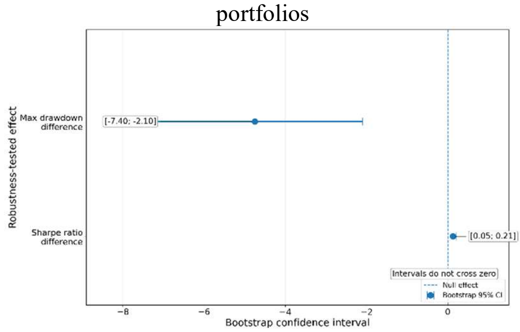
So, the results confirmed the sustainability of the previously established advantage: robo-advisory portfolios had lower drawdowns, faster recovery, lower capital outflows and better conditions for scaling in mature markets. At the same time, these conclusions needed a formal verification of statistical reliability. Therefore, the final analytical procedure focused on t-test, Mann–Whitney U test, bootstrap confidence intervals, VIF, and robust standard errors to confirm the significance and robustness of the obtained effects (Figure 7).



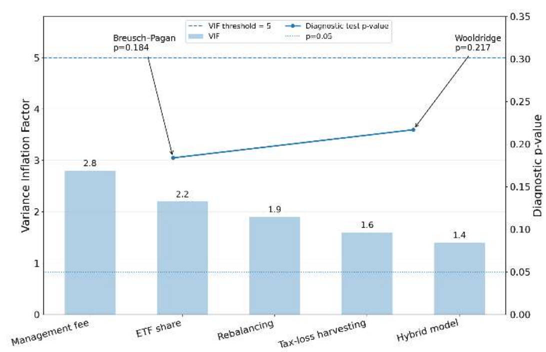
a. Statistical significance of key differences between robo-advisory portfolios and traditional advisory portfolios



b. Robustness of regression coefficients of economic determinants net annual return



c. Bootstrap 95% confidence intervals for key effects of risk-adjusted efficacy



d. Panel model quality diagnostics and multicollinearity testing

Figure 7: Statistical verification of the reliability and robustness of empirical results
Source: developed by the authors

Statistical testing confirmed that the observed advantage of robo-advisory portfolios was not a random sampling error. The Sharpe ratio difference between robo-advisory portfolios and traditional advisory portfolios remained significant (t=2.87; p=0.006), and the difference in max drawdown was confirmed by a nonparametric test (U=418.0; p=0.011). This directly supported previous results, where robo-advisory had a higher Sharpe ratio (0.74 vs. 0.61) and less drawdown (−18.4% vs. −23.7%) in the baseline comparison, as well as lower losses during the 2020 shock (−19.1% vs. −24.8%) (Figure 7, *a*).

The regression testing also preserved the economic logic of the previous analysis. Management fee had a persistent negative effect on net return (β=−1.24; p=0.003), ETF share remained a positive factor (β=0.018; p=0.019), and tax-loss harvesting provided a significant after-tax effect (β=0.46; p=0.021) (Figure 7, *b*). This confirmed that net investment returns were formed not only through market movements of assets, but through a combination of cost efficiency, ETF diversification, and tax optimization.

Bootstrap testing strengthened the reliability of the findings. The confidence interval for the Sharpe ratio difference was [0.05; 0.21], and for the max drawdown difference – [−7.4; −2.1] pp; both intervals did not cross zero (Figure 7, *c*). So, the advantage of robo-advisory in risk-adjusted performance and stress resistance remained robust after repeated sample modelling.

Model diagnostics did not reveal critical methodological limitations. VIF for key variables did not exceed 2.8, which was below the conditional threshold of 5.0. Accordingly, multicollinearity did not distort the estimates of the coefficients ((Figure 7, *d*). The use of robust standard errors further reduced the risk of misinterpretation of the regression results. As a result, the statistical test translated the previous analytical results into the plane of confirmed econometric interpretation.

So, empirical research confirmed that robo-advisory was a cost-effective tool for managing investment capital in developed stock markets. Its advantage was manifested not in radical market excess, but in a better return–risk–cost–stability ratio. Sharpe ratio increased by 0.13 points, max drawdown decreased by 5.3 pp, portfolio drift decreased by 34.2%, crisis-driven net outflows were lower by 3.8 pp. AUM, and after-tax return increased by 0.38–0.62 pp. per year. Statistical test confirmed the significance of key effects at the $p<0.05$ level, therefore robo-advisory was justified as a low-cost, algorithmically disciplined and scalable portfolio management mechanism, the effectiveness of which was most determined by ETF structure, lower commissions, regular rebalancing, tax-loss harvesting and maturity of the financial infrastructure.

So, the research hypothesis was confirmed. The results showed that robo-advisory increased the efficiency of investment capital management not through an isolated increase in profitability, but through a simultaneous improvement in risk-adjusted indicators, a reduction in costs, control of the portfolio structure and limitation of the behavioural reaction of investors under stressful conditions. Confirmation of the hypothesis was of a complex nature: the advantage of robo-advisory portfolios was recorded in terms of Sharpe ratio, max drawdown, portfolio drift, net outflows and after-tax return, and statistical testing showed that these effects remained significant and robust.

5. DISCUSSION

The discussion of the results was necessary to move from the internal interpretation of empirical indicators to a broader academic explanation of the role of robo-advisory in modern investment capital management. The obtained results were not reduced to fixing higher returns; they showed that the effectiveness of robo-advisory was shaped by the interaction of risk, costs, ETF structure, rebalancing, tax optimization, and institutional maturity of the market. That is why a comparison with alternative approaches was appropriate: it allowed us to determine whether the recorded advantage of robo-advisory is a separate empirical case or whether it reflects a more stable economic mechanism. The fact that this study combined portfolio metrics, regression estimates, stress tests and robustness testing is of particular importance, while individual directions of previous approaches mostly considered only behavioural, regulatory, technological or institutional aspects.

First of all, the behavioural and regulatory block of earlier studies outlined the conditions without which robo-advisory did not acquire full economic value. So [59] explained the importance of risk profiling as an input prerequisite for automated advice. Guo [60] and Ololude [61] focused on the legal status, trust, disclosure, audit and control of algorithmic decisions. The obtained results extended this approach: in developed markets, the appropriate institutional framework had already been transformed into a measurable portfolio effect, where the Sharpe ratio was 0.74, the max drawdown was reduced to −18.4%, and crisis-driven net outflows were lower –5.8% of AUM versus 9.6% in traditional advisory portfolios. So, previous authors rather identified the prerequisites of trust and regulatory suitability, while this study showed under what conditions these prerequisites produced an economic result.

Another line of work considered robo-advisory as a technological or methodological architecture, but did not always prove its stable portfolio advantage. Méndez-Suárez et al. [62] showed the potential of active AI-forecasting using a short/long trading simulation example, Snihovyi et al. [63] demonstrated a return of 16.5–31.8% in a crypto-oriented model. Beketov et al. [64] revealed the dominance of Modern Portfolio Theory among 219 robo-advisors. However, these results were either market specific or architecturally descriptive. Instead, this study confirmed a more moderate but more stable performance in developed stock markets: annualized return 7.8%, Sortino ratio 1.06,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Jensen's alpha +0.42 pp. So, the main advantage was not in aggressive price forecasting, but in the systematic optimization of return–risk–cost through ETF share over 80%, lower fees and regular rebalancing.

It is significant that some studies have emphasized the social and institutional value of robo-advisory, while the empirical results of this study clarified its economic aspect. Shetty et al. [65] linked WMRAs, RRAs and PRAs with return maximization, risk minimization and financial inclusion. Choudhari et al. [66] interpreted robo-advisory as a means of democratizing wealth management, and Baulkaran and Jain [67] showed the specifics of demand among younger, small and professionally employed investors. Against this background, the obtained results provided quantitative support: the advantage of robo-advisory was manifested in an increase in net return to 0.54 pp. with a high ETF share, a reduction in portfolio drift by 34.2% and a decrease in max drawdown by 5.3 pp. Compared to earlier studies, financial inclusion and behavioural stability were not only expected benefits but also part of a proven mechanism for effectiveness.

Finally, work on personalization, operational automation, and implementation barriers showed the limits of robo-advisory's versatility. Rico-Perez et al. [68] showed that the expansion of instruments, including fixed-income bonds, made instrument data validation and order management more difficult. Kaur and Kour [69] considered AI/RPA more broadly –as a means of digitizing financial forecasting. Nain and Rajan [70] emphasized that stock markets depend on transparency, trust, and a human touch. In contrast to these more cautious findings, this study showed that even a standardized ETF-oriented model in developed markets could be effective. Management fee had a significant negative impact on net return (β=−1.24; p=0.003), ETF share had a positive impact (β=0.018; p=0.019), and tax-loss harvesting added 0.62 percentage points to after-tax return. The problem was not just personalization or automation per se, but the market's ability to support a low-cost, transparent, and disciplined portfolio management model.

The reviewed studies confirmed that robo-advisory developed at the intersection of trust, regulation, algorithmic architecture, personalization and financial inclusion, but often left open the question of measurable portfolio effects in developed stock markets. This study closed this gap through a quantitative verification of the full economic chain. Robo-advisory portfolios provided an annualized return of 7.8%, a Sharpe ratio of 0.74, a Sortino ratio of 1.06 and a max drawdown of −18.4%, and their advantage was formed through an ETF share of over 80% (+0.54 pp to net return), lower management fees (+0.31 pp with a fee reduction of 0.25 pp), a reduction in portfolio drift by 34.2% and tax-loss harvesting with an increase in after-tax return of up to 0.62 pp per year. Unlike studies where robo-advisory was mostly treated as a technological or institutional innovation, the results obtained proved its applied economic function. During market stress, max drawdown was lower by 5.7 pp, recovery period was reduced from 8.6 to 6.9 months, and net outflows were 5.8% of AUM versus 9.6%. Statistical testing confirmed the robustness of the effects. The Sharpe ratio difference was significant (t=2.87; p=0.006), the difference in max drawdown was confirmed by the Mann–Whitney U test (U=418.0; p=0.011), and the key regression coefficients remained significant at p<0.05.

5.1 Limitation

The study was limited to a sample of 33 robo-advisory platforms from developed stock markets, so the results cannot be automatically transferred to markets with lower financial infrastructure, weaker investor protection or limited ETF availability. Although the panel covered the period 2018–2025 and up to 1,056 quarterly observations, some indicators depended on open platform reports, regulatory disclosures and aggregated benchmark data, which may have limited the detail on the actual portfolio structure, individual risk profiles and transaction costs. In addition, the study mainly assessed the average effect of robo-advisory, while the difference between conservative, balanced and aggressive portfolio strategies could change the value of Sharpe ratio, max drawdown, tax-loss harvesting effect and portfolio drift. A separate limitation is the lack of full access to the internal algorithms of the platforms, due to which the impact of rebalancing rules, asset allocation logic and tax optimization was estimated indirectly through economic results.

5.2 Recommendations

Further research should be expanded to include emerging markets, where the role of regulatory maturity, financial literacy, and trust in automated advice can significantly change the effectiveness of robo-advisory. Methodologically, it is promising to move from aggregated platform data to account-level or portfolio-level observations, which would allow for a more accurate measurement of the impact of risk profiling, investor age, investment horizon, behavioural reactions, and tax status on net annual return. It is also appropriate to separately test different portfolio modes: ETF-only, hybrid advisory, fixed-income-enhanced, and AI-driven active allocation, as their effectiveness may manifest itself differently in Sharpe ratio, Sortino ratio, portfolio turnover, and after-tax return. It is practically important to develop a standardized disclosure framework for robo-advisory platforms that would disclose data on fees, drift, rebalancing frequency, realized tax effects, and stress-period performance without disclosing commercially sensitive algorithms.

6. CONCLUSIONS

Research findings. The study confirmed that robo-advisory was a cost-effective tool for managing investment capital in developed stock markets, but its advantage did not lie in radically exceeding market returns. The average annual return of robo-advised portfolios was 7.8% versus 6.9% for traditional advisory portfolios and 7.2% for ETF benchmarks, while a more qualitative difference was evident in risk-adjusted performance. The Sharpe ratio reached 0.74, the Sortino ratio - 1.06, Jensen's alpha - +0.42 pp, and the max drawdown decreased to -18.4%. So, robo-advisory provided a better balance between return, risk, and portfolio stability, rather than simply a higher nominal return.

The economic mechanism for this advantage was related to lower costs, ETF diversification, rebalancing discipline, and tax optimization. A 0.25 pp reduction in management fees increased net return by 0.31 pp, an ETF share above 80% added 0.54 pp, quarterly rebalancing reduced portfolio drift by 34.2%, and tax-loss harvesting increased after-tax return by 0.38–0.62 pp per year. During the 2020 market stress, robo-advised portfolios had less drawdown (−19.1% vs. −24.8%) and faster recovery (6.9 vs. 8.6 months), and crisis-driven net outflows were 3.8 pp lower on AUM. Statistical testing confirmed the reliability of the results: the Sharpe ratio difference was significant ($t=2.87$; $p=0.006$), max drawdown – by Mann–Whitney U test ($U=418.0$; $p=0.011$), and key regression coefficients remained significant at $p<0.05$.

The academic novelty of the study is a comprehensive empirical justification of robo-advisory not only as a digital investment advisory service, but as a measurable economic mechanism for managing capital in developed stock markets. In contrast to approaches that focused mainly on risk profiling, AI architecture, trust, or regulatory prerequisites, the study combined risk-adjusted performance, net return determinants, stress-resilience analysis, and statistical robustness testing. This gave grounds to prove that the effectiveness of robo-advisory was formed through the interaction of return–risk–cost–tax–behavioural stability, and not through a separate technological or market factor.

The practical significance of the results is the possibility of using the obtained conclusions for the design, regulation, and evaluation of robo-advisory platforms in the field of wealth management. For providers, the results indicated the priority of low management fees, ETF share over 80%, automatic rebalancing and tax-loss harvesting as sources of net return growth. For investors, the study showed that robo-advisory was appropriate not as a tool for aggressively outperforming the market, but as a mechanism for stabilizing the portfolio, reducing costs and limiting crisis losses. For regulators, the results substantiated the need for transparent disclosure regarding fees, portfolio drift, rebalancing frequency, tax effects, and stress-period performance.

REFERENCES:

[1] Fortune Business Insights, *Robo advisory market size, share & industry analysis, by type (pure robo-advisors and hybrid robo-advisors), by end user (retail investors, high-net-worth individuals, and SMEs and corporate clients), by service type (direct plan-based/goal-based and comprehensive wealth advisory), and regional forecast, 2026–2034,* 2026. https://www.fortunebusinessinsights.com/robo-advisory-market-109986

[2] S. Khonsha and H. Sadeqi, "Designing and Implementing an Artificial Intelligence-Based Robo-Advisor to Assess Investors' Risk Tolerance: A Case Study of the S&P 500 Index", *Knowledge Economy Studies*, Vol. 1, No. 2, 2024, pp. 23-41,. https://doi.org/10.22034/kes.2024.2044079.1023

[3] C. Phore, P. Rajain and A. Talan, "Robo-advisors: A futuristic approach to wealth management", *International Journal of Services Operations and Informatics*, Vol. 13, No. (2/3/4), 2025, pp. 264–291,. https://doi.org/10.1504/ijsoi.2025.152353

[4] P. Khanna and S. Jha, "AI-Based digital product 'robo-advisory' for financial investors", *Vision: The Journal of Business Perspective*, 2024. https://doi.org/10.1177/09722629241298399

[5] F. S. Dias, "Current Trends for Robo-Advisors", In *Contributions to finance and accounting*, Cham: Springer Nature Switzerland, 2026,

pp. 25–46. https://doi.org/10.1007/978-3-032-18109-1_2

[6] R. Tao, C.-W. Su, Y. Xiao, K. Dai and F. Khalid, "Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets", *Technological Forecasting and Social Change*, Vol. 163, 2020, Art. No. 120421,. https://doi.org/10.1016/j.techfore.2020.120421

[7] K. Phoon and F. Koh, "Robo-Advisors and wealth management", *The Journal of Alternative Investments*, Vol. 20, No. 3, 2018, pp. 79–94,. https://doi.org/10.3905/jai.2018.20.3.079

[8] G. A. M. Salinas, *Assessment of the efficiency of investment robo-advisory* (Doctoral dissertation, Vilniaus universitetas), 2024. https://epublications.vu.lt/object/elaba:192051445/

[9] D'F. Acunto, N. Prabhala and A. G. Rossi, "The promises and pitfalls of robo-advising", *The Review of Financial Studies*, Vol. 32, No. 5, 2019, pp. 1983–2020,. https://doi.org/10.1093/rfs/hhz014

[10] A. Bhatia, A. Chandani, R. Atiq, M. Mehta and R. Divekar, "Artificial intelligence in financial services: A qualitative research to discover robo-advisory services", *Qualitative Research in Financial Markets*, Vol. 13, No. 5, 2021, pp. 632–654,. https://doi.org/10.1108/qrfm-10-2020-0199

[11] S. Arora, A. Rajesh, R. Misra and G. Singh, "Bridging technology and trust: The role of AI-driven robo-advisors in middle-class financial management", *Management Decision*, pp. 1–24, 2025. https://doi.org/10.1108/md-01-2025-0093

[12] I. M. Bonelli and J. Liu, "Revolutionizing robo-advisors: Unveiling global financial markets, AI-driven innovations, and technological landscapes for enhanced investment decisions", *Advances in Science, Technology and Engineering Systems Journal*, Vol. 9, No. 2, 2024, pp. 33–44,. https://doi.org/10.25046/aj090205

[13] A. H. Wani, B. Moharana, V. K. Singh, S. Maurya, S. Dey and T. Sarkar, "Transforming investment management strategies: The impact of intelligent systems on modern financial planning utilizing robo-advisor", In *2025 international conference on technology enabled economic changes (intech)*, IEEE, 2025, pp. 1530–1535. https://www.researchgate.net/publication/396833264_Transforming_Investment_Management_Strategies_The_Impact_of_Intelligent_Systems_on_Modern_Financial_Planning_Utilizing_Robo-Advisor

[14] S. Raturi, A. Singh, T. Gour and S. Avikal, "Robo-Advisors in investment management", In *Robo-Advisors and artificial intelligence in human resources management: Revolutionizing HR*, New York: Apple Academic Press, 2026, pp. 215–239. https://doi.org/10.1201/9781779641410-13

[15] D. Jung, V. Dorner, F. Glaser and S. Morana, "Robo-Advisory: digitalization and automation of financial advisory", *Business & Information Systems Engineering*, Vol. 60, No. 1, 2018, pp. 81–86,. https://doi.org/10.1007/s12599-018-0521-9

[16] R. M. Gaspar and M. Oliveira, "Robo advising and investor profiling", *FinTech*, Vol. 3, No. 1, 2024, pp. 102–115,. https://doi.org/10.3390/fintech3010007

[17] A. S. George, "Robo-Revolution: Exploring the rise of automated financial advising systems and their impacts on management practices", *Partners Universal Multidisciplinary Research Journal (PUMRJ)*, Vol. 01, No. 04, 2024, pp. 1–16,. https://doi.org/10.5281/zenodo.14059485

[18] U.S. Securities and Exchange Commission, *Form ADV and investment adviser reports*, 2025. https://adviserinfo.sec.gov

[19] U.S. Securities and Exchange Commission, *Investment adviser public disclosure*, 2025. https://www.sec.gov

[20] Federal Reserve Bank of St. Louis, *FRED economic data*, 2025. https://fred.stlouisfed.org

[21] Vanguard Group, *Digital Advisor reports and disclosures*, 2025. https://investor.vanguard.com

[22] Financial Conduct Authority, *Financial services register and reports*, 2025. https://www.fca.org.uk

[23] Organisation for Economic Co-operation and Development, *OECD data*, 2025. https://data.oecd.org

[24] Betterment, *Annual reports*, 2025. https://www.betterment.com

[25] European Central Bank, *ECB data portal*, 2025. https://data.ecb.europa.eu

[26] Deutsche Bundesbank, *Statistics portal*, 2025. https://www.bundesbank.de

[27] Swiss National Bank, *Data portal*, 2025. https://data.snb.ch

[28] The Investment Trusts Association, Japan, *Statistics and reports*, 2025. https://www.toushin.or.jp/en

[29] Bank of Japan, *Statistics*, 2025. https://www.boj.or.jp/en/statistics

[30] SBI Holdings, *Annual reports*, 2025. https://www.sbigroup.co.jp

[31] Monetary Authority of Singapore, *Statistics*, 2025. https://www.mas.gov.sg/statistics

[32] Reserve Bank of Australia, *Statistics*, 2025. https://www.rba.gov.au/statistics

[33] X. Chen, R. Li and J. Wang, “Asset allocation optimization in robo-advising:A perspective based on reinforcement learning”, *Multidisciplinary Research in Computing Information Systems*, Vol. 5, No. 3, 2025, pp. 323–340,. https://doi.org/10.71465/mrcis104

[34] C. Vijaya, K. Hati and M. Thenmozhi, “Developing a security risk assessment based smart beta portfolio model for robo advising”, *Australasian Business, Accounting and Finance Journal*, Vol. 18, No. 3, 2024, pp. 7–25,. https://doi.org/10.14453/aabfj.v18i3.02

[35] S. Israr, K. Balaji and S. Sharma, “Robo-Advisors: The evolution of automated investment management in fintech”, In *2025 international conference on sustainability, innovation & technology (ICSIT)*, IEEE, 2025 pp. 1–6. https://www.researchgate.net/publication/398893874_Robo-Advisors_The_Evolution_of_Automated_Investment_Management_in_FinTech

[36] A. A. Anuar, M. T. Mohamad and A. A. Sulaiman, “Robo-advisors and ai-driven funds: Catalysts in the dynamic evolution of asset management”, *International Journal of Banking and Finance*, Vol. 20, No. 2, 2025, pp. 60–90,. https://doi.org/10.32890/ijbf2025.20.2.4

[37] R. Caballero-Fernández, K. Cortez and D. Ceballos-Hornero, “Robo advisors vs. value investing strategies: A fuzzy jensen’s alpha assessment”, In *Digital era and fuzzy applications in management and economy*, Cham: Springer International Publishing, 2022, pp. 178–193. https://doi.org/10.1007/978-3-030-94485-8_13

[38] M. Dai, H. Jin, S. Kou and Y. Xu, “Robo-advising: A dynamic mean-variance approach”, *Digital Finance*, Vol. 3, No. 2, 2021, pp. 81–97,. https://doi.org/10.1007/s42521-021-00028-4

[39] F. S. Dias, “An introduction to robo-advisors, notable fintech implementations, and underlying theory”, In *Financial innovation and technology*, Cham: Springer Nature Switzerland, 2025, pp. 285–300. https://doi.org/10.1007/978-3-031-83402-8_11

[40] I. Kumar, “Evolution of financial advisory market with the advent of robo-advisors”, *Managerial Finance,* Vol. 51, No. 5, 2024. https://doi.org/10.1108/mf-03-2024-0240

[41] D. Barile, G. Secundo, M. Mariani and A. Brandonisio, *A new era: Managing green investments through robo-advisors*. *Management Decision*, 2025. https://doi.org/10.1108/MD-06-2024-1268

[42] D. Barile, G. Secundo and C. Bussoli, *Exploring artificial intelligence robo-advisor in banking industry: A platform model*. *Management Decision*. Advance online publication, 2024. https://doi.org/10.1108/MD-08-2023-1324

[43] G. K. S. Tan, “Robo-advisors and the financialization of lay investors”, *Geoforum*, Vol. 117, 2020, pp. 46–60,. https://doi.org/10.1016/j.geoforum.2020.09.004

[44] V. Verma, P. Singh and P. Kumar, “Digital transformation in wealth management: Exploring how robo-advisors moderate behavioral biases and shape investment decisions”, In *Robo-Advisors and artificial intelligence in human resources management: Revolutionizing HR*, New York: Apple Academic Press, 2026, pp. 147–159. https://doi.org/10.1201/9781779641410-9

[45] H. Wang and S. Yu, “Robo-Advising: Enhancing investment with inverse optimization and deep reinforcement learning”, In *2021 20th IEEE international conference on machine learning and applications (ICMLA)*. IEEE, 2021. https://www.researchgate.net/publication/358111643_Robo-Advising_Enhancing_Investment_with_Inverse_Optimization_and_Deep_Reinforcement_Learning

[46] N. Virk, “Sustainable Investing and the Role of AI-Driven Robo-Advisors”, In *Contributions to finance and accounting*, Cham: Springer Nature Switzerland, 2026, pp. 347–380. https://doi.org/10.1007/978-3-032-18109-1_15

[47] A. Capponi, S. Ólafsson and T. Zariphopoulou, “Personalized robo-advising: Enhancing investment through client interaction”, *Management Science,* Vol. 68, No. 4, 2021. https://doi.org/10.1287/mnsc.2021.4014

[48] F. D. Hodge, K. I. Mendoza and R. K. Sinha, “The effect of humanizing robo-advisors on investor judgments*”, *Contemporary Accounting Research,* Vol. 38, No. 1, 2020. https://doi.org/10.1111/1911-3846.12641

[49] W. Gao, M. Ju and S. Landue, “Robo-advisors of young enterprises vs. robo-advisors of established investment companies: Evidence from well-known robo-advisors”, *Eurasian Business Review*, 2026. https://doi.org/10.1007/s40821-026-00359-5

[50] M. Shanmuganathan, “Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions”, *Journal of Behavioral and Experimental Finance*, Vol. 27, 2020, Art. No. 100297,. https://doi.org/10.1016/j.jbef.2020.100297

[51] M. Arenas-Parra, H. Rico-Pérez and R. Quiroga-Garcia, “The emerging field of Robo Advisor: A relational analysis”, *Heliyon*, Vol. 10, No. 16, 2024, Art. No. e35946,. https://doi.org/10.1016/j.heliyon.2024.e35946

[52] M. Forlicz, T. Rólczyński, B. Franczyk and Z. Kes, “AI approach, risk attitude and the adoption of financial robo-managers – an incentivized experiment results”, In *Lecture notes in networks and systems*, Cham: Springer Nature Switzerland, 2026, pp. 135–150. https://doi.org/10.1007/978-3-032-13869-9_11

[53] K. Waliszewski and A. Warchlewska, “Attitudes towards artificial intligence in the area of personal financial planning: A case study of selected countries”, *Entrepreneurship and Sustainability Issues*, Vol. 8, No. 2, 2020, pp. 399–420,. https://doi.org/10.9770/jesi.2020.8.2(24)

[54] M. H. Baig, J. Xu, F. Shahzad, I. U. Rehman and R. Ali, “Exploring the impact of fintech innovation on dividend payout decisions: The roles of intellectual capital and board characteristics”, *International Journal of Emerging Markets,* Vol. 20, No. 12, 2024, pp. 4831–4857,. https://doi.org/10.1108/ijoem-05-2024-0780

[55] D. Caragea, T. Cojoianu, M. Dobri, A. Hoepner, O. Peia and D. Romelli, “Competition and innovation in the financial sector: Evidence from the rise of fintech start-ups”, *Journal of Financial Services Research,* Vol. 45, 2023, pp. 103–140,. https://doi.org/10.1007/s10693-023-00413-7

[56] A. Bihari, M. Dash, A. Kumar, K. Muduli, S. Luthra and A. Samadhiya, “The impact of AI-powered robo-advisors on investor decision-making: The moderating role of financial knowledge”, *VINE Journal of Information and Knowledge Management Systems*, 2026. https://doi.org/10.1108/vjikms-09-2025-0407

[57] S. K. Ooi, J. A. L. Yeap, P. W. Chin and D. Hu, “Two-wave time-lagged analysis of continuance usage in robo-advisory services: A sequential mediation approach”, *Marketing Intelligence & Planning*, Vol. 44, No. 3, 2025. https://doi.org/10.1108/mip-08-2024-0619

[58] H. Alsabah, A. Capponi, O. Ruiz Lacedelli and M. Stern, “Robo-Advising: Learning investors’ risk preferences via portfolio choices*”, *Journal of Financial Econometrics,* Vol. 19, No. 2, 2020, pp. 369–392,. https://doi.org/10.1093/jjfinec/nbz040

[59] M. K. P. So, “Robo-Advising risk profiling through content analysis for sustainable development in the hong kong financial market”, *Sustainability*, Vol. 13, No. 3, 2021, Art. No. 1306,. https://doi.org/10.3390/su13031306

[60] L. Guo, “Regulating investment robo-advisors in china: Problems and prospects”, *European Business Organization Law Review*, Vol. 21, No. 1, 2020, pp. 69–99,. https://doi.org/10.1007/s40804-020-00187-8

[61] R. A. Ololude, “Navigating the future: Robo-advisors in the financial landscape”, *ABUAD Law Journal*, Vol. 12, No. 1, 2024, pp. 104–118,. https://journals.abuad.edu.ng/index.php/alj/article/view/756

[62] M. Méndez-Suárez, F. García-Fernández and F. Gallardo, “Artificial intelligence modelling framework for financial automated advising in the copper market”, *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 5, No. 4, 2019, Art. No. 81,. https://doi.org/10.3390/joitmc5040081

[63] O. Snihovyi, V. Kobets and O. Ivanov, “Implementation of robo-advisor services for different risk attitude investment decisions using machine learning techniques”, In *Information and communication technologies in education, research, and industrial applications*, Cham: Springer International Publishing, 2019, pp. 298–321. https://doi.org/10.1007/978-3-030-13929-2_15

[64] M. Beketov, K. Lehmann and M. Wittke, “Robo Advisors: Quantitative methods inside the robots”, *Journal of Asset Management*, Vol. 19, No. 6, 2018, pp. 363–370,. https://doi.org/10.1057/s41260-018-0092-9

[65] J. P. Shetty, P. Singh and S. Verma, “Robo-Advisors in financial services: Redefining wealth management in the age of artificial intelligence”, *Finance Research Open*, Vol. 2, No. 1, 2026,

Art. No. 100090,. https://doi.org/10.1016/j.finr.2026.100090

[66] A. A. Choudhari, N. Moholkar, I. Kole, S. Sharma, D. Ingale and P. B. Deshmukh, "Automating wealth management: The impact of robo-advisors on personal investment strategies", In *International conference on modelling strategies in mathematics: Icmsm 2024*, AIP Publishing, 2025, Art. No. 030005. https://doi.org/10.1063/5.0275995

[67] V. Baulkaran and P. Jain, "Who uses robo-advising and how?", *Financial Review,* Vol. 58, 2023, pp. 65–89,. https://doi.org/10.1111/fire.12324

[68] H. Rico-Perez, M. Arenas-Parra and R. Quiroga-García, "Customized Robo-Advisor: Analysis of the inclusion of cash assets", *Qualitative Research in Financial Markets,* Vol. 18, No. 1, 2025, pp. 300–331,. https://doi.org/10.1108/qrfm-07-2024-0191

[69] B. Kaur and M. Kour, "Impact of artificial intelligence on investment decision-making", In *Advances in finance, accounting, and economics*, IGI Global, 2025, pp. 1–12. https://doi.org/10.4018/979-8-3693-7357-6.ch001

[70] I. Nain and S. Rajan, "Algorithms for better decision-making: A qualitative study exploring the landscape of robo-advisors in India", *Managerial Finance,* Vol. 49, No. 11, 2023, pp. 1750–1761,. https://doi.org/10.1108/mf-01-2023-0055