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Management Decision

The role of artificial intelligence in the decision-making process: a study on the financial analysis and movement forecasting of the world's largest stock exchanges

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Ewerton Alex Avelar
Accounting and Finance Department, UFMG, Belo Horizonte, Brazil, and
Ricardo Vinícius Dias Jordão
The Center for Advanced Studies in Management and Economics, CEFAGE-UE, Evora, Portugal;
Swiss Management Center, Zug, Switzerland and
Graduate Program in Business Administration, FPL, Pedro Leopoldo, Brazil

Abstract

Purpose – This paper aims to analyze the role and performance of different artificial intelligence (AI) algorithms in forecasting future movements in the main indices of the world's largest stock exchanges.

Design/methodology/approach – Drawing on finance-based theory, an empirical and experimental study was carried out using four AI-based models. The investigation comprised training, testing and analysis of model performance using accuracy metrics and F1-Score on data from 34 indices, using 9 technical indicators, descriptive statistics, Shapiro–Wilk, Student's *t* and Mann–Whitney and Spearman correlation coefficient tests.

Findings – All AI-based models performed better than the markets' return expectations, thereby supporting financial, strategic and organizational decisions. The number of days used to calculate the technical indicators enabled the development of models with better performance. Those based on the random forest algorithm present better results than other AI algorithms, regardless of the performance metric adopted.

Research limitations/implications – The study expands knowledge on the topic and provides robust evidence on the role of AI in financial analysis and decision-making, as well as in predicting the movements of the largest stock exchanges in the world. This brings theoretical, strategic and managerial contributions, enabling the discussion of efficient market hypothesis (EMH) in a complex economic reality – in which the use of automation and application of AI has been expanded, opening new avenues of future investigation and the extensive use of technical analysis as support for decisions and machine learning.

Practical implications – The AI algorithms' flexibility to determine their parameters and the window for measuring and estimating technical indicators provide contextually adjusted models that can entail the best possible performance. This expands the informational and decision-making capacity of investors, managers, controllers, market analysts and other economic agents while emphasizing the role of AI algorithms in improving resource allocation in the financial and capital markets.

Originality/value – The originality and value of the research come from the methodology and systematic testing of the EMH through the main indices of the world's largest stock exchanges – something still unprecedented despite being widely expected by scholars and the market.

Keywords Artificial intelligence (AI) and new technologies, Finance theory, Innovation in management, Information and decision-making, Efficient markets hypothesis (EMH)

Paper type Research paper

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1. Introduction

The changes brought about by the knowledge-based economy and the resulting digital transformation have ruptured the contemporary management paradigm (Caputo *et al.*, 2019; Secundo *et al.*, 2020; Durst and Leyer, 2022; Jordão, 2022; Jordão and Novas, 2023; Silva *et al.*, 2023). According to Jordão (2022), economic, political, social, legal, organizational, technological and environmental pressures have challenged organizations, cities, regions and countries to engage in innovative informational and technological initiatives with a view to wealth creation and sustainable development meanwhile, digitization and new technologies such as artificial intelligence (AI) have posed new challenges to management, economics, business, accounting, information and technology scholars and professionals.

Both academia and the market have recognized AI and its informational role in strategic analysis as well as in financial and managerial processes and decisions (Hawley *et al.*, 1990; Jordão, 2022). In this context, Issa *et al.* (2023) state that AI is a crucial driving force behind the superior innovation and performance of Industry 4.0. According to Lv *et al.* (2023), AI's robust development is the world's most outstanding achievement.

AI has not only changed the decision-making process but also supported management accounting and controlling activity by providing the identification of key variables, the analysis of alternatives and the reduction of time and costs, thus expanding organizational results in accordance with observations of Shrestha *et al.* (2019) and Oppioli *et al.* (2023). Likewise, AI-based systems have made it possible to analyze a large volume of data or forecast asset prices in the financial and capital markets with great accuracy, leading to significant informational, economic and managerial innovation (Rundo *et al.*, 2019; Awan *et al.*, 2021; Srivastava *et al.*, 2023; Beniwal *et al.*, 2024).

On the other hand, the efficient markets hypothesis (EMH) suggests that it would be theoretically impossible for economic agents to forecast the prices of financial assets to obtain abnormal profits in the capital market. In his classic work, Fama (1970) defines an efficient market as one in which prices always entirely reflect the information available. Thus, the EMH entails that an investor could not obtain an abnormal return, i.e. one higher than the market average. However, several studies using AI algorithms to forecast financial asset prices have run counter to this hypothesis and reported on innovative, highly predictive decision-making models that do leverage abnormal returns, such as Qian and Rasheed (2007), Shynkevich *et al.* (2017), Cao *et al.* (2019), Srivastava *et al.* (2023), Shaban *et al.* (2024) and Hung *et al.* (2024). Therefore, a great debate on the topic is emerging, mainly because these authors have used different accounting, financial and managerial information as inputs for estimating their AI-based models, putting in the EMH.

In addition to the accounting information released by companies periodically and which influences their trading value in the market in a very significant way, as highlighted by Mishra and Mohanty (2014) and Hall (2018), information from technical analysis has also been used in the development of asset price prediction models (e.g. Patel *et al.*, 2015; Shynkevich *et al.*, 2017; Cao *et al.*, 2019). Despite being usually seen as antagonistic to fundamental analysis (especially considering the use of accounting information for forecasting), technical analysis can be understood as complementary to this end (Mndawe *et al.*, 2022). Authors such as Murphy (1999) emphasize that both approaches can and should be used to predict asset prices, addressing the same phenomenon but with different approaches.

Strategic intelligence and forecast studies have employed supervised learning algorithms that use technical indicators as input and training data in their models, including Patel *et al.* (2015), Akram and Imran (2017), Nabipour *et al.* (2020) and Singh and Khushi (2021). According to Patel *et al.* (2015), if this information was pre-processed efficiently and the appropriate algorithms were applied, more assertive and robust decisions could be made about predicting trends or price movements of financial assets. In this context, Mndawe *et al.*

(2022) highlight the potential of using such indicators in addition to information from fundamental analysis, such as financial statements. However, this issue, although very relevant, still needs to be investigated in-depth, as academia and the market still lack proposals for analysis and methodologies that carry out systematic EMH testing and verify whether AI algorithms can effectively produce results superior to the market average. More than this, there is a need for studies on a global scale that investigate the behavior of the leading indices of the largest stock exchanges in the world and the predictability capacity of AI-based models in pricing them appropriately – as done in this study because we have performed a study on the financial analysis and movement forecasting of the world's largest stock exchanges.

In recognizing this research gap, the study presented here focused on the following research questions (RQ) that support hypothesis testing and empirical investigation.

RQ1. Are the performance of AI algorithms superior to the market average?

RQ2. Do different AI algorithms perform differently in a statistically significant way when it comes to predicting future index price movement?

RQ3. Does the performance of AI-based algorithms improve when they have the flexibility to choose their parameters?

Therefore, this article aims to analyze the role and performance of different AI algorithms in forecasting future movements in the main indices of the world's largest stock exchanges. To this end, an empirical and experimental study was carried out using four AI-based models.

This study is relevant because of its potential contributions to a substantial segment of society (see Jordão *et al.*, 2014; Jordão and Novas, 2023). More precisely, its contributions are threefold. Economically and socially speaking not only are financial and capital markets important for the countries' development, but they also play a major role as a source of long-term capital to finance business activities, in line with Cavalcante *et al.* (2016).

Theoretically, this study is original in both the methodology used to train the AI models and the systematic testing of the EMH based on the main indices of the world's largest stock exchanges in the context of extensive automation and AI application in capital market analyses and decision-making processes. This approach has been incipient in the literature despite scholars' and professionals' long interest. Also, this study expands the body of knowledge by providing robust evidence on the role of AI in producing information for financial analysis and decision-making. As it covers dozens of indices worldwide, it reports on a thorough investigation of the EMH in different contexts, substantially expanding previous discussions. It brings theoretical, informational and managerial contributions (see Ding and Qin, 2020), enabling both (1) strategic and financial discussion of the subject in a very complex economic moment and (2) price and movement forecasting of the world's largest stock exchanges. It paves the way for further research and the extensive use of technical analysis to support machine learning and decision-making.

In practical, informational and managerial terms, innovation is relevant for developing decision-making tools that better equip (1) economic agents, market analysts and regulators to forecast financial movements and (2) investors to maximize their gains and minimize their risks (Ding and Qin, 2020; Cavdar and Aydin, 2020). From the accounting and finance-based perspectives, the study highlights the driving role that technical analysis information can have as inputs in AI-based models for forecasting and decision-making, besides those coming from fundamental analysis, such as indicators derived from financial statements, as stressed by Dumiter and Turcaș (2022) and Mndawe *et al.* (2022).

In expanding previous studies, this research originally had the AI algorithms deal with each index contextually (i.e. using the best parameters for each situation). In fact, choosing the best time window for calculating the technical indicators in each context also represents an essential strategic and informational contribution. Such flexibility proved to add value to the technical analysis of financial assets (specifically, the indices) and to be an essential technological contribution of this study, thus confirming the role of AI in financial and managerial decision-making.

This article is divided into six sections, including this Introduction. Section 2 provides the theoretical background and hypotheses. Section 3 describes the methodology. Sections 4 and 5 report and discuss the findings, respectively. Finally, Section 6 contains the research conclusions, followed by its references.

2. Theoretical background and hypotheses development

Integrating strategy, innovation and finance theory is not only desirable but recommendable to help decision-makers adopt the best strategies and make the best use of business resources to achieve competitive advantages and superior performances (Taleb *et al.*, 2023). Scholars have reported on the significant role of innovation and new technologies in converting resources into organizational results and value creation, as illustrated by Weng *et al.* (2017), Caputo *et al.* (2019) and Lv *et al.* (2023).

According to Oppioli *et al.* (2023), a relevant group of studies has used AI in predictions, forecasting and information classification for management decisions, including financial assets. Authors such as Qian and Rasheed (2007), Shynkevich *et al.* (2017), Cao *et al.* (2019), Suárez-Cetrulo *et al.* (2019), Clarke *et al.* (2020), Padhi and Padhy (2021), Sadorsky (2021) and Singh and Khushi (2021) have observed that innovative AI-based models have a high informational capacity to forecast the prices of financial assets and potentially lead to abnormal returns for investors. These authors used both information from technical and fundamental analysis in their forecasting models.

According to Murphy (1999), both approaches can be used to predict the value of an asset in the market. However, each of them looks at the value forecast from different perspectives. While the technical approach focuses on the effect of market movements, the fundamentalist approach focuses on the cause of such movements, aiming to understand the reasons for them to estimate the asset's intrinsic value. Dumiter and Turcaș (2022) elucidate that the latter is primarily based on information from financial statements and other economic considerations to support decision-making, while the former is primarily based on information on prices and transaction volumes of a given asset in a market.

Regardless of the type of analysis used and individual preferences in choosing them, the finance-based theory advocates that asset prices always reflect the information (such as economic conditions, political events, interest rates, disclosure of accounting information and other company's specific aspects) available for all economic agents in efficient markets. According to Fama's (1970) classic perspective, it would not be possible to obtain abnormal returns in the market as such pieces of information would already be priced. Based on this hypothesis, known as EMH, Seong and Nam (2021) point out that market efficiency can be classified as (1) weak, i.e. the information contained in past asset prices is already reflected in their current prices and cannot help one forecast future price movements, (2) semi-strong, i.e. asset prices fully reflect all publicly available information and (3) strong, i.e. asset prices fully reflect all information, including insider information, which prevents any investor from consistently beating the market returns.

The present study focuses on the weak form of the EMH. From a strategic and managerial perspective, financial asset prices would follow a pattern known as "random walk", whereby the price-forecasting accuracy would be 50% for a given asset (Qian and Rasheed, 2007; Asadi *et al.*, 2012; Neifar and Gharbi, 2023; Hung *et al.*, 2024). From an informational and decision-making perspective, this would be the same as flipping a coin, i.e. we would have a limited capacity for planning and decision-making. In contrast, researchers and professionals have developed models for anticipating the capital markets' movements, particularly, through advanced AI techniques, thus paving the way for new possibilities for strategic and financial management and decision-making. Several AI-based models have beaten expected returns, especially: Artificial Neural Networks (ANN), k-Nearest Neighbors (KNN), Naive Bayes (NB) and Random Forest (RF) (see Qian and Rasheed, 2007; Shynkevich *et al.*, 2017; Cao *et al.*, 2019; Almehmadi, 2021; Srivastava *et al.*, 2023; Beniwal *et al.*, 2024; Shaban *et al.*, 2024). Research Hypothesis 1 (H1) was formulated to account for this controversy and put it to empirical testing:

H1. The performance of AI algorithms that produce information aimed at forecasting the future movement of financial indices is statistically higher than the market average.

Even though AI is a prominently discussed topic in both literature and practice nowadays, its roots date back to the 1950s, in works such as Turing (2009) (originally published in 1950), McCarthy *et al.* (2006) and Rosenblatt (1958). Turing (2009) study, in particular, is considered one of the foundational milestones of AI, significantly influencing the subsequent development of the field. Notably, in this seminal work, Turing (2009) proposed the widely discussed Turing test, addressing both philosophical and practical questions about what it means to be intelligent.

Although AI algorithms (ANN, KNN, NB and RF) were developed through a machine learning approach, they have specific characteristics that affect how they learn and, consequently, how well they perform. The ANN is inspired by abstract models of how the human brain is believed to work (Beniwal *et al.*, 2024). This algorithm is related to the classical study of Rosenblatt (1958). These networks are composed of simple processing units, responsible for implementing mathematical functions that emulate the neuron functions. Such units can bind to several other connections, simulating synapses, which allows the ANN to deal with non-linear problems to solve complex problems (Mitchell, 1997).

The KNN is a non-parametric category forecasting algorithm that classifies observations according to patterns, including asset prices (Cavalcante *et al.*, 2016). This algorithm is based on Euclidean distance and uses the similarity of previous observations of the model's training data to classify new observations. The forecast essentially depends on the parameter "k" established by the analyst (Kubat, 2017).

The NB assumes that attributes are mutually independent. It is possible to obtain an optimal classifier provided that the actual and the estimated distributions agree on the most probable classes and not much training data are required to estimate the parameters for the classification (Rich, 2001). Applying this algorithm has the advantages of (1) not depending on normal error distributions and (2) dealing with discrete data, which makes it suitable for forecasting price direction/movement (Malagrino *et al.*, 2018).

Finally, the RF classifier is integrated and generates multiple decision trees to obtain better performance, using randomly selected subsets of samples and training variables (Khaidem *et al.*, 2016; Srivastava *et al.*, 2023). Hypothesis 2 (H2) was formulated to account for the different learning characteristics of the four AI algorithms:

H2. There are statistically significant differences between the different AI algorithms' performances when it comes to forecasting the future movement of index prices.

The application of said algorithms tends to be supervised, i.e. it depends on previously labelled input data for training purposes. Technical indicators have stood out as a basis for training to forecast financial assets (Patel *et al.*, 2015; Nabipour *et al.*, 2020; Ecer *et al.*, 2020; Seong and Nam, 2021). These indicators arising from the technical analysis can help complement other accounting information, as discussed by Dumiter and Turcaș (2022) and Mndawe *et al.* (2022). Importantly, technical analysis could only support assertive decisions in the capital market, if the market were not efficient in its weak form (Seong and Nam, 2021).

From a strategic and decision-making perspective, some researchers (e.g. Akram and Imran, 2017; Shynkevich *et al.*, 2017; Carta *et al.*, 2021) have provided some degree of flexibility to AI algorithms for choosing the best window for price forecasting. Furthermore, the algorithms themselves have some variable parameters, which can also be made more flexible to allow a better estimation of each model (Qian and Rasheed, 2007; Asadi *et al.*, 2012; Beniwal *et al.*, 2024). This led to research Hypothesis 3 (H3):

H3. The algorithms' flexibility to select estimation parameters in each context improves model performance.

In summary, the literature supports the idea that AI algorithms can be used to produce information to both forecast future movements of stock exchange indices and test the EMH. As it seems, their performances can be higher than the market's expected return, and this can be used for financial, strategic and organizational decision-making.

3. Research methodology

This study is descriptive, quantitative and explanatory (Cooper and Schindler, 2006). It particularly examines and describes the future movement of stock exchange indices by using statistical techniques and hypothesis testing. This type of investigation, i.e. using AI-based models, has been reported as adequate to understand the phenomenon (Qian and Rasheed, 2007; Shynkevich *et al.*, 2017; Cao *et al.*, 2019; Almehmadi, 2021; Srivastava *et al.*, 2023; Beniwal *et al.*, 2024; Hung *et al.*, 2024).

The analysis of the rigor of the study observed the criteria of Cepeda and Martin (2005), expanded by Massaro *et al.* (2016) and Jordão and Novas (2023), seeking to highlight the validity and reliability of the research. The first refers to the description of the study methods and procedures. Internal validity refers to the findings' richness, significance, coherence and relationship. External validity refers to the results' density, transferability and connection with the previous theory. The latter is associated with the study's clarity, care, design and characteristics – issues that were analyzed, measured and implemented throughout the investigation process. In this sense, the links between the research subjects were documented, and the criteria, forms and method of data collection and analysis were described, besides the connection with the previous theory, to help build new understandings on the subject.

To increase the validity and reliability of the research, this study starts describing and discussing a topic and a valuable gap in a little-explored area of research (Cf. Massaro *et al.*, 2016), in addition to establishing, through inferences, the recording, interpretation, analysis and description of the observed relationships between the phenomenon researched within the analyzed context. Thus, the research meets the need to observe in a more objective and in-depth way the role of AI in the decision-making process and the performance of different AI algorithms in predicting movements of the largest stock exchanges in the world, meeting practical and theories aspects mentioned by authors such as Rundo *et al.* (2019), Awan *et al.* (2021), Srivastava *et al.* (2023) and Beniwal *et al.* (2024). Furthermore, this study may increase the capacity for inferences and contribute to the construction of theories on the topic throughout the process – in line with the objectives of this research.

Before the fieldwork, the state of the art on the topic was mapped to ensure a high level of rigor, involving compilation, scrutiny, interrelationship and analysis of the main theoretical–empirical results available in international literature, following recommendations of Jordão and Novas (2017). So, information from the two largest databases of the world was considered: Scopus and Web of Science, representing the largest database of peer-reviewed literature in the fields of management, economics, business, accounting and information and computer science. To map the state of the art, we observe the guidelines of the Preferred

Reporting Items for Systematic Reviews and Meta-Analyses (see Page *et al.*, 2021a, 2021b) in line with Caputo *et al.* (2019). The articles were selected and retrieved from the leading global databases and portals such as Ebsco, Proquest, Emerald, B-one, Science Direct, OECD iLibrary and Scholar Google, among others. The bibliographical investigation took place between 7th November 2022 and 30th March 2023. Then, it was updated to April 2024, seeking to identify and select the papers that best adhere to the themes of this study.

This process took place in three stages. Intending to consider the most extended possible period and including the classics, the research covered the past 70 years, from 1955 to 2024, encompassing six themes grouped into three main variables: (1) artificial intelligence (AI) and new technologies, (2) information and decision-making, (3) the theory of finance and the EMH. This first stage involved the selection of articles whose title, abstract or keywords addressed the three main variables. It includes both contemporary and seminal papers such as Turing (2009), McCarthy *et al.* (2006) and Rosenblatt (1958). Next, other studies published in top-leading journals in the past 20 years were included if they addressed two of the three variables or were cited as references for understanding the problem. Finally, other studies from the past five years were considered as long as the title, abstract and keywords addressed two of these variables and helped understand the subject's state of the art and development.

All in all, a Boolean search was used simultaneously with different terms related to AI and capital markets. It resulted in 392 records, of which 268 articles were selected after refinements and exclusions. Aiming at perfect adherence, a sample was obtained with 135 articles that used similar AI algorithms, out of which 21 articles focused specifically on index forecasting based on technical indicators. Table 1 presents the leading technical indicators that have been regularly used in such analyses in the capital market (see Patel *et al.*, 2015; Nabipour *et al.*, 2020; Suárez-Cetrulo *et al.*, 2019; Padhi and Padhy, 2021; Sadorsky, 2021). Finally, to assure the validity, reliability and rigor of the process, the analysis of the selected studies and the inferences derived formed the basis of the theoretical support of the research, following the recommendations of Jordão *et al.* (2020).

Data collection focused on the world's largest stock exchanges in terms of market value. The main indices of each stock exchange were obtained considering the 2022 Investing website classification. Stock market indices from different countries are widely used in studies that address the analyzed phenomenon (see Asadi *et al.*, 2012; Chandrasekara *et al.*, 2019; Padhi and Padhy, 2021; Beniwal *et al.*, 2024). Padhi and Padhy (2021) emphasize the relevance of this strategy, not only increasing the quality of model testing and expanding the ability to generalize the results. Even more emphatically, Beniwal *et al.* (2024) highlight the importance of using stock market indices from different countries to obtain a holistic view of the problem. They argue that such indices reflect these different nations' economies and help prove the robustness of AI-based models.

Their tickers were collected on "Yahoo!Finance" website, an important source of data for AI-based forecasting of financial asset prices (see Padhi and Padhy, 2021; Awan *et al.*, 2021; Sadorsky, 2021; Srivastava *et al.*, 2023). This website was selected because it allows free public access and data to be collected automatically from modules and packages of different programming languages. In that regard, the tickers' information was crucial for collecting the daily quotations of each index through R programming language and functions in the package Quantitative Financial Modeling Framework (quantmod). This package has helped market agents test and develop trading models in the capital market (Ryan *et al.*, 2020).

Based on these criteria, 34 indices were selected to comprise the final sample. They are traded on the market and correspond to the following Exchange Trade Funds (ETFs): DAX, Euro Stoxx 50, S&P Merval, S&P/ASX 200, ATX, BEL 20, Ibovespa, S&P/TSX, S&P CLX IPSA, Shanghai (SSE), Shenzhen Component (SZSE), Hang Seng, KOSPI, IBEX 35, Down Jones, Nasdaq 100, Nasdaq, S&P 500, PSEI Composite, CAC 40, AEX, BSE Sensex, Nifty 50,

Indicator	Calculation formula	Description
Simple Moving Average (SMA)	$\frac{C_1+C_{t-1}+\ldots+C_{t-n+1}}{n}$	It calculates the simple average of prices on previous days
Weighted Moving Average (WMA)	$\frac{nC_t+(n-1)C_{t-1}+\ldots+C_{t-n+1}}{n+(n-1)+\ldots+1}$	It is the same as the SMA used to forecast short-term future value; however, prices are weighted with those of previous days asymmetrically
Moving Average Convergence/ Divergence (MACD)	$MACD_t = EMA(12)_t - EMA(26)_t$	It is constructed by subtracting the stock's long-term moving average from its short-term moving average
Momentum (MOM)	$C_t - C_{t-n+1}$	It shows stock market fluctuation
Momentum Stochastic K % (STCK)	$\frac{C_t - LL_{t\_t-n+1}}{HH_{t\_t-n+1}+LL_{t\_t-n+1}} x\, 100$	It compares the closing price with the price of previous days
Stochastic Momentum D % (STCD)	$\frac{K_t+K_{t-1}+\ldots+K_{t-n+1}}{n} x\, 100$	It signals the change in the stock's trend, showing that the stock is either overvalued or undervalued
Relative Strength Index (RSI)	$100 - \frac{100}{1+(\sum_{i=1}^{n-1} UP_{t-i}) \Big/ (\sum_{i=1}^{n-1} DW_{t-i})}$	It compares the magnitude of recent gains to recent losses to determine an asset's overbought and oversold conditions
William's Percent R (WPR)	$\frac{HH_{t\_t-n+1} - C_t}{HH_{t\_t-n+1} - LL_{t\_t-n+1}} x\, 100$	It determines an asset's overbought and oversold conditions
Commodity Chanel Index (CCI)	$\frac{M_t - SM_t}{0.015\, D_t}$	It calculates the difference in the stock price and its change concerning the change in the average price

Note(s): n stands for the number of observations; D_t stands for the day; C_t represents the adjusted closing price of a stock at time t; L_t and H_t represent the minimum price and the maximum price at time t, respectively; LL_{t_t-n+1} and HH_{t_t-n+1} represent the lowest and highest prices on the last n days, respectively; EMA equals the exponential moving average; M_t equals the sum of the highest, lowest and closing prices on a day; SM_t equals the simple moving average; UP_t and DW_t represent an upward price change and a downward price change at time t, respectively

Source(s): Own elaboration based on Patel *et al.* (2015) and Nabipour *et al.* (2020)

Table 1.
Technical indicator characteristics

IDX Composite, ISEQ Overall, TA 35, Nikkei 225, KLCI, S&P/BMV IPC, NZX 50, FTSE 100, SMI, Taiwan Weighted and BIST 100.

Data collection took place between 20th December 2022 and 15th February 2023, and data analysis took place between 14th March 2023 and 27th May 2023. The index quotes were collected daily from 2010 through 2019, covering 10 years. The start period was 2010, shortly after the Great Recession. The end period was 2019, the dawn of the COVID-19 pandemic, which drastically affected asset prices in several markets (see Kaczmarek *et al.*, 2021; Avelar *et al.*, 2022; Cardillo *et al.*, 2023; Maciel, 2023; Hung *et al.*, 2024). As the AI algorithms have market prices as input data, this could distort results and negatively affect their forecasting ability.

All four algorithms in this study (ANN, KNN, NB and RF) were used for classification purposes to forecast the future movement of indices, i.e. whether financial asset prices (their returns) would rise or fall on the following trading day based on past information (the technical indicators in Table 1). Beniwal *et al.* (2024) highlight that this type of prediction based on AI algorithms is widely used in several studies. In addition, authors such as Sadorsky (2021) and Padhi and Padhy (2021) confirm the importance of this type of analysis for testing models based on AI algorithms in the financial market.

From a decision-making standpoint, the techniques used to sample training, test and simulation data (as detailed below) ensured effective measurement of the algorithms' forecasting capacity, even though they referred to past data. For model training and testing, random k-fold cross-validation was used as recommended by Qian and Rasheed (2007) and Weng *et al.* (2017) as shown in Figure 1. Lantz (2019) and Nwanganga and Chapple (2020) highlight the importance of using this form of sampling to adequately evaluate the performance of models based on AI algorithms, as it allows the calculation of the model's average performance instead of occasional random performance. The authors add that this choice also demonstrates the strategy's consistency. This figure shows how sampling was performed for test training, where "G" is equivalent to a randomly selected group. The observations were randomly split into ten groups; in each training cycle, nine groups were selected for training and the remaining group was used for testing. Notably, the division between training and test data is essential for developing models based on the selected AI algorithms, as Burguer (2018) and Lantz (2019) described. Furthermore, the use of the proportion of training data (approximately 80%) concerning test data (approximately 20%) is in line with the proportions used in previous studies for financial market forecasting, such as those by Srivastava *et al.* (2023), Hung *et al.* (2024) and Shaban *et al.* (2024). Eventually, 10 cycles of training and testing were performed for each model as Qian and Rasheed (2007).

The mean of the accuracy metrics (Equation 1) and F1-Score (Equation 4), both calculated for the test data, were chosen to estimate model performance. Importantly, estimating the F1-Score requires the prior calculation of both Recall (Equation 2) and Precision (Equation 3). These are measures widely used in models developed based on AI algorithms with specific category prediction (classification) purposes (see Burguer, 2018; Nwanganga and Chapple, 2020), such as the phenomenon addressed in this research. Such measures have already been used to measure the performance of these models in predicting price movements in the financial market in previous studies such as Huang *et al.* (2008), Weng *et al.* (2017), Carta *et al.* (2021), Chandrasekara *et al.* (2019) and Hung *et al.* (2024). In all equations, TP stands for "true positives," TN for "true negatives," FP for "false positives" and FN for "false negatives."

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Training cycle	Groups									
1	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
2	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
3	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
4	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
5	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
6	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
7	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
8	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
9	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
10	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10

Training

Testing

Source(s): Own elaboration, based on research data

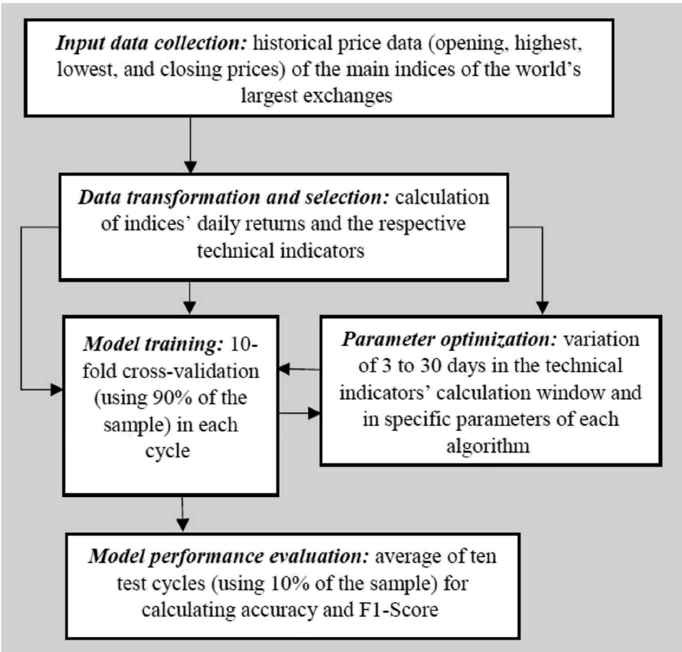
Figure 1.
Data sampling for training and testing

$$F1 - Score = \frac{2xPrecisionxRecall}{Precision + Recall} \quad (4)$$

Some parameters were adjusted for certain algorithms, namely: (1) for ANN, an architecture was chosen with 3 input neurons and 3 layers, (2) for KNN, a variation from 1 to 20 was admitted for parameter "k," so that the algorithm could select the best "k-nearest neighbors" for each index and (3) for RF, a variation from 3 to 30 estimated trees was admitted for the algorithm to select the number that would provide the best performance for each index, thus mitigating overfitting problems. Having the algorithm choose parameters by itself is an important choice as demonstrated by Qian and Rasheed (2007), Asadi *et al.* (2012), Carta *et al.* (2021) and Beniwal *et al.* (2024). Figure 2 shows how the models were trained and tested by drawing on Ferreira *et al.*'s (2021) basic flowchart for AI-based forecasting of financial asset prices.

All technical indicators were estimated for a period of 3–30 days, a similar approach as used by Akram and Imran (2017), Shynkevich *et al.* (2017) and Carta *et al.* (2021). This allowed each algorithm to select the best window for forecasting each index. However, unlike said authors, who established specific periods for the algorithms to select, the algorithms in the present study had decision-making autonomy; as such, they could apply any of the 28 days available.

The findings were analyzed through descriptive statistics (used to describe the model results), the Shapiro–Wilk test (used to analyze the normality of distribution) and Student's *t*-test and Mann–Whitney test (both used to assess the significance of differences between the AI algorithms' performances and between these performances and the market's). In this context, market performance refers to the random walk of its prices, as posited in the weak



Source(s): Own elaboration, based on research data

Figure 2.
Flowchart for using AI algorithms

EMH. This approach aims to compare the performance of both the models generated by the different algorithms and those about the random walk, as well as evaluate statistically the difference in performance, enabling statistical inference, in a similar way to that previously used by Qian and Rasheed (2007), Asadi *et al.* (2012), Suárez-Cetrulo *et al.* (2019) and Hung *et al.* (2024). Finally, Spearman's correlation coefficient was used to assess how the time window used to estimate each indicator relates to both the algorithms' performance and their different parameter values.

The significance level was set at 5%. All data were processed and analyzed using R with the following packages: Discrete Goodness-of-Fit Tests (dgof), quantmod, Functions for Classification (class), Breiman and Cutler's Random Forests for Classification and Regression (randomForest), A Grammar of Data Manipulation (dplyr) and eXtensible Time Series (xts).

Deduction and induction were used alternately throughout the analysis process, with the former prevailing over the latter (Cf. Jordão *et al.*, 2014; Jordão *et al.*, 2020). To overcome research limitations and increase reliability, internal validity and consistency, an attempt was made to triangulate information with other sources of evidence (Jick, 1979). Thus, whenever possible, the information obtained through one group as shown in Figure 1 was confronted with that of others to confirm or refute it (internal validity). Finally, external triangulation sought to confirm, complement and/or contradict findings, confronting them with the literature (external validity) and eventually producing new bodies of knowledge, as recommended by Jordão *et al.* (2022). For parsimony reasons, triangulation results are provided in the following sections along with the information that they either corroborate or refute. The procedures suggested by George and Bennett (2005) were followed in an attempt to include all possible levels of research and eventually provide relevant, consistent, theoretically grounded, context-bounded information.

4. Results

This section reports on the performance of the AI-based models considering two different performance metrics: accuracy and F1-Score.

Table 2 provides the descriptive statistics of accuracy and F1-Score for each AI-based model. Box plots for accuracy (Figure 3) and F1-Score (Figure 4) are provided and so is the relationship between the number of days (N) used to calculate the indicators and their performance as measured through the accuracy of the metric (Figure 5) and F1-Score (Figure 6).

Table 2 reveals that the AI-based models' average accuracy was approximately 56%. The highest level of accuracy was obtained by the RF algorithm (72.74%) for forecasting the S&P CLX IPSA. The ANN and the NB also had their highest accuracy for this index. The lowest accuracy was obtained by the NB (50.85%) for forecasting the Ibovespa. The ANN, the KNN and the RF had the lowest performance for forecasting the Euro Stoxx 50, the S&P/BMV IPC and the PSEI Composite, respectively.

The four algorithms showed different average accuracy values for forecasting the indices, but all of them achieved statistically better results (<1.0%) than the market average (random walk – RW). This difference in performance is evident in both Figures 3 and 4, in which the average performance is near 50.0% (according to EMH). All the measures presented on both box plots for RW are below the IA algorithms statistics. This was evidenced by the Mann–Whitney test, which was selected because none of the accuracy data distributions were normal, as indicated by the Shapiro–Wilk test. This result corroborates H1, indicating that AI algorithms can provide returns higher than the market average, which is consistent with Shynkevich *et al.* (2017), Ding and Qin's (2020), Srivastava *et al.* (2023), Shaban *et al.* (2024) and Hung *et al.* (2024).

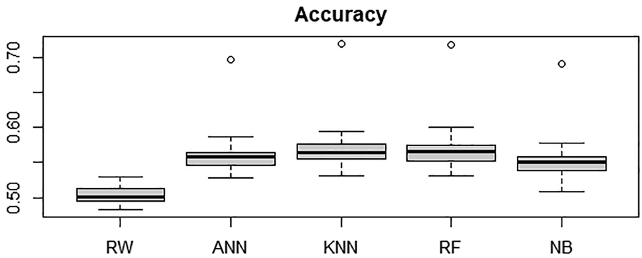
Table 2.
Descriptive statistics of performance

Performance metric	Accuracy				F1-score			
Indices/Algorithms	ANN	KNN	RF	NB	ANN	KNN	RF	NB
DAX	0.5433	0.5548	0.5527	0.5417	0.6842	0.6474	0.6438	0.6836
Euro Stoxx 50	0.5315	0.5309	0.5316	0.5117	0.6784	0.5510	0.5841	0.5421
S&P Merval	0.5622	0.5796	0.5821	0.5500	0.6777	0.6667	0.6693	0.6103
S&P/ASX 200	0.5667	0.5698	0.5748	0.5778	0.6439	0.6536	0.6744	0.6829
ATX	0.5472	0.5584	0.5652	0.5584	0.6543	0.6238	0.6185	0.6232
BEL 20	0.5541	0.5942	0.6004	0.5629	0.6789	0.6357	0.6446	0.6400
Bovespa	0.5430	0.5430	0.5383	0.5427	0.6173	0.5903	0.5908	0.6087
S&P/TSX	0.5711	0.5762	0.5780	0.5708	0.7078	0.6532	0.6923	0.7151
S&P CLX IPSA	0.6964	0.7196	0.7173	0.6904	0.5467	0.5973	0.5980	0.5503
Shanghai	0.5622	0.5414	0.5470	0.5215	0.5475	0.6140	0.6256	0.6169
Shenzhen	0.5578	0.5780	0.5753	0.5514	0.3953	0.5228	0.5183	0.5407
Hang Seng	0.5700	0.5600	0.5600	0.5381	0.6475	0.5769	0.5869	0.6181
KOSPI	0.5491	0.5701	0.5673	0.5505	0.5624	0.6541	0.6642	0.6343
IBEX 35	0.5573	0.5455	0.5474	0.5440	0.6177	0.6372	0.6371	0.5815
Down Jones	0.5698	0.5747	0.5724	0.5281	0.6746	0.6814	0.6802	0.6368
Nasdaq 100	0.5543	0.5607	0.5711	0.5578	0.7050	0.6875	0.6917	0.7161
Nasdaq	0.5636	0.5633	0.5671	0.5558	0.6826	0.7004	0.6774	0.7145
S&P 500	0.5578	0.5641	0.5705	0.5080	0.7153	0.6688	0.6742	0.6019
PSEI Composite	0.5285	0.5504	0.5504	0.5230	0.6337	0.6496	0.6472	0.5107
CAC 40	0.5300	0.5404	0.5423	0.5230	0.6592	0.6139	0.6086	0.5324
AEX	0.5645	0.5782	0.5723	0.5776	0.7049	0.6728	0.6677	0.6796
BSE Sensex	0.5650	0.5833	0.5609	0.5489	0.6320	0.6471	0.6335	0.5743
Nifty 50	0.5542	0.5648	0.5648	0.5556	0.6408	0.6426	0.6453	0.5738
IDX Composite	0.5638	0.5784	0.5784	0.5538	0.6479	0.6655	0.6655	0.6853
ISEQ Overall	0.5400	0.5482	0.5503	0.5762	0.5287	0.6157	0.6196	0.6028
TA 35	0.5493	0.5584	0.5654	0.5442	0.6952	0.6358	0.6437	0.6080
Nikkei 225	0.5635	0.5643	0.5667	0.5385	0.7095	0.6554	0.6540	0.5985
KLCI	0.5302	0.5563	0.5540	0.5304	0.5266	0.6087	0.6074	0.5379
S&P/BMV IPC	0.5579	0.5598	0.5601	0.5406	0.4926	0.5895	0.5941	0.5606
NZX 50	0.5865	0.5916	0.5893	0.5616	0.7184	0.7152	0.7141	0.6500
FTSE 100	0.5375	0.5333	0.5375	0.5309	0.6442	0.6070	0.6186	0.6238
SMI	0.5466	0.5645	0.5687	0.5600	0.6758	0.6567	0.6554	0.6545
Taiwan Weighted	0.5687	0.5569	0.5569	0.5225	0.7032	0.6606	0.6569	0.5826
BIST 100	0.5599	0.5751	0.5769	0.5528	0.6499	0.6258	0.6292	0.5785
Descriptive statistics								
Mean	0.5589	0.5673	0.5680	0.5500	0.6382	0.6360	0.6392	0.6138
Median	0.5578	0.5637	0.5660	0.5495	0.6521	0.6448	0.6442	0.6095
Standard deviation	0.0278	0.0311	0.0304	0.0307	0.0737	0.0407	0.0392	0.0556
Coefficient of variation	0.0498	0.0547	0.0535	0.0558	0.1155	0.0640	0.0614	0.0906
Minimum	0.5285	0.5309	0.5316	0.5080	0.3953	0.5228	0.5183	0.5107
Maximum	0.6964	0.7196	0.7173	0.6904	0.7184	0.7152	0.7141	0.7161
Shapiro–Wilk	0.66**	0.91**	0.87**	0.59**	0.92*	0.9400	0.9900	0.9600

Source(s): Own elaboration, based on research data

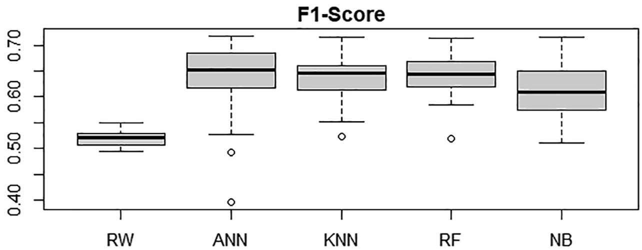
The RF results were statistically better (<5.0%) than those obtained through all other AI algorithms. However, the NB accuracy results were statistically lower (<5.0%) than the KNN accuracy results, according to the non-parametric test. This difference in IA algorithms' accuracy is shown in Figure 3. This corroborates H2, suggesting that the specific characteristics of each learning algorithm affect its performance for forecasting financial ratios. This, in turn, corroborates Qian and Rasheed (2007) and Chung and Shin (2020).

The analyses of the possible correlation between accuracy and the number of days used to calculate the technical indicators did not show statistically significant coefficients. This corroborates H3, i.e. the greater flexibility provided to the algorithms to estimate their parameters improved their performance, confirming the procedures of Akram and Imran



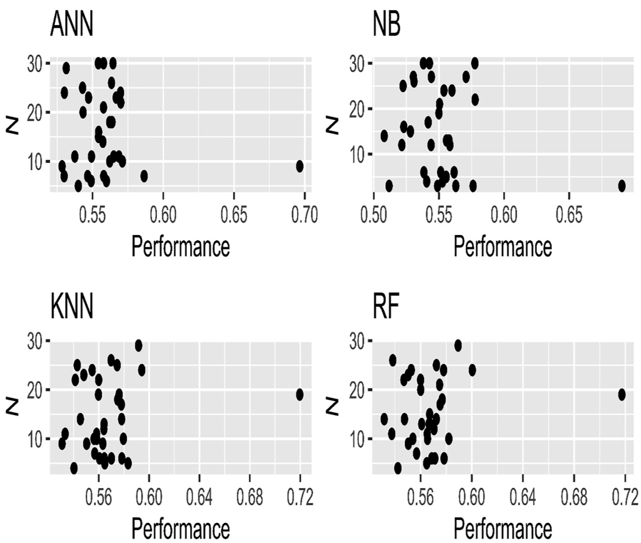
Source(s): Own elaboration, based on research data

Figure 3. Accuracy box plot of the models



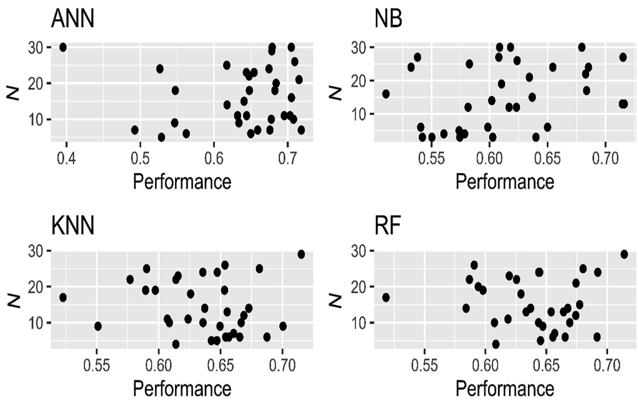
Source(s): Own elaboration, based on research data

Figure 4. F1-score box plot of the models



Source(s): Own elaboration, based on research data

Figure 5. Relationship between the N and performance measured through the accuracy of the metric



Source(s): Own elaboration, based on research data

Figure 6.
Relationship between the N and performance measured through the F1-Score

(2017), Shynkevich *et al.* (2017) and Carta *et al.* (2021). The non-significant correlation shows that the best parameter depends on each context, with the flexibility given to the algorithms allowing them to make the best choices. The scatter plots between accuracy and window for estimating technical indicators (N) in Figure 5 show this information. There is no visible pattern of data, indicating that the best fitting depends on the context.

As shown in Table 2, the Shapiro–Wilk test indicated that only the ANN distribution was not normal for the F1-Score. Consequently, the Student's *t*-test was relevant for comparisons that did not involve such an algorithm.

According to Table 2, the average F1-Score was approximately 63% for all models. The highest performance was obtained by the RF (72.70%) for forecasting the NZX 50. This index also featured the best performance for the KNN. The best NB performance was for the Nasdaq (72.45%). The lowest F1-Score was obtained for the ANN (45.89%) in forecasting the Shenzhen Component (SZSE). This index also experienced the worst forecasting performance among all other algorithms.

Again, all AI algorithms obtained statistically higher results (<1.0%) than the market, as evidenced by the Student's *t*-test and Mann–Whitney test. This corroborates H1, ratifying the results of previous studies on the phenomenon, as Cao *et al.* (2019), Chun and Ko (2020), Padhi and Padhy (2021) and Sadorsky (2021).

The RF forecasting performances were statistically better (<5.0%) than those of all other AI algorithms. The superiority of the RF in both performance metrics demonstrated its good performance in forecasting the price movements of future assets, as anticipated by Almehmadi (2021). As there were no significant differences between the other AI algorithms, the superiority of RF confirms H2, as it shows that the choice of algorithm affects performance when it comes to forecasting future movements of asset prices. This difference among IA algorithms' F1-Score is also clear in Figure 4. This is consistent with Sadorsky (2021), Carta *et al.* (2021) and Qian and Rasheed (2007).

Again, the analyses of associations between the number of days used to calculate the technical indicators and performance, now measured by the F1-Score, did not result in statistically significant correlation coefficients as shown in Figure 6. These scatter plots between the F1-score and N also show this information. As in the cited case of accuracy, there is not a visible pattern of data. This is consistent with Akram and Imran (2017), Shynkevich *et al.* (2017) and Carta *et al.* (2021), while also reinforcing the importance of incorporating flexibility and decision-making autonomy into the AI algorithms to improve their forecasting performance. Therefore, this corroborates H3.

5. Discussion of the results and research implications

The findings point to several considerations on the application of AI algorithms to account for the future return of the main indices of the world's largest stock exchanges based on technical indicators. First, all AI-based models performed better than the market expectations, expanding the users' informational capacity and supporting financial, strategic and organizational decisions. This confirms H1 and corroborates previous studies such as Shynkevich *et al.* (2017), Cao *et al.* (2019), Ding and Qin (2020) and Chun and Ko (2020). Thus, it seems that not all past information (the basis for calculating technical indicators) has been considered by the markets around the world – which runs counter to expectations based on Fama's (1970, 1991) weak EMH. This finding is quite relevant as such a hypothesis has been systematically tested in dozens of markets and using different AI algorithms. In all cases, the algorithms performed better than expected based on the random walk derived from the weak EMH. Thus, this study not only adds robust evidence on the need to deeply discuss this hypothesis in the context of widespread automation and AI application but also points to the need to expand the financial and strategic discussion on the subject.

Some of the AI algorithms were found to perform differently from each other, especially regarding the accuracy metric. This difference in performance corroborates H2, which is supported by studies such as Chung and Shin (2020), Carta *et al.* (2021) and Qian and Rasheed (2007). Notably, the RF models showed better results than those based on other AI algorithms, regardless of the performance metric adopted. The RF was superior in forecasting indices when compared to reports in previous studies, such as Carta *et al.* (2021). However, these authors substantially limited variation in the number of trees generated by the algorithm, which may have significantly reduced its forecasting performance. Consequently, the AI algorithms' decision-making freedom and autonomy played a relevant role in forecasting the index prices of the 34 world's stock exchanges analyzed.

Among the other algorithms, the NB presented lower performances compared to the KNN when accuracy was considered as a performance metric. This can be explained by authors such as Murphy (1999), who states that some technical indicators would not be as suitable for forecasting market indices as for forecasting individual stocks. This phenomenon may have been more evident for the NB, widely used for forecasting individual stocks, as observed by Patel *et al.* (2015) and Akram and Imran (2017). Thus, it is apparent that the choice of AI algorithm for forecasting assets seems to be significantly associated with its performance.

AI performance was influenced by the flexibility provided to the algorithms for estimating the parameters themselves and the time window for calculating the technical indicators. This finding corroborated H3, a hypothesis based on studies such as Akram and Imran (2017) and Shynkevich *et al.* (2017). However, unlike such studies, the present study gave the algorithm broader flexibility to determine the time window and some context-bound parameters. The superiority of the RF in forecasting asset movements against that reported by Carta *et al.* (2021), for example, can be explained by the latter authors' lower flexibility in decision tree generation. Thus, having each algorithm adapt to each context should be an important decision when it comes to forecasting the phenomenon.

The present study contributes to the discussion of the use of new technology-supported technical analyses, such as the use of AI algorithms. Despite its use since the 19th century, as evidenced by Murphy (1999), the ability of AI algorithms to analyze patterns allows much more contextual analyses for indicator application, particularly, regarding the time window of historical data used for calculations. The present findings show that such estimates vary contextually to enable the best performance. These results bring profound and significant implications for accounting, finance-based and management theory and practice by confirming and expanding the driving role of AI algorithms in improving performance and expanding their potential for creating organizational wealth for shareholders and other stakeholders. Previous studies have already focused on this aspect, but more restrictively, such as Patel *et al.* (2015), Nabipour *et al.* (2020) and Ecer *et al.* (2020). So, this also reinforces the role of AI-based models in adding value to technical analysis.

These findings gain special significance for the field of accounting and finance, considering that authors such as Moll and Yigitbasioglu (2019) consider it urgently necessary to investigate the implications and impact of new technologies such as AI on accounting in the digital era, seeking to understand how these technologies can affect the work and decision-making of finance, accounting and management professionals. Furthermore, our findings align with the observations of Begkos *et al.* (2023) who highlight the implications of new technologies, datafication and digital transformation on accounting and management control. The authors highlight that these processes are revolutionizing economic and social reality as well as accounting and financial practices, at the same time as they create inter-organizational tensions and a need for a greater understanding of datafication practices, new technologies and digital infrastructures on decision-making.

The results of the study also highlight the importance of technical analysis information (such as technical indicators) as inputs in AI-based models for forecasting asset prices. Such information can be used by investors, managerial accountants, controllers, managers, market analysts and other economic agents in addition to those from fundamental analysis, such as indicators from financial statements. In this sense, our findings reinforce and shed light on the results of Dumiter and Turcaș (2022), Mndawe *et al.* (2022) and Oppioli *et al.* (2023). Our findings also empirically confirm Shirur's (2013) statement, which emphasizes that aspects of both fundamentalist and technical approaches are essential pillars of modern corporate finance.

Given the above, this study brings a series of contributions and implications from different informational, technological, economic, accounting and managerial perspectives, in line with the observations of Jordão (2022), based on the epistemological reasoning of Gupta *et al.* (2019). First, it provides evidence that AI algorithms can be used to forecast the movement of indices in the world's main capital markets. They can be used to produce information that can improve resource allocation in such markets, which is essential for long-term corporate financing. Also, the algorithms' superior performance compared to the market average can be widely exploited by economic agents, such as investors and analysts. The present flexibility approach to train algorithms with technical indicators can be extensively applied not only to indices but also to other financial assets, improving the performance obtained from technical analysis.

From the economic and social perspectives, the findings support the use of AI algorithms as an innovative information technology by various economic agents, who can improve resource allocation in the capital markets as well as boost entrepreneurship and economic growth in countries, expanding on the observations of Lv *et al.* (2023). These results also corroborate and expand on Rundo *et al.* (2019) and Awan *et al.* (2021) findings, who argue that new technologies such as AI have made it possible to analyze a large volume of data or forecast asset prices in the financial and capital markets with great accuracy, producing significant informational and managerial innovation.

From a theoretical perspective, the originality of this study resides especially in its systematic testing of the EMH through the main indices of the world's largest stock exchanges. By having a global scale and employing four AI-based models simultaneously, this study points to the need to discuss the EMH deeply in the context of broad automation and AI applications. This corroborates Shrestha *et al.* (2019), for whom AI has not only promoted changes in the decision-making process but also supported the identification of key variables, the analysis of alternatives and the reduction of time and costs, thereby expanding organizational results. As such, this study expands the body of knowledge by presenting robust evidence on the role of AI in financial analysis, decision-making and movement forecasting of the world's largest stock exchanges. This in turn integrates finance theory with new visions and possibilities brought about by new informational and management technologies. As theoretical, strategic and managerial contributions, this enables the discussion of the EMH in a complex economic reality, one in which the use of automation and AI has been expanded.

The original methodology used to train the models allowed the different AI algorithms to determine parameters and generate information flexibly to achieve the best contextual performance. Therefore, this study paves the way for the extensive use of machine learning-supported technical analysis, thereby expanding Patel *et al.* (2015), Akram and Imran (2017), Nabipour *et al.* (2020) and Singh and Khushi (2021). The present findings confirm that innovative models employing AI algorithms have had not only good forecasting power to provide strategic information on financial asset prices but also high decision-making performance. In addition, they show that incorporating flexibility into AI algorithms for them to determine their own parameters and the time window of their technical indicators leads to contextually adjusted models that can provide better performance.

These findings reinforce theoretical, informational and managerial contributions (see Ding and Qin, 2020), enabling both 1) strategic and financial discussion of the subject in a very complex economic moment and 2) price and movement forecasting of the world's largest stock exchanges. This paves the way for further research and for the extensive use of technical analysis as a support for machine learning and decision-making. These findings are also relevant when considering Jordão's (2022) argument that analyzing how information and technology relate can boost business results, while also supporting organizations to create alternatives and strategies that help them overcome moments of crisis – such as the current one in the aftermath of the COVID-19 pandemic and amidst the Russia–Ukraine war.

All this reinforces the theoretical and practical role of AI as a technological innovation capable of adding value to technical analysis. These contributions are deeper in a context of informational, cognitive and management paradigm rupture. In fact, how organizations manage their information and knowledge and extract intellectual capital from them has been a decisive factor in their competitiveness and in their ability to produce innovation, wealth and business performance (see Jordão and Novas, 2017; Jordão *et al.*, 2020; Durst and Leyer, 2022; Jordão and Novas, 2023; Lv *et al.*, 2023). This is a cornerstone for a sustainable society, one with technology at the service of people and welfare.

Finally, the systematically higher performance of AI-based models (compared to the market average) resulting from their flexibility to determine their parameters and the time window can be widely explored informationally and managerially in the decisions made by investors, managers, market analysts and other economic agents. This emphasizes the role of such algorithms in improving resource allocation in the financial and capital markets.

Therefore, this study makes a series of contributions to research on the use of AI algorithms to forecast the movement of financial asset indices in capital markets worldwide: (1) it obtained robust evidence of the AI algorithms' usefulness and relevance for forecasting price movements and obtaining abnormal returns on the world's main stock exchanges, (2) it highlighted the importance of providing the algorithms with flexibility to determine their parameters and thus improve forecasting performance and (3) it showed that technical indicators can help in value-adding decisions if they are combined with AI techniques.

6. Conclusions, limitations and future research recommendations

This study aimed to analyze the performance of different AI algorithms for forecasting the movements of the main indices in the world's largest stock exchanges. To this end, daily data of 34 indices from 2010 through 2019 were collected, and their movements were estimated using four major AI algorithms, namely, ANN, KNN, NB and RF. These algorithms were trained with nine technical indicators widely used in the technical analysis of financial assets.

The results pointed out that such algorithms provided returns above the market average. This runs counter to the weak EMH and suggests that it is possible to exploit the inefficiencies of different capital markets around the world by using AI algorithms. The performance of some algorithms varied according to the performance metric used. While the RF performed better than the others regardless of the metrics used, the NB presented the worst performance when considering accuracy. Besides, allowing the algorithm to choose the number of days used for calculating technical indicators and their essential parameters proved to be a decisive choice, especially when they are not fully clear to analysts.

No research is without limitations. In this sense, it is recognized that the selected technical indicators are only a subset of the available technical analysis tools. The data analysis was also limited until 2019 so the results would not be distorted. The findings do not consider the recent crises that affected stock market prices worldwide: the COVID-19 pandemic and the Russian invasion of Ukraine. Moreover, besides the stock market indices reflecting the idiosyncrasies of the different nations, the estimated models did not explicitly consider different features to contextualize the results, such as classifying them in developed or developing countries, among other features. These limitations are beyond the scope of the research and do not invalidate the results or their interpretation, as the strategy used was robust enough to analyze them in the context studied. Still, they serve to understand better the scope and extent of the findings and as a means of verifying new avenues of investigation. In this sense, we can suggest future studies on a comparative basis. Whether testing momentum before and during the pandemic, evaluating global or local contexts or employing additional metrics and models.

It is also important to mention that we use model performance measures focused on classification capacity. However, we do not measure the financial return an investor could obtain using models for forecasting in comparison to a random buy-sell strategy (random walk) in studied markets. Last, our AI algorithms do not explicitly deal with time series. We can advise using algorithms as the long short-term memory (LSTM) network to overcome this limitation in future research. In recognizing these limitations, new studies should use further input data (such as the evolution of historical prices) for algorithm training. Besides, whenever feasible, an individual or group analysis of technical indicators should be made to understand their effects on the algorithms' performance. Natural language processing should also be used for sentiment analysis to improve the models with a different form of training. Finally, individualized values of the main stocks of each capital market, to the detriment of indices, can be used for comparative purposes to advance the topic.

In sum, hypothesis test results allowed us to answer the three RQ, showing that (1) all AI-based models performed better than the market average, (2) the RF models yielded better results than those based on other AI algorithms regardless of the performance metric adopted and the (3) different numbers of days used to estimate the technical indicators enabled improved decision-making models. Our study provides theoretical, informational and managerial contributions, expanding the informational and decision-making capacity of investors, managerial accountants, controllers, managers, market analysts and other economic agents.

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About the authors

Ewerton Alex Avelar is Assistant Professor and researcher at the Accounting and Finance Department at the Federal University of Minas Gerais (Brazil), besides serving as the Director of the BBA in Accounting at this university. Dr. Avelar has served as Associate Editor and Co-Editor for The Bottom Line (Emerald). He holds a Ph.D. in Management and Finance from this university with dozens of papers (100+), including scientific and technological articles published in Brazil and abroad. His research interests are management accounting, finance, intellectual capital, artificial intelligence and management accounting and control systems.

Ricardo Vinícius Dias Jordão is Full Professor of Finance, Accounting and Law, Executive (CEO) and internationally renowned speaker. He holds a European Ph.D. with distinction (Magna Cum Laude) at the University of Évora (Portugal) with a sandwich period at the Swiss Management Center (Switzerland). Dr. Jordão is the Director of the Academic Board of the Latin American Council of Management Schools (CLADEA), having chaired and coordinated many activities for international organizations such as the "CLADEA BALAS HARVARD Case Consortium" in partnership with Harvard University. He is sitting in several editorial roles and has served in several top-leading journals in key positions (e.g. Editor-in-Chief of The Bottom Line, Emerald). Dr. Jordão has been teaching and/or researching at prestigious top-ranked universities around the world (e.g., USP, UFMG, UFOP, PUC-Minas, IBMEC, Dom Cabral Foundation, CEFAGE-UE, Swiss Management Center and SKEMA

Business School) with dozens of papers (100+), including scientific and technological articles, books and book chapters published in Brazil and abroad. Among several awards and distinctions, he was honored by the Marquis Who is Who in the world for his prominence and remarkable influence. Casa America Latina in Portugal has laureated his Ph.D. thesis as the best in Ibero-America in all economics, management, and business fields. His research interests include finance, accounting, management, law, economics and business. Ricardo Vinícius Dias Jordão is the corresponding author and can be contacted at: jordaorvd@gmail.com