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Article

The present scenario of artificial intelligence and machine learning in financial services: An empirical study

Mohammed Arshad Khan[1,*], Hamad Alhumoudi[1], Abdullah Alakkas[1], Syed Mohd Minhaj[2,*], Mohammed Alhashem[1]

[1] Accounting Department, College of Administrative and Financial Sciences, Saudi Electronic University, Riyadh 11673, Saudi Arabia
[2] Department of Management, DSEU, PUSA, New Delhi 110012, India
*** Corresponding authors:** Mohammed Arshad Khan, m.akhan@seu.edu.sa; Syed Mohd Minhaj, syedminhaj125@yahoo.com

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Abstract: The financial services industry is experiencing a swift adoption of artificial intelligence (AI) and machine learning for a variety of applications. These technologies can be employed by both public and private sector entities to ensure adherence to regulatory requirements, monitor activities, evaluate data accuracy, and identify instances of fraudulent behavior. The utilization of artificial intelligence (AI) and machine learning (ML) has the potential to provide novel and unforeseen manifestations of interconnectivity within financial markets and institutions. This can be represented by the adoption of previously disparate data sources by diverse institutions. The researchers employed convenience sampling as the sampling method. The form was filled out over the period spanning from July 2023 to February 2024, and it was designed to be both anonymous and accessible through online and offline platforms. To assess the reliability and validity of the measurement scales and evaluate the structural model, we employed Partial Least Squares (PLS) for model validation. Specifically, we have used the software package Smart-PLS 3 with a bootstrapping of 5000 samples to estimate the significance of the parameters. The results indicate a positive and direct connection between artificial intelligence (AI) and either financial services or financial institutions. On the contrary, machine learning (ML) exhibits a strong and positive association among financial services and financial institutions. Similarly, there exists a positive and direct connection between AI and investors, as well as between ML and investors.

Keywords: AI; ML; financial services; financial institution; investors

1. Introduction

Advanced strategies have been created by researchers in the fields of computer science and statistics to extract valuable insights from huge and diverse data sets. Data can exhibit many characteristics, originate from diverse origins, and possess varying degrees of reliability (both structured and unstructured data). These strategies have the potential to make use of computers' processing capability to carry out a variety of jobs, including image recognition and NLP, through experiential learning. The wide term AI refers to the utilization of computing tools to tackle activities that have historically relied on human expertise (Ojokoh et al., 2020). The field of AI has been in existence for a considerable number of years. In light of recent advancements in processing power and the growing accessibility and abundance of data, there has been a renewed interest in exploring the possible uses of AI. These applications are currently employed for the purpose of disease diagnosis, language translation, and autonomous driving, with a growing utilization within the financial industry. Prior continue, it is necessary to provide definitions for the many terms used in characterizing this particular topic. The term "big data" does not have a fixed definition, but it is often used to refer to the collection, organization, and analysis of large and complex datasets using various methods, notably artificial intelligence (FSB, 2017).

The term "artificial intelligence" (AI) describes a computer system's capacity to do tasks normally associated with human intelligence, therefore allowing the system to effectively achieve a certain objective. In essence, AI refers to a mechanized system capable of engaging in problem-solving activities with the objective of attaining a desired outcome. Technology is already exerting a significant influence inside the finance and banking domain, encompassing the payments business as well (Khan, Vivek, et al., 2023). It can be asserted with confidence that the phenomenon is garnering the attention of corporations on a global scale. The environment of payments is seeing rapid expansion, propelled by the advancement of technologies and the process of digital transformation across several sectors. It is evident that digital commerce has extended its reach beyond traditional desktop platforms and even beyond mobile devices. As the expansion of the Internet of Things (IoT) persists and individuals establish connectivity across several domains, encompassing devices, apparel, and household equipment, the capacity to engage in transactions at any location and moment will further permeate society (Rathore et al., 2021). ML and AI are being rapidly embraced for numerous purposes in the financial services business. These technologies can be employed by both public and private sector entities to ensure adherence to regulatory requirements, monitor activities, evaluate data accuracy, and identify instances of fraudulent behavior. AI and ML could bring about new and unexpected ways for the financial system and its participants to stay connected. By leveraging machine learning to streamline the payment procedure at multiple levels, AI has the ability to improve and speed up the current situation. (Khan, 2021). AI is being employed in the background to efficiently manage and safeguard money transactions. The utilization of ML and bots by criminals for the purpose of engaging in online fraud is on the rise. This trend presents a unique difficulty for companies involved in the sale of high-value items, such as the travel industry.

ML can be defined as a computational approach that involves the development of algorithms to address problems by optimizing their performance via experience, with minimal or no human interaction (Lu, 2018). The utilization of these methodologies enables the identification of patterns within extensive datasets (often referred to as big data analytics) derived from an expanding array of diverse and pioneering sources. Various ML technologies leverage statistical methods that are widely recognized and utilized by researchers. These encompass the expansion of linear regression models to accommodate a potentially vast number of inputs, or the utilization of statistical methodologies to condense extensive datasets for the purpose of facilitating straightforward visualization. However, ML frameworks include intrinsic flexibility as they are not limited to linear correlations, which are typically prevalent in economic and financial analysis, allowing them to spot patterns more effectively. In a broad sense, the field of ML primarily focuses on automated processes related to optimization, prediction, and categorization, rather than on causal inference. To clarify, the task of determining whether a company's debt will be classified as investment grade or high yield in the future can be accomplished through the utilization of ML techniques (Gandomi et al., 2023). However, the task of identifying the elements that have influenced the magnitude of bond yields would probably not be accomplished through the utilization of ML techniques (Arshad Khan and Alhumoudi, 2022).

ML can be used for a wide range of problems, including classification and regression analysis. Technologies for categorization, which are widely used in real-world settings, categorize observations into a limited number of distinct groups. Classification algorithms are probabilistic in the environment since they determine the category that exhibits the highest probability of being the appropriate classification (Kibria et al., 2017). One potential illustration involves the automated analysis of a sell-side report, wherein the report is assessed and categorized as either 'bullish' or 'bearish' with a certain degree of likelihood. Additionally, the task of estimating the initial credit rating of an unrated company might be considered. On the other hand, situations with an infinite number of solutions and a continuous set of expected results are best estimated using regression techniques. The aforementioned result can be complemented by the inclusion of a confidence interval. Regression algorithms have the potential to be employed in the process of determining the prices of options. Regression methods can also serve as an intermediary step inside a classification system.

Numerous machine-learning approaches have been in existence for a considerable period of time. Neural networks, which form the fundamental notion underlying deep learning, were initially formulated during the 1960s. Nevertheless, following an early surge of enthusiasm, ML and AI were unable to fulfil their anticipated potential, resulting in a decline in funding for a period of more than ten years (Srivastava and Gopalkrishnan, 2015). This decline can be attributed, at least in part, to the inadequate availability of computational resources and data. During the 1980s, there was a rebound in financing and a heightened level of interest in various applications. This period witnessed the development of numerous research concepts that would later pave the way for significant advances (Minhaj et al., 2024).

Recognizing machine learning's shortcomings is critical, especially its failure to detect causal correlations. As a whole, machine learning algorithms can spot patterns that show how one event or tendency is related to another. The patterns identified by ML algorithms are primarily correlations, some of which may not be readily discernible to human observers (Minhaj and Khan, n.d.). Nevertheless, economists and various professionals are increasingly utilizing AI and ML technologies to get insights into complicated relationships, in conjunction with other tools and domain-specific knowledge (Haider et al., 2024)

1.1. Purpose of the study

ML and AI technologies enable the automation of routine and manual tasks in financial processes. As a result, there is a boost in productivity, shorter processing durations, and lower operational expenses. Technologies based on machine learning can sift through mountains of financial data in real time, revealing patterns and developments. This analysis can be used to assist in the assessment and management of risks. Machine learning models have the capability to analyse past data in order to forecast future market patterns and asset prices. This helps financial institutions and investors make more informed investment decisions and optimize their investment portfolios. AI can optimize portfolio management by continuously analyzing market conditions and adjusting investment portfolios accordingly. This dynamic approach can lead to better returns and risk management (Khan et al., 2021). To fully grasp how advances in technology can revolutionize conventional procedures, research into Machine Learning and Artificial Intelligence within the framework of financial services is crucial, enhance decision-making, and bring about efficiencies that benefit both financial institutions and their customers (Khan et al., 2022).

1.2. Scope of the study

Research on the use of AI and ML in the banking sector is massive and constantly developing. A study is now underway to determine how machine learning and artificial intelligence may affect the fierce rivalry of the financial services industry. This involves studying market trends, identifying key players, and assessing the potential for disruption.

The scope of the study is dynamic, evolving with technological advancements, regulatory changes, and market dynamics. Researchers and practitioners in this field need to continuously adapt and explore new avenues to fully comprehend and harness the potential of ML and AI in revolutionizing financial services.

2. Review of literature

Trading organizations are increasingly turning to AI and ML techniques in order to leverage data for enhancing their sales capabilities to clients. For instance, conducting an analysis of previous trading patterns can aid in predicting a client's subsequent order (Zamani et al., 2023). The act of trading produces substantial volumes of data, which is generally necessary for ML technologies to operate well. If the ongoing inclination towards the growing adoption of voice-to-text services persists, it will result in the generation of supplementary data derived from phone-based trade executions. subsequently, this data might be combined with the current data set that comes via electronic platforms. By allowing proactive management of exposure to hazards, AI and ML may improve the handling of risks. (Luan et al., 2020). ML has the potential to be utilized as a foundational tool for exchanges in the development of risk modelling techniques. This enables exchanges to effectively identify instances where the trading account positions of its members exhibit heightened risk profiles, consequently necessitating appropriate intervention measures (Rahmani et al., 2021). Major trading corporations, such as financial institutions, have successfully utilised a centralised risk trading system and risk management strategies based on extensive research of large datasets. These strategies have facilitated the firm's ability to effectively handle risks and enhance its capital utilization by consolidating risks originating from different segments of its operations.

Within the realm of portfolio management, the utilization of AI and ML technologies has become increasingly prevalent. These tools serve the purpose of identifying novel signals pertaining to price fluctuations, hence enabling a more efficient utilization of the extensive pool of data and market research in comparison to existing models (Data and Analytics, 2000). The core ideas that support the long-standing analytical methods used in systematic investing are the bedrock upon which ML technologies are built. Finding trends in the data that can inform forecasts of future price levels and volatility is the main goal. These forecasts aim to provide higher returns that are not influenced by other factors, across different time periods. ML is predominantly employed by systematic funds, particularly those operating as hedge funds, within the asset management industry. An AI unit typically functions as a member of a larger team inside an asset management firm, providing assistance in the process of portfolio development. A prevailing perspective within the business posits that in order for AI and ML to yield optimal outcomes, having thorough oversight and understanding of the instruments used is crucial for quants and traders alike. Some quantitative funds are waiting to fully automate and run a model until they thoroughly understand the process behind a particular prediction. The prevalence of ML tools inside quant funds is indicative of the underlying nature of ML as a methodology for deriving predictive capabilities from data, setting it apart from investment strategies that rely more heavily on subjective discretion and judgment (Najafabadi et al., 2015).

Regulated institutions are employing AI and ML methodologies to ensure adherence to regulatory compliance, while authorities are utilizing these approaches for the purpose of supervision. Regulatory Technology (RegTech) is commonly acknowledged as a branch of Financial Technology (FinTech) that concentrates on enhancing the efficiency and effectiveness of regulatory compliance, surpassing the capabilities of current systems. Throughout the year 2023, the RegTech market is projected to be worth $9.45 billion, growing at a CAGR (Lu, 2018) of 76%. When these technologies are used by public sector regulation and monitoring agencies, it’s called SupTech. AI and ML applications within SupTech aim to improve the efficacy and efficiency of monitoring and security operations. However, they have potential uses in this field and have not yet been implemented by regulatory or supervisory organizations. To make it easier for you to understand how the use cases are interrelated, we have categorized them into many groups: regulatory reporting, data quality, monetary policy, monitoring, and identifying fraudulent activity.

Automation of macroprudential analysis and data quality assurance are two areas where AI and ML could greatly enhance macroprudential surveillance. Financial institutions are requiring more resources due to the surge in reported data volume and frequency, as a result of a proliferation of new reporting requirements across countries (Inci, 2023). Consequently, standard approaches may prove insufficient in fully harnessing the data’s potential. Furthermore, it is commonly observed that newly acquired datasets tend to exhibit a higher frequency of significant errors, empty fields, and other difficulties related to data quality. Consequently, it becomes imperative to conduct supplementary examinations and implement measures for ensuring data quality assurance. ML has the ability to enhance data quality through the automated detection of anomalies, hence alerting statisticians and/or data providers to potential inaccuracies. Administrators may be able to reduce costs, strengthen reporting quality, and increase the efficacy and productivity of information processing and macroprudential enforcement using this approach (Haider et al., 2024).

In a similar vein, the utilization of AI and ML holds the potential to assist trade repositories (TRs) in addressing concerns related to data quality. This has the potential to enhance the significance of TR data for both regulatory bodies and the general public. According to official sources, the persistent obstacle of data quality concerns remains a significant hurdle in fully harnessing the potential of TR data. Throughout the future, machine learning may help enhance the accuracy of TR data, especially for OTC derivatives and, if relevant, other kinds of transactions like swaps for derivatives or securities financing transactions. Missing data, discrepancies in the data, and errors caused by human input blunders can all be successfully detected by well-trained ML systems (Goodell et al., 2021). Additionally, these algorithms can be employed to identify probable matches between pairs of transactions and to estimate missing data values through interpolation techniques. The identical methodologies can be employed by the governing bodies themselves (Khan et al., 2022). A machine learning system that is supervised has been developed by the FinTech Laboratory. This system has the capability to recognise particular categories within the unstructured free text fields that are included in over-the-counter derivatives data. This includes the floating leg of swaps. The objective of the on-going effort to implement this algorithm-based alert is to detect transactions that do not meet the mandatory clearance conditions automatically (Khan et al., 2021).

Research gap

Investigating the function of AI and ML in the banking sector is an enormous and ever-expanding field of study. The impact of machine learning and artificial intelligence on the financial services industry's competitive environment is being studied. This involves studying market trends, identifying key players, and assessing the potential for disruption.

The scope of the study is dynamic, evolving with technological advancements, regulatory changes, and market dynamics. Researchers and practitioners in this field need to continuously adapt and explore new avenues to fully comprehend and harness the potential of ML and AI in revolutionizing financial services.

3. Hypotheses development

3.1. Possible effects of AI and ML on financial markets

The utilization of AI and ML holds significant promise in augmenting the effectiveness of information processing, leading to a reduction in information asymmetries. Thus, the financial system's information function could be strengthened with the deployment of AI and ML (Cao, 2021). There are several processes through which this enhancement may occur (Arshad Khan et al., 2021).

For certain market players, AI and ML may one day make it easier to gather and analyze data on a bigger scale. For instance, in the field of sentiment analysis. This has the potential to mitigate knowledge asymmetries, hence enhancing market efficiency and stability.

Artificial intelligence and machine learning could help market participants lower their trading costs. (Papers et al., 2020). Additionally, the utilization of AI and ML has the potential to facilitate the adaptation of trading and investment strategies to dynamic environments, resulting in enhanced price discovery and decreased transaction costs within the system.

H01: AI have a positive effect on financial services.

H02: ML have a positive effect on financial services.

H07: Financial services have influencer mediates the association between AI and financial institutions.

H08: Financial services have influencer mediates the association between ML and financial institutions.

3.2. Possible effects of AI and ML on financial institutions

AI and ML have the potential to increase financial organisations' efficiency and profits by reducing risks and expenses in several ways (Soni, 2021). Enhanced profitability has the potential to contribute to the accumulation of reserves, hence promoting overall stability within the system.

AI and ML have the potential to boost the efficiency of computer-based processing in financial institutions, leading to improved financial performance through increased revenues and decreased costs. For instance, the utilization of AI and ML in identifying customers' needs and optimizing product targeting and customization can enable financial institutions to effectively allocate resources towards serving high-value customers who generate significant fees or exhibit growth potential (OECD, 2021). The automation of normal corporate activities has the potential to result in reduced operational expenses.

Enhanced risk quantification in real time is one area where AI and ML might improve risk management. Financial institutions could potentially enhance their risk management capabilities by leveraging AI and ML techniques to facilitate decision-making processes. This could be achieved by utilizing historical correlations among asset prices to inform and guide risk management strategies. The utilization of tools that effectively address tail risks can yield significant advantages for the overall system (Kühl et al., 2019). Additionally, the utilization of AI and ML can be employed in the realm of anticipating and identifying instances of fraudulent activity, suspicious transactions, default, and the potential for cyber-attacks. The use of AI and ML in this way may lead to better methods of controlling risks. On the other hand, it must be stressed that AI and ML systems might not pick up on new dangers and events if they rely too much on past data, a phenomenon known as overtraining. The potential for enhancing risk management through the utilization of AI and ML tools is widely recognized (Mukhamediev et al., 2022). However, it is important to note that the current implementation of these tactics lacks empirical evidence about their effectiveness in mitigating risk amidst dynamic financial circumstances.

Researchers in the domains of artificial intelligence and machine learning use an open-source approach and rely heavily on data. Institutions and other industries, such those in the sharing economy and e-commerce, may form collaborations due to this feature.

H03: AI have a positive effect on financial institutions.

H04: ML have a positive effect on financial institutions.

H09: Financial institutions. has influencer mediates the association between AI and investors.

H10: Financial institutions. has influencer mediates the association between ML and investors.

3.3. Possible effects of AI and ML on consumers and investors

The implementation of AI and ML technologies in the financial services sector has been shown to result in cost reduction and improved operational efficiency (Cioffi et al., 2020). As a result, consumers stand to gain numerous advantages from these advancements.

The potential reduction in costs for various financial services through the implementation of AI and ML could lead to decreased fees and borrowing costs, hence benefiting consumers and investors.

There is potential for an expanded scope of financial services to be made available to both consumers and investors. For instance, the utilization of AI in the context of robo-advice has the potential to enhance individuals' engagement with diverse asset markets while making investment decisions (Srivastava and Gopalkrishnan, 2015). Additionally, the utilization of AI and ML techniques in the context of advanced credit scoring for FinTech lending has the potential to expand the range of funding options accessible to both consumers and small and medium companies (SMEs).

AI and ML have the potential to enhance the provision of financial services by leveraging big data analytics to offer more tailored and individualized solutions. For instance, the utilization of AI and ML techniques might potentially enhance the examination of large datasets, thereby elucidating the distinctive attributes of individual consumers and/or investors. This, in turn, enables companies to develop precisely tailored services. However, the utilization of consumers' data may give rise to concerns over data privacy and information security. Furthermore, given the capabilities of AI and ML analytics to examine the attributes of individual customers using publicly available data, it becomes imperative to address the safeguarding of customer analysis outcomes (Luan et al., 2020). This entails ensuring the preservation of consumer anonymity, while simultaneously enabling the secure and effective utilization of big data to enhance service provision. Furthermore, it is imperative to build meticulously crafted governance frameworks for financial service providers that utilize AI and ML technologies, as this is crucial for safeguarding the interests of consumers and investors.

H05: AI have a positive effect on investors.

H06: ML have a positive effect on investors.

4. Research methodology

4.1. Sampling and data collection

The research was conducted on a population of persons aged 18 or older residing in India who possessed prior knowledge about financial markets, AI, and ML. This choice was made due to our focus on prospective early adopters within the target demographic. The researchers employed convenience sampling as the sample method. The completion of the form took place within the time frame of July 2023 to February 2024, and it was conducted through an online platform that ensured anonymity of the participants. A total of 405 forms were collected, with 18 forms being excluded due to the absence of documented prior expertise in financial markets, AI, and ML.

4.2. Measurement of variables

These characteristic's items have been evaluated using a Likert scale, where a score of 1 indicates strong disagreement and a score of 5 indicates strong agreement. In order to make the variables work for the present study, they were tweaked from previous studies.

4.3. Data analysis

In order to evaluate the structural model and find out how reliable and valid the measurement scales were, the PLS method was used for model validation. In order to determine whether the parameters were statistically significant, this study used the software program Smart-PLS 3, which applied a bootstrapping procedure using 5000 samples. In situations when predicting and identifying the elements that impact investor behavior is the main goal of the research, PLS (Partial Least Squares) is considered appropriate.

5. Finding and analysis's

There are two parts to the test, each with its own set of 35 questions. Half of the research was devoted to answering questions about the participants' demographics, and the other half was broken down into five indicators standing for various concepts: artificial intelligence, machine learning, financial services, financial institutions, and investors. In order to evaluate the data collected from participants, a simplified method known as a "rating scale" was employed. A portion of 387 responses were selected from 405 responses to enable data processing in the study. For the purpose of conducting a quantitative analysis. For this research, we used SmartPLS 3. The results and discoveries that came from the research are detailed in this section.

5.1. Background information of the respondents

The people who filled out the surveys are shown in this section as a sample. In **Table 1** we can see a summary of the replies according to the study's selected demographic variables. Initial sources provide the foundation of the data that is offered here.

Table 1. Baseline data of the participants (*N* = 387).

Basis	Categories	F	%
Gender	M	254	65.63
	F	133	43.36
Age Group	Up to 20 years	55	14.21
	21–30 years	121	31.26
	31–40 years	165	42.63
	41 and above	46	11.88
Educational Qualification	U. G	39	10
	G	78	20.15
	P. G	121	31.26
	Ph.D.	40	10.33
	P. D. H	109	28.16
Occupational Status	Govt. Employees	81	20.93
	Private. Employees	149	38.50
	Business and self. Employees	121	31.26
	Students	36	0.93
Monthly Income	≤ Rs 10,000	36	0.93
	Rs 10,000–Rs 20,000	86	22.22
	Rs 20,001– Rs 40,000	145	37.46
	> Rs 40,000	120	31

The socioeconomic features of those taking part are summarized in **Table 1**. This includes, among other things, the following: gender, age group, educational attainment, work status, and monthly income. The information collected shows that men made up the majority of the sample responses (65.63 percent), with females making up the remaining 43.36%. The results showed that a large percentage of respondents (42.63%) were between the ages of 31 and 40. Furthermore, 31.26 percent were in the 21–30 age range, while 11.88 percent were in the 40+ age bracket. Plus, among those who participated in the study, 14.21% were between the ages of 21 and 20.

In terms of academic achievement, 10% of the survey respondents reported being Undergraduate (U. G.), 20% as Graduation (G.), 31.26% as Postgraduate (P. G.), 10.33% as Ph.D. holders, and 28.16% as PDH holders. Based on their occupation, the participants are divided into four groups: those working for the government (20.93 percent), those in the private sector (38.50 percent), those running their own businesses or self-employed (31.26%), and students (0.93%).

The results show that when looking at monthly income, 0.93% of those polled had incomes below Rs 10,000 and 22.22% had incomes between Rs 10,000 and 20,000. And although 31.46% of those surveyed say they make between 20,000 and 40,000 rupees a year, 31% say they make more than 40,000 rupees a year.

5.2. Measurement model evaluation

A combination of "internal consistency, convergent validity, and discriminant validity" was used to validate the measurement model.

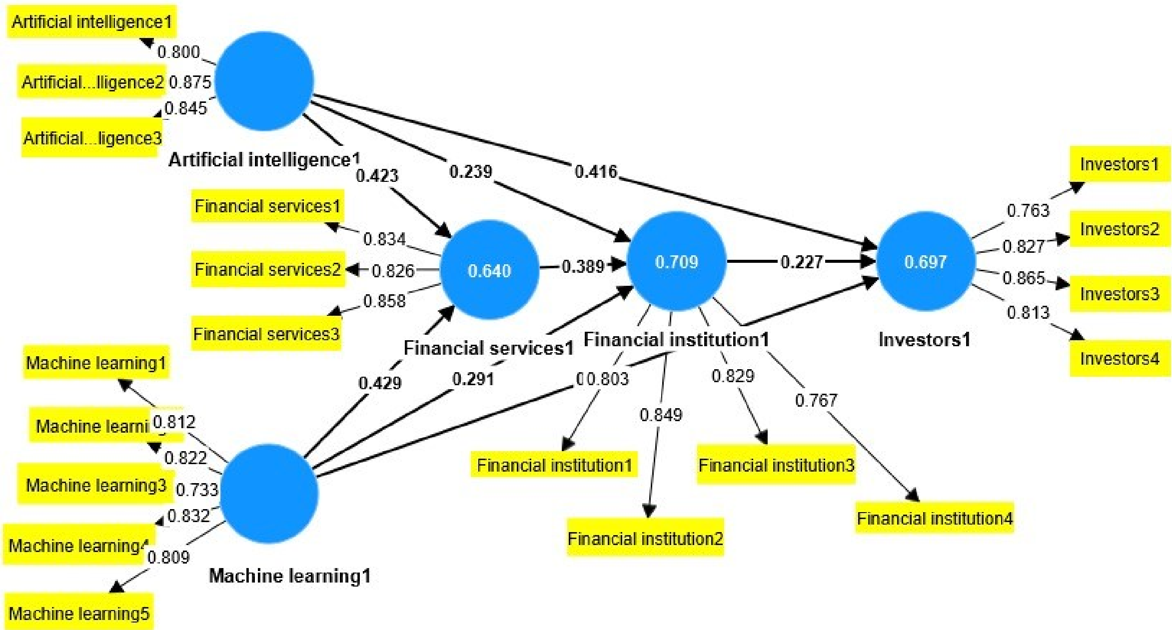

Figure 1. Measurement model from SmartPLS 3.0.

The rectangles in **Figure 1** represent the latent constructs used in the study, which include artificial intelligence (AI), machine learning (ML), investors, financial services, and financial institutions. You can see the three statement codes for AI, five for ML, three for financial services, four for financial institutions, and four for investors next to the arrows that indicate the corresponding items or constructs. Each of these measures something different. Each item or building has its factor loading values displayed near the corresponding arrows.

Table 2 shows that in the domains of artificial intelligence (AI), machine learning (ML), financial services (FS), financial institutions (FIs), and investors (I), a positive response is suggested when the average values of all the components inside a specific construct above a 3 threshold. "Strongly Disagree" (1) and "Strongly Agree" (5) were the possible outcomes on the five-point "Likert scale" that the researcher employed. Factor loadings higher than the specified threshold of 0.70 are present in each construct. Each statement provides a thorough explanation of its own theoretically postulated construct.

With "Composite Reliability" (C.R) values over 0.7 and "Average Variance Extracted" (AVE) values over 0.5, all five constructs fulfilled the necessary standard limit, as demonstrated in **Table 3** (Ventre and Kolbe, 2020). Values of "Cronbach's Alpha and rho-a" that were considerably higher than 0.7 were used to confirm internal consistency (Adepoju and Adeniji, 2020). According to Khanifar et al. (2012), the idea of "convergent validity" was born out of this need.

Table 2. Mean, SD and loadings of constructs.

Construct	Item	Mean	SD	Loading
Artificial intelligence (AI)	AI 1	3.89	0.75	0.73
	AI 2	4.11	0.81	0.84
	AI 3	3.98	0.76	0.81
Machine learning (ML)	ML 1	4.09	0.81	0.83
	ML 2	4.09	0.88	0.83
	ML 3	4.17	0.78	0.78
	ML 4	4.21	0.81	0.85
	ML 5	4.27	0.79	0.77
Financial services (FS)	FS 1	3.89	0.76	0.80
	FS 2	4.11	0.79	0.83
	FS 3	3.54	0.82	0.84
Financial institution (FI)	FI 1	3.77	0.71	0.72
	FI 2	4.10	0.74	0.83
	FI 3	4.21	0.84	0.84
	FI 4	3.86	0.75	0.77
Investors	Investors 1	3.83	0.84	0.75
	Investors 2	4.15	0.81	0.79
	Investors 3	4.02	0.77	0.75
	Investors 4	3.94	0.74	0.81

Table 3. Convergent validity result.

Factor	Cronbach's Alpha	Rho-A	C.R	A.V.E
Artificial intelligence (A1)	0.783	0.775	0.867	0.722
Machine learning (ML)	0.841	0.864	0.901	0.632
Financial services (FS)	0.799	0.821	0.843	0.676
Financial institution (FI)	0.831	0.810	0.841	0.687
Investors	0.801	0.793	0.812	0.698

5.3. Discriminant validity result

Using the "Fornell-Larcker and cross-loading criteria," we verified the discriminant validity. What is meant by "the extent to which the indicator is effectively identifiable from related constructs inside the nomological net" is what discriminant validity indicates.

As shown in **Table 4**, the square roots of the "Average Variance Retrieved" values for the required constructs must be obtained in order to determine the "Fornell-Larcker" criterion. Overall, the findings show that the associations between AL and ML were higher than the associations between any of the other constructs (0.821), (0.841), financial service (0.833), financial institution (0.807), and investors (0.812). The "Fornell-Larcker" criterion, proposed by Fornell and Lacker in 1981, was used for determining discriminant validity.

Table 4. Discriminant validity—Fornell-Larcker criterion.

Factors	Artificial intelligence (A1)	Machine learning (ML)	Financial services (FS)	Financial institution (FI)	Investors
Artificial intelligence (AI)	0.821				
Machine learning (ML)	0.712	0.841			
Financial services (FS)	0.741	0.755	0.833		
Financial institution (FI)	0.768	0.714	0.762	0.807	
Investors	0.789	0.746	0.801	0.761	0.812

Table 5. Discriminant validity-loading and cross-loading criterion.

Factor	Artificial intelligence (AI)	Machine learning (ML)	Financial services (FS)	Financial institution (FI)	Investors
AI 1	0.798	0.656	0.603	0.625	0.712
AI 2	0.875	0.717	0.701	0.683	0.665
AI 3	0.848	0.545	0.681	0.587	0.721
ML 1	0.646	0.803	0.592	0.616	0.631
ML 2	0.632	0.849	0.649	0.662	0.687
ML 3	0.506	0.827	0.588	0.693	0.712
ML 4	0.667	0.771	0.582	0.511	0.732
ML 5	0.712	0.789	0.676	0.712	0.654
FS 1	0.567	0.596	0.762	0.572	0.523
FS 2	0.651	0.614	0.827	0.701	0.687
FS 3	0.724	0.630	0.865	0.671	0.702
FI 1	0.688	0.733	0.680	0.812	0.659
FI 2	0.590	0.568	0.602	0.821	0.721
FI 3	0.563	0.543	0.594	0.732	0.684
FI 4	0.571	0.567	0.611	0.831	0.711
Investors 1	0.630	0.631	0.535	0.809	0.756
Investors 2	0.731	0.632	0.598	0.641	0.812
Investors 3	0.654	0.722	0.661	0.649	0.798

Several constructions showed loadings that were larger than the cross-loadings with other constructs across the columns, as shown in **Table 5**, which proves that the cross-loading requirement is applicable. In order to prove discriminant validity, the cross-loading criterion was used (Henseler et al., 2015).

5.4. Structural equation model

The possibility of multicollinearity must be taken into consideration when examining the structural model because it might greatly affect the dependability of the results. According to the research done by Akinwande et al. (2015), the "Variance Inflation Factor" (VIF) values were between 1.603 and 2.597, which means that the model does not have multicollinearity. The structural model was then validated with 5000 resamples using the bootstrapping approach to determine the hypothesis's usefulness in **Figure 2**.

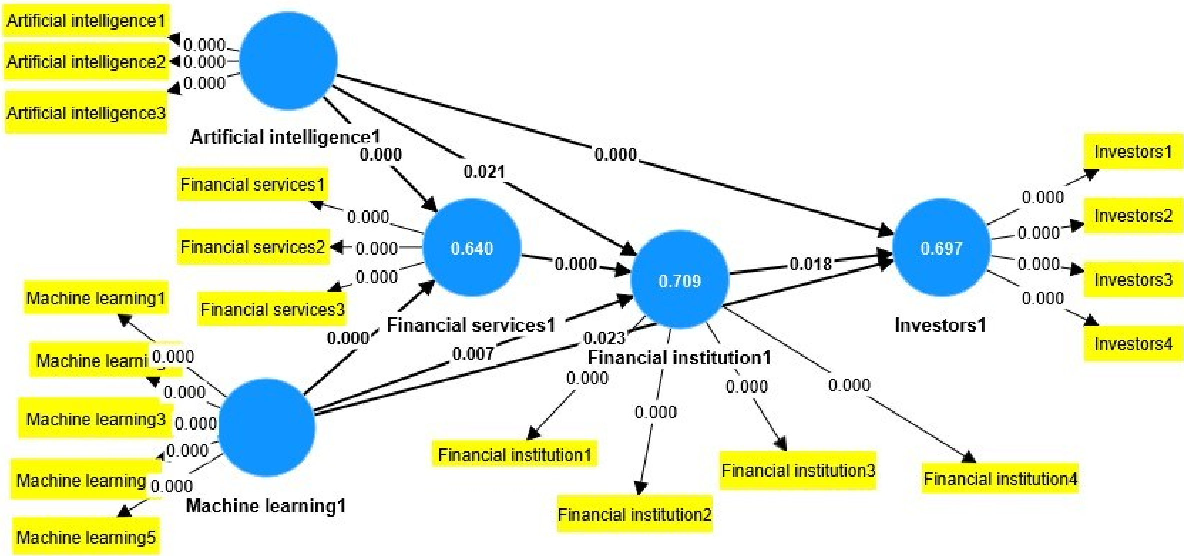

Figure 2. Structural equation model (SEM).

In order to ensure the results are reliable, it is important to examine the structural model with the possibility of multicollinearity in mind. The absence of multicollinearity in the model was confirmed by the findings of Akinwande et al. (2015), who found "Variance Inflation Factor" (VIF) values ranging from 1.603 to 2.597. To test the hypothesis, the structural model was re-tested with 5000 samples using the bootstrapping method.

Table 6. Direct impact of AI and ML on financial services and financial institution.

Hypothesis	Path	β	*t*-value	*p*-value	Result
H01	AI → financial services	0.513	5.210	$P \leq 0.001$	Supported
H02	ML → financial services	0.380	5.701	$P \leq 0.005$	Supported
H03	AI → financial institution	0.298	3.917	$P \leq 0.001$	Supported
H04	ML → financial institution	0.401	2.790	$P \leq 0.001$	Supported
H05	AI → investors	0.4764	3.809	$P \leq 0.005$	Supported
H06	ML → investors	0.378	2.901	$P \leq 0.005$	Supported

Table 6 shows that hypotheses H01, H02, H03, H04, H05 and H06 were supported. AI is also directly and positively related to financial services (β = 0.513, *t*-value = 5.210, and $p < 0.001$). ML is also directly and positively related to financial services (β = 0.380, *t*-value = 5.701, and $p < 0.005$). Similarly, AI are directly and positively related to financial institution (β = 0.298, *t*-value = 3.917, and $p < 0.001$). ML are also directly and positively related to financial institution (β = 0.401, *t*-value = 2.790, and $p < 0.001$). Although, AI is directly and positively related to the investors (β = 0.424, *t*-value = 4.949, and $p < 0.005$). Similarly, ML are directly and positively related to investors (β = 0.476, *t*-value = 3.809, and $p < 0.001$). ML are also directly and positively related to investors (β = 0.378, *t*-value = 2.901, and $p <$ 0.001).

Table 7 shows that hypotheses H07, H08, H09 and H10 were supported. In terms of AI, financial services have a mediated or indirect effect on financial institutions (β = 0.381; t-value = 2.780; p < 0.005). In the case of ML, financial services have a mediated or indirect effect on the financial institutions (β = 0.209, t-value = 2.773, and p < 0.005). Similarly, in terms of AI, financial institutions have a mediated or indirect effect on investors (β = 0.080; t-value = 2.172; p < 0.005). In the case of ML, financial institutions have a mediated or indirect effect on the investors (β = 0.178, t-value = 2.343, and p < 0.005).

Table 7. Mediating or indirect impact of satisfaction and hypothesis testing.

Hypothesis	Path	β	t-value	p-value	Result
H07	AI → financial services→ financial institutions	0.381	2.780	$P \leq 0.005$	Supported
H08	ML → financial services→ financial institutions	0.209	2.773	$P \leq 0.005$	Supported
H09	AI → financial institutions→ investors	0.080	2.172	$P \leq 0.005$	Supported
H10	ML → financial institutions→ investors	0.178	2.343	$P \leq 0.005$	Supported

6. Discussion

Likewise, the application of AI and ML techniques in the development of novel and independent trading methods by hedge funds may contribute to an increased variety of market dynamics. Enhancing the efficiency of information processing has the potential to alleviate the accumulation of macro-financial price imbalances by facilitating the earlier identification and reduction of price misalignments.

However, if market participants employ AI and ML techniques to reduce capital or margins and enhance expected returns on capital (while adhering to regulatory constraints, but neglecting risk assessment), ML and AI are employed could potentially amplify risks. In particular, ML and AI are employed in optimization processes may facilitate the implementation of more stringent liquidity buffers, increased leverage, and accelerated maturity transformation compared to scenarios where these technologies were not employed.

When applied to the financial services industry, AI and ML could provide substantial benefits for preserving financial stability. These advantages primarily manifest as enhanced operational efficiencies in the delivery of financial services, as well as improved capabilities for monitoring and mitigating regulatory and systemic risks. Increased productivity in the financial system could be possible with better processing of information related to credit risks and cheaper client involvement. There is potential for cost-effective, enhanced risk oversight, recognition of fraud, and legal compliance with the use of AI and ML to internal (back-office) applications. When it comes to managing portfolios, the use of AI and ML could greatly improve market-wide efficiency and robustness through improved data interpretation.

7. Practical implication

The depth and breadth of "directional" trading operations could be significantly altered by the incorporation of AI and ML into the trading industry. The divergent development of trading apps by a wide range of market participants could, under favorable circumstances, help keep the financial system stable. For instance, the utilization of ML in robo-advisors may result in the provision of personalized recommendations to individuals, leading to investment activities that are more aligned with individual tastes and potentially less dependent on other trading tactics. By mitigating the obstacles that hinder retail consumers from participating in investment activities, these applications have the potential to broaden the investor pool inside capital markets. The utilization of AI and ML by financial market participants, such as hedge funds and market makers, might potentially yield both advantageous and disadvantageous consequences in relation to leverage, liquidity, and maturity change. Financial market accessibility could be enhanced by the use of AI and ML to optimize the speed and efficiency of trading processes. With the use of AI and ML, complicated financial operations and high-risk transactions might be better identified, and specific financial institutions could benefit from better risk management strategies. There is hope that reliance on conventional bank loans might decrease with the use of new technologies, which pave the way for the creation of innovative credit platforms that connect borrowers with financial institutions directly (also called FinTech credit). As a result, this could cause banks to have less debt and promote a system where risks are spread out more evenly across the entire financial system.

8. Conclusions

Numerous financial services are being delivered in a whole new way thanks to the use of AI and ML. Although there is a scarcity of comprehensive data regarding the level of adoption in different markets, discussions with participants in the market indicate that certain sectors within the financial system are actively utilizing AI and ML. There is a noticeable increase in the popularity and usage of fraud detection, capital optimisation, and portfolio management software. The prevailing sentiment among industry participants is that there would be a further use of AI and ML technologies. Given the circumstances, it is crucial to commence contemplating the ramifications on financial stability at once rather than waiting till the probable consequences materialize. The analysis is inherently limited and would be enhanced by a more comprehensive comprehension of use cases in the future. Furthermore, a significant number of the aforementioned modifications are unlikely to have a substantial impact on financial stability, thus rendering them beyond the purview of this analysis.

This improvement can be achieved by promptly identifying and rectifying price misalignments, as well as potentially mitigating the occurrence of crowded transactions, assuming favorable conditions. Ultimately, through the utilization of use cases by regulators and supervisors, there exists the possibility of enhancing supervisory efficacy and doing more proficient systemic risk analysis within financial markets. Simultaneously, the future may witness the emergence of supplementary third-party dependencies due to the network effects and scalability of novel technologies. Consequently, the formation of new entities with systemic importance may occur as a result of this. The provision of AI and ML services is witnessing a growing trend among a select number of prominent technological companies. Similar to other platform-based industries, there is potential value for financial institutions to engage with third-party providers who possess a strong reputation, extensive scale, and interoperability. The existence of natural monopolies or oligopolies is a possibility. The competition concerns, which are significant in terms of economic efficiency, may give rise to financial stability hazards if technology businesses gain substantial market dominance in specific parts of the financial industry. The potential systemic consequences of third-party dependencies and interconnections become apparent in the event of a significant interruption or insolvency experienced by a large organization.

Most current financial services AI and ML solution providers may not be well-versed enough in the applicable rules and regulations or may be operating beyond the scope of regulatory supervision. In cases when financial institutions depend on third-party providers of AI and ML services for essential operations, and regulations around outsourcing may be absent or insufficiently comprehended, these service providers may operate without adequate monitoring and oversight. In a similar vein, should the providers of said tools commence offering financial services to institutional or retail consumers, it is conceivable that financial activities may transpire beyond the confines of the regulatory boundaries. The monitoring of the applications of AI and ML should be upheld. As advancements in underlying technology continue to progress, there exists the possibility for a broader adoption beyond the use cases examined within the scope of this paper. It is imperative to sustain the monitoring of these advances and to periodically revise this assessment in subsequent instances.

9. Future research and limitation

In order to make comparisons with studies that have used non-probability sampling, it would be beneficial for future studies to adopt probability sampling. This study limited its sample size to Saudi Arabians who have already implemented AI and ML systems. More studies involving opponents and analyses of their data using the suggested model are required. We were unable to undertake in-depth study using a mixed-method approach due to time and budget constraints. A mixed-methods technique can be used in future studies to gain greater clarity.

At the outset, generalizations regarding Saudi Arabians as a whole are problematic due to the study’s tiny sample size. The success of artificial intelligence and machine learning is highly debatable if companies can’t reach Saudi Arabia’s rural class, which accounts for a bigger portion of the population. Therefore, future research may broaden the scope of the study to encompass Saudi Arabia’s rural class. The practicality of the respondents was also a factor in their selection for this study. Results may not be applicable to a broader population unless future research use probability sampling methods.

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