UNIVERSITY OF TURKU

ABSTRACT

	Bachelor's thesis
X	Master's thesis
	Licentiate's thesis
	Doctoral dissertation

Subject	Information Management	Date	13.06.2023
Author(s)	Thomas Kruger	Number of pages	59+appendices
Title	Enhancing the potential of AI in Hedge Funds: AI-powered asset management		
Supervisor(s)	Dr. Francesco Lelli		

Abstract

Artificial intelligence in the financial industry is a rapidly growing trend, and the alternative asset management industry is no exception. This paper studied the key success factors for AI adoption in alternative investment firms. The author, who recently joined the alternative investment industry, was able to gather insights from his network. This paper seeks to explore the opportunities and risks associated with employing AI in alternative asset management as well as the challenges related to automating manual tasks across front, middle, and back offices, considering the impact of automation implementation on employee roles and responsibilities. A literature review on the application of AI in finance, specifically in hedge funds, as well as the barriers of AI adoption in organizations is presented. A research survey resulted in 103 responses from individuals working in the industry, enabling us to draw conclusions on formulated hypotheses, supported by statistical analysis.

Key words	Artificial intelligence, machine learning, alternative asset management, Hedge fund

UNIVERSITY OF TURKU
Turku School of Economics

Enhancing the potential of AI in Hedge Funds: AI-powered asset management

Master's Thesis
in Information Management

Author(s):
Thomas Kruger

Supervisor(s):
Dr. Francesco Lelli

13.06.2023
Luxembourg, Luxembourg

TABLE OF CONTENTS (ESIMERKKI TÄLLE DOKUMENTILLE)

LIST OF FIGURES (ESIMERKKI)

LIST OF TABLES (ESIMERKKI)

Acronyms and Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
Fintech	Financial Technology
US	United states
AuM	Asset under management
AIF	Alternative investment fund
ROE	Return on equity
IT	Information technology

This research was undertaken while working for an alternative asset manager, managing distressed loan portfolios. I would like to thank my colleagues and stakeholders for taking part in this study.

1 INTRODUCTION

1.1 Introduction

1.1.1 Problem indication

In recent years, Alternative investment funds and especially Hedge Funds have been growing rapidly, resulting in an increase in trading volumes and complexity of their investment strategies. Alternative investment funds (AIF) are pooled investment vehicles that involve collective investments in unconventional tangible and intangible assets. AIFs include hedge funds, funds of hedge funds, venture capital and private equity funds, as well as real estate funds. Alternative investments are supplementary and complementary strategies to the holdings of bonds, stocks, and cash. Investors contribute their capital to an investment vehicle, and the potential returns are sharing among the participants (BlackRock, 2023). The main operations of these organizations, including back, middle, and front-office processes have remained largely manual over the years, resulting in a significant amount of time and resources spent on non-value adding tasks. The adoption of Artificial Intelligence (AI) and Machine Learning (ML) in the alternative investment industry represents a significant challenge for companies seeking to remain competitive. Despite the potential for these technologies to optimize portfolios, generate trading ideas, and analyze vast amounts of data, their implementation in the industry remains limited. One of the main obstacles faced by data scientists and engineers working in finance is the difficulty of effectively communicating the value of these technologies to employees and top management. AI technologies are currently being applied in the industry to optimize the execution of trades in terms of speed and to analyze press releases as well as financial reports for market-moving keywords (Satariano & Kumar, 2017). While AI technologies may not have yet achieved widespread success in the public market, these technologies have noteworthy potential in the private market (BlackRock, 2019). The increasing automation of daily operations through AI has the potential to free up professionals' time for more value-added tasks that require their expertise, human intelligence, and judgement. Yet, the current level of AI and ML adoption in the industry stays low. A survey directed by EY in 2019 found that only 26% of Hedge funds were using AI, whereas 41% did not expect to use such technology in the coming years. The percentage is even lower for Private Equity funds, with only 15% using AI. In contrast, nearly 90% of investors surveyed stated that they believe it is important for their Hedge Fund and Private Equity managers to make AI a central strategy in their investment decision-making process (EY, 2019).

1.1.2 Reviva Capital

This research was performed in parallel with a job as a full-time Analyst at Reviva Capital, an alternative asset management firm and loan servicer based in Luxembourg. Reviva was established as a response to the Financial Crisis of 2008 and specialized in managing distressed, asset-backed and new loan portfolios owned by DavidsonKempner Capital Management, a global investment management firm based in the US. With a total of €5.7 billion in assets under management (AuM), Reviva is a reputable financial services provider in Europe, known for its expertise in distressed debt advisory, workout management, underwriting portfolios, and restructuring.

1.1.3 DavidsonKempner Capital Management

DavidsonKempner, with approximately $38 billion in AuM, has been actively seeking distressed opportunities since the launch of its first Distressed Opportunities Fund in 2011 (DavidsonKempner, 2017). The US based Asset Manager holds the belief that the resolution of non-performing loans (NPLs) will remain a priority for the European Central Bank. However, sourcing and purchasing loans and assets from European banks can serve as a barrier to entry for many investors. For this reason, the Hedge Fund, with strong conviction in the long-term opportunities presented by distressed debt investing, has formed partnerships with European operators like Reviva Capital.

1.2 Research question

The alternative investment industry has experienced significant growth over the past few decades, with hedge funds being one of the key players (Bharathan & Rao, 2017). Despite their complex nature and high levels of automation in trading and portfolio management, Hedge funds still involve a lot of manual tasks in their front, middle, and back-office operations. Automation has the potential to shape the future of alternative asset management by modernizing and optimizing operations to increase efficiency. The management of alternative assets, which are often characterized by their complexity and high cost, is particularly challenging due to the unstructured nature of the data associated with them. As a result, the ability to effectively manage large quantities of unstructured data has become a critical aspect of successful alternative asset management. This research explores the current state of AI adoption in the industry and identifies the critical success factors for AI adoption in Hegde funds.

The research question will be:

"What are the key success factors for implementing AI-driven asset management in alternative investment firms?"

To ensure the readability and organization of the research, the following sub-questions will drive the study:

- What are the opportunities and risks of using AI in alternative asset management?
- What are the challenges of automating manual tasks in front, middle, and back-offices?
- How can the implementation of automation affect the roles and responsibilities of employees?

1.3 Relevance

The aim of this paper is to identify the key success factors for AI technologies adoption in alternative investment firms. With the interest rates hike and the current economic challenges, the number of alternative asset managers financing the real economy through direct lending is likely to increase. It becomes interesting to study how AI technologies are being used and deployed by these alternative lenders, also called the shadow banks (Savov, 2017). The shadow banking system comprises financial institutions that look like banks, operates like banks, borrow, lend, and invest like banks, but are not regulated like banks (Roubini & Mihm, 2011).

The researcher is particularly keen to conduct this research to bring a new perspective that focuses on individuals and their appetite towards AI technologies. Previous research mostly focused on applications of AI in asset management, often bringing debate on potential risks and drawbacks of AI adoption (Mattioli, Perico, & Robic, 2020). Though, the aim of this paper is to identify the critical success factors for AI implementation and to determine the factors that would drive alternative investment firms to adopt AI technologies. By gathering insights from employees within the industry, we might be able to get a deep understanding of the elements influencing firms' decisions to adopt AI or not. AI-driven funds may attract more investors than traditional ones. Managers must explain AI-driven methodologies to investors, who may be tempted by strategies coming from supercomputers to process vast amounts of data and learn to respond to market dynamics in real-time. When managers explain to investors that AI technologies can assist in generating trading ideas and optimizing portfolios, they might be willing to invest more in AI-driven investment vehicles (Bajulaiye, Fenwick, Skultetyova, & Vermeulen, 2020). Hence, it becomes essential to study investment professionals' feelings, appetites, and thoughts regarding AI technologies. Their expectations, apprehensions and fears may greatly influence AI adoption, integration and use into their working habits. Therefore, this study will be executed by gathering insights and feedback from employees working for alternative investment firms, investment banks as well as alternative lenders. Through this research, technological barriers, such as data quality and integrity, infrastructure requirements, people and skill sets will be studied. We will see how these barriers are interconnected and can impact AI adoption in investment firms. A literature review will give theoretical background and support the choice of constructs for the survey. Theoretical models such as the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, Task-Technology fit, Diffusion of Innovations as well as the Technology Organization Environment will be presented and slightly adapted to integrate the factors identified in the literature review. This will provide background and knowledge before presenting the research model for this study and incorporating the factors as constructs for the quantitative data collection. In the data analysis section, hypotheses and relationships between constructs will be assessed. The data analysis will provide insights and facts on investment professionals' thoughts and views on AI and what could be the key success factors for AI implementation in the forthcoming years.

2 LITERATURE REVIEW

2.1 Introduction

2.1.1 AI in Finance

AI corresponds to software with self-learning algorithms that can enhance and support human decision-making in accomplishing tasks (Deloitte, 2023). AI systems continue to make noticeably progress and become particularly powerful to execute tasks that usually necessitate human intelligence. These techonologies could assist humans across various functions and replace them in their daily repetitive tasks to boost productivity (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). AI potential value in the banking sector could even reach $1 trillion (McKinsey, 2020). AI adoption is slower in the banking sector than in the investment management industry even though an accelaration in recent years was noticed (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). Historically, the adoption of AI in the banking industry has been slowed by the need for confidentialy and the proprieatry nature of data in this sector. Yet, the situation is likely to change because of the rising competiton from Fintech lenders (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). At its core, the use of AI in Finance combines mathematics and statistics to make informed and quantitatively backed decsions. Investment managers use statictical models to optimize the allocation of different assets in a portfolio to manage risk and return (Cao, AI in Finance: Challenges, Techniques and Opportunities, 2022). Additonally, statistics and machine learning are often used to analyze historical data and forecast future trends. (Cao, AI in Finance : A Review, 2020). Moreover, modern analytics and learning methods have dramatically transformed financial analysis, financial forecasting and decision-making. With the increasing complexity and volume of data, machine learning enables algorithms to learn from data and to make data-driven decisions. Machine learning (ML) is a type of AI that empowers software applications to strenghen their predictive capabilities without explicit programming (Wagstaf, 2012). ML algorithms can be trained on vast datasets to recognize patterns, trends, and correlations that would not be detectable and therefore usable by human analysts. On top of that, with ML algorithms, professionals can make more accurate predictions regarding the market evolutions. Non-linear relationships and complex interaction can be added in their analysis to generate more precise forecasts (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). Furthermore, as metionned in the paper from Xiao-lin Zheng, *FinBrain: when finance meets AI 2.0*, ML can be used for credit scoring, where algorithms evaluate the risk profile of borrowers, considering a wider range of variables than traditonal models. With AI's advanced algorithms, the technology can automate underwriting processes as well as detect fraud and anomalies. This can help banks and financial institutions to mitigate risks (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). Computational intelligence methods such as neural networks and evolutionary computation have opened up new avenues for financial modeling as well ; credit system that integrates a diverse range of data sources can be constructed using tree models, neural netwoks, and support vector machine model (Zheng, Zhu, Li, Chen, & Tan, 2019). Also, ML had a transformative impact on algotihmic trading through future market trends predictions. These new types of algorithms can incorporate alternative data sources such as articles, social media contents and press releases (Ferreira, Gandomi, & Cardoso, 2021).

The following figure (Figure 1) based on the challenges, techniques and opportunities of AI in Finance, summarizes the family of Data Science and AI used and applied in Finance (Cao, AI in Finance: Challenges, Techniques and Opportunities, 2022). The outcome of the paper is that AI and Data Science represents both considerable opportunities and challenges for financial institutions. To keep pace with technology developments and therefore benefit from the full potential of AI, financial institutions must confront and effectively tackle these challenges to secure competives advantages.

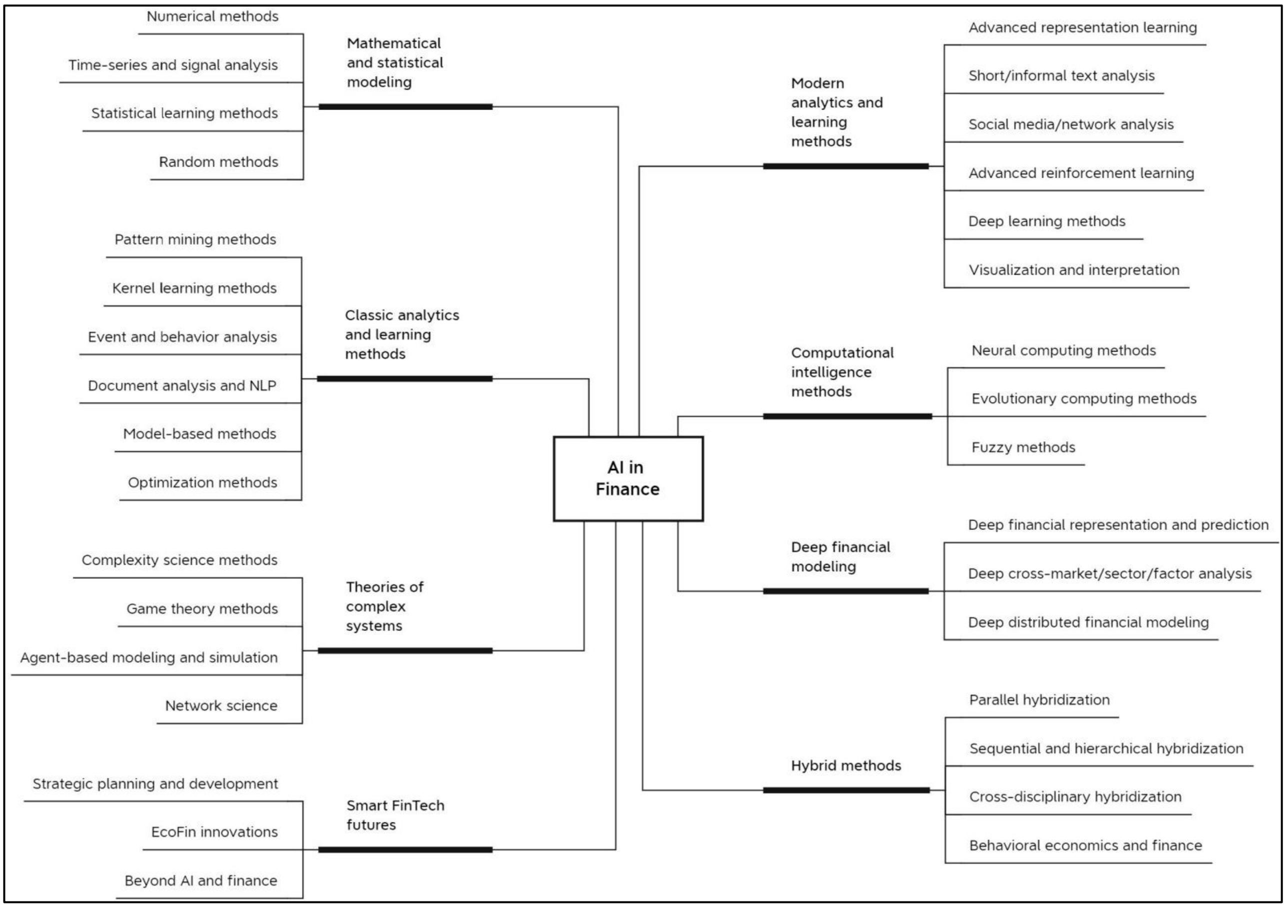

Figure 1 The Technical Family of AI and Data Science in Finance (Cao, AI in Finance: Challenges, Techniques and Opportunities, 2022)

2.1.2 Hedge Funds

Alfred Winslow Jones settled the first hedge fund in 1949. His strategy involved both long- and short-term positions to mitigate market risks (Stulz, 2007). Alfred W. Jones introduced the concept of charging a performance fee on top of management fee to incentivize fund managers. Hedge funds offer their investors investment strategies to diversified portfolios to spread the risks across different exposures. Their investors are usually high-net-worth individuals and institutions who meet specific requirements fixed by regulators such the SEC in the US (Stulz, 2007). Hedge funds are generally very opaque to the public. For quite some time, institutional investors and high-net-worth individuals have exhibited a persistent interest in Hedge funds as alternative investments to diversify their traditional assets portfolio*s* (Hsieh & Fung, 1999). This paper provides an overview of the regulatory environment of US based Hedge funds and information on their investment strategies (Hsieh & Fung, 1999). Hedge funds are less regulated than Mutual funds for instance, and consequently it offers investment managers more flexibility in their trades and investment strategies. The inception of the first mutual fund can be traced back to 1774 in The Netherlands. In terms of AuM, mutual funds rank among the two largest financial intermediaries in the US. Fundamentally, they are investment vehicles that pool money from various investors to purchase securities. They operate without employees and are overseen by a board of directors who are elected by the investors themselves. There are four types of mutual funds: open-ended, closed-end, exchange-traded, and unit investment trust funds (Elton & Gruber, 2013). On top of that, Hedge funds generally seek arbitrage opportunities that can yield low-risk profits (Stulz, 2007). Alternative investment firms such as Hedge funds can provide capital to companies as alternative lenders as well. They diverged from traditional banks though, because they are less regulated, granting more flexibility in terms of funding solutions and investment strategies. The shadow banking system comprises lenders, brokers and other credit intermediaries that operate outside the scope of traditional regulated banking. Unlike traditional banks, shadow banking is less regulated and not subject to the same risk, liquidity, and capital requirements. The shadow banks came in a diverse range of entities. These entities include nonbank mortgage lenders; structured investment vehicles that financed themselves through complex short-term loans known as asset-backed commercial paper (Roubini & Mihm, 2011). Additionally, part of these institutions are investment banks and broker-dealers, money market funds reliant on short-term funding from investors, or hedge funds and private equity funds. These institutions counted on borrowing from short-term and liquid markets to invest in long-term and illiquid assets. Over time, these financial institutions improved and evolved to the extent that they rivaled the conventional banking system, lending comparable amounts of money (Roubini & Mihm, 2011). Alternative financing channels are expected to gain weight in the future. Consequently, the asset management industry role in direct lending is becoming more important (Elliot, Kroeber, & Qiao, 2015). Considering shadow banking activities, China has witnessed an emergence of alternative lenders these past years. In China, securitized asset and derivatives became key vehicles for capital deployment (Elliot, Kroeber, & Qiao, 2015). Through these financial instruments, alternative investment firms can hedge risks and provide investors with exposure to diversified portfolios. Some businesses may have difficulty in securing traditional loans with banks. Securitization allows shadow banks to provide additional funding to these businesses (Shin, 2009). Regarding Chapter 11 and distressed debt investment strategies, Hedge funds have the possibility to acquire debt from distressed borrowers (Jiang, Li, & Wang, 2012). This paper offers a description of hedge funds' roles and attractiveness in Chapter 11 processes. Chapter 11 is defined as *"the reorganization under the bankruptcy laws of the United States. Available to every business, whether organized as a corporation, partnership or sole proprietorship, and to individuals, although it is most prominently used by corporate entities"* (Wikipedia, 2022). The paper from Wei Jiang, Kai Li and Wei Wang written in 2012 illustrated Hedge fund's appetite for debt and equity investment strategies. Generally, Hedge funds setting investment pools for distressed investment purposes tend to have a long-term strategy compared to traditional Hedge funds that seek quicker turnover for their investors (Jiang, Li, & Wang, 2012). In this paper, the authors used a sample of Chapter 11 firms from 1996 to 2007 to illustrate the role of Hedge funds in the restructuring process (Jiang, Li, & Wang, 2012). Hedge funds' investment strategies are mostly based on the management style and vison of fund managers (Stefanini, 2010). Though, these strategies are subject to constant evolution according to the economic context (Stefanini, 2010). The following figure (Figure 2) attempts to summarize the investment strategies adopted by Hedge funds over the years, it is worth noting that these strategies are not an exact science and will always evolve.

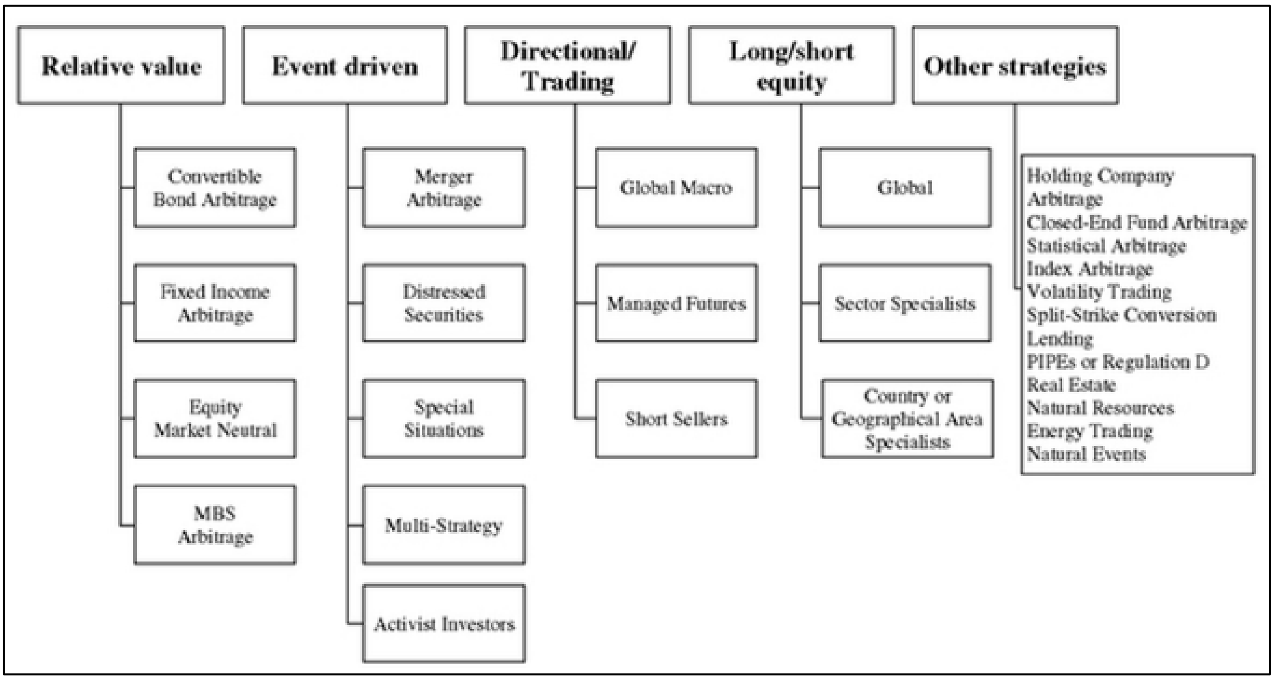

Figure 2 Hedge Funds' investment strategies (Stefanini, 2010)

Hedge funds investing in distressed opportunities require a larger time horizon to get back profits. Plus, returns generated are impacted by the credit market cycle. In 2007, distressed hedge funds represented only 5.64% of the entire hedge fund ecosystem (Thomas Della Casa, 2008). Unlike Private Equity funds, Hedge funds do not actively engage in the operational processes of companies. They rather focus on trading opportunities associated with outstanding stocks and bonds of companies (Thomas Della Casa, 2008).

The following are definitions of well-known investment strategies used by hedge funds. We will not define all the strategies, but only some that are relevant for the Hedge fund on which the research is based:

- **Even Driven:** Hedge funds monitor and track specific events that could impact companies or entire industries. They assess different scenarios and invest in anticipation of potential market reactions.
- **Distressed Securities:** Hedge funds invest in debt, equity, or distressed borrowers. They purchase securities at discounted prices, and eventually benefit from companies' recoveries and restructuring.
- **Multi-Strategy:** Hedge funds combine different investment strategies to optimize portfolio diversification.
- **Long/Short Equity:** Hedge funds can alternate between long and short positions, to capitalize on both upwards and downwards price movements. Therefore, they can generate returns in many different market scenarios.
- **Global Macro:** Hedge funds make investment decisions based on macroeconomic trends. The factors that are observed by investment managers are geopolitical context, inflation, interest rates…

2.1.3 AI application in alternative asset management

AI in the financial industry is a rapidly growing trend, and the alternative asset management industry is no exception (Kabak & Benjelloun, 2023). Over the past few years, some Hedge funds have begun to exploit AI technologies to improve their operations and gain a competitive edge in the market (BarclayHedge, 2018). Alternative asset management has always been characterized by complex, opaque, and data-intensive investment strategies, which require sophisticated analysis and decision-making. AI technologies have the potential to reduce human involvement, by automating repetitive tasks in order to minimize human errors. These technologies can be used as booking and monitoring assistants in accounting departments for example. AI can strengthen operational efficiency, effectiveness, and scalability by allowing employees to concentrate on creativity and strategy. However, the widespread adoption of AI in asset management could lead to mass unemployment in the coming years (Satariano & Kumar, 2017). Even though, AI can help investment managers and analysts to identify and exploit arbitrage opportunities, and to develop and test new investment strategies in a more efficient and cost-effective manner (Kaal, 2021, p. 240). AI and especially ML is used in portoflio management and optimization, risk management as well as algorithmic trading. Then, middle and back-offices are terms used in the financial industry to categorize areas of operations. The middle-office can be defined as the brighe between the front and the back-offices, where tasks such as risk management, trade reconciliation and documentation are performed. On the other hand, the back office handles the administrative and operational functions of a firm such as accounting and bookkeeping, data management or compliance (Safizadeh, Field, & Ritzman, 2003). Therefore, tasks performed in middle and back-offices in alternative investment firms are often manual and time-consuming. AI-powered tools can help automate these tasks, reducing errors, improving efficiency, and freeing up employees to focus on more value-added activities. For example, AI can help extract data from unstructured documents, such as invoices and contracts, and reconcile it with the firm's accounting system (Kaal, 2021, p. 233). Moreover, AI can help generate customized reports and dashboards, providing real-time insights into portfolio performance and risk exposure.

AI algorithms deployed in Hedge funds, for instance, have the capability to identify investment strategies that humans may have overlooked (Satariano & Kumar, 2017). Additionally, through Natural language processing associated to deep learning and statistical models, asset managers can review contracts and generate insightful reports in a more effective way. Report generation shared with warehouse banks, stakeholders and even investors can be automated. This could save significant time and resources for asset managers (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). Furthermore, with AI, portfolio managers can customize investment portfolios. In addition to developing new returns profiles, it goes beyond traditional and well-known strategies to personalize investment experience for investors. With ML, portfolio managers can learn from past performance and make informed decisions for future portfolio adjustments and allocations (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021).

2.2 Challenges of implementing AI

In the following section, the main barriers for AI adoption will be outlined. This section aims to present papers bringing knowledge and background on the challenges organizations face when implementing AI technologies.

2.2.1 Technological challenges

In most financial institutions, the information technology (IT) function reflects the largest functional expense and is a paramount area of management concern. It impacts nearly every aspect of management operations and has a major effect in determining an institution's overall profitability (Ernst & Young LLP, 1994). Unstructured data is everywhere in alternative investment. It presents a substantial challenge for the training and deployment of traditional algorithms. The cost of storing data has noticeably decreased. Yet, organizations struggle in fully utilizing and exploiting data they accumulated over time (Satariano & Kumar, 2017). AI technologies such as ML and NLP have huge potential in processing and analyzing such complex data (Kumar, Grover, & Singh, 2023). However, the data must be collected, cleaned, and organized requiring strong data processing systems. In the research on AI adoption in SMEs proposed by Andrea Bettino and her peers (Bettoni, Matteri, & Montini, 2021), interviews with two managers to gain an understanding of the key barriers to AI adoption in companies were conducted. The findings showed the need for structured and automated data collection as a top priority for companies willing to implement AI. Managers emphasized that for SMEs seeking to integrate AI into their daily operations, implementing necessary systems for data collection is essential. Companies must automate data collection and processing to ameliorate the efficiency of the overall AI implementation process. Moreover, SMEs often find themselves grappling with limited data availability. This can be due to lack of data infrastructure, or proper IT infrastructure in general (Bettoni, Matteri, & Montini, 2021). To successfully collect and process data, data management processes are needed within organizations. A company should have well-defined procedures and policies on data management (Kruse, Wunderlich, & Beck, 2019). It is paramount for all stakeholders to speak the same language when it comes to data processing. Organizations must foster data governance as well to ensure data authority and integrity (Bettoni, Matteri, & Montini, 2021). Sometimes companies and banks are challenged to provide the necessary quantity and quality of data needed to train AI algorithms (Kruse, Wunderlich, & Beck, 2019). Even though, collecting and processing the appropriate data is fundamental to benefit from the full potential of AI systems.

2.2.2 Compliance, Regulation and Ethical challenges

By implementing data governance, organizations assure compliance with existing and new regulations. They can mitigate and manage risk exposure related to data exploitation (Bettoni, Matteri, & Montini, 2021). The regulatory environment related to data privacy, cybersecurity and financial crimes varies depending on the jurisdictions in which a firm operates. Although, these complex and evolving regulations pose challenges to effective design of AI regulatory and compliance frameworks (Zhang, Ashta, & Barton, 2021). With the storing and processing of large quantities of sensitive data, ensuring data privacy as well as cybersecurity is of utmost importance. Having strong measures and infrastructure to preserve data privacy and cybersecurity became imperative in data management strategy (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). AI algorithms analyze and process data, and therefore could memorize information from the training set, including personal information about individuals. How can organizations safeguard data privacy while maintaining the integrity of patterns in the training data set is a significant concern (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). Furthermore, there is an increasing demand for transparency regarding the implementation of AI. The association between compliance issues and ethical concerns can make AI adoption challenging. Indeed, by providing transparency to users and regulators, organizations could improve AI acceptance and adoption (Kruse, Wunderlich, & Beck, 2019). In this paper, one of the findings is that the lack of transparency into the AI "Black Box" is too frequently met with caution and leads to slower AI adoption (Kruse, Wunderlich, & Beck, 2019). AI algorithms can be so opaque that even their creators did not fully understand the rationale behind the trades they execute (Satariano & Kumar, 2017). As long as algorithms remain black boxes, their utilization will be limited. This lack of explainability makes it difficult for users to understand and trust the decisions made by ML algorithms. Furthermore, it can expose organizations to vulnerabilities and risks (Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021). To secure satisfactory levels of reliability and transparency in predictive systems, a new methodology known as White Box AI emerged, to promote interpretable algorithm models. White Box AI should explain how algorithms learn from data and the types of relationships it can uncover (Wanner, Herm, Heinrich, Janiesh, & Zschech, 2020). One of the key requirements to manage to implement responsible AI, is the integration of explainability. To guarantee the responsible adoption of AI technologies, organizations must integrate ethical considerations into their AI applications and processes. AI applications must be founded on trust and transparency to promote responsibility in the deployment of AI technologies (Wanner, Herm, Heinrich, Janiesh, & Zschech, 2020).

2.2.3 AI skill gaps

IT and therefore AI is a highly complex area and requires specialized technical knowledge for comprehension and effective application (Ernst & Young LLP, 1994). Indeed, there is an established and growing recognition of a talent gap in the alternative investment industry (Deloitte, 2023). By exploiting AI techniques, routine tasks can be automated, and professionals could gain insights from data to make data-driven decisions. Integration of AI tools into daily operations can be a substantial shift from traditional ways of working. Even though investment professionals are generally highly educated and willing to tackle new challenges to advance their careers. From an employee's point of view, transparency and consensus are key factors to effectively managing change within an organization (Gonçalves, 2012). However, for the employees who have been working for extended periods for the same firm, the transition to AI techniques can be more challenging. This resistance to change could stem from apprehensions about learning new technologies or concerns about job maintenance. As mentioned in the paper of Gonçalves, there are a multitude of factors that lead employees to demonstrate resistance to change. One prominent aspect of this resistance is the fear of the new and the unknown, which is often linked to leaving one's comfort zone. (Gonçalves, 2012). Indeed, automation and optimization may render employees' roles redundant. They may feel uncertain about how AI integration might affect a firm's dynamics, hierarchy, and even its core values. Employees' attitudes toward organizational change are generally derived from their past experiences. In addition, employees' perception of trust in management is an essential factor. The way employees perceive the competence and integrity of management plays a significant role in their willingness to adopt a certain change within the organization (Blanca & Ramona, 2016). In many organizations, people at every level often find themselves overwhelmed with tasks. Therefore, they tend to be resistant to the notion of change while still being expected to deliver their assigned results and maintain smooth communications with collaborators (Ford & Ford, 2010). As described in the paper from Ranjan, to successfully implement AI techniques, a combination of skills is required. These skills are Data Scientists, Software Developers as well as AI Researchers (Ranjan, 2020). As outlined in the paper, Data scientists' expertise is necessary to turn structured and unstructured data into meaningful insights to make data-driven decisions. Regarding the required infrastructure to successfully implement and integrate AI technologies to existing systems, Software developers' skills became a must. In addition, AI researchers' skills can help organizations to stay ahead of the curve in terms of AI innovations. It became clear that successful AI adoption relies on a synergic collaboration between these different skills. The empirical study conducted by Ulrich, Frank and Kraat showed the challenges of AI adoption among German SMEs. As a result, one of the key findings is the lack of awareness regarding the potential benefits that AI can bring to their businesses (Ulrich, Frank, & Kratt, 2021). Besides the lack of necessary skills to successfully implement AI, there is also a lack of understanding of AI's disruptive potential. Even though this lack of awareness can be linked to limited budget as well as inadequate human skills, SMEs might be willing to invest part of their resources in exploring AI possibilities in the future (Bettoni, Matteri, & Montini, 2021). To keep pace with technological developments, organizations should hire engineers as well as data scientists. (Satariano & Kumar, 2017).

2.2.4 Financial challenges

The absence of a clear method to measure and estimate the costs, benefits and return on equity (ROE) associated with AI implementation has always been a challenge for organizations. Investing in AI can have a long-term positive impact, though, measuring the ROE can be difficult. The positive outcome from AI investments may not manifest immediately, making it difficult to quantify the benefits of the investment. Furthermore, AI adoption can result in a multitude of diverse and sometimes synergistic outcomes, complicating the attribution of specific benefits from AI investments (Bierly & Coombs, 2006). Organizations that have a deeper understanding of AI and have greater resources to explore AI potential are well-positioned to generate impressive returns on their investments. However, most organizations lack clarity and understanding on the applications of AI, how to implement it, and the expected outcomes from specific use cases. Implementing AI-based systems requires considerable investments to customize assets and capabilities according to the organization's context and data requirements. Further to this, AI systems generate large volumes of data, demanding efficient storage and processing techniques. For that reason, organizations may need to make important investments in robust data storage infrastructure, which can be financially cumbersome (Johnk, Weibert, & Wyrtki, 2021). Thereupon, AI investment decisions can appear sophisticated and ambiguous, leading many organizations to stay on the sideline. Indeed, companies cannot use traditional metrics to quantify a potential investment in AI. Consequently, lots of organizations opt for known and established approaches instead (Bettoni, Matteri, & Montini, 2021).

2.3 Theoretical background

In the field of information systems, lots of theoretical models have been developed to assess the adoption and implementation of new technologies within organizations. Multiple theoretical frameworks will be described for their relevance. Even though not all of them will be used to theorize the study, it will provide background knowledge for the research purposes. Knowing that they all could have been used integrally or partially for the research purposes.

2.3.1 Technology Acceptance Model

TAM stands for Technology Acceptance Model. This Model is a theoretical framework widely used in the field of information systems and technology research. It was originally proposed by Fred Davis in 1989 and has since been expanded upon and modified by various researchers (Gangwar, Date, & Raoot, 2014). The Model seeks to explain and predict the acceptance and adoption of new technologies by individuals (Lules, Omwansa , & Waema, 2012). It suggests that the perceived usefulness and ease of use of a technology are the primary factors influencing an individual's intention to use that technology (Chtourou & Souiden, 2010). **Perceived Usefulness** refers to the degree to which a person believes that using a particular technology will enhance their job performance and efficiency. Besides, **Perceived Ease of Use** refers to the degree to which a person believes that using the technology will be free of effort. According to the TAM, if individuals perceive a technology to be useful and easy to use, they are more likely to have a positive attitude toward it and intend to use it which will make its implementation smoother (Yen, Wu, Cheng, & Yu-Wen Huang, 2010). The TAM has been influential in understanding user behavior and has provided valuable insights into the factors that influence technology acceptance. It has also served as a basis for the development of other models and theories in the field of technology acceptance, adoption, and implementation such as the UTAUT (Attuquayefio & Addos, 2014).

2.3.2 Unified Theory of Acceptance and Use of Technology

The UTAUT proposed by Venkatesh et al. in 2003 is an integrated model combining multiple technology models, including the TAM.

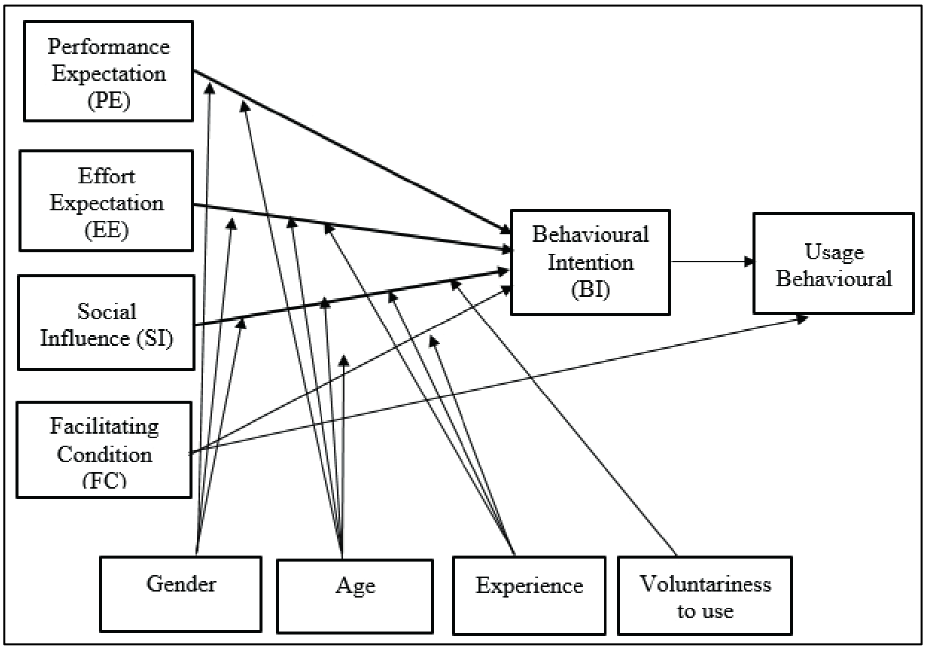

Figure 3 UTAUT model (Venkatesh et al., 2003)

UTAUT stands that technology acceptance is influenced by:

- **Performance Expectancy (PE):** defined as the degree to which an individual believes that using the system or the technology will help him or her to improve productivity.

- **Effort Expectancy (EE):** corresponds to the degree of ease associated with the system or the new technology.

- **Social Influence (SI):** defined as the degree to which an individual perceives that important others believe he or she should use the system or the new technology.

- **Facilitating Conditions (FC):** defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the system.

2.3.3 Task-Technology Fit

Proposed by Goodhue & Thompson (1995), The Task-Technology Fit (TTF) model proposes that a user's usage and attitude towards technology significantly influence their individual performance, solving one of the main weaknesses of the TAM in understanding the use of information technologies (Tam & Oliveira, 2016). The model promotes the alignment between the requirements of the user's tasks and the capabilities offered by the available information technology (Klopping & McKinney, 2004).

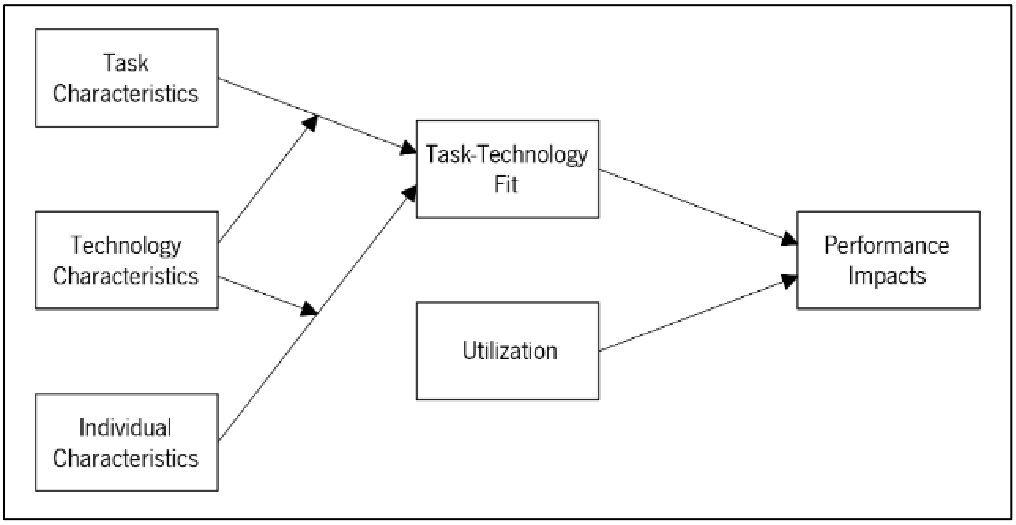

Figure 4 The Task-Technology (Goodhue & Thompson 1995)

- **Task Characteristics:** The nature of the task the individual needs to perform.

- **Technology Characteristics:** The functionalities and features offered by the technology.

- **Individual Characteristics:** The individual user's attributes.

- **Task-Technology Fit:** The degree to which a technology supports a user in performing their tasks.

- **Utilization:** The actual use of the technology by the individual.

- **Performance Impacts:** The outcome variable of the model.

2.3.4 Diffusion Of Innovations

The DOI model was developed by Everett Rogers in 1995. The purpose of the framework was to explain the adoption of new innovations within a social system. Moreover, the DOI model helps researchers to get a deep understanding of processes involved in the adoption of innovations (Oliveira & Martins, 2011).

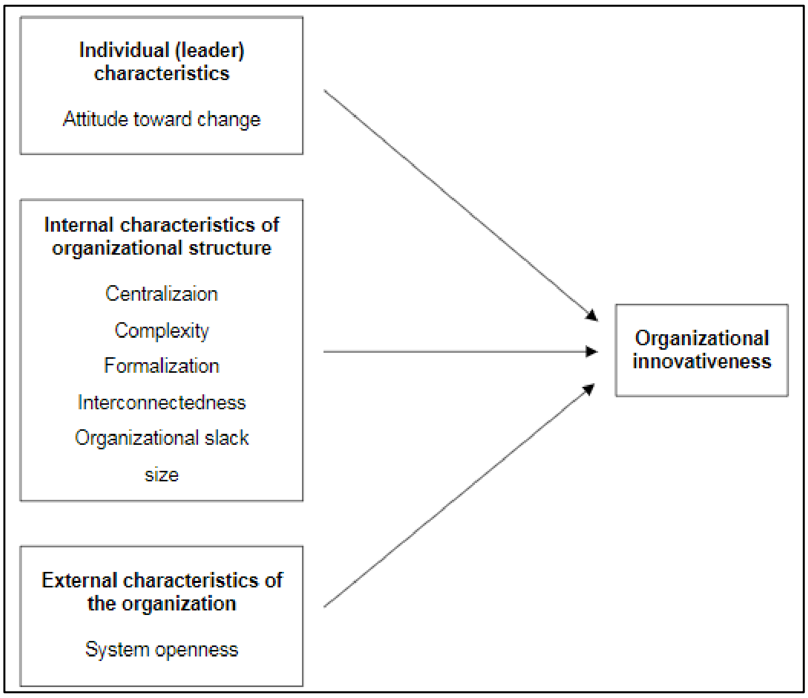

Figure 5 DOI (Rogers 1995)

According to the DOE model at a firm level, the adoption of innovation is influenced by the following variables:

- **Individual (leader) characteristics:** the leader's attitude toward change.

- **Internal characteristics of organizational structure:** "centralization is the degree to which power and control in a system are concentrated in the hands of a relatively few individuals"; "complexity is the degree to which an organization's members possess a relatively high level of knowledge and expertise"; "formalization is the degree to which an organization emphasizes its members' following rules and procedures"; "interconnectedness is the degree to which the units in a social system are linked by interpersonal networks"; "organizational slack is the degree to which uncommitted resources are available to an organization"; "size is the number of employees of the organization".

- **External characteristics of the organization:** refer to system openness.

2.3.5 Technology Organization Environment

The Technology-Organization-Environment (TOE) model developed in the field of information systems explains how the adoption and use of new technologies are influenced by various factors such as characteristics of the technology that an organization is trying to adopt, the organizational context in which the technology is used, and the external environment in which the organization operates. The model was developed by Tornatzky & Fleischer (1990) to study the adoption and implementation of different types of IT innovation (Oliveira & Martins, 2011).

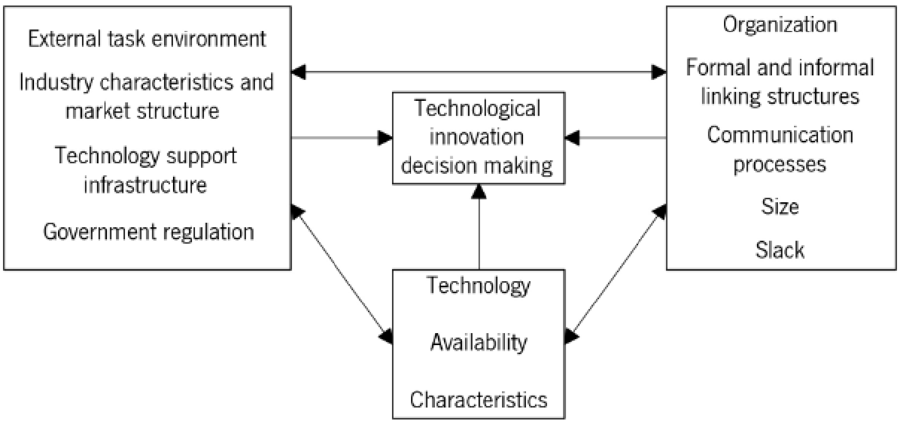

Figure 6 TOE (Tornatzky & Fleischer 1990)

- **Technological context:** describes both the internal and external technologies relevant to the firm.

- **Organizational context**: refers to descriptive measures about the organization such as scope, size, and managerial structure.

- **Environmental context:** is the area in which a firm conducts its business, its industry, competitors, and dealings with the government or regulator.

2.4 Summary of literature review

Papers	Object	Methodologies
(Boukherouaa, AlAjmi, Deodoro, Farias, & Ravikumar, 2021)	Overview of AI Utilization in Finance	Literature review
(Cao, AI in Finance: Challenges, Techniques and Opportunities, 2022)		Literature review
(Cao, AI in Finance : A Review, 2020)		Literature review
(Zheng, Zhu, Li, Chen, & Tan, 2019)		Literature review
(Ferreira, Gandomi, & Cardoso, 2021)		Literature review
(Wagstaf, 2012)		Literature review
(Stulz, 2007)	Hedge Funds: Operations and Characteristics	Literature review
(Hsieh & Fung, 1999)		Case study
(Elliot, Kroeber, & Qiao, 2015)		Case study
(Shin, 2009)		Literature review
(Jiang, Li, & Wang, 2012)		Case study
(Stefanini, 2010)		Literature review
(Thomas Della Casa, 2008)		Case study
(Roubini & Mihm, 2011)		Literature review
(BarclayHedge, 2018)	AI and Its Role in Enhancing Alternative Asset Management	Survey
(Satariano & Kumar, 2017)		Case study
(Kaal, 2021)		Literature review
(Safizadeh, Field, & Ritzman, 2003)		Survey
(Kumar, Grover, & Singh, 2023)	Technological Challenges in AI Implementation	Literature review
(Bettoni, Matteri, & Montini, 2021)		Interview
(Kruse, Wunderlich , & Beck, 2019)		Interview
(Ernst & Young LLP, 1994)		Literature review
(Zhang, Ashta, & Barton, 2021)	Compliance, Regulation and Ethical challenges in AI implementation	Survey
(Wanner, Herm, Heinrich, Janiesh, & Zschech, 2020)		Literature review

(Kruse, Wunderlich, & Beck, 2019)		Interview
(Deloitte, 2023)	Confronting the AI Skills Gap: A Barrier to Implementation	Survey
(Gonçalves, 2012)		Literature review
(Ranjan, 2020)		Case study
(Ulrich, Frank, & Kratt, 2021)		Case study
(Blanca & Ramona, 2016)		Case study
(Ford & Ford, 2010)		Case study
(Bierly & Coombs, 2006)	Financial challenges associated with AI implementation	Survey
(Johnk, Weibert, & Wyrtki, 2021)		Interview
(Tam & Oliveira, 2016)	Theoretical frame-works	Survey
(Klopping & McKinney, 2004)		Survey
(Oliveira & Martins, 2011)		Literature review
(Gangwar, Date, & Raoot, 2014)		Literature review
(Chtourou & Souiden, 2010)		Survey
(Yen, Wu, Cheng, & Yu-Wen Huang, 2010)		Survey
(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)	Literature-Based Constructs for the Survey Design	Survey
(Gupta, Ghardallou, Pandey, & Sahu, 2022)		Survey
(Nguyen, Le, & Vu, 2022)		Survey
(Sharma, 2017)	Survey Methodol-ogy: Insights from Existing Literature	Literature review
(Marshall, 1996)		Literature review
(Etikan, Musa, & Alkassim, 2016)		Literature review
(Stratton, 2021)		Literature review
(Smith & Noble, 2014)		Literature review
(Pannucci & Wilkins, 2010)		Literature review
(Dinh & Thai, 2018)		Literature review
(Sandner, Gross, & Richter, 2020)		Literature review
(Kruse, Wunderlich , & Beck, 2019)		Literature review
(Hussain & Al-Turjman, 2021)		Survey

Table 1 Summary of related work on AI-powered alternative asset management

3 THEORETICAL MODEL AND HYPOTHESIS

In this section, the theoretical model and hypothesis are introduced. The TOE framework has been broadly used to study technology implementation in organizations and will serve as the foundation for this research. The model was extended and revisited to answer the specific research question. The theoretical model for this research is constructed by applying literature findings and industry knowledge. Furthermore, hypotheses are formulated among the model's variables, besides we will theorize that these variables influence and impact the willingness of alternative investment firms to incorporate AI technologies into their operations and processes. To strengthen construct validity and reliability, all constructs used in this study were derived from existing research and adapted to suit the study's purposes.

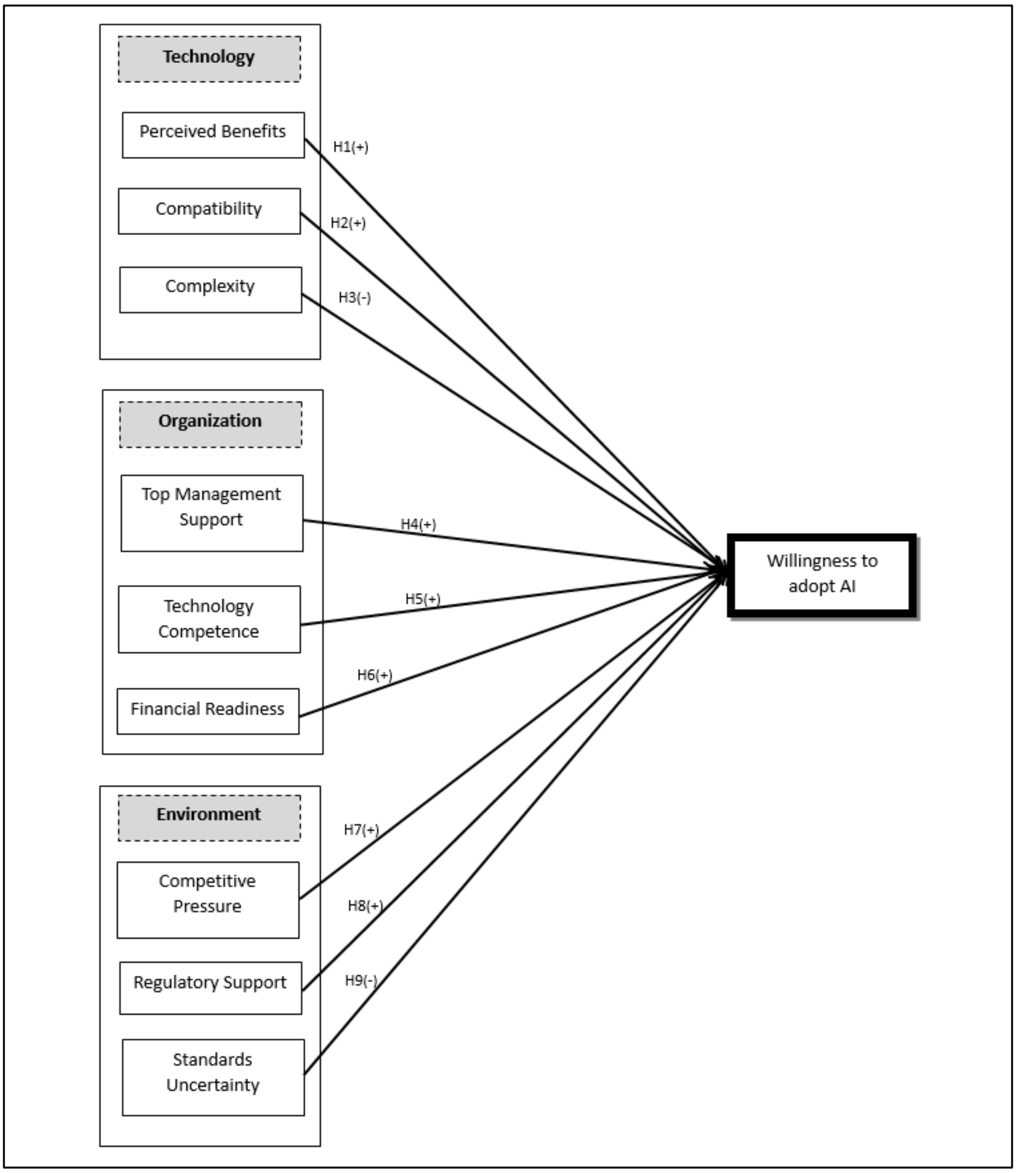

Figure 7 Research Model (Constructs based on literature and industry knowledge)

The relationships between the variables illustrated in the model are presented through the following hypotheses. The hypotheses will provide a clear and structured framework for the data collection and analysis.

- **Hypothesis 1 (H1):** Perceived Benefits (PB) positively influence Willingness to adopt AI (WTAAI).

Perceived benefits refer to the extent to which organizations identify an innovation as disruptive and beneficial for their business operations. Organizations that evaluate the potential outcomes of implementing AI, might be willing to adopt it.

- **Hypothesis 2 (H2):** Compatibility (CP) positively influences Willingness to adopt AI (WTAAI).

The way organizations perceive the compatibility, consistency and complementarity between AI technologies and its existing IT infrastructure.

- **Hypothesis 3 (H3):** Complexity (CX) negatively influences Willingness to adopt AI (WTAAI).

The level of resistance that we could observed in the alternative investment industry is related to the complexity and intricacy of AI application. If organizations sense AI technologies as intricate and laborious to use, they might not be willing to adopt it.

- **Hypothesis 4 (H4):** Top Management Support (TMS) positively influences Willingness to adopt AI (WTAAI).

  Management support is key and paramount in an organization's decision to adopt new technology. The level of support from management considerably affects the probability of adopting AI technologies.

- **Hypothesis 5 (H5):** Technology Competence (TC) positively influences Willingness to adopt AI (WTAAI).

The internal technological resources, infrastructure, and skills of an organization represent an important role in the adoption and implementation of AI technologies. Besides, a strong IT infrastructure is required to run AI applications.

- **Hypothesis 6 (H6):** Financial Readiness (FR) positively influences Willingness to adopt AI (WTAAI).

Organizations must be willing to invest in AI and have the financial stability to support such investments. Organizations must have an adequate budget to be able to allocate enough resources to AI technologies implementation.

- **Hypothesis 7 (H7):** Competitive pressure (CP) positively influences Willingness to adopt AI (WTAAI).

Organizations may experience fears of losing their competitive advantage to competitors. To stay ahead of their competitors in the technology integration race, they could be willing to adopt AI technologies.

- **Hypothesis 8 (H8):** Regulatory Support (RS) positively influences Willingness to adopt AI (WTAAI).

Regulatory support stands for policies, initiatives and incentives introduced by governments and financial regulators to facilitate the adoption of AI technologies. By providing a supportive regulatory framework, regulators can foster organizations to implement AI into their operations.

- **Hypothesis 9 (H9):** Standards Uncertainty (SU) negatively influences Willingness to adopt AI (WTAAI).

If there is an absence of formal standards and regulations for AI technologies, organizations might not be willing to adopt it. When there is a lack of established standards in their regulatory environments and ecosystems, organizations may feel skepticism regarding the potential benefits of AI implemetation.

4 MEHODOLOGY

A survey analysis was deemed appropriate to gather information directly from the individuals working for alternative investment firms. By analyzing their responses, we might get an understanding of how they perceive and apprehend AI integration in the industry. Hence, in this part of the research, we will present the experimental research design, the purposes of the literature review as well as the survey methodology. The experimental research design gives us the framework within which the survey will be designed. Additionally, the literature review contextualizes the survey findings, especially by summarizing the existing body of knowledge of AI applications in the alternative investment industry.

4.1 Experimental Research Design

The study followed a quantitative research method, showing an accurate representation of a certain population working in alternative investment firms. Hypotheses have been formulated and tested against the survey results. These hypotheses served as assertions about the relationships between variables. The outcomes of this experimental research will be used to answer the hypotheses formulated in the previous section. Hence, this study flows an experimental design, which involves the introduction and manipulation of variables to examine their effects (Quick & Hall, 2015). The analysis of the data collected will be done through statistics. The use of quantitative measurements and statistical analysis enable researchers to derive objective conclusions from the data (Quick & Hall, 2015).

4.2 Literature Review

A literature review was completed to identify the key findings that have been previously established on AI utilization in Finance and particularly in the alternative investment industry. It was also necessary to define research objectives and formulate hypotheses. A systemic review, also known as a research synthesis, offered a consolidated overview of existing studies within a single paper. Systemic reviews provide the researcher an overview of previously published research on a specific subject (Quick & Hall, 2015).

The purpose is not to generate new knowledge, but rather to synthesize compile existing knowledge (Aromataris & Pearson, 2014).

4.3 Survey Methodology

Performing a survey is a highly effective method to obtain information about an individual's experiences, thoughts, and perceptions (Selm & Jankowski, 2006). It allowed us to gather data from many respondents. A large sample size improves the validity and accuracy of the statistical findings. To validate the research model (Figure 7) and the hypotheses described in the previous section, existing quantitative studies and relevant literature have been reviewed. Once the constructs were identified from existing literature and industry knowledge, a questionnaire was prepared. The questionnaire was built using the selected constructs displayed and explained in the proposed research model (Figure 7). Duplicates, long questions, technical and specialized terms were avoided. The objective was to gather as much insight as possible without overwhelming respondents with technicality. To ensure quality and a well-structured survey, we receive feedback and approval from our academic supervisor. To validate the understandability of the questions, the questionnaire was reviewed by experts working in the alternative investment industry as well. They provided input and feedback to improve questions' clarity and coherence. The questionnaire was exclusively delivered in English, considering all respondents have a sufficient level of English to understand and respond accurately to the questions. The questionnaire is provided in Appendix 2.

4.3.1 Sample

Sampling is a method used by researchers to select a smaller but representative group of items or individuals from a larger population for the purpose of studying or conducting experiments. This technique involves systematically selecting a subset of subjects from a pre-defined population in order to observe and gather data aligned with the objectives of the research (Sharma, 2017). The method commonly used is random or probability sampling. With a random sample, the characteristics of the population are defined, and every member of the population have an equal probability of being selected (Marshall, 1996). Convenience sampling is a versatile method that can be utilized in qualitative and quantitative research, although it is predominantly used in quantitative study (Etikan, Musa, & Alkassim, 2016). In this research, convenience sampling was used for its cost and time efficiency compared to other sampling methods. Moreover, this sampling method is especially useful when generating hypotheses (Stratton, 2021). Our research achieved a sample size of 103, respecting the range of 30 to 500. The sample size of our research is seen as acceptable and adequate for the purpose of this research (Hill, 1998).

4.3.2 Research biases

When conducting research, biases can manifest at different stages of the study (Smith & Noble, 2014). To mitigate this risk in the quantitative data collection performed, certain measures have been taken. The survey was designed to be concise and easily accessible. The survey distribution involved multiple individuals to spread the invitation to maximize the number of respondents. However, considering that some level of bias is almost always present in published studies, it is essential for readers to be mindful of how bias can potentially influence research's conclusions and outcomes (Pannucci & Wilkins, 2010).

5 METHOD

In this section, the experimental part of the research is presented. The survey has been designed to gather relevant information pertaining to the research topic. This information is used for hypotheses testing and comparison with existing literature.

5.1 Data Collection

A survey was conducted to gather valuable insights from employees working in a US based Hedge Fund, investment banks as well as alternative asset management service providers based in Luxembourg, Denmark, Portugal, Germany, France, and the UK. The survey aims to capture investment professionals' thoughts and to identify what would enable their firm to implement AI based systems. The survey was distributed online, an internet connection was therefore required to take it. Most items and variables were measured based on 7-Points Likert Scale introduced by Rensis Likert in 1932, allowing participants to rate their level of agreement or disagreement with specific statements. Initially defined as a commonly employed psychometric response scale in questionnaire for obtaining participants' preferences or measuring their level of agreement with a statement or series of statements (Bertram, 2007). The method originally includes five response options, ranging from "strongly disagree" to "strongly agree" (Joshi, Kale, & Pal, 2015). Although, to capture more meaningful data from the respondents, a 7-Points Likert Scale was chosen instead of the traditional 5-Point Scale. With a greater range of options, respondents can provide more nuanced and precise feedback, avoiding ambiguity. Indeed, respondents could hesitate between options 4 and options 5 on a five points scale (Joshi, Kale, & Pal, 2015). Whereas the seven points scale offers respondents a clear differentiation between the different options, enabling them to provide more precise responses (Joshi, Kale, & Pal, 2015). Furthermore, it could enhance respondents' engagement, encouraging them to carefully consider their choices and therefore contributing to the quality of the data collected (Joshi, Kale, & Pal, 2015). Screening questions were also added to ensure the reliability of the data collected. It was particularly useful to streamline the data collection process and focus on the target population. Even though a purposive sampling technique was employed to identify and recruit participants who possess relevant knowledge and experience related to the research question. Qualtrics was used to distribute the survey to potential participants, ensuring a timely and efficient data collection process. We were able to use the licensed version of the Qualtrics online survey software due to our student status at Tilburg University. The research adhered to ethical guidelines, ensuring that participants' confidentiality and anonymity are maintained throughout the study. Indeed, informed consent was obtained from all participants, and they were informed about the purpose of the study, their rights to withdraw at any time, and the measures taken to protect their privacy.

5.2 Constructs Explanation

Perceived Benefits represent the level to which investment professionals believe that using AI technologies will make them increase their asset management performance in terms of effectiveness and efficiency. This construct is used in a research paper exploring factors that impact the adoption of blockchain technology in organizations (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). Considering that blockchain and AI are among the catalyst innovation today, the same construct was used for the purpose of this research (Dinh & Thai, 2018).

Compatibility construct has been used in a significant number of studies showing a positive relationship between compatibility and willingness to adopt new technologies. The construct was used in a study examining the readiness of firms in adopting AI at the organizational level (Alsheibani, Cheung, & Messom, 2018). Moreover, this construct was also used in the research paper on blockchain adoption (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). Successful AI implementation should be aligned with the organization's strategies for proper integration into existing workflows and processes (Alsheibani, Cheung, & Messom, 2018).

Complexity was also used in various studies to show the negative relationship between the construct and the adoption of new technologies. The construct was borrowed from the two papers mentioned previously (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021) and (Alsheibani, Cheung, & Messom, 2018). The complexity of new technologies such as AI impacts the general adoption rates. Besides there is a notable convergence between AI and blockchain technologies (Dinh & Thai, 2018). The full potential of these emerging technologies can only be realized when they are combined (Sandner, Gross, & Richter, 2020).

Top Management Support to adopt new technologies has been widely recognized. Research consistently mentions the necessary support from top management in driving successful technology adoption. This construct was used in a research paper that explored the challenges encountered by organizations in adopting AI, with a specific focus on the financial services industry (Kruse, Wunderlich , & Beck, 2019). Therefore, this construct was well suited for the intended purpose of this research.

Technology Competence is necessary to implement AI into a firm's operations processes. An organization must have the required skills and expertise related to AI technologies. This construct was used in a research study focusing on the adoption of AI in the insurance industry (Gupta, Ghardallou, Pandey, & Sahu, 2022). Due to certain operational similarities between the insurance and alternative investment industry, this construct was relevant in the context of this research.

Financial Readiness is explained by the fact that AI often requires significant investments in infrastructure, hardware, software, and AI-specific technologies. Organizations must have the financial resources to support AI investments. This construct was also used in the paper from (Gupta, Ghardallou, Pandey, & Sahu, 2022) on AI adoption in the insurance industry. As a result, we believed that financial readiness was a relevant construct applicable to AI adoption in Hedge funds.

Competitive Pressure represents the fear of losing competitive advantage. It is a driving force for organizations to adopt new technologies. If organizations want to enhance their competitive position, they must adopt AI. Once again, this construct was used in the paper studying the adoption of AI in the insurance industry (Gupta, Ghardallou, Pandey, & Sahu, 2022). Moreover, the construct was applied in the paper on AI-readiness at Firm-Level as well (Alsheibani, Cheung, & Messom, 2018). Therefore, we believed this construct was pertinent for analyzing the potential impact of competitive pressure on AI adoption within the alternative investment industry.

Regulatory Support is necessary to facilitate the adoption of AI technologies. Regulators create environments that encourage the responsible and widespread use of AI technologies. The construct was applied in the paper for blockchain technologies adoption in organizations (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). With the strong synergy between AI and blockchain technologies, it was interesting to test this construct in the context of this research (Hussain & Al-Turjman, 2021).

Standards Uncertainty and new technologies adoption have been shown as a negative relationship in previous studies. When faced with uncertainty organizations tend to avoid the adoption of new technologies as shown and tested in the paper on blockchain adoption (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). For this reason, we have tested this construct in this research as well.

5.3 Execution

The survey comprised a total of 21 questions, with the initial section dedicated to gathering demographic data through 6 screening questions. Table 2 below provides an overview of the constructs and items incorporated in the survey.

Construct	***Measuring item***	***Source***
Perceived Benefits	**PB1**: AI saves time while accomplishing tasks **PB2:** AI increases the firm's overall productivity **PB3:** AI can provide the firm competitive advantage	(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)
Compatibility	**CPY1:** AI is compatible with your firm IT's infrastructure **CPY2:** AI fits well with technological skills **CPY3:** AI fits well with business	(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)
Complexity	**CX1:** AI requires extra technical skills to be used **CX2:** AI is conceptually difficult to understand from a technical perspective **CX3:** The firm does not understand how AI will benefit the firm in its growth	(Gupta, Ghardallou, Pandey, & Sahu, 2022)
Top Management Support	**TMS1:** Provides the necessary resources for AI adoption **TMS2:** Considers AI as strategically important **TMS3:** Actively involved in IT-related decisions	(Nguyen, Le, & Vu, 2022)

	TMS4: Actively seek new ideas	
Technology Competence	**TC1:** The firm has an excellent AI-based infrastructure **TC2:** Employees of the firm are well trained in AI applications **TC3:** The firm has good knowledge about AI	(Gupta, Ghardallou, Pandey, & Sahu, 2022)
Financial Readiness	**FR1:** The firm would have the financial resources **FR2:** The financial budgets of the firm is enough	(Gupta, Ghardallou, Pandey, & Sahu, 2022)
Competitive Pressure	**CP1:** Feel the fear of losing a competitive advantage if the firm does not adopt it **CP2:** See competitors benefiting from adopting AI **CP3 :** Feel pressure when competitors have adopted AI	(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)
Regulatory Support	**RS1:** Policies support the adoption of AI **RS2:** There is legal support for the use of AI in alternative investment **RS3:** The laws and regulations that exist nowadays are sufficient to protect the use of AI in alternative investment	(Gupta, Ghardallou, Pandey, & Sahu, 2022)
Standards Uncertainty	**SU1:** See AI has not reached its maturity **SU2:** See AI still requires changes to become more efficient compared with existing technologies **SU3:** Cannot predict that AI would become an industry standard in the near future	(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)
Willingness to adopt AI	**WTAAI1:** Adopt AI whenever they will have access to it in the future **WTAAI2:** Adopt AI in the future **WTAAI3:** Adopt AI frequently in the future	(Malik, Chadhar, Vatanasakdakul, & Chetty, 2021)

Table 2 Constructs, their measuring items, and source

5.3.1 Control Variables

The survey included multiple screening questions to optimize the data collection and increased the reliability of the results. The following sub-section presents an overview of the control variables that have been integrated into the questionnaire.

Location: The location of the respondents is fundamental to capture the characteristics of a country. It provides a more accurate understanding of the factors influencing respondents' responses.

Job title: The role and responsibilities of respondents should reflect their expertise and knowledge. Potential divergence in viewpoint based on job positions are captured. Respondent's point of view may differ from those in higher or lower positions in the firm.

Work experience: Work experience accumulated over time by the respondents may influence their responses. They might have been exposed to more diverse projects and working environments. They can have more conviction in their responses, providing unique and meaningful insights into the alternative investment industry.

Technology knowledge: Respondents' technological knowledge can influence their willingness to adopt AI. Those with higher technological knowledge can have a better understanding of AI benefits.

Organization type: In this survey, when asking about the type of organization respondents work for, we mean banks, private equity funds, hedge funds, private debt funds… These different entities have unique characteristics, processes, and practices.

Size of the organization: The numbers of employees in an organization within a firm may reflect its organizational structure and complexity. Furthermore, firms with large numbers of employees may have extensive resources impacting the firm's ability to undertake projects.

Level of education: We consider the level of education of the respondents to capture the diverse educational backgrounds in our sample.

6 FINDINGS AND DATA ANALYSIS

We have gathered 103 responses through the survey. After carefully reviewing the data collected, we observed a 100% completion rate among all participants. This was possible because the survey was distributed through the author's network composed of individuals working in the alternative investment industry. Moreover, each respondent received a personalized notification inviting them to participate in a survey destined at helping someone they knew, or at least seen once. Therefore, there were no participants dropping out or skipping questions. Otherwise, we would have been constrained to exclude certain responses for data analysis accuracy. The data, which was collected anonymously using Qualtrics, is securely stored at the University of Tilburg, guaranteeing compliance with GDPR regulations. Data will remain available for a period of 10 years.

6.1 Demographic data

Table 3 offers a demographic profile of the survey participants, giving valuable insights into the composition of the sample studied. This information allows us to understand and contextualize how certain factors influence the survey results.

Control variable	***Item***	***Count (%)***
Location	United Kingdom	17.17% (17)
	United States	24.24% (24)
	France	10.10% (10)
	Denmark	5.05% (5)
	Portugal	24.24% (24)
	Germany	2.02% (2)
	Luxembourg	17.17% (17)
Job title	Analyst	24.27% (25)
	Asset Management Manager	19.42% (20)
	Chief Financial Officer	1.94% (2)
	Chief Technology Officer	0.00% (0)
	Chief Executive Officer	1.94% (2)
	Software Engineer	10.68% (11)
	IT Manager	6.80% (7)
	Accountant	14.56% (15)
	Compliance Officer	1.94% (2)
	Fund Administrator	10.68% (11)
	Marketing Specialist	1.94 (2)
	Human Resources Manager	3.885 (4)
	Legal Counsel	1.94% (2)
Education	No formal education	0.00% (0)

	College degree	0.00% (0)
	Bachelor's degree	41.75% (43)
	Master's degree	58.25% (60)
	Doctorate or PhD	0.00% (0)
Work experience	1-3 years	5.83% (6)
	3-5 years	20.39% (21)
	5-10 years	38.83% (40)
	10-15 years	21.36% (22)
	15-20 years	9.71% (10)
	More than 20 years	3.88% (4)
Size of the organization	0-10 employees	0.00% (0)
	10-30 employees	12.62% (13
	30-80 employees	48.51% (51)
	80-200 employees	3.88% (4)
	More than 200 employees	33.98% (35)
Type of the organization	Hedge fund	24.27% (25)
	Private equity	33.01% (34)
	Private debt	15.53% (16)
	Bank	10.68% (11)
	Venture capital	4.85% (5)
	Alternative lender	11.65% (12)

Table 3 Demographic analysis of study participants

6.2 Construct validity

To guarantee consistency among the items in the scale and questionnaire, Cronbach's alpha was applied to each construct. It is generally used to determine if the items within a construct are continuously measuring the same underlying construct. Considering that the constructs in this research are often measured using only three items, or sometimes even two items, the overall primarily Cronbach's alpha indicated a value of 0.622. Normally, the alpha coefficient is considered relatively low if below 0.700 (A. Gliem & R. Gliem, 2003). Referring to Appendix 4, we can see that the measuring item CX_3 from the Complexity construct shows lower reliability. Therefore, Cronbach's alpha analysis if item deleted was conducted in order to assess the viability of the construct in this research. The output indicated an increase in the alpha coefficient (Appendix 4). However, the reliability of the construct remained unsatisfactory. Therefore, we made the decision to remove it from the analysis. This construct was initially borrowed from a study on blockchain adoption (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). Two measuring items were taken from the construct used in the paper, along introducing a new item. In the paper on blockchain adoption, the construct was used properly to validate an hypothesis. Although, in this research, the items and consequently the construct itself, were not usable. The implementation of the measuring items in the questionnaire did not work as expected. Similar finding was observed for the measuring item SU_3 from the construct Standard Uncertainty. The construct was borrowed from the same paper on blockchain adoption. The same measuring items were implemented in the survey, though, adapted to the context of AI adoption instead of blockchain adoption. Surprisingly, the construct did not work as expected either. This can be related to several factors such as differences in respondents or in the inherent divergences between blockchain and AI in terms of standard uncertainty. Despite this, and after removing SU_3 from the analysis, the construct's reliability reached an acceptable level. allowing us to keep it to proceed further with the analysis (Appendix 5). Accordingly, when combining all the constructs together, we get a new alpha coefficient of 0.719 (Appendix 3), affirming the survey's level of internal consistency and allowing us to proceed further with the analysis (A. Gliem & R. Gliem, 2003).

Construct	***Item***	***Mean***	***Standard deviation***	***Cronbach's Alpha***
Perceived Benefits	PB_1	4.96	0.868	0.637
	PB_2	4.98	0.845	
	PB_3	5.39	0.793	
Compatibility	CPY_1	4.75	0.747	0.570
	CPY_2	3.33	0.700	
	CPY_3	4.54	1.358	
Top Management Support	TMS_1	5.79	1.003	0.633
	TNS_2	5.87	0.944	
	TM_3	5.23	0.935	
	TM_4	5.16	0.854	
Technology Competence	TC_1	4.81	0.665	0.676
	TC_2	5.34	0.771	
	TC_3	5.23	0.819	
Financial Readiness	FR_1	5.66	0.823	0.741
	FR_2	5.90	0.851	
Competitive Pressure	CP_1	4.96	0.807	0.796
	CP_2	4.92	1.065	
	CP_3	4.59	1.443	
Regulatory Support	RS_1	4.40	1.449	0.925
	RS_2	4.56	1.349	
	RS_3	4.13	1.816	
Standards Uncertainty	SU_1	5.01	0.735	0.682
	SU_2	4.82	0.983	
	SU_3	5.35	0.861	

Willingness to adopt AI	WTAAI_1	4.54	1.163	0.833
	WTAAI_2	5.05	0.973	
	WTAAI_3	5.27	0.956	

Table 4 Construct descriptive statistics

6.3 Statistics

To conduct a thorough statistical analysis, each measuring item was stored as separate variables. For the construct Standard Uncertainty, a reversal process was applied. To accommodate the Likert Scale with a maximum value of 7, a simple transformation was conducted. We subtracted the response number of each item from 8. After that, we used the Sum method to aggregate the measuring items within each construct. Hence, we had to create new variables representing each construct for further analysis. Moreover, to improve the analysis accuracy, we created additional variables representing the mean scores of each construct. This was realized by summing the items within a construct and dividing the result by the number of items to obtain the mean value. Accordingly, we were able to generate correlation matrices for both the constructs and their respective means (Appendices 6 and 7). This allowed us to assess the accuracy of the results and identify any inconsistencies within the matrices.

6.3.1 Correlation analysis

Correlation analysis is a valuable and meaningful method when researchers seek to evaluate the presence of relationships between variables (O'Brien & Scott, 2012). Hence, we will provide a brief description of selected relationships between our constructs. However, for a detailed analysis, please refer to Appendix 6 and 7. Both correlation matrices show the same outcomes. Although one matrix is based on the constructs, whereas the other used their corresponding means. There is a positive relationship between perceived benefits (PB) and willingness to adopt AI (WTAAI) with $r = 0.670$ and p-value = <0.001. For individuals working in the alternative investment industry, if perceived benefits from the use of AI are identified by the workers, their organization is more likely to adopt AI technologies. This correlation insinuates that as the perceived benefits from technology increase, the willingness to adopt such technology increases as well.

Between compatibility (CPY) and willingness to adopt AI (WTAAI), r = 0.699 and p-value = <0.001. When organizations perceive a higher level of compatibility between AI technologies and their existing IT infrastructure, they may lean towards AI technologies adoption. On the other hand, r = -0.152 and p-value = 0.216 for the relationship between financial readiness (FR) and willingness to adopt AI (WTAAI) as shown in the correlation matrix (Appendix 6). The statistical reliability of this variable is not sufficient to draw definitive conclusions on this relationship though. Further research will be needed to assess the relationship between the financial readiness of an organization and especially alternative investment firms, and their willingness to adopt AI. However, in line with the hypothesis stating that financial readiness has a positive influence on the willingness to adopt AI, we cannot support it in this research. The construct was adapted from a previous study on AI adoption in the insurance industry (Gupta, Ghardallou, Pandey, & Sahu, 2022). Due to limited access to the original measuring items used by the authors, we made our own measuring items to assess this construct. The hypothesis proposed in the insurance industry paper, stating that financial readiness has a positive influence on the intention to adopt AI was supported though. But in this research, considering the unsatisfactory quality and reliability of our measuring items, we are unable to support the same hypothesis. Moreover, as shown in Appendix 6, R between Standard Uncertainty, and willingness to adopt AI is -0.539 and p-value = <0.001. There is a strong negative relationship between the two variables which is what we expected from the reversal process made in SPSS. This means that as standard uncertainty about the future of AI technologies and their trajectory increase, the less likely alternative investment firms will be willing to adopt AI. More standards and adapted regulations could positively influence organizations' intentions regarding AI adoption and implementation.

In addition, we performed two separate correlation analyses, based on the country of the respondents. Interestingly, when analyzing the responses from participants in the United States, we observed two constructs that noticeably impact their firm’s willingness to adopt AI (Appendix 9). Compatibility has r = 0.551 p-value = 0.005. This suggests that individuals in the US have higher willingness to adopt AI when they perceive compatibility between AI technologies and their existing systems or IT infrastructure. Moreover, regulatory support has r = 0.670 and a p-value = <0.001. This indicates that participants in the US are more likely to adopt AI when there are supportive regulations in place. For respondents working in alternative investment firms located in the UK, there are two interesting correlations to consider in relation to their willingness to adopt AI. R between perceived benefits and willingness to adopt AI is 0.591. As the perceived benefits of AI adoption increase, alternative investment firms are more likely to adopt the technology. R between Standards uncertainty and willingness to adopt AI is -0.573. If alternative investment firms perceive a lack of standards and therefore remain uncertain about the trajectory and future of AI within their industry, they are less likely to give it a try. These findings suggest that promoting the benefits of AI adoption in terms of productivity improvement for instance, and addressing concerns related to standards uncertainty are both important factors to consider when supporting the adoption of AI in the UK. To see the full analysis on both correlation matrices including only US respondents or UK respondents, please refer to Appendices 8 and 9.

6.3.2 Regression analysis

Regression analysis is an effective method for assessing the predictive strength of independent variables, the constructs proposed, on the dependent variable, the willingness to adopt AI (O'Brien & Scott, 2012). After examining the Model summary and ANOVA table (Appendix 11), we observed that the p-value is < 0.001, suggesting that the regression model has statistical significance. Furthermore, The R2 value achieved is 0.706, showing that 70.6% of the variance in the willingness to adopt AI (WTAAI) can be assigned to perceived benefits (PB), compatibility (CPY), top management support (TMS), technology competence (TC), financial readiness (FR), regulation support (RS), competition pressure (CI), and standards uncertainty (SU). These findings demonstrate a strong relationship between the independent variables and the outcome variable. If you refer to Appendix 10, you will see the Coefficient table from the regression analysis. A t-value greater than zero suggests that the estimated coefficient for the construct is positively impacting the dependent variable. Following this logic, a larger t-value provides stronger evidence of a significant positive relationship between variables. perceived benefits (PB), compatibility (CPY), regulatory support (RS), competitive pressure (CP), top management support (TMS), and technology competence (TC) have a positive impact on the willingness to adopt AI (WTAAI). However, Financial readiness (FR) appears to lack a meaningful relationship with the willingness to adopt AI (WTAAI). The correlation table presented in Appendix 12 provides us with an interesting visualization of our findings, making it easier to interpret the outcomes. With the exclusion of the Complexity construct, as explained earlier in the paper, our sample is about 102 respondents. We observed that all independent constructs have R coefficient ranging from 0.704 to 0.202, with p-values ranging from 0.021 to <0.001. The Standard Uncertainty construct has an R coefficient of -0.589, as expected due to the earlier explained reversal process done in SPSS. This negative correlation suggests a negative relationship between standards uncertainty and willingness to adopt AI. However, the Financial Readiness construct shows r = -0.151 with a p-value of 0.065. We can say that the relationship is not statistically significant as the conventional significance level is established at $p < 0.05$. Further investigation would be needed to assess the relationship between financial readiness and willingness to adopt AI. The obtained results, Hypothesis 1 (H1), Hypothesis 2 (H2), Hypothesis 4 (H4), Hypothesis 5 (H5), Hypothesis 7 (H7), Hypothesis 8 (H8), Hypothesis 9 (H9) were verified and are supported. Nevertheless, we were not able to confirm Hypothesis 3 (H3) and Hypothesis 6 (H6). There will not be supported in this research and will require further investigation, and additional data may be needed to derive meaningful conclusions on both constructs.

Factor	***Independent construct***	***Relationship***	***Dependent construct***	***Hypothesis***
	PB	+		Supported
Technology	CPY	+		Supported
	CX	-		Not supported
	TMS	+		Supported
Organization	TC	+	Willingness to adopt AI	Supported
	FR	+		Not supported
	CP	+		Supported
Environment	RS	+		Supported
	SU	-		Supported

Table 5 on hypothesis status

7 DISCUSSION

The aim of this research is to establish the key success factors for AI technologies adoption within alternative investment firms. Using the Technological-Organizational-Environmental (TOE) framework, we evaluated the different factors on technological, organizational, and environmental that would contribute to the willingness to adopt AI technologies. In addition, the constructs competitive pressure (CP) and standard uncertainty (SU) have been incorporated into the theoretical research model for the purpose of this study. The findings support most of the hypotheses formulated in this research. However, further investigation is required for two hypotheses relating to financial readiness and complexity, and their potential impact on the willingness to adopt AI. These two constructs may necessitate the use of alternative measuring methods or statistical techniques such as PLS-SEM, which is widely used in quantitative data analysis as well.

7.1 Technology

The technological constructs studied in this research are perceived benefits, compatibility as well as complexity. The analysis confirmed that both constructs perceived benefits and compatibility have a positive impact on the willingness to adopt AI technologies. The individuals working in alternative investment firms that took part in this study see both factors as meaningful for successful AI adoption and implementation. Nonetheless, due to the lack of reliability of the construct Complexity, in this research, we have been forced to reject the hypothesis stating that complexity has a negative impact on the willingness to adopt AI technologies. It is possible that the hypothesis is valid and can be verified. Yet, the measuring items used in this study were not sufficiently reliable to capture necessary information to conclude anything on the hypothesis.

7.2 Organization

The constructs related to the Organization factor are top management support, technological competence, and financial readiness. When you have the support from your top management, it facilitates the implementation of new technologies such as AI. It is imperative for top management to provide the necessary resources and especially to allocate resources effectively for successful AI implementation. If they recognize AI as strategically important and they are engaged in IT-related decisions, the implementation of AI technologies within an alternative investment firm can be smoother. If the firm is not totally unfamiliar with AI technologies, along with employees who are trained in AI, it can accelerate the AI adoption process as well. Despite that, the research did not provide sufficient information to support the hypothesis stating that financial readiness of an organization positively impacts the willingness to adopt AI technologies. Further research using alternative methodologies to validate the hypothesis will be needed.

7.3 Environment

The constructs that belong to the Environment factor are competitive pressure, regulatory standard, and standard uncertainty. To seek competitive advantage, by enhancing their processes, services, underwriting portfolios, and investor reporting, alternative investment firms could use AI technologies. They could improve their predictive capabilities and strengthen their asset management practices, differentiating themselves from competitors. Regulations, laws, and policies must be adapted. If there is a legal framework around AI technologies, it could significantly influence firm’s willingness to adopt it. Alternative investment firms may remain hesitant to adopt AI technologies if they perceive that the technology has not yet reached its maturity though. They could prioritize and invest in established technology rather than taking risks on emerging ones, especially if they cannot foresee AI becoming an industry standard in the future.

8 CONCLUSION

This research was conducted to identify the key success factors for implementing AI-driven asset management in alternative investment firms. This study directly gathered insights from individuals working in alternative investment firms to understand the decision-making process behind their firm's adoption choices. A literature review was performed reviewing AI in Finance, with a specific focus on hedge funds representing alternative investment firms. Besides exploring the application of AI in alternative asset management and examining the various challenges associated with its implementation. This literature review brought knowledge and background for the research. A survey was designed and distributed to individuals working in alternative investment firms mostly in the UK and the US. It gathered 103 responses through measuring items and constructs derived from existing literature and industry knowledge of the authors. The perceived benefits of AI have a significant role in shaping firms' decisions to adopt it. Compatibility represents AI alignments with a firm's investment strategies and operational requirements. When this alignment is strong, firms are more likely to integrate AI into their operations. Alternative investment firms must access skilled talent capable of using AI as well as the technology infrastructure to support AI systems. The willingness and openness of top management is essential as well. Furthermore, alternative investment firms consider the regulatory framework and industry standards. Supportive regulatory environments and ecosystems, besides industry standards vison, influence firms in their willingness to adopt AI. The research presented an overview of the key success factors that contribute to the success of alternative investment firms in adopting AI or increasing their willingness to adopt the technology.

9 LIMITATIONS

In this research, nine constructs were used, derived from existing literature found by the author. These constructs may not represent all factors relevant to be studied to evaluate the willingness to adopt AI. The scope of the paper is limited to the literature included within the study. In addition, the survey was distributed only to individuals within the author's network, introducing a limitation inherent to this specific network. The survey sample was obtained through non-probability sampling, not all members of the population had an equal opportunity to participate. Besides, the study included a limited representation of different alternative investment firms. Also, the data was collected through a quantitative method, though, incorporating qualitative data collection could offer valuable insights into individual's reflections on AI adoption within their firms.

10 FURTHER RESEARCH

As mentioned in the paper, the survey's measuring items were unable to capture the complexity adjacent to AI adoption. This construct was excluded from the analysis. This omission represents an opportunity for future research to explore, assess, and evaluate the impact of technology complexity on the willingness to adopt AI. Also, we were unable to support the hypothesis on the financial readiness of organizations. The impact of financial readiness on the willingness to adopt AI must be studied further, with new and more adequate measuring items. Interestingly, respondents working in investment banks expressed a higher level of involvement in AI deployment from their organizations compared to those working in hedge funds. Consequently, research can be conducted to compare the level of AI involvement between investment banks and hedge funds. It would be necessary to collect data from diverse investment banks and hedge funds with different investment strategies to achieve generalizable results.

REFERENCES

Ernst & Young LLP. (1994). *Ernst and Young Guide to Performance Measurement for Financial Institutions: Methods for Managing Business Results.* Mc Graw Hill.

Johnk, J., Weibert, M., & Wyrtki, K. (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, 5-20.

A. Gliem, J., & R. Gliem, R. (2003). Calculating, Interpreting, and Reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *Association for Information Systems*.

Aromataris, E., & Pearson, A. (2014). The Systematic Review: An Overview. *AJN, American Journal of Nursing*, 53-58.

Attuquayefio, S., & Addos, H. (2014). REVIEW OF STUDIES WITH UTAUT AS CONCEPTUAL FRAMEWORK. *European Scientific Journal*.

Bajulaiye, O., Fenwick, M., Skultetyova, I., & Vermeulen, E. P. (2020). Digital Transformation in the Hedge Fund and Private Equity Industry. *ecgi*.

BarclayHedge. (2018). *Majority of Hedge Fund Pros Use AI/Machine Learning in Investment Strategies.*

Bertram, D. (2007). Likert Scales.

Bettoni, A., Matteri, D., & Montini, E. (2021). An AI adoption model for SMEs: a conceptual framework. *ScienceDirect*.

Bhalerao, K., Kumar, A., & Pujari, P. (2022). A study of barriers and benefits of artificial intelligence adoption in small and medium enterprsie. *Academy of Marketing Studies Journal*.

Bharathan, S. K., & Rao, G. (2017). ALTERNATIVE INVESTMENT FUNDS IN INDIA: UNLOCKING SOPHISTICATED INVESTMENT. *NLS Business Law Review*.

Bierly, P. E., & Coombs, J. E. (2006). Measuring technological capability and performance. *R&D Management*.

BlackRock. (2019). *AI: Alternative Investment meet artificial intelligence.*

BlackRock. (2023). Retrieved from https://www.blackrock.com/us/individual/investment-ideas/alternative-investments

Blanca, G., & Ramona, T. (2016). CHANGE, RESISTANCE TO CHANGE AND ORGANIZATIONAL CYNICISM . *Studies in Business and Economics*, 47-54.

Boukherouaa, E., AlAjmi, K., Deodoro, J., Farias, A., & Ravikumar, R. (2021). *Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance.* International Monetary Fund.

Cao, L. (2020). AI in Finance : A Review. *University of Technology Sydney; University of Technology Sydney (UTS) - Data Science Institute*, 7.

Cao, L. (2022). AI in Finance: Challenges, Techniques and Opportunities.

Chtourou, M. S., & Souiden, N. (2010). Rethinking the TAM model: time to consider fun. *Journal of Consumer Marketing*.

DavidsonKempner. (2017). *Davidson Kempner Long-Term Distressed Opportunities Fund IV LP.*

Deloitte. (2023). *Finance Survey Innovation.*

Dinh, T. N., & Thai, M. T. (2018). AI and Blockchain: A Disruptive Integration. *Future of AI*, 48-53.

Elliot, D., Kroeber, A., & Qiao, Y. (2015). Shadow banking in China: A primer. *Economic Studies at Brookings*.

Elton, E. J., & Gruber, M. J. (2013). Mutual Funds. *Handbook of the Economics of Finance*, 1011-1061.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, 1-4.

EY. (2019). *When focusing on the future, where do you look? 2019 Global Alternative Fund Survey.*

Ferreira, F. G., Gandomi, A. H., & Cardoso, R. T. (2021). Artificial Intelligence Applied to Stock Market Trading: A Review. *IEEE*, 11.

Ford, J. D., & Ford, L. W. (2010). Stop Blaming Resistance to Change and Start Using It. *ScienceDirect*, 24-36.

Gangwar, H., Date, H., & Raoot, A. (2014). Review on IT adoption: insights from recent technologies. *Journal of Enterprise Information Management*.

Gonçalves, J. M. (2012). Overcoming resistance to changes in information technology. *Procedia Technoogy*, 295.

Gupta, S., Ghardallou, W., Pandey, D. K., & Sahu, G. P. (2022). Artificial intelligence adoption in the insurance industry: Evidence using the technology–organization–environment framework. *ELSEVIER*.

Hill, R. (1998). WHAT SAMPLE SIZE is "ENOUGH" in INTERNET SURVEY RESEARCH? *Interpersonal Computing and Technology: An Electronic Journal for the 21st Century*.

Hsieh, D. A., & Fung, W. (1999). A primer on hedge funds. *Journal of Empirical Finance*, 309-331.

Hussain, A. A., & Al-Turjman, F. (2021). Artificial intelligence and blockchain: A review. In A. A. Hussain, & F. Al-Turjman, *Transactions on Emerging Telecomminications Technologies.*

Introduction to Alternative Investments. (n.d.). Retrieved from CFA Institute: https://www.cfainstitute.org/en/membership/professional-development/refresherreadings/introduction-alternative-investments#:~:text=Alternative%20investments%20are%20supplemental%20strategies,%2C%20real%20estate%2C%20and%20infrastructure.

Jiang, W., Li, K., & Wang, W. (2012). Hedge Funds and Chapter 11. *The Journal of Finance*.

Joshi, A., Kale, S., & Pal, C. (2015). Likert Scale: Explored and Explained.

Kaal, W. A. (2021). *The Oxford Handbook of Hedge Funds.*

Kabak, S., & Benjelloun, A. (2023). Artificial Intelligence Technologies Applied to Asset Management: Methods, Opportunities and Risks. In *Third Congress on Intelligent Systems* (pp. 639-650). Congress on Intelligent Systems.

Klopping, I. M., & McKinney, E. (2004). Extending the Technology Acceptance Model and the Task-Technology Fit Model to Consumer E-Commerce.

Kruse, L., Wunderlich , N., & Beck, R. (2019). Artificial Intelligence for the Financial Services Industry: What Challenges Organizations to Succeed .

Kruse, L., Wunderlich, N., & Beck, R. (2019). Artificial Intelligence for the Financial Services Industry: What challenges Organizations to Suceed. *HICSS*.

Kumar, R., Grover, N., & Singh, R. (2023). Imperative Role of Artificial Intelligence and Data in Finance and Banking Sector.

Lules, I., Omwansa , T. K., & Waema, T. M. (2012). Application of Technology Acceptance Model (TAM) in M-Banking Adoption in Kenya. *International journal of computing & ICT*.

Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors Affecting the Organizational Adoption of Blockchain Technology: Extending the Technology–Organization–Environment (TOE) Framework in the Australian Context. *Sustainability*.

Marshall, M. N. (1996). Sampling for qualitative research. *Family Practice*, 522-526.

Mattioli, J., Perico, P., & Robic, P.-O. (2020). Artificial Intelligence based Asset Management. *IEEE*.

McKinsey. (2020). AI-bank of the future: Can banks meet the AI challenge?

Nguyen, T. H., Le, X. C., & Vu, T. H. (2022). An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation: Empirical Evidence from Vietnam. *Journal of Open Innovation: Technology, Market and Complexity*.

O'Brien, D., & Scott, P. S. (2012). Correlation and Regression . *A Guide for Dissertation Students,*.

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level.

Pannucci, C. J., & Wilkins, E. G. (2010). Identifying and Avoiding Bias in Research. *NIH Public Access*, 619-625.

Quick, J., & Hall, S. (2015). Part three: The quantitative approach. *Journal of perioperative Practice*.

Ranjan, S. (2020). ARTIFICIAL INTELLIGENCE IN FINANCIAL ACUMEN: CHALLENGESAND OPPORTUNITIES. *Cosmos*, 4.

Roubini, N., & Mihm, S. (2011). *Crisis Economics: A Crash Course in the Future of Finance.* Allen Lane.

Safizadeh, H., Field, J. M., & Ritzman, L. P. (2003). An empirical analysis of financial services processes with a front-office or back-office orientation. *Journal of Operations Management*, 557-576.

Sandner, P., Gross, J., & Richter, R. (2020). Convergence of Blockchain, IoT, and AI. *frontiers in Blockchain*.

Satariano, A., & Kumar, N. (2017). The Massive Hedge Fund Betting on AI.

Savov, A. M. (2017). The Macroeconomics of Shadow Banking. *The journal of Finance*.

Selm, M. V., & Jankowski, N. W. (2006). Conducting Online Surveys. *Quality and Quantity*, 435-456.

Sharma, G. (2017). Pros and cons of different sampling techniques. *International Journal of Applied Research*, 749-752.

Shin, T. A. (2009). *The Shadow Banking System: Implications for Financial Regulation.* New York: Federal Reserve Bank of New York.

Smith, J., & Noble, H. (2014). Bias in research. *Research made simple*.

Stefanini, F. (2010). *Investment Strategies of Hedge Funds.* Wiley Finance.

Stratton, S. J. (2021). Population Research: Convenience Sampling Strategies. *Cambridge University Press*, 373-374.

Stulz, R. M. (2007). Hedge Funds: Past, Present, and Future. *Journal of Economic Perspectives*, 175-194.

Tam, C., & Oliveira, T. (2016). Performance impact of mobile banking: using the task-technology fit (TTF) approach. *New University of Lisbon, Lisbon, Portugal*.

Thomas Della Casa, M. R. (2008). Hedge fund investing in distressed securities. *Man Investments*.

Ulrich, P., Frank, V., & Kratt, M. (2021). Adoption of Articial Intelligence in German SMEs - Result from an Empirical Study.

Wagstaf, K. L. (2012). Machine Learning that Matters. *Jet Propulsion Laboratory*.

Wanner, J., Herm, L. V., Heinrich, K., Janiesh, C., & Zschech, P. (2020). White, Grey, Black: Effects of XAI Augmentation on the Confidence in AI-based Decision Support Systems. *Effects of XAI Augmentation on AI-based DSS Confidence*.

Wikipedia. (2022). Retrieved from Wikipedia.

Yen, D., Wu, C.-S., Cheng, F.-F., & Yu-Wen Huang. (2010). Determinants of users' intention to adopt wireless technology: An empirical study by integrating TTF with TAM. *Computers in Human Behavior*, 906-915.

Zhang, B. Z., Ashta, A., & Barton, E. M. (2021). Do FinTech and financial incumbents have differentexperiences and perspectives on the adoption of artificialintelligence? *Wiley*.

Zheng, X.-l., Zhu, M.-y., Li, Q.-b., Chen, C.-c., & Tan, Y.-c. (2019). FinBrain: when finance meets AI 2.0. *Frontiers of Information Technology & Electronic Engineering*, 914–924.

APPENDIX 1: SURVEY CONTROL VARIABLES

Set of questions for the control variables

Location

1. Which country do you belong to? Please select from the list of countries given below.

Job title

2. Please indicate which of the following job titles best describes your role?

Level of education

3. What is your level of education?

Work experience

4. How many years of knowledge/experience of alternative investment do you have?

Technology knowledge

5. How would you rate your knowledge of AI technology?
6. What is/was the status of involvement of your organization with AI technology?
7.

Size of the organization

8. What is/was the size of your organization in terms of the number of employees?

Organization type

9. Which of the following describes what your organization is doing?

APPENDIX 2 : SURVEY QUESTIONNAIRE

Survey Questionnaire – 7-Point Likert Scale

Constructs	***Questions***
Perceived Benefits	In my opinion, alternative investment firms adopt AI when they perceive that: **PB1**: AI technologies save time while accomplishing tasks **PB2:** AI technologies increase the firm's overall productivity **PB3:** AI technologies can provide the firm competitive advantage
Compatibility	In my opinion, alternative investment firms adopt AI when they perceive that: **CPY1:** AI technologies is compatible with your firm IT's infrastructure **CPY2:** AI technologies fits well with technological skills **CPY3:** AI technologies fits well with business
Complexity	In my opinion, alternative investment firms do not adopt AI when they perceive that: **CX1:** AI technologies require extra technical skills to use **CX2:** AI technologies are conceptually difficult to understand from a technical perspective **CX3:** The firm does not understand how AI technologies will benefit the firm in its growth
Top Management Support	In my opinion, alternative investment firms adopt AI when: **TMS1:** Their top management Provides the necessary resources for AI technologies adoption **TMS2:** Their top management **c**onsiders AI technologies as strategically important **TMS3:** Their top management actively involved in IT-related decisions **TMS4:** Their top management actively seek new ideas

Technology Competence	In my opinion, alternative investment firms adopt AI when they perceive that: **TC1:** The firm has an excellent AI-based infrastructure **TC2:** Employees of the firm are well trained in AI applications **TC3:** The firm has good knowledge about AI technologies
Financial Readiness	In my opinion, alternative investment firms adopt AI when they perceive that: **FR1:** The firm would have the financial resources **FR2:** The financial budgets of the firm is enough
Competitive Pressure	In my opinion, alternative investment firms adopt AI when they perceive that: **CP1:** They could lose a competitive advantage if the firm does not adopt it **CP2:** Competitors benefit from adopting AI technologies **CP3:** There is a constant pressure when competitors have adopted AI technologies
Regulatory Support	In my opinion, alternative investment firms adopt AI when they perceive that: **RS1:** Policies support the adoption of AI technologies **RS2:** There is legal support for the use of AI in alternative investment **RS3:** The laws and regulations that exist nowadays are sufficient to protect the use of AI technologies in alternative investment
Standards Uncertainty	In my opinion, alternative investment firms do not adopt AI when they perceive that: **SU1:** AI technologies have not reached its maturity **SU2:** AI technologies still require changes to become more efficient compared with existing technologies **SU3:** They cannot predict that AI technologies would become an industry standard in the near future

Willingness to adopt AI	In my opinion: **WTAAI1:** Alternative investment firms would adopt AI technologies whenever they will have access to it in the future **WTAAI2:** Alternative investment firms would adopt AI technologies in the future **WTAAI3:** Alternative investment firms would adopt AI technologies frequently in the future

Open question

Are there any specific aspects or considerations that you feel are essential for AI implementation success in your firm that were not covered in this survey?

APPENDIX 3 – RELIABILITY STATISTICS

Reliability Statistics

Cronbach's Alpha	N of Items
,719	9

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived_Benefits	112,2059	124,244	,713	,651
Compatibility	112,8922	120,671	,690	,647
Top_Management_Support	105,4902	142,431	,147	,738
Technology_Competence	112,1275	130,350	,617	,669
Financial_Readiness	115,9608	162,870	-,182	,758
Competitive_Pressure	113,0686	104,065	,776	,608
Regulatory_Support	114,5392	89,300	,609	,654
Willingness	112,6667	105,314	,818	,603
New_SU	121,3627	184,907	-,709	,804

APPENDIX 4 – COMPLEXITY CONSTRUCT

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CX_1	10,01	2,450	,160	,382
CX_2	10,23	2,098	,374	,050
CX_3	10,53	1,511	,177	,449

APPENDIX 5 – STANDARD UNCERTAINTY CONSTRUCT

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SU_1	10,17	1,764	,438	,106
SU_2	10,35	1,340	,385	,118
SU_3	9,81	2,252	,067	,686

APPENDIX 6 – MEAN CORREALTION MATRIX

Correlations

		mean_PB	mean_CPY	mean_TMS	mean_FR	mean_CP	mean_RS	mean_WTAAI	mean_TC	mean_SU
mean_PB	Pearson Correlation	1	,521**	,275**	,062	,639**	,532**	,670**	,436**	-,477**
	Sig. (2-tailed)		<,001	,005	,531	<,001	<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
mean_CPY	Pearson Correlation	,521**	1	,009	-,203*	,711**	,667**	,699**	,503**	-,559**
	Sig. (2-tailed)	<,001		,930	,040	<,001	<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
mean_TMS	Pearson Correlation	,275**	,009	1	,292**	,023	-,050	,203*	,293**	-,069
	Sig. (2-tailed)	,005	,930		,003	,820	,614	,040	,003	,489
	N	103	103	103	103	103	103	103	102	103
mean_FR	Pearson Correlation	,062	-,203*	,292**	1	-,297**	-,390**	-,152	,014	,100
	Sig. (2-tailed)	,531	,040	,003		,002	<,001	,126	,889	,315
	N	103	103	103	103	103	103	103	102	103
mean_CP	Pearson Correlation	,639**	,711**	,023	-,297**	1	,827**	,764**	,530**	-,693**
	Sig. (2-tailed)	<,001	<,001	,820	,002		<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
mean_RS	Pearson Correlation	,532**	,667**	-,050	-,390**	,827**	1	,704**	,467**	-,721**
	Sig. (2-tailed)	<,001	<,001	,614	<,001	<,001		<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
mean_WTAAI	Pearson Correlation	,670**	,699**	,203*	-,152	,764**	,704**	1	,532**	-,589**
	Sig. (2-tailed)	<,001	<,001	,040	,126	<,001	<,001		<,001	<,001
	N	103	103	103	103	103	103	103	102	103
mean_TC	Pearson Correlation	,436**	,503**	,293**	,014	,530**	,467**	,532**	1	-,429**
	Sig. (2-tailed)	<,001	<,001	,003	,889	<,001	<,001	<,001		<,001
	N	102	102	102	102	102	102	102	102	102
mean_SU	Pearson Correlation	-,477**	-,559**	-,069	,100	-,693**	-,721**	-,589**	-,429**	1
	Sig. (2-tailed)	<,001	<,001	,489	,315	<,001	<,001	<,001	<,001	
	N	103	103	103	103	103	103	103	102	103

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX 7 – CONSTRUCT CORREALTION MATRIX

Correlations

		Perceived_Benefits	Compatibility	Top_Management_Support	Financial_Readiness	Competitive_Pressure	Regulatory_Support	Willingness	Technology_Competence	New_SU
Perceived_Benefits	Pearson Correlation	1	,521**	,275**	,062	,639**	,532**	,670**	,436**	-,477**
	Sig. (2-tailed)		<,001	,005	,531	<,001	<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
Compatibility	Pearson Correlation	,521**	1	,009	-,203*	,711**	,667**	,699**	,503**	-,559**
	Sig. (2-tailed)	<,001		,930	,040	<,001	<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
Top_Management_Support	Pearson Correlation	,275**	,009	1	,292**	,023	-,050	,203*	,293**	-,069
	Sig. (2-tailed)	,005	,930		,003	,820	,614	,040	,003	,489
	N	103	103	103	103	103	103	103	102	103
Financial_Readiness	Pearson Correlation	,062	-,203*	,292**	1	-,297**	-,390**	-,152	,014	,100
	Sig. (2-tailed)	,531	,040	,003		,002	<,001	,126	,889	,315
	N	103	103	103	103	103	103	103	102	103
Competitive_Pressure	Pearson Correlation	,639**	,711**	,023	-,297**	1	,827**	,764**	,530**	-,693**
	Sig. (2-tailed)	<,001	<,001	,820	,002		<,001	<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
Regulatory_Support	Pearson Correlation	,532**	,667**	-,050	-,390**	,827**	1	,704**	,467**	-,721**
	Sig. (2-tailed)	<,001	<,001	,614	<,001	<,001		<,001	<,001	<,001
	N	103	103	103	103	103	103	103	102	103
Willingness	Pearson Correlation	,670**	,699**	,203*	-,152	,764**	,704**	1	,532**	-,589**
	Sig. (2-tailed)	<,001	<,001	,040	,126	<,001	<,001		<,001	<,001
	N	103	103	103	103	103	103	103	102	103
Technology_Competence	Pearson Correlation	,436**	,503**	,293**	,014	,530**	,467**	,532**	1	-,429**
	Sig. (2-tailed)	<,001	<,001	,003	,889	<,001	<,001	<,001		<,001
	N	102	102	102	102	102	102	102	102	102
New_SU	Pearson Correlation	-,477**	-,559**	-,069	,100	-,693**	-,721**	-,589**	-,429**	1
	Sig. (2-tailed)	<,001	<,001	,489	,315	<,001	<,001	<,001	<,001	
	N	103	103	103	103	103	103	103	102	103

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX 8 – CORRELATION MATRIX US

Correlations

		Perceived_Benefits	Compatibility	Top_Management_Support	Financial_Readiness	Competitive_Pressure	Regulatory_Support	Willingness	Technology_Competence	New_SU	Which country do you belong to? Please select from the list of countries given below.
Perceived_Benefits	Pearson Correlation	1	,343	-,702**	,000	,370	,641**	,367	,287	-,322	.[b]
	Sig. (2-tailed)		,101	<,001	1,000	,075	<,001	,078	,174	,125	.
	N	24	24	24	24	24	24	24	24	24	24
Compatibility	Pearson Correlation	,343	1	-,398	-,367	,335	,679**	,551**	,090	-,162	.[b]
	Sig. (2-tailed)	,101		,054	,077	,109	<,001	,005	,676	,448	.
	N	24	24	24	24	24	24	24	24	24	24
Top_Management_Support	Pearson Correlation	-,702**	-,398	1	,276	-,396	-,649**	-,122	,098	,162	.[b]
	Sig. (2-tailed)	<,001	,054		,191	,055	<,001	,570	,647	,448	.
	N	24	24	24	24	24	24	24	24	24	24
Financial_Readiness	Pearson Correlation	,000	-,367	,276	1	,042	-,254	-,049	,285	-,282	.[b]
	Sig. (2-tailed)	1,000	,077	,191		,845	,231	,818	,178	,182	.
	N	24	24	24	24	24	24	24	24	24	24
Competitive_Pressure	Pearson Correlation	,370	,335	-,396	,042	1	,486*	,409*	,179	-,377	.[b]
	Sig. (2-tailed)	,075	,109	,055	,845		,016	,047	,402	,069	.
	N	24	24	24	24	24	24	24	24	24	24
Regulatory_Support	Pearson Correlation	,641**	,679**	-,649**	-,254	,486*	1	,670**	-,062	-,224	.[b]
	Sig. (2-tailed)	<,001	<,001	<,001	,231	,016		<,001	,773	,292	.
	N	24	24	24	24	24	24	24	24	24	24
Willingness	Pearson Correlation	,367	,551**	-,122	-,049	,409*	,670**	1	,181	-,381	.[b]
	Sig. (2-tailed)	,078	,005	,570	,818	,047	<,001		,397	,066	.
	N	24	24	24	24	24	24	24	24	24	24
Technology_Competence	Pearson Correlation	,287	,090	,098	,285	,179	-,062	,181	1	-,068	.[b]
	Sig. (2-tailed)	,174	,676	,647	,178	,402	,773	,397		,753	.
	N	24	24	24	24	24	24	24	24	24	24
New_SU	Pearson Correlation	-,322	-,162	,162	-,282	-,377	-,224	-,381	-,068	1	.[b]
	Sig. (2-tailed)	,125	,448	,448	,182	,069	,292	,066	,753		.
	N	24	24	24	24	24	24	24	24	24	24
Which country do you belong to? Please select from the list of countries given below.	Pearson Correlation	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]
	Sig. (2-tailed)	.	.	.	.	.	.	.	.	.	
	N	24	24	24	24	24	24	24	24	24	24

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

b. Cannot be computed because at least one of the variables is constant.

APPENDIX 9 – CORRELATION MATRIX UK

Correlations

		Perceived_Benefits	Compatibility	Top_Management_Support	Financial_Readiness	Competitive_Pressure	Regulatory_Support	Willingness	Technology_Competence	New_SU	Which country do you belong to? Please select from the list of countries given below.
Perceived_Benefits	Pearson Correlation	1	,395	,179	,349	,356	,370	,591[*]	,392	-,535[*]	.[b]
	Sig. (2-tailed)		,117	,493	,170	,161	,143	,012	,120	,027	.
	N	17	17	17	17	17	17	17	17	17	17
Compatibility	Pearson Correlation	,395	1	-,428	-,095	,770[**]	,541[*]	,410	,316	-,630[**]	.[b]
	Sig. (2-tailed)	,117		,087	,717	<,001	,025	,102	,217	,007	.
	N	17	17	17	17	17	17	17	17	17	17
Top_Management_Support	Pearson Correlation	,179	-,428	1	,385	-,417	-,440	,054	,218	,040	.[b]
	Sig. (2-tailed)	,493	,087		,127	,096	,077	,838	,401	,879	.
	N	17	17	17	17	17	17	17	17	17	17
Financial_Readiness	Pearson Correlation	,349	-,095	,385	1	-,074	-,193	,152	-,262	-,227	.[b]
	Sig. (2-tailed)	,170	,717	,127		,778	,458	,560	,310	,382	.
	N	17	17	17	17	17	17	17	17	17	17
Competitive_Pressure	Pearson Correlation	,356	,770[**]	-,417	-,074	1	,825[**]	,329	,426	-,794[**]	.[b]
	Sig. (2-tailed)	,161	<,001	,096	,778		<,001	,197	,088	<,001	.
	N	17	17	17	17	17	17	17	17	17	17
Regulatory_Support	Pearson Correlation	,370	,541[*]	-,440	-,193	,825[**]	1	,300	,445	-,681[**]	.[b]
	Sig. (2-tailed)	,143	,025	,077	,458	<,001		,242	,073	,003	.
	N	17	17	17	17	17	17	17	17	17	17
Willingness	Pearson Correlation	,591[*]	,410	,054	,152	,329	,300	1	,142	-,573[*]	.[b]
	Sig. (2-tailed)	,012	,102	,838	,560	,197	,242		,587	,016	.
	N	17	17	17	17	17	17	17	17	17	17
Technology_Competence	Pearson Correlation	,392	,316	,218	-,262	,426	,445	,142	1	-,437	.[b]
	Sig. (2-tailed)	,120	,217	,401	,310	,088	,073	,587		,079	.
	N	17	17	17	17	17	17	17	17	17	17
New_SU	Pearson Correlation	-,535[*]	-,630[**]	,040	-,227	-,794[**]	-,681[**]	-,573[*]	-,437	1	.[b]
	Sig. (2-tailed)	,027	,007	,879	,382	<,001	,003	,016	,079		.
	N	17	17	17	17	17	17	17	17	17	17
Which country do you belong to? Please select from the list of countries given below.	Pearson Correlation	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]
	Sig. (2-tailed)	.	.	.	.	.	.	.	.	.	
	N	17	17	17	17	17	17	17	17	17	17

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

b. Cannot be computed because at least one of the variables is constant.

APPENDIX 10 – COEFFCIENT TABLE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3,815	2,990		-1,276	,205
	Perceived_Benefits	,301	,117	,212	2,583	,011
	Compatibility	,313	,105	,250	2,973	,004
	Top_Management_Support	,142	,068	,135	2,086	,040
	Technology_Competence	,068	,113	,044	,605	,547
	Financial_Readiness	,000	,127	,000	-,001	,999
	Competitive_Pressure	,252	,114	,269	2,217	,029
	Regulatory_Support	,121	,074	,194	1,645	,103
	New_SU	,013	,158	,007	,081	,936

a. Dependent Variable: Willingness

APPENDIX 11 – REGRESSION RESULTS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,840[a]	,706	,681	1,53129	,706	27,895	8	93	<,001

a. Predictors: (Constant), New_SU, Top_Management_Support, Financial_Readiness, Technology_Competence, Perceived_Benefits, Compatibility, Regulatory_Support, Competitive_Pressure

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	523,272	8	65,409	27,895	<,001[b]
	Residual	218,071	93	2,345		
	Total	741,343	101			

a. Dependent Variable: Willingness

b. Predictors: (Constant), New_SU, Top_Management_Support, Financial_Readiness, Technology_Competence, Perceived_Benefits, Compatibility, Regulatory_Support, Competitive_Pressure

APPENDIX 12 – CORRELATION MATRIX FROM REGRESSION STATISTICS

Correlations

		Willingness	Perceived_Benefits	Compatibility	Top_Management_Support	Technology_Competence	Financial_Readiness	Competitive_Pressure	Regulatory_Support	New_SU
Pearson Correlation	Willingness	1,000	,670	,700	,202	,532	-,151	,764	,704	-,589
	Perceived_Benefits	,670	1,000	,521	,274	,436	,064	,638	,531	-,476
	Compatibility	,700	,521	1,000	,005	,503	-,200	,711	,664	-,561
	Top_Management_Support	,202	,274	,005	1,000	,293	,293	,021	-,054	-,069
	Technology_Competence	,532	,436	,503	,293	1,000	,014	,530	,467	-,429
	Financial_Readiness	-,151	,064	-,200	,293	,014	1,000	-,296	-,388	,100
	Competitive_Pressure	,764	,638	,711	,021	,530	-,296	1,000	,827	-,693
	Regulatory_Support	,704	,531	,664	-,054	,467	-,388	,827	1,000	-,723
	New_SU	-,589	-,476	-,561	-,069	-,429	,100	-,693	-,723	1,000
Sig. (1-tailed)	Willingness	.	<,001	<,001	,021	<,001	,065	<,001	<,001	<,001
	Perceived_Benefits	,000	.	,000	,003	,000	,262	,000	,000	,000
	Compatibility	,000	,000	.	,481	,000	,022	,000	,000	,000
	Top_Management_Support	,021	,003	,481	.	,001	,001	,418	,295	,247
	Technology_Competence	,000	,000	,000	,001	.	,444	,000	,000	,000
	Financial_Readiness	,065	,262	,022	,001	,444	.	,001	,000	,160
	Competitive_Pressure	,000	,000	,000	,418	,000	,001	.	,000	,000
	Regulatory_Support	,000	,000	,000	,295	,000	,000	,000	.	,000
	New_SU	,000	,000	,000	,247	,000	,160	,000	,000	.
N	Willingness	102	102	102	102	102	102	102	102	102
	Perceived_Benefits	102	102	102	102	102	102	102	102	102
	Compatibility	102	102	102	102	102	102	102	102	102
	Top_Management_Support	102	102	102	102	102	102	102	102	102
	Technology_Competence	102	102	102	102	102	102	102	102	102
	Financial_Readiness	102	102	102	102	102	102	102	102	102
	Competitive_Pressure	102	102	102	102	102	102	102	102	102
	Regulatory_Support	102	102	102	102	102	102	102	102	102
	New_SU	102	102	102	102	102	102	102	102	102