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ROBO-ADVISORS AND AI-DRIVEN FUNDS: CATALYSTS IN THE DYNAMIC EVOLUTION OF ASSET MANAGEMENT

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ABSTRACT

Integrating Artificial Intelligence (AI) into investment finance has been transformative; however, its dynamic evolution in asset management remains underexplored. This study aims to comprehend and investigate the presence of AI in Malaysian asset management, its evolution in relation to current traditional practices, and its performance. A mixed-methods approach was employed. Qualitative text analysis was conducted on 702 fund reports and official AMC documents to identify the presence of AI technologies and their role in transforming traditional practices. Quantitative methods were utilised to evaluate performance: user ratings of robo-advisor applications were analysed to measure adoption and satisfaction, while Welch's t-test compared the annual returns of AI-driven and human-managed equity funds to assess performance. This study identified two prominent AI in asset management: robo-advisors and AI-driven funds. Robo-advisors automate investor profiling and fund recommendations, whereas AI-driven funds use algorithms for autonomous trading decisions. AI adoption varies among asset management companies (AMCs), with differing levels of integration. This transformation has supplanted traditional unit trust consultants (UTCs) with robo-advisors and human fund managers with AI-driven funds. Preliminary findings indicate high user satisfaction with robo-advisors because of their efficacy and convenience. AI-driven funds yield annual returns comparable to those of human-managed funds in the equity category, demonstrating their proficiency in managing complex investment strategies. These findings illuminate AI's transformative potential in asset management, suggesting it could replace traditional roles and achieve competitive performance. This study lays the groundwork for future research on AI's long-term impact and scalability in the industry, enriching the understanding of AI's evolving role in finance.

Keywords: AI-driven fund, asset management, investment, Artificial Intelligence, robo-advisor.

INTRODUCTION

Investment funds aggregate capital from multiple investors and deploy it across various securities, including stocks, bonds, and money market instruments (Coleman, 2016). These funds are professionally managed, enabling individual investors to access diversified portfolios and participate in a broader spectrum of investment opportunities than they can achieve independently (Ratanabanchuen & Saengchote, 2020). Investment funds take various forms such as mutual funds, exchange-traded funds, and hedge funds, each with distinct investment strategies, risk profiles, and regulatory frameworks (Hammond et al., 2023; Mirabile, 2016) managed by Asset Management Companies (AMCs). Investment funds play a vital role in financial markets by aggregating the resources of individual and institutional investors and deploying them across diverse opportunities. Certain investors opt to delegate investment decisions to fund managers with the objective of capital appreciation rather than personally conducting market analysis to determine which securities to acquire and divest, making the investment fund industry, particularly mutual funds, attractive. Professional management enables investors to navigate the complexities of the market, optimize returns, and manage risks more effectively than they can achieve independently (Tanos, 2022).

The asset management industry has historically relied on human expertise, with financial advisors and fund managers playing pivotal roles in providing investor advisory services and overseeing fund management tasks. This human-centric approach has been the cornerstone of the industry for decades. Human financial advisors have been instrumental in assisting investors in identifying appropriate investment funds aligned with their risk-return preferences and tolerance levels (Galloppo, 2021). Likewise, fund managers have been central in making critical trading choices, performing investment analyses (Mirabile, 2016) and trading in the securities market. Nevertheless, the rapid progress of AI has disrupted these established practices, presenting new opportunities for enhanced efficiency and decision-making within the industry (Lessambo, 2021). In forex trading, robo-advisors are automated trading systems that trade funds directly (Cofnas, 2018). In asset management, the terms robo-advisors and AI-driven funds are frequently used but should be clearly distinguished. Robo-advisors refer to client-facing tools that automate investor profiling, risk assessments, and fund recommendations, enhancing accessibility to financial advice. Conversely, AI-driven funds function as back-end systems that utilise advanced algorithms to autonomously manage investment portfolios autonomously, focusing on optimising returns without human intervention. However, a specific and defined definition of these words is essential in practice to reduce ambiguity and maintain uniformity throughout the sector. Comprehending these technologies is essential, since prior studies have generalised AI applications (Fernández-Loría et al., 2022; Hung et al., 2024) without elucidating their unique functions in asset management. There is a deficiency of empirical study about their existence in Malaysian AMCs. Are these AI technologies used by all Asset Management Companies, and if so, are they implementing robo-advisors, AI-driven funds, or both? Moreover, research has not investigated the potential impact of new technologies on conventional positions such as Unit Trust Consultants (UTCs) and fund managers. This gap underscores the need for targeted study in Malaysia to evaluate the presence, integration, and influence of AI technology on asset management methods.

Given its recent emergence in the market (Dwivedi et al., 2021; Kraiwanit et al., 2022), the widespread adoption of AI technologies has not been accompanied by a commensurate increase in empirical evidence regarding their efficacy, particularly in the domains of robo-advisors and AI-driven funds. Whilst extant literature has predominantly concentrated on the technological capabilities (Gu et al., 2020; Umer Ghani et al., 2019) and theoretical advantages (Jiang, 2021; Nti et al., 2020) of AI in asset management, such as process automation (Helms et al., 2022; Lee & Moon, 2023), cost reduction

(Nimalendran et al., 2024; Setty et al., 2024), and enhanced decision-making (Cabrera et al., 2019; Paiva et al., 2019), there remains a notable dearth of user-centric evaluations. These evaluations, encompassing app adoption rates and user satisfaction, are paramount in ascertaining whether robo-advisors fulfil investor expectations and are effectively integrated as contemporary service tools. Furthermore, although previous research has explored general AI applications in trading and investment strategies (Hung et al., 2024; Lee & Moon, 2023), there is a conspicuous absence of specific analyses on the performance of AI-driven funds, particularly about their ability to generate annual returns comparable to those of human-managed funds. This study addresses this gap in Malaysia, where the asset management industry presents a unique perspective as an emerging market embracing cutting-edge technologies.

This study addresses this research gap by examining data from 39 AMCs in Malaysia comprising 762 fund reports to identify AI's prevailing applications in the industry. This study aims to explore the existence and integration of AI within the asset management landscape, focusing on robo-advisors and AI-driven funds. It seeks to understand these technologies, examine their deployment within Malaysian AMCs, and discuss their transformative impact on traditional practices, such as substituting UTCs and fund managers. Additionally, the study evaluates their performance to gain preliminary insight; robo-advisors are evaluated through application ratings to ascertain user adoption and satisfaction with this contemporary service approach, while AI-driven funds are analysed based on annual returns to determine their efficacy in comparison to human fund managers in managing pooled investments and trading in the securities market. this analytical framework was motivated by the distinct operational characteristics inherent to robo-advisors and AI-driven funds. Robo-advisors, functioning as direct interfaces with investors, necessitate the consideration of user satisfaction as a crucial parameter in evaluating their performance efficacy. On the other hand, AI-driven funds operate independently, handling pools of funds from investors and executing trades in capital markets to generate returns, all without direct client interaction. As such, their performance is more appropriately evaluated through quantitative measures such as annual returns. By addressing these AI applications separately, this study ensures that the evaluation methods align with their distinct functionalities and roles within asset management and achieve the objectives effectively.

This study comprehensively explores the transformations brought about by AI in the asset management industry. It identifies that AI deployment and utilization in the asset management industry may differ from other investment facets, such as forex, thus offering insights into AI's expansive role in reshaping traditional practices. The focus is on initial AI capabilities, evaluating technologies such as robo-advisors and AI-driven funds. This will elucidate and systematically categorize AI terminology within the asset management industry. This study's novelty lies in assessing these underexplored aspects of AI performance. User satisfaction ratings provide preliminary measures of robo-advisors' acceptance and usability, while annual returns of AI-driven funds offer insights into their performance relative to human fund managers. These methods are critical indicators of AI's current capabilities and industry adoption. The adoption of AI in AMCs necessitates a comprehensive understanding of its impact as the industry undergoes digital transformation. This study offers empirical evidence on AI's deployment and performance, assisting stakeholders and researchers in strategically navigating the industry's evolution by clarifying AI's transformative landscape, this research provides a foundation for further investigations into AI's long-term impact and scalability in asset management.

LITERATURE REVIEW

AI represents a transformative technological advancement promising to revolutionise industries, enhance human capabilities, and redefine societal norms (Huang & Rust, 2018). AI encompasses diverse techniques and applications that enable computers to perform tasks traditionally requiring human intelligence (Miller, 2019). Early AI systems primarily focused on rule-based reasoning and symbolic processing approaches to simulate and replicate cognitive functions (Elmahjub, 2023). AI aims are multidimensional and are driven by the desire to automate tasks, augment human capabilities, and advance scientific understanding. AI enables machines to perceive their surroundings, reason logically, learn from data, and adapt autonomously to shifting circumstances (Mariani et al., 2023). The influence of AI has expanded to the diverse realms of finance. In fraud detection, AI algorithms analyse real-time transaction data to identify suspicious patterns, enhance security, and reduce financial losses to banks and payment processors (Zhou et al., 2023). AI-powered chatbots and virtual assistants have revolutionised customer service, handling inquiries, providing personalised recommendations, and streamlining interactions across the banking, insurance, and fintech sectors (Khan & Rabbani, 2020). Additionally, AI's predictive analytics capabilities are leveraged in credit scoring and loan underwriting, where machine learning models assess borrower creditworthiness based on data analysis, optimizing lending decisions and improving risk management (Chen et al., 2018). AI's predictive abilities also extend to insurance underwriting, where machine learning models assess policyholder risks based on data analytics and enhance pricing accuracy (Deprez et al., 2021). Furthermore, AI technologies automate regulatory reporting, ensure adherence to financial regulations, reduce compliance costs, and improve transparency within institutions (Jobin et al., 2019). These AI-powered algorithms analyse data to assess creditworthiness, detect fraud, optimize loan approval processes, enhance operational efficiency, and minimise risk (Cherednik, 2021). Previous studies have investigated the application of AI in investment finance, frequently focusing on terms such as "robo-advisor" (Chung et al., 2023; Oehler et al., 2022) and "AI-driven fund" (Hung et al., 2024; Rui & Jinjuan, 2022). However, these terms are utilized inconsistently across investment finance, including forex trading and asset management, creating ambiguity in their definitions and roles. For instance, whilst some research equates robo-advisors with automated trading systems (Chung et al., 2023), others suggest they function as advisory tools (Capponi et al., 2022) without directly managing funds. Similarly, the distinction between robo-advisors and AI-driven funds remains unclear, particularly in how these technologies are applied in specific industry practices such as unit trust management. This lack of clarity underscores the necessity to comprehensively examine the terminology and application of Artificial Intelligence within the asset management landscape.

In the financial domain, investment entails the allocation of capital to generate returns over time (Mayo, 2020). This process involves carefully weighing risk dynamics and returns to preserve and grow financial assets (Frederick, 2019). Within the framework of investment funds, particularly mutual funds, this concept materialises in structured financial vehicles designed to pool investor resources for collective investment purposes (Galloppo, 2021). Investment funds, including mutual funds, operate based on the principle of pooled investments. Investors aggregate their monetary resources into a professionally managed portfolio comprising various securities such as stocks, bonds, and other financial instruments (Galloppo, 2021). These funds are structured to provide diversification across asset classes and sectors, mitigating individual investor risk while offering the potential for capital appreciation and income generation (Tanos, 2022).

Mutual funds are governed by a structured process that adheres to regulatory frameworks and investment mandates (Galloppo, 2021). Investors purchase shares or units in the fund, each representing the proportional ownership of the underlying assets. Fund managers overseeing fund operations make investment decisions based on stated objectives, market conditions, and investor preferences (Durán-Santomil et al., 2023). Portfolio composition evolves dynamically as managers buy, sell, or adjust their holdings to align with their strategic goals and market opportunities. Mutual funds' operational dynamics involve rigorous adherence to investment strategies, regulatory compliance, and transparent reporting to investors (Zhuang et al., 2023). Plus, investor relations and communications are pivotal in ensuring clear information on fund performance, fees, and investment strategies to maintain investor confidence and trust (Zhuang et al., 2023).

The front-end operations of mutual funds encompass client-facing aspects of fund management, focusing primarily on investor acquisition, engagement, and servicing (Jain et al., 2023). These front-end activities begin with the onboarding process in which consultants or advisors engage prospective investors through marketing, educational content, and personalised advisory services. Effective front-end operations prioritize client relationship management, ensuring ongoing communication, transparency, and responsiveness to investor inquiries (Jain et al., 2023). This fosters trust and loyalty among investors, crucial for maintaining long-term relationships and facilitating fund growth. Traditionally, mutual funds have relied on human financial advisors or unit-trust consultants to provide personalized guidance to investors (Jain et al., 2023). These advisors evaluate investors' risk tolerance, financial goals, and investment preferences through direct consultation or remote interactions (Wang et al., 2023). They leverage their expertise and market knowledge to recommend suitable funds, assist investors in navigating complex financial decisions, and educate them on market trends, performance expectations, and long-term investment strategies. The advisor's role extends beyond mere fund selection suitable for investors as it helps investors understand the nuances of portfolio diversification, asset allocation, and risk management (Wang et al., 2023). These personalised advisory and financial planning services are designed to empower investors by enabling them to make informed investment decisions and achieve their financial goals (Jain et al., 2023; Wang et al., 2023). Additionally, the advisor is responsible for monitoring the performance of funds and providing regular updates to investors (Sommer et al., 2023).

The back-end operations of mutual funds involve administrative, regulatory, and investment management functions, which are essential for fund performance and compliance (Mirabile, 2016; Ratanabanchuen & Saengchote, 2020). Fund managers oversee back-end operations by strategically allocating pooled assets across various securities and asset classes to generate reasonable returns through capital gains or current income (Stein, 2023). Additionally, back-end operations encompass rigorous risk management practices to safeguard investor assets and ensure regulatory compliance (Ronald & Edgar, 2019). This includes monitoring portfolio performance, conducting stress tests, and adhering to legal frameworks that govern mutual fund operations. Efficient back-end operations streamline administrative tasks such as trade settlement, fund accounting, and performance reporting (Herbert & Michael, 2023). Fund managers play a pivotal role in mutual funds' back-end operations and are responsible for strategically allocating pooled funds across a diversified portfolio of assets into the securities market. These professionals conduct in-depth research and analysis to identify investment opportunities, manage risks, and optimize investor returns. They employ sophisticated analysis, leverage big data analytics, and collaborate with research teams to make informed investment decisions (Lee & Shin, 2018; Li et al., 2024). Portfolio diversification, asset allocation, and timely trading decisions are critical aspects of achieving fund objectives while adhering to regulatory guidelines (Horn & Oehler, 2020; Li et al., 2024). Fund managers are responsible for the ongoing assessment of market

conditions, analysis of emerging trends, and modification of portfolio compositions to respond to dynamic economic environments and fulfil the changing requirements of investors (Abdullah et al., 2007; Hoberg et al., 2018).

The financial services sector has experienced a significant transformation due to the swift integration of AI (Ahmed et al., 2022). Artificial Intelligence, through sophisticated machine learning algorithms and advanced data analytics, has facilitated the automation of processes, improved decision-making, and provided personalised services tailored to individual client requirements (Huang & Rust, 2018). This technological revolution has disrupted traditional financial services, paving the way for more efficient, data-driven, customer-centric operational models (Dhiman et al., 2023). The emergence of AI in asset management has led to a transformation in service delivery models, questioning the conventional function of human financial advisors (Huang & Rust, 2018; Minh et al., 2022). AI-driven platforms provide scalability and cost efficiency; however, they also raise concerns regarding job displacement and the future of professional advisory services (Miller, 2019; Xu et al., 2023). Hybrid models integrating AI and human expertise are developing to reconcile automation with personalised interactions, highlighting the changing dynamics of financial advisory services in the digital era (Zhang et al., 2023). At the same time, regulators worldwide are grappling with algorithmic bias, data security, and the ethical implications of AI-driven decision making (Amirzadeh et al., 2022; Silva & Fonseca, 2019; Wall, 2018). Achieving equilibrium between innovation and regulatory oversight remains a critical challenge for industry stakeholders and policymakers, particularly affecting existing human employment (Grassa, 2015; Baek & Kim, 2023). While specific studies emphasize the significance of evaluating AI's societal implications, such as labour displacement and ethical considerations (Jiang et al., 2017; Smuha, 2019), examining its specific impacts on industry practices remains limited. Extant research broadly highlights AI's transformative potential; offering insights into automation and efficiency but rarely addressing how AI is practically deployed in distinct sectors like asset management. Scholars have increasingly called for more targeted investigations (Dwivedi et al., 2021; Haefner et al., 2021), recognizing that understanding AI's real-world applications is crucial to bridging the gap between theoretical advancements and practical implementation. These calls underscore the importance of studying AI's deployment and performance outcomes, particularly in reshaping traditional roles and operational frameworks in industries undergoing technological evolution. Existing literature has explored AI's broad applications of AI in financial markets, such as predictive analytics (Al Janabi, 2022; Bertsimas & Kallus, 2020; Deprez et al., 2021) and automated trading systems (Alaminos et al., 2024; Chang & Lee, 2017; Chen & Hao, 2018; Wang et al., 2022). However, there is limited comprehensive documentation of how AI reshapes traditional practices in mutual fund operations. Understanding where and how AI technologies are implemented, whether in front-end advisory services, such as dealing with investors, or back-end tasks, such as portfolio management and trading, has critical implications for industry stakeholders, regulators, and investors.

Robo-advisors, a platform for investors to manage their investments, is a manifestation of digital transformation in banking and finance, offers enhanced efficiency, cost reduction, and increased accessibility for a wider investor base through digital platforms, primarily mobile applications, provided by fintech companies, AMCs, and other financial institutions, revolutionizing the investment industry (Mhlanga, 2020; Seiler & Fanenbruck, 2021). These platforms streamline and automate investment processes like investor profiling, risk assessment, fund recommendations, and transactions through algorithms and user-friendly interfaces (Hong et al., 2023; Kraiwanit et al., 2022). In contrast to traditional practices that relied on personalized, face-to-face interactions to establish trust and provide investment guidance (Linnainmaa et al., 2021; Wang et al., 2023), robo-advisors operate entirely within the digital domain, depending on user satisfaction with their application experience to establish trust

and fulfil their advisory role. Notwithstanding the extensive research highlighting robo-advisors' potential to enhance financial service accessibility and mitigate human biases (Bhatia et al., 2020), there remains a paucity of investigations into their empirical efficacy from the end-user perspective. Quantifiable parameters, such as application adoption frequencies and user ratings, could offer tangible, data-driven insights into how these platforms fulfill investor expectations regarding usability, reliability, and advisory proficiency.

The debate regarding the comparative performance of AI-managed and human-managed investment funds remains an ongoing discourse. Existing research has yielded mixed findings. In a developed market context Miguel & Chen (2021), suggest that AI-driven funds tend to deliver more consistent returns, particularly in volatile market environments, because of their capacity to process substantial data volumes in real-time. Conversely, Rui & Jinjuan (2022) indicated that human fund managers' intuition and experience can occasionally outperform AI, especially under complex or unpredictable market conditions. Despite these insights, a comprehensive analysis directly comparing the performance of AI-managed and human-managed funds under the same market conditions and timeframe is lacking in the current literature. The literature underscores that AI-driven funds are engineered to mimic or augment the decision-making processes of human fund managers, with a particular emphasis on trading strategies (Immenkötter, 2024). Whilst a substantial portion of existing research relies on simulations (Snow, 2019) or theoretical models to showcase AI's potential (Naga et al., 2024), advocates for empirical assessments of crucial performance indicators, such as annual returns. These evaluations aim to determine whether AI-driven funds can effectively rival or outperform their human-managed counterparts. Such initial assessments are considered adequate to establish whether AI-driven funds can fulfil the fundamental responsibilities traditionally undertaken by human fund managers, laying the groundwork for further exploration of AI's transformative impact on asset management.

METHODOLOGY

This study employs a mixed-methods approach combining qualitative and quantitative techniques to comprehensively explore the existence of AI and its transformation into asset management. This methodological integration aligns with the study’s objectives as each component addresses distinct research queries (Creswell & Clark, 2017). The primary objective of this study is to explore the existence of AI within AMC's business and operation, as well as the subsequent transformations it has catalysed to date. The term "robo-advisors" started to appear more frequently in the release of AMCs, webpages, announcements, and FAQs. Concurrently, the term "AI-driven funds" emerged from the Fund's name, descriptions, news, and announcements. Questions arise regarding the most prominent AI mentioned and called in the industry, such as robo-advisors and AI-driven funds. What are their functions and distinctions? Thus, the qualitative method is ideal for examining the presence and distinctions of these AIs in asset management by analysing textual data from industry practices, thereby enhancing understanding (Bowen, 2009; Morgan, 2022). The distinction between robo-advisors and AI-driven funds is made by analysing their unique roles, offering a clear understanding of their functions. This was followed by an observation of AI adoption across 39 AMCs, confirming its practical deployment. This progression connects the theoretical definitions of these AI tools with their real-world applications. Subsequently, the discussion examines how AI deployment substitutes for traditional practices, reflecting the industry's dynamic evolution in the age of AI.

This study also examines the performance of robo-advisors to date. The second objective of this study is to evaluate whether robo-advisors have transformed traditional advisory practices by assessing their current performance regarding user satisfaction. This is quantitatively achieved through the analysis of user rating data from digital platforms, as these ratings indicate the degree to which robo-advisors fulfil investor expectations and emulate the advisory functions traditionally carried out by UTCs. Conversely, this study is also curious about the capabilities of AI-driven funds in generating investment returns so far, which have taken on the role traditionally performed by fund managers in making investment decisions to trade the pool of funds. Thus, the third objective of this study, which is to examine the differences in annual returns generated by AI-driven funds and traditionally managed funds, can be achieved through quantitative analysis that evaluates the annual performance metrics of both AI-driven and traditionally managed funds. This is to assess and evaluate the capabilities of AI to match human trading skills, thus transforming the investment management industry. The second and third objectives are further examinations that follow the primary objective, which explores AI's existence and comprehension of AI in asset management. These objectives are driven by curiosity about AI's capabilities, allowing us to observe the dynamic evolution that has transformed the industry. Although AI deployment is relatively new to the industry, the available data may be limited but sufficient for a preliminary study to provide timely and early insights into this emerging area.

Sampling

To investigate the presence and comprehend the distinct functionalities of AI within the asset management sector, this study examines a sample comprising 39 asset management companies and 762 associated fund reports, prospectuses, and factsheets. These AMCs, registered with the Securities Commission Malaysia, were selected based on their status as established and legitimate investment fund providers offering publicly accessible and rich textual information on their fund strategies, operational descriptions, and technology adoption practices. Notably, fintech companies acting as third-party platforms for reselling AMC unit trust funds were excluded as the focus was solely on the AMCs. By emphasizing the core industry players, the sample ensured that the analysis captured AI-related practices that are directly integral to the asset management industry rather than peripheral trends influenced by external parties (Creswell & Clark, 2017; Flemming et al., 2019). This detailed sampling approach enabled identifying AI systems, such as robo-advisors and AI-driven funds, which are prominently featured within the industry. The depth of this sampling was critical for uncovering patterns and themes supporting the comprehensive exploration required to meet the study's objectives (Creswell & Clark, 2017; Sankofa, 2023).

For the second objective, which focused on examining how well robo-advisors are currently transforming traditional advisory roles, this study analysed the user ratings of robo-advisor applications identified on the Apple App Store (AS) and Google Play Store (GS), collecting the data in their raw form. This study did not use third-party datasets, institutional input, or prior research but collected and analysed it firsthand. Although the platforms host the data, collecting and analysing them firsthand is integral to the study's methodology, aligning with standard definitions of primary data in research. (Creswell & Clark, 2017). These platforms were selected because they host user reviews and ratings and provide a rich source of feedback from a broad and diverse user base. Utilizing both platforms ensured comprehensive coverage and captured user sentiments across different ecosystems (Brumen et al., 2023). The ratings provided insights into user satisfaction with AI's capacity to replicate or enhance the functions traditionally carried out by human UTCs. The data collected included ratings and the number of user ratings. The inclusion criteria stipulated that robo-advisor applications must be explicitly associated with Malaysian AMCs, meaning that they are directly developed, operated, or officially

offered by the AMCs themselves, as opposed to fintech-based third-party companies that provide robo-advisory technology or platforms but do not manage their funds and instead resell AMC-managed funds to investors through their platform. Additionally, the applications must have been publicly available for at least one year and possess a minimum of 30 user ratings across the platforms. Conversely, the exclusion criteria involved excluding applications with fewer than 30 ratings to ensure statistically meaningful analysis and robo-advisor applications whose functionalities are embedded within general financial applications or co-existing features. This means that only standalone robo-advisor applications from AMCs were included. This sampling approach provided a reliable dataset for assessing client satisfaction with robo-advisors' current capabilities, reflecting their success in fulfilling advisory roles. The methodology ensured academic rigour and data reliability, representing a broad spectrum of user experiences.

The third objective of this study is to assess the performance capabilities of AI-driven funds compared to traditionally managed funds. The sample includes 33 equity funds from two asset management companies adopting AI-driven funds. The focus on these two AMCs was intentional, as they were the only AMCs offering both AI-driven and human-managed equity funds, allowing for a direct and unbiased comparison under the same conditions. Including AMCs without AI-driven funds would introduce bias and inconsistency, as the comparisons would not align. This targeted approach ensured analytical rigour and valid results (Creswell & Clark, 2017). Furthermore, the selection was limited to equity funds because the AI-driven funds in these AMCs specifically trade equities, aligning with the skill sets of traditional human fund managers specializing in equity trading. On the other hand, data availability varied, with two AI-driven equity funds available in 2021 and five in 2022-2023. This targeted sampling ensured a consistent and fair comparison by maintaining uniformity in equity investment and eliminating confounding variables associated with different fund types, such as risk profiles and objectives. Through accurate comparisons, the evaluation of whether AI, a relatively novel technology in the industry that some AMCs have implemented, can match human fund managers' trading skills and strategies.

Data Collection Methodology

To examine AI's presence and distinct functionalities in asset management, data were collected from 39 AMCs through publicly available materials, including fund prospectuses, reports, fact sheets, FAQs, and AMCs' websites. These sources provide comprehensive insights into fund strategies, operational descriptions, and the adoption of AI technologies. Particular attention was given to identifying explicitly mentioned AI systems, such as robo-advisors and AI-driven funds. To enhance accuracy and ensure reliability, thorough cross-data collection was conducted appropriately, and discrepancies were minimised. These textual data from websites and FAQs offer a detailed insight into each AMC's articulation of robo-advisors and AI-driven funds, including their definitions, functionalities, and applications. These data are crucial for achieving the first objective and addressing the first research question (Flemming et al., 2019; Morgan, 2022), as they enable a comprehensive understanding of the presence of AI and its distinct roles within the asset management industry.

For the second objective, quantitative data were extracted from the user ratings on the AS and GS. These ratings are publicly available and are submitted by individual users of the robo-advisor applications. Each user rates the application based on their experience, and the platforms automatically aggregate these ratings into average scores and display the total number of ratings. This data is not derived from surveys, third-party institutions, or other researchers but reflects raw, user-generated feedback provided directly on the platforms. The data collection process focused on standalone robo-

advisory applications explicitly associated with Malaysian AMCs, excluding fintech third-party providers. Key data points included the average ratings, where the numerical scores (1–5) indicate overall satisfaction, and the number of ratings, such as total user responses, reflecting engagement and adoption. The rating data were collected as of the most recent period when this study was conducted to ensure their currency and reflection of contemporary user experiences. Ethical guidelines were strictly adhered to, as only aggregate and publicly accessible data were utilized without identifying individual users. This approach provided a reliable dataset for assessing the performance of robo-advisors in meeting client expectations.

For the third objective, this study collected return performance data from fund reports and prospectuses of 33 equity funds managed by two AMCs offering AI-driven and human-managed funds. These data include annual returns for 2021, 2022, and 2023. The focus on collecting input only on equity funds was deliberate to maintain consistency in investment strategy and ensure comparability between AI-driven and human-managed funds. Data were sourced directly from AMC's reports and supplemented by cross-verification with third-party financial databases for accuracy. This ensured a robust and comprehensive dataset to support comparative performance analysis.

Data Analysis

A systematic and structured approach was adopted to address the first objective of exploring AI technologies' existence, deployment, and distinction in asset management. A thematic analysis was conducted on textual data collected (Braun & Clarke, 2006; Vaismoradi et al., 2013) from fund reports and websites to identify and categorize themes related to the presence and functionality of AI in asset management. The analysis revealed two key themes related to the presence and functionality of AI in asset management: "robo-advisors" a front-end client-facing tool that automate investor profiling, portfolio recommendations, and risk assessments, enhancing accessibility for retail investors and "AI-driven funds" a back-end system leveraging advanced algorithms that autonomously manage the pool of funds to trade in the market and generate returns. These themes emerged organically from the textual data as they were the most prevalent and significant concepts identified within this domain. These themes demonstrate AI's existence and distinctness of AI in asset management across businesses and operations, such as in the front- and back-ends. Therefore, the analysis aimed to define robo-advisors and AI-driven funds, identify their deployment across AMCs, and examine their transformative impacts on industry practices.

The initial stage of the analysis focused on comprehending the definitions and operational frameworks of robo-advisors and AI-driven funds, as outlined in the AMC data sources. The process involved extracting key terms and descriptions of "robo-advisor," "algorithm-based investment advice," "AI-driven," "rules-based," and "no human intervention." A manual coding approach was adopted to ensure a nuanced understanding of textual data and the specific context (Bowen, 2009; Morgan, 2022; Vaismoradi et al., 2013) of AI adoption in asset management. This method provides context-specific insights that automated tools might have overlooked, particularly given the varied language and terminology used in the data sources. Manual coding facilitated the accurate interpretation of the data, capturing subtle nuances in how these terms and applications were presented in the reports (Bengtsson, 2016; Bowen, 2009; Morgan, 2022; Vaismoradi et al., 2013).

One notable example involved a fund named "Artificial Intelligence," which, upon closer inspection, was found not to be AI-driven. Instead, the Fund invests in the AI and technology sectors but relies on human fund managers for investment decisions. This underscores the importance of manual coding in

accurately interpreting textual data and distinguishing between funds that genuinely involve AI-driven decision making and those that do not. Additionally, the manual coding approach facilitated the iterative refinement of the identified themes, ensuring they aligned with the study's objectives (Bengtsson, 2016; Morgan, 2022).

Inter-coder reliability checks were conducted throughout the analysis to enhance the reliability and minimize subjectivity, thus verifying the robustness and consistency of the findings (Vaismoradi et al., 2013). This qualitative analysis provides an in-depth exploration of the presence and application of AI technologies in the asset management industry. Plus, a comparative review of the textual descriptions was conducted to identify commonalities and distinctions between robo-advisors and AI-driven funds. This approach provides a structured framework for identifying AI technologies and categorizing their functionalities. This phase provides a nuanced understanding of the functional role of AI technologies in asset management. The textual definitions that demonstrated the presence of AI employed by the AMCs were tabulated, and a definition was concluded accordingly.

The second phase focused on determining the extent to which AI technologies were being adopted by the 39 asset management companies registered with the Securities Commission Malaysia to assess the dynamic evolution of AI's presence in the industry. A thorough review of AMCs' websites, FAQs, fund prospectuses, and fact sheets was conducted to identify explicit references to robo-advisors and AI-driven funds. AMCs deploying robo-advisors were identified through their advertising, promotion, and descriptions of client-facing tools that provide automated investment advice. Similarly, AMCs managing AI-driven funds were identified by analysing fund strategies and operational descriptions emphasising autonomous decision-making. To ensure consistency, mentions of AI were cross-referenced across multiple sources, such as matching AI-driven strategies and rules-based or no-human-intervention descriptions in fund prospectuses with the corresponding fund reports. This phase established a comprehensive inventory of AMCs deploying AI, categorized by front-end and back-end applications. The findings were then tabulated in a table listing the AMCs that have adopted AI, such as robo-advisors and AI-driven funds, along with remarks on the specific AI technologies they have implemented. This provides a clear overview of the companies that have embraced AI and the extent of its adoption, thereby illustrating the existence and evolution of the industry in this regard.

The next phase in achieving the first objective involves deductively analysing how AI deployment has influenced traditional AMC practices and provides insights into the transformative evolution of the industry. This approach ensured a thorough examination of AI technologies and offered insights into their transformational evolution and operational significance within the industry. Robo-advisors were analysed in terms of their replacement of traditional roles. The analysis explored their offerings and assessed their impact on democratizing financial services. Additionally, AI-driven funds were analysed to determine how they replaced human fund managers' traditional portfolio management practices. The deductive approach explores the benefits offered by these systems, highlighting their role in the industry's dynamic evolution. Insights from the analysis were used to contextualize the broader implications of AI adoption, including its impact on operational processes and strategic practices within AMCs. This methodology aligns with this study's objective of understanding the existence, deployment, and distinction in asset management. This qualitative approach offers insights into the evolving role of AI in asset management and illuminates industry-wide trends in robo-advisory and AI-driven fund management.

Upon comprehension of the existence and deployment of AI technologies, the study evaluates the performance of robo-advisors, addressing the research question of how effectively these systems have transformed traditional advisory practices. The performance evaluation was based on an analysis of user ratings (Al-Natour & Turetken, 2020; Lebo et al., 2016), as these ratings reflect investor satisfaction and engagement with robo-advisor platforms. The decision to utilize user ratings was predicated on their ability to quantitatively capture user sentiment, trust, and overall satisfaction with robo-advisory systems, offering an empirical measure of their perceived effectiveness (Al-Natour & Turetken, 2020; Brumen et al., 2023; Lebo et al., 2016). Evaluating robo-advisors through user feedback ratings was particularly valid in this context, as these tools are client-facing technologies, and their success mainly depends on meeting user expectations.

To analyse this data, descriptive statistics were employed to assess the overall performance of AI robo-advisors by analysing aggregate metrics for user satisfaction and engagement across platforms. This approach facilitated understanding whether AI robo-advisors meet expectations as alternatives to UTCs. The metrics utilised were the average ratings, total engagement, and the correlation between engagement and satisfaction. These metrics were sufficient to address the research objective, as they provided insights into the performance of robo-advisors, thus reflecting the transformational dynamic changes they introduced, such as potentially replacing traditional human advisory services. This quantitative approach ensured that the evaluation of robo-advisors was both empirical and meaningful, allowing the study to measure their efficacy in transforming client engagement practices.

A. Average Ratings Across Platforms

$$\text{Average Rating (Platform)} = \frac{\text{Sum of Ratings (Platform)}}{\text{Number of Apps}}$$

$$\text{Overall Average Rating} = \frac{\text{Average Rating (AS)} + \text{Average Rating (GS)}}{2}$$

In this study, average ratings across platforms were measured to determine user satisfaction with robo-advisors. The expectation is that a higher overall average rating would indicate that users are satisfied with the performance of robo-advisors. Ratings around or below three might signal unmet expectations or room for improvement.

B. Total Engagement Across Platforms

$$\text{Total Engagement (Platform)} = \sum \text{Number of Ratings (Platform)}$$

$$\text{Total Engagement (Overall)} = \text{Total Engagement (AS)} + \text{Total Engagement (GS)}$$

The total engagement Across Platforms is helpful as it measures how widely robo-advisors have been adopted and whether users are engaging with them. The expectation is that high engagement levels indicate a strong interest and adoption of robo-advisors, even if ratings vary.

C. Correlation Between Engagement and Satisfaction

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

Where:

- Xi: Engagement level (number of ratings) for app i.
- Yi: Average rating for app i.
- $\bar{X}$: Mean engagement.
- $\bar{Y}$: Mean rating.

The correlation between Engagement and Satisfaction is relevant, as it investigates whether higher user adoption (more ratings) leads to higher or lower satisfaction. The expectation is that a negative correlation may suggest that increased adoption exposes performance or scalability issues. A positive correlation would indicate consistent quality as adoption grows.

Finally, the overall insights are provided by combining the metrics. This study can infer how satisfied users are with robo-advisors as a concept and whether robo-advisors are gaining traction as viable replacements for UTCs. This analysis is pertinent as it provides a comprehensive overview of the performance and adoption of AI robo-advisors, addressing a general inquiry regarding their user satisfaction and engagement levels without exploring intricate specifics. This offers insights into the perception of these tools as alternatives to human UTCS.

To further investigate the transformative potential of AI, this study analyses the annual return performance of AI-driven funds compared to human-managed funds. This analysis aims to address the question of whether AI-driven funds replicate or surpass the traditional fund management capabilities of human managers. The comparison was conducted using quantitative analysis, focusing on equity funds managed by AMCs that offer both AI-driven and human-managed funds. This analysis addresses whether AI-driven funds replicate or surpass human managers' traditional fund management capabilities. Utilising data from the same AMC ensures comparability by analysing equity funds managed within identical organizational, operational, and market contexts, thereby mitigating variability that could arise from differences in management styles, organisational strategies, or external market influences.

Annual calendar returns of 2021, 2022, and 2023 were selected, as they provide a consistent performance measure over comparable timeframes, enabling a reliable assessment of fund performance trends. By focusing on equity funds managed within the same AMCs, the analysis isolated the impact of AI from other organizational or strategic differences, ensuring an unbiased comparison. This study calculated the mean returns and variances to evaluate the performance distributions of AI-driven and human-managed funds. Descriptive statistics were employed to summarise these performance metrics, providing initial insights into the central tendencies and variability of the returns.

Welch's t-test (Welch, 1947) was used to compare the mean returns of the AI-driven and human-managed funds to ensure statistical rigor. This method was deemed appropriate given the unequal sample sizes and variances between the two groups (West, 2021), where only a few AMCs deployed AI-driven funds; thus, this statistical method is well suited to adjust for these imbalances, leading to more accurate results. Welch's t-test determines whether performance differences are statistically significant, providing a robust evaluation of AI's capabilities in portfolio management. As a

straightforward and reliable method, it identifies initial differences in performance between AI-driven and traditional management without complex modelling, making it practical and scientifically sound for early insights into AI's impact on asset management. This methodology has been extensively employed in comparable studies, such as analyses of Islamic and conventional unit trusts, wherein distinct categories are examined under analogous conditions (Al Rahahleh & Bhatti, 2023; Herlambang, 2020; Sari et al., 2021; Surono et al., 2021). Given that this study provides only preliminary insights into the performance of AI-driven funds, Welch's t-test is deemed sufficient for drawing initial comparisons and establishing a foundational understanding of their efficacy relative to human-managed funds.

The t-test, appropriate for analysing two variables with multiple inputs (West, 2021), suits this study's objective of evaluating performance differences between AI and human brain capabilities, specifically comparing the returns of AI-driven funds to those managed by humans. This method assesses whether performance variations stem from management approaches rather than random fluctuations. An independent t-test yielded two key metrics.

1. t-statistic: This quantifies the ratio of the difference between the group means to the variability within the data, with larger absolute values indicating greater distinction between the groups.

2. p-value: Estimates the likelihood that the observed difference is due to chance. This study uses A significance level of 0.05, signifying that p-values below this threshold were considered statistically significant.

The t-test analysis was performed using Microsoft Excel data analysis metrics. The formula for the t-statistic in an independent t-test is:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

Where:

- $\overline{X_1}$ and $\overline{X_2}$ are the means of the two groups (e.g., AI-managed funds and human-managed funds).
- S_1^2 and S_2^2 are the variances between the two groups.
- n_1 and n_2 are the sample sizes for the two groups.

This t-test assesses whether AI-driven equity funds perform similarly to human-managed funds, highlighting the impact of AI on equity fund trading in AMCs. The findings are then presented and interpreted. This section links data insight into practical implications and clarifies AI's strategic value, benefits, and limitations in the industry. Contextualizing the results provides valuable guidance for future research and practical applications, which are essential for understanding the transformative role of AI in asset management.

This methodological approach provided empirical evidence to address the study's objective of understanding how AI-driven funds perform relative to human-managed funds. The results, tabulated and followed by a deductive discussion, delivered meaningful insights into the effectiveness of AI-driven funds in transforming traditional fund management practices. This process contributed to a comprehensive exploration of the dynamic evolution brought about by AI in the asset management

industry. This study adhered to ethical guidelines by relying on publicly available data and anonymizing all information to protect funds and investor confidentiality. Data are aggregated across AMCs, ensuring that individual fund identities remain confidential while allowing for robust industry-wide insights.

RESULTS AND DISCUSSION

By examining the deployment of AI within AMCs, this study identifies two prominent AI entities in the industry: robo-advisors and AI-driven funds. Based on textual data analysis, the findings are structured to distinguish between robo-advisors and AI-driven funds, followed by a list of AMCs deploying these technologies, confirming the industry's embrace of AI. The accordance is coherent because they first establish a foundational understanding by clearly distinguishing between the two AI applications, robo-advisors, and AI-driven funds, based on their distinct roles and functionalities. This distinction is critical for contextualising deployment and function within asset management practices. Building on this, the study observes the presence of these AI technologies among 39 AMCs to validate their actual adoption in practice. This continuation is relevant because it bridges the theoretical understanding of these AI tools with their real-world applications, demonstrating the extent to which Malaysian AMCs have embraced AI. By showing where AI exists within these firms, the findings confirm its presence and provide evidence of the industry's dynamic evolution toward integrating advanced technologies, making the analysis both structured and progressively insightful. Further discussion elaborates on how robo-advisors and AI-driven funds align with or substitute existing traditional practices, showcasing the dynamic evolution of AMCs in the age of AI. Subsequently, this study provides preliminary insights into the performance of robo-advisors as reflected by user ratings and AI-driven funds, evaluated through their annual return capabilities, offering a foundation for understanding their impact on the industry.

The AI in AMCs

The terms "robo-advisor" and "AI-driven fund" are prominently associated with AI deployment in investment finance. However, their practical applications in asset management may differ significantly. These two AI tools serve distinct roles within the industry: robo-advisors focus on automating investor profiling and fund recommendations, AI-driven funds employ advanced algorithms to manage investment decisions autonomously for the pool of funds, optimizing returns without human intervention. This distinction reflects how AI is utilized in asset management practices, highlighting its transformative impact on traditional methods. The robo-advisor, as defined and introduced by AMC, is shown in Table 1 of the Robo-advisor definition by AMC.

Table 1

Robo-advisor Definition by AMC

Robo-advisor by AMCs	Definition/Keywords of Robo-advisor
KDI by Kenaga Investment	• *At Kenanga Digital Investing (KDI), our Robo-advisor uses machine learning Artificial Intelligence (AI) that is driven by complex mathematical calculations, lots of real-time data, and investor behavioural patterns to devise algorithms that will provide you with best-fit investment advice.* • *Our A.I.-driven investment solution has been designed to be forward-thinking and transparent, with the ability to automatically balance portfolio and predict risk-reward levels.* • *Your Robo-advisor tracks portfolio meticulously and checks it against market performance to help make the most out of your investments. This way, you have peace of mind knowing that we are working around the clock to ensure you get the returns you deserve.*
Ria by PNB	• *Ria works by using algorithms and Modern Portfolio Theory to create and manage personalized investment portfolios. After assessing your risk profile and investment preferences, Ria allocates your investments across a diverse selection of ASNB unit trust funds, aiming to optimize returns while minimizing risk.* • *Ria is an investment service that is designed to help investors grow their wealth through a diversified portfolio of Fund*
BEST by BIMB Investment	• *BEST is a non-automated discretionary Robo-Intelligence unit trust online investing platform.* • *BEST is an online unit trust investing platform that applies Robo-Intelligence and Big Data technology to assist its investors in making a sound decision to achieve their investment objectives* • *Do It For Me" is an investing approach where BEST will suggest a package of a well-diversified unit trusts investment portfolio that can be customized according to your preferences on fund (s) selection and investment amount.* • *The portfolio creation will be based on your investment suitability profile and investment goal(s), which will consist of how much and when to achieve it.*
UOBAM Invest	• *UOBAM Invest is a digital platform that offers corporate investors access to investment services such as digital advisory.* • *Digital Adviser is offered to corporate investors who need financial advisory online. Simply go through a risk profiling questionnaire and decide on the final portfolio allocation against your financial goals set. Once your setup is final, simply raise a cash contribution to your account. Digital Adviser will execute the orders against your latest authorized setup upon receipt of your funds.*

Robo-advisors, such as Kenanga Investment's KDI, PNB's Ria, BIMB Investment's BEST, and UOBAM Invest, are AI-powered platforms that use algorithms, risk assessments, and data analysis to provide personalized investment advice and portfolio management. These robo-advisors or intelligence platforms evaluate investors through risk profiling questionnaires and other input-based mechanisms and then utilize algorithms to analyze the collected data and provide tailored investment portfolios or fund recommendations aligned with the investor's goals, risk tolerance, and preferences. Across the industry, the core functionality of robo-advisors appears consistent, as they primarily focus on offering personalized investment recommendations. Based on these definitions, robo-advisors can be understood as AI tools that enhance accessibility and efficiency in the investment advisory process by automating

tasks traditionally performed by UTCs. This innovation represents a significant evolution in asset management practices, transitioning from manual consultant-driven processes to streamlined algorithm-based systems enabled by AI.

On the other hand, the AI-driven funds, as defined and introduced by the AMC, as gathered from the annual report, prospectus, and fund fact sheet, as shown in Table 2 of the AI-driven fund definition by AMC; specifically, they can be gained from the fund strategy, policy, and definition section.

Table 2

AI-driven Fund Definition by AMC

AI-driven Fund by AMCs	Definition/keywords of AI-driven Fund
AI-driven Fund by BIMB Investment	*The Fund invests through a rules-based investment process into listed companies…..* *The Fund is not actively managed as it employs a quantitative approach…The quantitative approach refers to the stock selection process, which is fully Artificial Intelligence (AI) based and without human intervention.* *Its AI Engine uses a wide range of machine learning algorithms, such as Deep Learning models, to analyze and identify investment opportunities in the equity markets.*
AI-driven Fund by Kenanga Investment	*…strategy is an AI-system that identifies and profits from patterns in price and volume data.* *…tracks the daily price movement of highly liquid global indices using advanced Artificial Intelligence techniques derived from modeling biological systems,…*

Examining industry definitions reveals that AI-driven funds are autonomous investment vehicles designed to make investment decisions on behalf of pooled funds to generate returns in the financial market without human intervention. BIMB Investment describes its AI-driven funds using a rule-based quantitative approach, utilising machine learning and deep learning models to analyse and identify equity market opportunities. Similarly, Kenanga Investment defines its AI-driven fund as leveraging AI systems to detect and profit from price and volume data patterns, tracking global indices using advanced AI techniques inspired by biological systems. These funds consistently rely on AI to process large amounts of data, identify patterns, and execute strategies aimed to optimise returns. This exploration highlights the function of AI-driven funds as AI in asset management, which automates the decision-making processes traditionally performed by human fund managers. Consequently, AI-driven funds are AI-powered systems that autonomously analyse data and make investment decisions on behalf of pooled funds to generate returns from financial market trading activities. This innovation represents a significant evolution in fund management, transforming the practices traditionally performed by fund managers into a fully automated, data-driven approach.

Among the 41 registered AMCs listed by the Securities Commission, 39 actively managed approved unit trust funds, whereas the remaining two focused exclusively on Exchange Traded Funds (ETFs). Table 3 of the List of AI presence among Malaysian AMCs provides details of these 39 AMCs, illustrating the presence of AI in their operations. Certain AMCs have fully implemented AI technologies, either through robo-advisors to assist investors or through AI-driven funds for autonomous trading, while others utilise AI only partially, and some do not employ AI at all. This demonstrates the heterogeneous approaches to AI adoption across industries, confirming its presence and integration within asset management practices.

Table 3

List of AI Presence in Malaysian AMC

No.	Management Company	Number of Funds Managed	AI Presence Robo-advisor/ Intelligence	AI-driven Funds	Remarks
1	Abrdn Islamic Malaysia Sdn. Bhd.	1	x	x	-
2	AHAM Asset Management Berhad	47	x	x	-
3	AIIMAN Asset Management Sdn. Bhd.	3	x	x	-
4	Amanah Saham Nasional Berhad	18	/	x	Robo-advisor name: Ria
5	Amanah Saham Sarawak Berhad	1	x	x	-
6	AmanahRaya Investment Management Sdn Bhd	6	x	x	-
7	AmFunds Management Berhad	39	x	x	-
8	Areca Capital Sdn Bhd	10	x	x	-
9	Astute Fund Management Berhad	8	x	x	-
10	BIMB Investment Management Berhad	14	/	/	Robo-advisor name: BEST AI-driven Fund: -BIMB-Arabesque Global Shariah-ESG AI Technology Fund - MYR -BIMB-Arabesque Global Shariah-ESG AI Technology Fund - MYR Hedged -BIMB-Arabesque Global Shariah-ESG AI Technology Fund - USD
11	BOS Wealth Management Malaysia Berhad	3	x	x	-
12	Berjaya Mutual Sdn. Bhd.	4	x	x	-
13	Eastspring Investments Berhad	28	x	x	-
14	Franklin Templeton GSC Asset Management	1	x	x	-

(continued)

No.	Management Company	Number of Funds Managed	AI Presence Robo-advisor/ Intelligence	AI-driven Funds	Remarks
	Sdn Bhd				
15	Hong Leong Asset Management Bhd	22	x	x	-
16	KAF Investment Funds Berhad	16	x	x	-
17	Kedah Islamic Asset Management Berhad	1	x	x	-
18	Kenanga Investors Berhad	40	/	/	Robo-advisor name: KDI AI-driven Fund: -Kenanga Global Multi Asset Fund - MYR -Kenanga Global Multi Asset Fund - USD
19	Manulife Investment Management (M) Berhad	47	x	x	-
20	Maybank Asset Management Sdn Bhd	33	x	x	-
21	MIDF Amanah Asset Management Berhad	8	x	x	-
22	Muamalat Invest Sdn Bhd	2	x	x	-
23	Nomura Asset Management Malaysia Sdn Bhd	8	x	x	-
24	Opus Asset Management Sdn Bhd	4	x	x	-
25	Pengurusan KUMIPA Berhad	1	x	x	-
26	Permodalan BSN Berhad	4	x	x	-
27	PHB Asset Management Berhad	1	x	x	-
28	Pheim Unit Trusts Berhad	8	x	x	-
29	Phillip Mutual Berhad	14	x	x	-
30	PMB Investment Berhad	17	x	x	-

(continued)

No.	Management Company	Number of Funds Managed	AI Presence Robo-advisor/ Intelligence	AI-driven Funds	Remarks
31	Principal Asset Management Berhad	74	x	x	-
32	PTB Unit Trust Berhad	1	x	x	-
33	Public Mutual Berhad	170	x	x	-
34	RHB Asset Management Sdn Bhd	47	x	x	-
35	RHB Islamic International Asset Management Bhd	13	x	x	-
36	Saham Sabah Berhad	1	x	x	-
37	Saturna Sdn Bhd	2	x	x	-
38	TA Investment Management Berhad	26	x	x	-
39	UOB Asset Management (Malaysia) Berhad	19	/	x	Robo-advisor name: UOBAM Invest

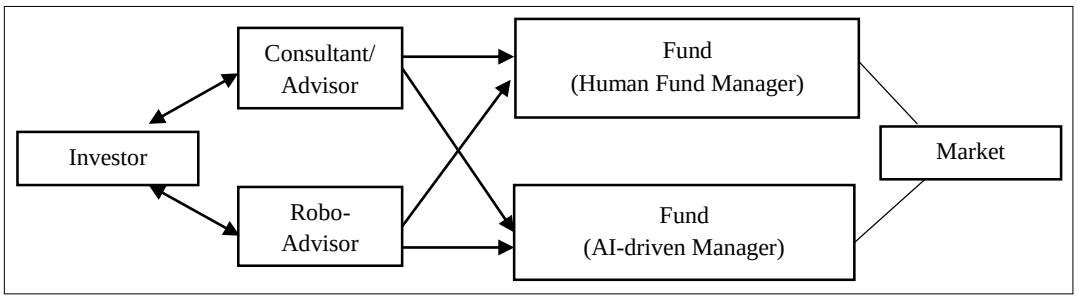
Four of Malaysia's 39 asset management companies have deployed AI as robo-advisors, including Amanah Saham Nasional Berhad, BIMB Investment Management Berhad, Kenanga Investors Berhad, and UOB Asset Management. Furthermore, two AMCs, BIMB Investment and Kenanga Investment, operate AI-driven funds, where AI autonomously makes investment decisions, underscoring the presence of AI within Malaysia's asset management landscape. As an emerging economy and developing country in the South Pacific, Malaysian AMCs actively embrace AI technologies, signifying a commitment to innovation and progression in this sector. This integration of AI reflects the early adoption phase, where organizations begin to recognize the perceived usefulness and ease of use of new technologies. The adoption of robo-advisors highlights a transition toward automated client advisory services, whereas AI-driven funds reflect advancements in autonomous portfolio management. These findings demonstrate that AI is present and evolving in Malaysia's asset management industry, marking the beginning of a shift from traditional human-centric practices to innovative technology-driven solutions.

The table illustrates two AI applications in the asset management industry: robo-advisors and AI-driven funds. These technologies serve different purposes and are independently adopted by the AMC. For instance, some AMCs employ robo-advisors without implementing AI-driven funds, while others adopt both robo-advisor and AI-driven funds. Thus, the presence of a robo-advisor does not necessarily indicate that the funds it recommends to investors are AI-managed; however, the recommended funds are still managed by human fund managers, as robo-advisors primarily focus on investor profiling and fund recommendations, rather than autonomous fund management. This distinction underscores the diverse approaches to AI adoption within the industry, demonstrating that one AI application does not imply the existence of another.

The deployment of AI in AMCs signifies a dynamic evolution in which traditional practices are increasingly being complemented or substituted by advanced technologies. Robo-advisors, for instance, automate tasks previously handled by unit-trust consultants, such as investor profiling, personalised fund recommendations, and portfolio adjustments, offering a more streamlined and cost-effective solution. Similarly, AI-driven funds substitute human fund managers by autonomously analysing markets, identifying opportunities, and executing trades with faster and more precisely. These advancements illustrate how AI enhances operational efficiency and challenges traditional human-driven approaches in asset management. The dynamic interplay between AI and traditional practices reflects the ongoing transformation of AMCs in the AI age, as illustrated in Figure 1 of the dynamics of AI and humans as task performers across asset management.

Figure 1

Dynamic of AI and Humans as Task Performer across Asset Management



Integrating AI robo-advisors in the front-end operations of the investment fund industry has significant implications. The adoption of AI-powered robo-advisors in front-end operations is widespread. The routine and less critical nature of the tasks typically handled by UTCs allows for more seamless automation of these front-end services. Technological advancement democratises financial services by making personalised financial advice more accessible, particularly for previously underserved retail investors. As more investors enter the market, growing demand for financial products can stimulate broader economic growth. Furthermore, automating front-end services through robo-advisors reduces investors' costs. These cost savings can translate to higher profitability. This attracts a more extensive investor base, contributing to the expansion and growth of the financial sector. However, adopting AI technologies, particularly in the front-end operations of AMCs, signifies a broader trend towards digital transformation within the financial services industry. AMCs that invest in AI are positioned at the forefront of this technological evolution, gaining competitive advantage through enhanced customer experience, personalised services, and improved operational efficiency.

However, the limited deployment of AI in complex back-end investment processes highlights the potential benefits and challenges of integrating advanced technologies into this domain. Although the successful implementation of AI in trading and investment analysis can yield superior portfolio performance (Rui & Jinjuan, 2022) and more effective risk management (Cherednik, 2021), the slow pace of adoption indicates the presence of significant barriers, such as the complexity and high costs associated with implementing AI systems for these intricate tasks. In addition, many AMCs rely heavily on the expertise of fund managers, whose skills in navigating financial markets and making informed trading decisions are highly valued. The specialised expertise of fund managers in interpreting market signals, assessing risks, and making strategic decisions remains crucial, and AI systems cannot fully replicate these critical skills. The industry's cautious approach to fully automating these high-stakes back-end responsibilities highlights the challenges of entrusting AI to these critical tasks.

Consequently, the dynamic evolution of Artificial Intelligence (AI) in asset management has significantly transformed traditional practices by automating key investment functions previously executed by human professionals. Robo-advisors function as digital alternatives to UTCs and efficiently manage tasks such as investor profiling, fund recommendations, and client interactions. Similarly, AI-driven funds autonomously handle the complex responsibilities of formulating investment strategies and executing trading decisions, demonstrating their capacity to manage pooled investments effectively. These advancements reflect the asset management industry's adoption of AI technologies, a transformation already in progress and advancing even within smaller emerging markets.

Assessment of Robo-Advisors Capabilities in Terms of User Satisfaction

Analysing user ratings and engagement data for AI robo-advisory applications reveals informative input regarding their overall performance via rating feedback and user adoption. Across platforms, the aggregated ratings indicate that robo-advisors meet user expectations to a moderate degree. The results of the robo-advisor rating metrics are presented in Table 4 of the robo-advisor application metrics.

Table 4

Robo-advisor Application Metrics

Robo-Advisor App	Rating (AS)	Rating Numbers (AS)	Rating (GS)	Rating Numbers (GS)	Average Rating	Total Engagement
BEST	1.9	33	2.3	534		
KDI	2.4	71	2.5	198		
UOBAM Invest	5	1	4.2	215		
Aggregated Metrics	3.1	105	3	947	3.05	1052

The AS and GS exhibit comparable average ratings of 3.10 and 3.00, respectively, yielding an overall mean rating of 3.05. These figures suggest that, while users find the applications adequate, there remains scope for enhancing the user experience to better meet their expectations and requirements. User engagement data revealed a marked interest in robo-advisors, particularly in the GS, which garnered 947 ratings in contrast to the AS's 105. Cumulative engagement across both platforms, totalling 1,052 ratings, indicates a growing inclination towards exploring these AI tools. The disparity in engagement between platforms underscores the potential influence of platform-specific factors, such as accessibility, demographic variations, and marketing approaches, on adoption rates.

A salient pattern emerged when examining the relationship between engagement levels and user satisfaction. Applications boasting higher engagement, exemplified by BEST, with 534 ratings on the GS, tended to receive lower average ratings. This trend suggests that increased adoption may unveil performance and user experience limitations. Conversely, applications with lower ratings, such as UOBAM Invest, demonstrate higher satisfaction levels, potentially indicating a niche appeal or more effective quality assurance catering to a smaller, more specialised user base.

Therefore, the findings suggest that robo-advisors are gaining traction as alternatives to human UTCs, although they face challenges in consistently meeting user expectations as their user base expands. The existence of AI, such as robo-advisors, is indicative of the transformative impact of AI on the dynamic

evolution of asset management. These tools exemplify how AI reshapes traditional financial advisory services by offering scalable, accessible, and automated solutions to users. While the analysis revealed moderate user satisfaction, the significant engagement levels highlight the growing acceptance of AI in managing investments. This trend underscores the potential of robo-advisors to redefine the role of human consultants, fostering a new era in which AI innovations cater to a broader, technologically adept audience. As these technologies continue to mature, they are poised to play a pivotal role in advancing the integration of AI into asset management, signalling a shift towards more data-driven, personalized, and efficient financial solutions.

Performance Comparison of AI-Driven Funds with Non-AI-driven Funds for 2021, 2022, and 2023

This section reveals the results and presents a comparative analysis of the performance of AI-driven equity funds and their non-AI-driven counterparts, which are human-managed funds. This study facilitates fair comparisons by focusing solely on equity funds, enabling a valid evaluation of AI versus human management in equity trading. To evaluate the performance differences between 2021, 2022, and 2023, this study employs Welch's t-test. This robust statistical technique that accounts for unequal variances and sample sizes, as shown in Table 5 of AI-driven fund vs. human-managed fund performance.

Table 5

AI-Driven Fund vs. Human-Managed Fund Performance in 2021,2022 and 2023

2023 t-Test: Two-Sample Assuming Unequal Variances						
	2021		2022		2023	
	AI	Human	AI	Human	AI	Human
Mean	95.785	3.998929	-8.848	-15.3925	4.838	8.156786
Variance	59.73245	57.77654	159.0487	43.50092	1331.577	71.26833
Observations	2	28	5	28	5	28
Hypothesized Mean Difference	0		0		0	
df	1		4		4	
t Stat	16.2435		1.133031		-0.2024	
P(T<=t) one-tail	0.019571		0.160255		0.42474	
t Critical one-tail	6.313752		2.131847		2.131847	
P(T<=t) two-tail	0.039143		0.32051		0.84948	
t Critical two-tail	12.7062		2.776445		2.776445	

By 2021, the t-statistic is 16.2435, indicating a substantial difference in the mean returns between AI-driven and human-managed funds relative to the variability within each group. The p-value of the one-tailed test was 0.0196, while that of the two-tailed test was 0.0391. Both p-values were less than 0.05, suggesting the mean difference was statistically significant. The degree of freedom (df) is 1, which is very low owing to the extremely tiny sample size of the AI-managed funds. The critical t-value of the one-tailed model was 6.3138, whereas that of the two-tailed model was 12.7062. The absolute value of the t-statistic is 16.2435, which is significantly greater than the critical t-values for both one-tail and two-tail tests. This finding reinforces the conclusion that a statistically significant difference exists between AI-driven and human-managed funds by 2021.

In 2022, the t-statistic is 1.1330, indicating a moderate difference in the mean returns between AI-driven and human-managed funds relative to the variability within each group. The p-value of one-tailed was 0.1603, while that of two-tailed was 0.3205. Both p-values were significantly higher than 0.05, suggesting that the mean difference was insignificant. Four degrees of freedom (df) are relatively low because of the small sample size of AI-managed funds. The critical t-value of the one-tailed model was 2.1318, whereas that of the two-tailed model was 2.7764. The absolute value of the t-statistic is 1.1330, which is less than the critical t-value for both the one-tailed and two-tailed tests. This reinforces the conclusion that there is no statistically significant difference between AI-driven and human-managed funds in 2022.

In 2023, the t-statistic is -0.2024, indicating that the difference in mean returns between AI-managed- and human-managed funds is very small relative to the variability within each group. The one-tailed p-value was 0.4247, whereas the two-tailed p-value was 0.8495. Both p-values were significantly higher than 0.05, suggesting that the mean difference was insignificant. Four degrees of freedom (df) are relatively low because of the small sample size of AI-managed funds. The critical t-value of the one-tailed model was 2.1318, whereas that of the two-tailed model was 2.7764. The absolute value of the t-statistic is -0.2024, which is much lower than the critical t-values for both the one-tailed and two-tailed tests, reinforcing the conclusion that there is no statistically significant difference between AI-driven and human-managed funds in 2023.

For 2021, the t-test results indicate a statistically significant difference in the mean returns of AI-managed and human-managed funds. The superior performance of the AI-driven funds observed in 2021 implies that the AI strategies were particularly well-suited to the prevailing market conditions that year. This suggests that AI-driven funds were able to identify and capitalize on unique market opportunities or trends that human investment managers may have failed to recognize or exploit effectively. In 2022 and 2023, the t-test results indicated no statistically significant difference in the mean returns of AI-managed and human-managed funds. The comparable performances of AI-driven funds and skilled human fund managers in 2022 and 2023 can be attributed to several factors. The AI's capacity to rapidly adapt to market conditions, access extensive datasets, make impartial decisions, effectively manage risk, and continuously learn and improve mirrors the capabilities of experienced human professionals. While the high variability in AI-driven funds indicates inconsistency, it also reflects AI's dynamic responsiveness to market dynamics, which can be both a strength and a challenge. The findings suggest that AI-driven funds can deliver returns on par with skilled human-managed funds, particularly when market conditions favour data-driven adaptive strategies. However, the lack of statistically significant outperformance also underscores the need to refine AI algorithms.

CONCLUSION

This study reveals that AI in the asset management industry is predominantly known as robo-advisors and AI-driven funds, representing significant advancements in AI adoption. A more apparent distinction between these applications is established, where robo-advisors gather investor inputs, such as risk profiles and investment preferences, to recommend suitable funds. In contrast, AI-driven funds autonomously make investment decisions, determining when and what to buy or sell on behalf of the pooled Fund. In Malaysia, these technologies have been embraced by AMCs, signalling their readiness to adopt AI despite being based in a smaller, developing South Pacific country. The notable deployment of AI among Malaysian AMCs highlights its contribution to the global evolution of AI-driven asset management. However, AI adoption is not uniform across the industry; some AMCs deploy only robo-

advisors, some incorporate both robo-advisors and AI-driven funds, and some have not deployed any AI. Plus, robo-advisors are emerging as replacements for traditional UTCs in front-end operations, performing tasks such as attracting investors, profiling, recommending suitable funds, and assisting with fund management activities. Investors benefit from robo-advisors through lower fees, greater convenience, and more effective recommendations. Conversely, AI-driven funds powered by machine learning algorithms are a substitution for human fund managers by autonomously analysing markets, identifying opportunities, and executing trades.

The adoption of AI in Malaysian AMCs represents a transformative shift in the industry. This study contributes to the preliminary findings, which indicate that robo-advisors are well received, with significant user adoption, positive app ratings, and growing investor confidence owing to their convenience and cost-effectiveness. Similarly, AI-driven funds achieved annual returns comparable to those of human-managed funds within the equity fund category, showcasing their ability to manage investments autonomously and effectively. By providing clear distinctions between robo-advisors and AI-driven funds, this study provides valuable insights into the evolving landscape of AI in asset management. This highlights AI technologies' adoption, user engagement, and initial performance, offering a foundation for further exploration in this rapidly evolving field.

Future research should conduct longitudinal studies to assess the performance of AI-driven funds across various market conditions over extended periods, building on the findings of this study. This is critical for understanding these funds' long-term performance and durability, especially in tumultuous markets, since this research found that AI-driven funds may produce yearly returns equivalent to human-managed funds in the early stages. Researchers may employ historical data and advanced metrics, including Sharpe ratios, Jensen's alpha, and Treynor ratios, to evaluate risk-adjusted returns and market adaptability. This continuation is important, as it offers deeper insights into the evolving capabilities of AI in fund management, assisting stakeholders in assessing its viability and scalability. Future research should investigate investor perceptions and trust concerning robo-advisors and AI-driven funds, as this study underscores their increasing adoption in Malaysian asset management companies. Understanding investor trust in these technologies is critical for determining their broad acceptability and identifying impediments to their deployment. Surveys, interviews, and sentiment analyses of user reviews on digital platforms can facilitate this achievement. This research is important as it examines the human aspect of AI integration, providing practical insights for AMCs to improve AI solutions and optimise user experience.

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