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Article

Implications of Artificial Intelligence (AI) and machine learning-based fintech for the financial assets related traditional investment theories

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Abstract: New technologies always have an impact on traditional theories. Finance theories are no exception to that. In this paper, we have concentrated on the traditional investment theories in finance. The study examined five investment theories, their assumptions, and their limitation from different works of literature. The study considered Artificial Intelligence (AI) and Machine Learning (ML) as representative of financial technology (fintech) and tried to find out from the literature how these new technologies help to reduce the limitations of traditional theories. We have found that fintech does not have an equal impact on every conventional finance theory. Fintech outperforms all five traditional theories but on a different scale.

Keywords: artificial intelligence; machine learning; fintech; traditional investment theories; financial assets

1. Introduction

Fintech is a term that is frequently used in the modern era. This term is derived from a mashup of finance and technology. When these two terms are combined, a new term and dimension are created: Fintech. Fintech is defined as the application of technology to financial services. Financial technology (Fintech) is at the forefront of recent technological developments (Alessio and Mosteanu, 2021). There are now numerous components of technology being utilized in this industry. For the sake of this study, we will focus on the most prominent and influential technology available: artificial intelligence (AI).

Artificial intelligence (AI) is a potent technology with a variety of characteristics that are becoming increasingly evident in all industries today (Regona and Tan, 2022). Artificial intelligence applications in finance have been extensively discussed (Butaru et al., 2016; Harris, 1992). We generally use the term "AI" to refer to computer software capable of learning from experience and occasionally making decisions on its own. Recognizing the crucial need for a more data-driven approach to investing, some scholars have focused on developing quantitative methodologies for company appraisal. Bhat and Zaelit (2011) forecasted the emergence of private enterprises using qualitative data and random forest algorithms. Dixon and Chong (2014) devised a Bayesian technique for business ranking by training a collection of

Support Vector Machines (SVM) models on many feature pairs.

This application of AI technology enables us to make better decisions, particularly in finance, and forces us to reconsider the applicability of current investing ideas (Gazi et al., 2024, Qing et al., 2023; Karim et al., 2023). Earlier generations of economists, like Irving Fisher, John Maynard Keynes, Benjamin Graham, and others (Leo-Wenstein and Elster, 1992), placed a premium on the fallibility of human decision-making. Modern finance eschews such realistic depictions of human behavior in favor of representative agent models in which everyone in the economy is supposed to be rational and capable of forecasting. However, there are reasons to maintain the assumptions of universal rationality. Consider Milton Friedman's (1953) "as if" defense, for example, He thinks that hypotheses should be evaluated based on their predictive ability.

We believe it is now appropriate to revisit the theories' assumptions and oversimplifications as artificial intelligence (AI) transforms business models (Méndez and Mariano, 2019). We will rely on AI to accomplish this. We may investigate the picture more closely using AI in conjunction with various large data scenarios and complex with and without assumption scenarios. From the above discussion, we can see that assumptions have many complicacies. Prior to the advent of artificial intelligence, those were genuine instances of "complicity." As finance professionals, we are well aware that the four most costly words in the English language are "This time is different." We can work with large amounts of data and sufficient knowledge to study human and natural characteristics in this new era. In today's data-driven world, businesses have two options: 1) embrace data or 2) go out of business. If a business chooses to be overwhelmed by the massive amount of data, it will be overwhelmed; however, if it joins the AI wave, it will harness all of the data to its advantage.

We have attempted to analyze current investing theories, their underlying assumptions, and their limitations in light of various works of literature. We attempted to portray how AI may contribute to issue solving and which investing theory is more compatible with AI or Fintech.

2. Scope of the study

It took decades to build and implement the different financial theories like Portfolio Theory, Efficient Market Hypothesis (EMH), Capital Asset Pricing Model (CAPM), Black-Scholes (B-S) Option Pricing Model, and Arbitrage Pricing Theory properly. Over time, several changes are made to adapt to the congaing environment. Now, in this modern time of technology, it is time we can inaugurate technology with these theories to improve their performance (Rabbi et al., 2024). This is the most significant scope of this study.

For instance, portfolio theory's performance is deeply related to the stock price movement. Before the modern age, using financial news titles as an input variable to forecast share prices was impossible. However, Vargas et al. (2018) employed a deep learning algorithm to estimate the daily trend movement of a stock using technical indicators and financial news titles as input. Also, Agrawal et al. (2019) developed a long short-term memory (LSTM) classification model to forecast the movement of stock trends using adaptive stock technical indicators. In this article, we have tried to identify the effect of introducing AI to reduce the limitations of traditional investment theories.

3. Traditional investment theories and their limitations

We have considered the five most relevant and influential traditional investment theories to understand their weakness and how AI can play a constructive role in better decision-making through these theories. We have started with Portfolio Theory, and after that, we have studied Efficient Market Hypothesis (EMH), Capital Asset Pricing Model (CAPM), Black-Scholes (B-S) Option Pricing Model, and Arbitrage Pricing Theory.

3.1. Portfolio theory

Based on Markowitz's (1952, 1959) work, Portfolio Theory revolutionized finance theory and laid the groundwork for developing other pricing models. Portfolio Theory does not assess the risk of an individual investment by its deviation from expected and actual return; instead, it considers how an asset contributes to the overall risk of the asset's portfolio. That's why diversification can effectively reduce the risk at a given expected return.

Principles of Portfolio Theory are based on the idea that investing in multiple securities is always better than investing in just one, and the underlying concept is that a rational investor will rationally select the portfolio that will satisfy their level of risk and will provide the highest possible return at the same time (Correia et al. 1993; Viljoen, 1989).

3.1.1. Portfolio theory assumptions

The present outline of portfolio theory assumptions was developed by Hendriksen and Van Breda (1992), Linley (1992), and O'Brien and Srivastava (1995).

Investors view investment returns as a reliable indicator of the investment's long-term performance, as investment returns are normally distributed (Amin et al., 2024; Amin & Oláh, 2024; Mustafi et al., 2024). According to investors, their portfolio's risk is proportionate to its expected return variability. Investors make investment decisions based solely on perceived risk and projected return parameters for a fixed period of the investment horizon. Rational and risk-averse investors prefer a high expected return for lower risk; for a given level of risk, they prefer greater compensation, which is a higher return.

Some other assumptions are that the capital market is competitive, there is no transaction cost and taxes, and securities can be diversified completely. Consequently, individual investors' activities will have no meaningful impact on market pricing. Investment returns are received at the end of the term, and investors are unconcerned about the difference between income and capital gains when these amounts are equal.

Efficiencies of portfolios are defined as the absence of any other portfolio that provides a greater expected return for a given level of risk or the absence of any other portfolio that generates a lower expected return for a given level of risk (Linley, 1992).

3.1.2. Portfolio risk

Portfolio Theory's essential assumption is that a portfolio's risk is not merely the weighted average of the risk of the portfolio's investments. Portfolio risk is defined by the relationship between different investment returns and individual investment risk (Correia et al., 1993; Sharpe, 1985; Van Horne, 1992).

When investment returns are perfectly correlated, portfolio risk is maximized. Diversification aims to include investments in the portfolio that correlate as inexactly as possible, reducing risk to a minimum (Hendriksen and Van Breda, 1992). The correlation coefficient evaluates how much individual investment returns move in lockstep (correlate). While returns are typically favorably correlated, they are unlikely to be perfectly positively or negatively correlated (Correia et al., 1993).

We can see the portfolio risk equation below

$$\sigma_P^2 = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_{12} \quad (1)$$

3.1.3. Portfolio return

When comparing alternative security combinations, it is crucial to consider both their standard deviation (risk) and expected return. As previously stated, it is straightforward to calculate the expected return on a portfolio, which is just the weighted average of projected returns on the portfolio's investments divided by the proportional value of the portfolio (Clark et al., 1979; Ross et al., 1990; Sharpe, 1985; Weston and Copeland, 1992).

The portfolio return equation is

$$\text{Expected Return} = \sum x_i E(R_i) \quad (2)$$

3.1.4. The efficient frontier and portfolio selection

There are many ways to make money, but only some can be called efficient (undominated). Each person who invests has a set of possible portfolios (opportunities) that they can choose from, depending on how much risk and return they want to take. An efficient portfolio has the following characteristics (Clark et al., 1979; Markowitz, 1991; O'Brien and Srivastava, 1995; Rees, 1995).

- No other portfolio has a lower risk profile for a given projected return.
- No other portfolio has a higher risk profile for a given expected return.
- No other portfolio offers a better-predicted return at a lower risk level.

3.1.5. Portfolio selection and capital budgeting

Capital project portfolio selection is more challenging than portfolio selection for securities investments. This is because most capital projects are indivisible and cannot be divided into homogenous units, unlike securities investments, which are divisible into units with the same expected rate of return and risk for each common stock of a single firm. Compared to investing in securities, an investor rarely can acquire a significant portion of a capital project and thereby partake in its return and risk (Clark et al., 1979).

3.1.6. Criticism of portfolio theory

Portfolio Theory's principal critique as a model for constructing optimal portfolios is the high number of difficult computations needed. For a portfolio of 100 equities, correlation coefficients of roughly 5000 are necessary (Clark et al., 1979; Dobbins et al., 1994; Linley, 1992; Viljoen, 1989). Additionally, the basic assumptions of Portfolio Theory, including the lack of transaction costs and taxes, the total divisibility of securities, investors' equal access to knowledge, freely available information, and investors' similar time horizons, are oversimplified. It ignores the practical difficulties of investing in well-diversified portfolios. Instead, it allows the evaluation of investment decision-making in hypothetical scenarios (Linley, 1992; O'Brien and Srivastava, 1995).

Furthermore, while Portfolio Theory predicts that riskier assets should earn a greater rate of return, it does not explain how this risk premium is calculated. The underlying principle of Portfolio Theory is that the risk associated with securities is determined by the relationship between the returns on the various assets (Linley, 1992). The fourth objection addressed at Portfolio Theory is that investing in proportion to all available securities is impractical for most investors. Only a few unit trusts and pension funds may resemble a market portfolio (Correia et al., 1993).

In addition, the difficulties associated with predicting cash flow probabilities in capital budgeting constitute another significant criticism of Portfolio Theory, as they prevent it from being used in capital budgeting (Clark et al., 1979).

3.2. Efficient market hypothesis (EMH)

The Efficient Market Hypothesis (EMH), based on Fama's work and discoveries from 1970, significantly impacted how the capital market operated. The EMH says that because capital markets are efficient, price changes in securities are uncorrelated and accurately reflect the price implications of all publicly available data.

3.2.1. Assumptions for market efficiencies for performing EMH

In an efficient capital market, we can see the below assumptions for EMH.

Market efficiency says that extraordinary profits can only be made by chance and that the best thing for investors to do is diversify their portfolios and cut down on transaction costs. This reduces the chance that their investments will fail (Keane, 1983). Securities' best worth estimation can be determined from their market price, and for investors, it is a waste of time to find the mispriced asset (Rees, 1995).

In an efficient market, it is pointless to get an abnormal return by trading on a particular piece of data (Hendriksen and Van Breda, 1992). It is impossible for anyone to consistently exceed the market regarding investing returns (Correia et al., 1993; Keane, 1983; Ross et al., 1990). Investment advisors' goal is to get the best return for their clients from their investment of available resources. They do not try outperforming the market because of the market efficiency concept (Keane, 1983).

Additionally, the concept of market efficiency has accounting implications:

Any piece of accounting information is worth what it does to share prices. Their effect on stock prices can determine alternative accounting rules and practices' value. Accounting principles and practices should be chosen so that share prices experience the least long-term volatility (Firth, 1977). Because capital markets aren't fooled by accounting gimmicks and manipulations, they can read information from any format and only include information that changes expectations about the risk and return of a share (Hendriksen and Van Breda, 1992).

Efficient markets demonstrate that the only means to generate large profits on capital markets are "by chance" and "by luck," not by inventiveness. Thus, it is not sufficient to demonstrate market inefficiency by demonstrating that excessive profits were earned but rather by demonstrating that they were earned via skill and on a constant rather than one-off basis (Keane, 1983).

3.2.2. Limitations of EMH regarding market efficiencies

Several anomalies have questioned the effectiveness of the capital markets. Research on these anomalies was done to see whether they are long-term or whether they may be exploited. Some of the details are below.

When a mechanical investment strategy is used for quarterly earnings announcements, as demonstrated by the Jones and Litzenberger study, the market can outperform, resulting in the prospect of generating excess returns (Firth, 1977).

Brown and Kennelly's study looked at the relationship between share price movements and quarterly earnings releases. Their analysis found that by utilizing the information provided in such reports, investors can achieve above-average returns (Henderson et al., 1992).

Dimson (1979) and Roll (1981) recognized the small firm impact, but both maintained that this phenomenon results from insufficient risk measurement for small enterprises. Standard risk assessments do not account for the infrequency of tiny enterprises' traded shares. Consequently, their risk is understated (Keane, 1983; Van Rhijn, 1994).

Basu's (1977) analysis discovered that firms with low P/E ratios typically generate larger returns than expected. Thus, the prior P/E ratio and future stock market performance are believed to be correlated. This contrasts market efficiency, as it permits investors to earn abnormally high investment returns (Dobbins et al., 1994; Van Rhijn, 1994).

Similarly, the French (1980) study discovered evidence of the weekend effect, with abnormally high returns on shares on Fridays and negative returns on Mondays (Ross et al., 1990).

Rosenberg et al. discovered yet another anomaly intimately linked to the tiny firm and the price/earnings effects. According to the researchers (Dobbins et al., 1994), investing in companies with low share price to book value ratios is a good investment decision as it allows investors to earn unusual returns.

3.3. Capital asset pricing model (CAPM)

It was with help from Treynor (1961), Lintner (1965), and Mossin (1966), who added to Markowitz's (1952, 1959) work. This led to the now-famous Capital Asset Pricing Model (CAPM). CAPM's main idea is holding the portfolio of investments is a handy way to diversify some of the investment risk.

This can be shown as

$$Eri = Rf + \beta i\ (Erm - Rf) \tag{3}$$

3.3.1. CAPM assumptions

The CAPM is based on many simple assumptions. EMH and Portfolio Theory assumptions are similar to some of these assumptions but unique to CAPM. The following assumptions are required to derive the CAPM:

CAPM describes investors' behavior under the assumption like all investors are rational. They are risk-averse and want to maximize their return at the end of their investment horizon. Investors have specific risk and return preferences, which dictate their expected utility of the wealth (Harrington, 1987; Seneque, 1987). It is vital to discuss how investors choose investments to maximize their wealth's utility. Investors solely consider the predicted risk and return to make their investment decisions. That is why they make decisions about their portfolios based on expected returns and the standard deviations (or beta) of the expected returns (Elton and Gruber, 1995; Harrington, 1987). There is no capital market equilibrium if investors disagree on the market price of risk. This assumption is necessary for a capital market equilibrium where all investments will have the price rational to their level of risk (Elton and Gruber, 1995; Harrington, 1987; Jones, 1998).

CAPM is a single-period model where investors' period is also a single period for investment decisions. This makes the comparison easy as investors have to create their investment portfolio at the same time in the present and have to sell at an unidentified time point in the future, which will be the same too (Anderson, 1978; Elton and Gruber, 1995; Harrington, 1987). CAPM can only be used if capital markets are efficient and investors agree on the prospects of stocks. These presuppositions are necessary for the CAPM to work (Harrington, 1987; Laing, 1988; Viljoen, 1989). CAPM considers that the assets are risk-free and that investors can lend and borrow money as per their needs at a risk-free rate.

This suggests that investors need to be more concerned with the risk associated with specific stocks. Because investors are concerned about their overall portfolio risk change while adding a risk-free asset or assets, those are finances through risk-free borrowing (Harrington, 1987; Keogh, 1994).

There are no market imperfections, which means that there are no transaction costs, no limits on short sales, and dividend and capital gain income are not taxed differentially (Harrington, 1987; Seneque, 1987). As Keogh (1994) says, all investors are treated the same because no one can exploit these flaws. Due to the fixed number of shares, new offerings of shares are likely to be ignored (Harrington, 1987). Second, because shares are infinitely divisible, investors of any wealth level can create any type of portfolio they desire (Elton and Gruber, 1995). Thirdly, shares are liquid and can be traded at market price, which means they are marketable securities (Oosthuizen, 1992). Investors are price takers therefore they act as though their own purchasing or selling decisions do not affect pricing (Elton and Gruber, 1995; Jones, 1998).

3.3.2. Limitations of the CAPM's assumptions

Many, if not all, of these assumptions have been found to be wrong by Elton and Gruber (1995) and Pike and Neale (1996). As an expectational model, the CAPM should be evaluated based on how well it predicts expected outcomes (Harrington, 1987; Seneque, 1987). It is challenging for investors to achieve a true

Capital Market Line (CML) or efficient frontier through CAPM, as even relaxing the assumptions cannot reach the theoretical market equilibrium conditions (Anderson, 1978).

Asset prices will move to a point where an asset's proportional returns match the asset's total risk, giving investors a wide range of efficient portfolios to choose from. Many things will not align with the CML, so the CML and efficient opportunity set will differ (Anderson, 1978).

However, Milton (1953) warned against judging a theory just by how realistic its assumptions are unless the theory tries to describe and explain how people act accurately. Considering assumptions is unimportant if the predictive model's results can be tested against reality. This is especially true if the predictions are shown to be reasonably close to reality (Pike and Neale, 1996).

3.3.3. Limitations of CAPM model

Though expected (ex-ante) returns cannot be observed, most tests employ realized (ex post) returns even though the CAPM is an expectational model. That is why the model may be accurate for expected returns, while actual returns may differ and create doubts about the validity of the model, which is a problem (Viscione and Roberts, 1987). A risk-free asset somehow does not exist, while a risk-free rate of return is significant for CAPM, making the model questionable (Pike and Neale, 1996; Viscione and Roberts, 1987).

Since there is no market portfolio from which to compare share returns, a proxy must be utilized, which may result in various Security Market Lines (SMLs) depending on the proxy selected. It's also possible that the index utilized as a proxy is inefficient, which would affect the test results (Pike and Neely, 1995, 1996); Viscione and Roberts, 1987; Rees, 1995).

3.4. Model of Black-Scholes (B-S) option pricing

Black-Scholes (B-S) Option Pricing Model was developed by Black and Scholes in 1973 and greatly contributed to option pricing. A model that can be used to price other financial instruments, like bonds, currencies, and so on, works in the same way as the CAPM model. This makes them more meaningful.

Risk and return of shares are the main concerns for CAPM and Arbitrage Pricing Theory (APT), while there are different types of investments in the market, like bonds, debenture, and options. Options have been getting much attention recently because they comprise the core of many hybrid securities (Hendriksen and Van Breda, 1992).

An option is a security that represents a claim (a claim on a particular share or group of shares) that an investor can purchase instead of directly trading in shares of stock. This option gives the holder the right to receive or deliver shares subject to fulfilling certain conditions set down in advance. However, options' majority face value is mainly delivered from the company's equity value they are driven. However, options are not generally exercised, leading to the creation of equity-derived securities, which investors can buy or sell (Jones, 1998). For pricing, the option B-S option model is widely used.

We can show B-S Option pricing model as

$$\mathrm{C} = \mathrm{S_t}\,\mathrm{N}(\mathrm{d_1}) - \mathrm{k_e^{-rt}}\mathrm{N}(\mathrm{d_2}) \tag{4}$$

where

$$d_1 = \left[s_t \ln\frac{s_t}{k} + \left(\gamma_1 + \frac{\sigma^2}{2}\right)t\right] \,/\, \sigma\sqrt[s]{t} \tag{5}$$

and

$$d_2 = d_1 - \sigma_s \sqrt{t} \tag{6}$$

where

C = Call option price,

S = Current stock (or other underlying) price,

K = Strike price,

R = Risk-free interest rate,

T = Time to maturity,

N = A normal distribution.

3.4.1. Black-Scholes (B-S) option pricing model's assumptions

For the B-S model to be valid, the following conditions must be met. However, model modifications often work even when these conditions are not met. Experiments show that the B-S equation and its variants appropriately value call options when dividends are taken into consideration (Ross et al., 1990).

Only European options that are only exercisable on their expiration date are considered. This model also includes the popular assumption of no transaction fees or taxes. When options are structured correctly, there are no flaws, no limits on shorting, and short sellers collect the whole proceeds of their trades.

Investors can borrow money and lend at a fixed short-term interest rate constant over the option's life. Dividends aren't paid on the share that owns them. The market operates continuously, with a constant variant of return, and market participants know that stocks move in the same direction all the time without any big changes in the price movement (Levy and Sarnat, 1994; Ross et al., 1990, Van Horne, 1992).

Simister (1988) notes that the majority of the B-S model's flaws are due to market imperfections. These flaws include the following:

- The cost of transactions is not zero.
- Prices do not move continuously.
- Prices follow neither a normal nor a lognormal distribution.
- Markets do not have an infinite depth.

3.4.2. Limitations of B-S model

There is a problem with empirical testing of the B-S model since tests are integrated assessments of the assumptions of efficiency of markets, synchronization of markets, validity of models, and data accuracy. Since share returns are non-stationary, the B-S model's volatility estimator cannot accurately predict volatility (Galai, 1982). Transaction fees and taxes can affect options market price, which aren't considered in the B-S model or any other model (Galai, 1982). The trading approach used, and the absence of market synchronization could have altered the findings of various studies (Galai, 1982).

If no dividend assumptions of the B-S Model are dropped or violated, then the model may produce inaccurate pricing. However, in the case of covered dividend American call options pricing, the same model performs without bias (Blomeyer and Klemkosky, 1982).

3.5. Arbitrage pricing theory

After the invention of the Arbitrage Pricing Theory by Ross (1976) as an alternative to CAPM, finance theory has grown. While the CAPM addresses market risk, the APT also considers several unknown risk factors. Regarding asset pricing and the APT's development, there is a lot of discussion and debate about its flexibility and usefulness compared to CAPM in calculating all of the risk variables that must be addressed. We can write Arbitrage Pricing Theory as below.

$$R_j = E(R_j) + b_{j1}f_1 + b_{j2}f_2 + \cdots + b_{jn}f_n + \epsilon_j \tag{7}$$

where,

R_j = The rate of return on asset j during a specified time period,

$E(R_j)$ = The expected rate of return on asset j,

b_j = The sensitivity of asset's returns to a factor,

f = A common factor with zero mean that influences the returns on all assets under consideration,

ϵ_j = A random error term, unique to asset, that, by assumption, is completely diversifiable in large portfolios and has a mean of zero

3.5.1. APT's assumptions

Seneque (1987) considers APT a simpler theory than CAPM because it makes fewer more complicated assumptions. It also shares some CAPM assumptions:

Though investors are risk-averse, they take a risk by investing, and as compensation for their risk, investors attempt to maximize their terminal wealth by seeking returns (Harrington, 1987; Laing, 1988; Linley, 1992). Harrington (1987) believes investors do not consider the mean and variance of return during their investment decision-making, and he flagged that there is no critical assumptions about the distribution of return. Investors can borrow and lend at a particular interest rate (risk-free rate) (Harrington, 1987; Linley, 1992). Though mentioning borrowing or lending rates is a common property of any pricing model, CAPM does not have that Harrington (1987).

Every investor has access to the same information simultaneously and for free. Markets are perfect; imperfections like transaction costs, taxes, or short-selling restrictions are absent (Harrington, 1987; Laing, 1988; Linley, 1992).

In addition to these assumptions, there are some unique assumptions for APT like below:

Different numbers and factors impact the systematic pricing of the assets, and investors agree on those (Harrington, 1987; Laing, 1988; Linley, 1992). This assumption of the theory implies that asset returns depend not only on the market but also on several factors. These factors influence the systematic pricing of assets, and investors know this (Harrington, 1987; Linley, 1992).

There are no profit opportunities for arbitrage. This assumption describes investors as proactive in their search for risk-free profits, and their actions close down these opportunities (Harrington, 1987; Linley, 1992).

3.5.2. Limitations of APT model

Even though the APT has few assumptions, it is unsuccessful at identifying pricing components and the relationship between these systemic elements and expected returns. The APT components must be priced as the sole risk variables to obtain the expected outcomes using APT. The empirical evidence must establish that the selected variables are unrelated and no additional significant variables exist. If facts support these assumptions, the APT adequately captures the pricing mechanism (Harrington, 1987).

A big problem with the APT is that it doesn't say the factors that make stocks rise or fall. Instead, it asks for them to be proven by testing them (Seneque, 1987). APT can also achieve the efficient set easily (Ross et al., 1990).

Investment analysts have criticized the APT because computer analysis programs pick out the elements, which are meaningless on their own, so they don't make sense. This makes it hard to predict with the APT (Viscione and Roberts, 1987).

CAPM and APT both hold that risk and expected return are linked. However, APT does not use the underlying market portfolio as the primary source of risk. This is a fundamental shortcoming of the APT, as the theory does not identify the economic risk variables that could affect returns.

4. Artificial intelligence (AI) in the improvement of investment theories

Computer simulations that extend and augment human intelligence are known as artificial intelligence (AI), which integrates theory, technique, technology, and application systems. Artificial intelligence has traditionally been introduced through a fully automated procedure that has been ongoing for a long time (Rahman et al., 2024). Mechanization enabled a portion of manual labor automation in the late nineteenth and early twentieth centuries. In contrast, information technology advancements in the middle and late twentieth decades resulted in the standardization of data processing automation (Korinek and Stiglitz, 2017).

We have started our investment theory discussion with Portfolio Theory. In this section, we will start with how AI can play its role in overcoming the limitations and/or developing the theories' performance. The first criticism about the portfolio theory was that many calculations are needed for Portfolio Theory. AI has made this point disappear. AI can compute big data in nanoseconds. Following this, as AI advances, the usage of genetic algorithms (GA) increases, and investment portfolios are optimized through the use of GA (Dubinskas and Urbiene, 2017). GA is a subset of evolutionary computing used to address combinatorial optimization problems, a subset of problems in artificial intelligence (Dubinskas and Urbiene, 2017). Also, introducing Robo advisory, which is also a part of AI, increased the performance of Modern Portfolio Theory (Beketov et al., 2018; Islam et al., 2023).

The new theory known as the inefficient market hypothesis (IMH), which asserts that financial markets are not always considered efficient markets (Ritika and Gagan, 2021). Zhang (2015) and Ding et al. (2017) believed that investors' "irrationality" was particularly significant in China, which rattled the theoretical foundation of EMH. According to Kourentzes et al. (2014), the integrated Neural Network (NN) model outperformed the single model, and integrated learning could enhance prediction accuracy and robustness. This theory also tries to captures cost-effectiveness, trust, data security, behavioral biases, and investor mood were found to be important factors that had a big impact on investors' perceptions (Bhatia et al., 2021).

Machine Learning algorithms perform better in forecasting asset prices than classic statistics and finance models, which has been acknowledged by many academics recently (Ioannis and Kyriakou, 2019; Luyang and Chen, 2019; Shihao and Gu, 2018). The classical CAPM findings have been outperformed by machine learning (ML), a form of AI (Philip, 2020). A significant advantage of Machine Learning over traditional finance theories like the CAPM is that Machine Learning algorithms can use around 200 times series variables on each target US equity to forecast the returns (Philip, 2020).

Artificial intelligence has come a long way in imitating human reasoning and thought processes in the last four decades. Artificial intelligence tools have traditionally been limited to sequential processing and the representation of fairly basic knowledge and logic. A more modern approach to AI is to build a computer that can replicate the human brain and have enough processing power for reasoning processes like humans. These insights enable building high-processing-power knowledge representations, understanding the bid data in nanoseconds, and recognizing the patterns from past experiences. Neural computing, often known as Artificial Neural Networks, is a type of artificial intelligence technology (ANN).

This Artificial Neural Network (ANN) which gives a tough fight with Black-Scholes (B-S) Option Pricing Model. Qi and Maddala (1996) examined the performance of an ANN and Black-Scholes in pricing European-style call options on the S&P500 index, concluding that the ANN was superior. Garcia and Gençay (1998, 2000), Gençay and Qi (2001), Gençay and Salih (2001), Ghaziri et al. (2000), Liu (1996), and Saito and Jun (2000) all found a similar conclusion. Dugas, Bengio, Bélisle, Nadeau, and Garcia (2002) discovered that restricting the ANN resulted in more favorable prices for European-style call options on the S&P500 index than an unconstrained ANN. Kelly (1994) used an ANN and the binomial option pricing model to price American-style put options on four US companies. As per Kelly, the binomial model cannot perform as good as ANN.

Investors have traditionally made investment decisions based on a company's income statements, balance sheets, and other publicly available information. High-quality fundamental data is easily available nowadays, and this data allows investors and researchers to examine their invested assets, especially focused on asset pricing methodologies such as Graham and Dodd's (1951) systematic value investing. Because empirical asset pricing models evidenced that all types of risk do not affect an asset's performance, it is essential to find the main factors influencing asset valuation (Pastor and Stambaugh, 2000). As a result, ML may better adapt the Asset pricing model to execute.

5. A conceptual framework for implementing fintech in traditional finance theories

Before introducing AI, traditional portfolio theory works to develop an optimal portfolio for ensuring better returns on investment. After introducing the AI Techniques in the same portfolio theory, it is performing better. Xiaoqiang and Ying (2017) illustrated a realistic illustration of this in their article. They constructed a portfolio based on spectral clustering (SC) connected to a stock complex network for the chain stock market. They discovered that investments in stocks that occupy the network's center could generate a higher return, leading them to the conclusion that an artificially intelligent algorithm can effectively boost the investment return. We got almost the same result from Yu et al. (2008), who explained that a neural network-based methodology could construct a mean–variance-skewness optimal portfolio quickly and efficiently.

CAPM makes it easy to find all the factors that are good predictors, but the traditional method fails when the number of predictors is close to or greater than the number of observations. Also, these models can fail due to high multicollinearity, which is inevitable given how similar many possible predictors are (Bielinski, 2021). Machine learning offers degrees of freedom optimization and reduces the difference between predictors using tools like principal component Analysis, Random Forest, and Factor Analysis, which are widely available (Fodor, 2002). AI-optimized CAPM calculation method has proven to provide more accurate return estimates than traditional CAPM calculation methods (Budiartha et al., 2022).

We have got almost the same results for the B-S Option pricing model. Hutchinson et al. (1994) tested three ANNs to the Black-Scholes model for pricing American-style call options on S&P500 futures and discovered that all three ANNs outperformed Black-Scholes. Yao et al. (2000) used ANNs to price call options on American-style Nikkei 225 futures and found that they did better than Black-Scholes.

Shin-Yuan (1996) has shown a new way to help with portfolio management that combines the arbitrage pricing theory (APT) and artificial neural networks (ANN). The integrated approach uses how well APT and ANN work together to find risk factors, predict the trend of each risk factor, make candidate portfolios, and choose the best portfolio. It uses quadratic programming to predict factor returns by finding surrogate portfolios in APT and ANN. Based on real-world results, the integrated method does better than the traditional method, which uses the ARIMA model.

All this past literature allows us to draw the conceptual framework through **Figure 1**, where we can say using AI Techniques will bring better results from the same traditional investment theories. For examining this framework researchers can use secondary most preferably from the capital market for a length of at least 5 years.

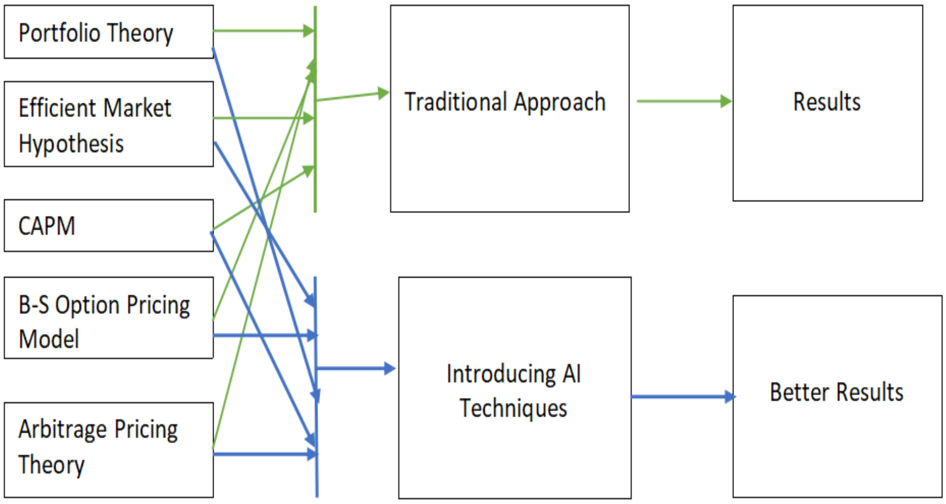

Figure 1. Implicating fintech techniques.

6. Practical implications

In recent years, there has been a growing utilization of artificial neural networks in the creation of diverse research models. These neural networks represent a facet of AI technology that excels when confronted with numerous variables, intricate interdependencies, or scenarios where multiple solutions are required, consistently yielding favorable outcomes. Consequently, artificial neural network technology has emerged as a prominent method within the financial domain (Cerullo and Cerullo, 1999; Chen and Du, 2009; Koskivaara, 2004; Tsai and Wu, 2008; Wong et al., 2000).

Within the annals of Wall Street's history, many fraudulent listed companies have left an indelible mark. It behooves successive generations of investors to possess a discerning eye when perusing Pearl's offerings in search of potential listed companies and cultivate a comprehensive understanding of these offerings, thereby steering clear of the treacherous "mines" that lurk in the depths of the market. Notably, the specter of deceit is not confined solely to Wall Street; the sphere of Chinese listed companies has seen its fair share of such malfeasance. There is a roster of over 4000 listed companies with shares in circulation. The scrutiny of their voluminous financial reports and the authentication of the data contained therein are tasks that strain human resources to their limits. Nevertheless, experts assert that deploying artificial intelligence, particularly algorithms, can mitigate some risks (Chu, 2018; Killeen and Chan, 2018). This AI is the part of FinTech that will help us to reduce fraud. This will also increase the efficiency of the present theories.

The growing market demand has led to increased public awareness of many AI-based models, including MACD (moving average index of smooth similarities and differences), KDJ (random index), RSI (relative strength index), and others. The parameters mentioned frequently exhibit an advanced age that hinders their ability to respond to contemporary market fluctuations effectively. In their study, Patel et al. (2020) examined using a machine-learning framework to forecast fluctuations in individual stocks and stock price indices. Four prediction models were used to analyze the data: Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Naive Bayes. The study conducted by Patel et al. (2015,

2020) examines the performance of two prominent organizations, Reliance Industries, and Infosys Ltd., as well as two stock price indices, namely CNX Nifty and S&P Bombay Stock Exchange (BSE), over the period from 2003 to 2012. In their study, Khedr et al. (2017) introduced a framework for analysis and optimization to minimize error rates and enhance the accuracy of predictions in determining the performance mode of stock prices. This Fintech introduction also minimizes the traditional financial theories' weakness, which improves their performance.

Besides these, fintech will have an impact on financial assets through Investment advisors (Yu and Peng, 2017), Risk management (Mashrur et al., 2020), and marketing (Yu, 2019). Industry 4.0 has introduced automation in almost every financial sector which is a collaboration of fintech (Tao et al., 2021).

The digital financial sector in Saudi Arabia is undergoing a revolution thanks to artificial intelligence (Mollah et al., 2024). Al-Baity (2023) has provided a comprehensive framework that describes the macro and micro levels of management required to guide AI growth and integration. This paradigm highlights the significance of ethical and regulatory considerations, implying that taking these important factors into account is necessary for the financial sector to successfully implement AI.

7. Conclusion

AI's use in financial services is one of the most forward-thinking things in today's international financial field. AI has been used increasingly in financial asset trading, wealth and asset management, insurance and banking, customer service, credit lending, and many other fields. AI is also used as a prediction tool. Even the principles of demand and supply are becoming more personalized with the help of AI. Each customer's prices will differ (Mankiw and Taylor, 2011). So, traditional investment theories also needed to be examined in the light of AI.

This study has examined the different articles of different periods regarding investment theories. Firstly, we have studied the traditional theories, assumptions, and limitations. Then, we have gone through the different literature to find out how artificial intelligence can positively impact reducing the limitations of these traditional investment theories. We have found from different studies that AI has outperformed all the five traditional investment models examined here from different studies. AI has outperformed all five traditional investment theories but on a different scale. Portfolio Theory and CAPM are the biggest beneficiaries of AI use. AI will allow better forecasting through these two theories in the near future. This investigation has carefully explored the moral landscape of Artificial Intelligence (AI) integration in the context of financial decision-making, revealing the relationship between the necessity of adjustments and remarkable technological breakthroughs.

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writing—review and editing, MBA, MSH, SB and MA; visualization, RSC and MA; supervision, SB and MA; project administration, MBA and MA; funding acquisition, MBA and MA. All authors have read and agreed to the published version of the manuscript.

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