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Modeling the Financial and Psychological Dynamics in the Healthcare Sector Using the Lazy Learning Algorithms

Sağlık Sektöründeki Finansal ve Psikolojik Dinamiklerin Tembel Öğrenme Algoritmaları ile Modellenmesi

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ABSTRACT

The healthcare sector is highly sensitive to financial fluctuations and psychological factors. Notably, during crises like the COVID-19 pandemic, decision-makers in this sector must consider macroeconomic data and the crises' effects on financial markets. This study aims to assess the impact of psychological factors and market actors' expectations on the healthcare sector. In analyzing the determinants of the MSCI World Healthcare Index, psychologically based economic indicators, the MSCI Volatility Index, and the Consumer Confidence Index were utilized as independent variables. The impact of these psychological factors was modeled using the IBk, K-Star, and LWL algorithms from the lazy learning models. The analysis utilized daily data spanning from January 1, 2020, to September 30, 2024, a period marked by heightened uncertainty due to the COVID-19 pandemic. The decrease in the MSCI Healthcare Index was predicted with 95% accuracy using LWL, 86% with K-Star, and 68% with IBk. The increase was predicted with 23% accuracy using LWL, 35% with K-Star, and 50% with IBk. Performance and error analysis determined that the K-Star algorithm is the most effective method for evaluating the effects of psychological factors in the healthcare sector. The algorithms demonstrated low accuracy in the uptrend class but high accuracy in the downtrend class. This indicates that while the models are effective in predicting adverse market conditions, such as crises and crashes, their ability to accurately forecast positive market movements remains limited. The findings of the study emphasize the critical importance of considering psychological factors, such as volatility and the consumer confidence index, in making effective decisions in dynamic and crisis-sensitive markets, particularly in sectors like healthcare.

KEYWORDS

Financial markets, MSCI world healthcare index, Volatility, Consumer confidence index, Lazy learning

ÖZET

Sağlık sektörü, finansal dalgalanmalara ve psikolojik faktörlere karşı hassas bir yapıdadır. Özellikle COVID-19 salgını gibi kriz dönemlerinde bu sektördeki karar vericiler makroekonomik verileri ve krizlerin finansal piyasalar üzerindeki etkilerini göz önünde bulundurmalıdır. Bu doğrultuda, çalışmada, psikolojik faktörler ve piyasa aktörlerinin beklentilerinin sağlık sektörü üzerindeki etkilerinin değerlendirilmesi amaçlanmıştır. MSCI Dünya Sağlık Endeksi'nin belirleyici unsurlarının analizinde, psikolojik temelli ekonomik göstergeler olan MSCI Volatilite Endeksi ve Tüketici Güven Endeksi bağımsız değişkenler olarak kullanılmıştır. Bu psikolojik faktörlerin MSCI Sağlık Endeksi üzerindeki etkisi tembel öğrenme modellerinden IBk, K-Star ve LWL algoritmaları kullanılarak modellenmiştir. Analizde, COVID-19 salgını nedeniyle belirsizliğin arttığı 1 Ocak 2020 - 30 Eylül 2024 tarihleri arasındaki günlük veriler kullanılmıştır. Analiz bulgularına göre MSCI Sağlık bakım endeksinin düşüşü LWL algoritmasıyla %95, K-Star algoritmasıyla %86 ve IBk algoritmasıyla %68 doğruluk oranı ile tahminlenirken; yükselişi LWL algoritmasıyla %23, K-Star algoritmasıyla %35 ve IBk algoritmasıyla %50 doğruluk oranı ile tahminlenmektedir. Performans ve hata bulgularına göre, K-Star algoritmasının psikolojik faktörlerin sağlık sektöründeki etkilerini değerlendirmede en etkili yöntem olduğu belirlenmiştir. Algoritmaların yükseliş sınıfındaki doğruluk oranı düşük, düşüş sınıfındaki doğruluk oranı ise yüksek bulunmuştur. Bu durum, modellerin olumsuz piyasa koşullarını, krizleri ve çöküşleri doğru şekilde öngörebildiğini; ancak olumlu piyasa hareketlerini öngörmede daha düşük doğruluk oranıyla sınırlı kaldığını göstermektedir. Çalışmanın bulguları, sağlık sektörü gibi dinamik ve krizlere duyarlı piyasalarda doğru kararlar alabilmek için volatilite ve tüketici

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güven endeksi gibi psikolojik faktörlerin de göz önünde bulundurulmasının oldukça önemli olduğunu göstermektedir.

ANAHTAR KELİMELER

Finansal piyasalar, MSCI dünya sağlık bakım endeksi, Volatilite, Tüketici güven endeksi, Tembel öğrenme

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INTRODUCTION

The increasing integration of financial markets due to globalization has led to the incorporation of national financial markets into the global system, resulting in more complex dynamics. This has resulted in the dissolution of the unbreachable barriers between financial markets, causing local markets to be more influenced by global effects. During crises, effectively managing the responses of the healthcare market to fluctuations becomes crucial (Choi & Jung, 2022). Many healthcare organizations have been forced to make significant strategic decisions due to the impacts of fluctuations; these decisions often lead to solutions such as changes in service prices or the cessation of unprofitable services (Dranove et al., 2013). At this point, it is essential for healthcare sector actors to be aware of the need to respond more quickly and effectively to market fluctuations.

The increase in financial fluctuations within the healthcare sector has gained more attention, particularly with the exacerbation of sectoral impacts during crises. The Covid-19 pandemic deeply affected the globalization and integration processes within the healthcare sector, creating new risks for investors due to demand fluctuations in healthcare services, supply chain issues, and rapid changes in government policies (IMF, 2020; Uçakkuş & Arslan Çilhoroz, 2022; Akbal, 2020). This crisis has shown that healthcare decision-makers must consider not only macroeconomic data related to health but also the financial market impacts of health crises.

The Lucas Critique emphasizes that basing economic analyses and forecasts solely on historical data can be misleading, as the expectations of economic decision-makers and market participants can change over time (Lucas, 1976; Şıklar, 1992). The COVID-19 pandemic has concretely demonstrated this situation, initiating a period where expectations and risks in the healthcare sector evolved rapidly. Therefore, it is crucial to examine whether, in financial analyses within the healthcare sector, not only macroeconomic indicators but also psychological factors and the expectations of market actors play a decisive role. In this context, the study aims to assess the impact of both macroeconomic indicators and psychological factors, along with market participants' expectations, in the healthcare sector. While analyzing the key elements of the MSCI World Healthcare Index, economic indicators such as the MSCI Volatility Index and the Consumer Confidence Index were used as variables. Thus, the impact of psychological factors on the World Healthcare Index, within the framework of the Lucas Critique, has been modeled using machine learning algorithms with daily data from January 1, 2020, to September 30, 2024, covering the broadest available range that encompasses the uncertainty caused by COVID-19. The findings provide insights into the dynamic relationship between the healthcare sector and economic and psychological indicators, offering strategic guidance for both investors and policymakers. Moreover, they contribute a new perspective to the limited literature on these relationships.

The study comprises four sections. The first section investigates whether the healthcare sector is influenced by psychological factors, as posited in the Lucas Critique. The second section reviews prior research on the effects of the Volatility Index and the Consumer Confidence Index on stock markets, establishing the conceptual framework. The third section models the movements of the MSCI World Healthcare Index using IBk, K-Star, and LWL lazy learning algorithms, with the MSCI Volatility Index and the Consumer Confidence Index serving as financial and psychological indicators. Finally, the fourth section discusses the findings and compares them with the existing literature.

1. LITERATURE

The Volatility Index, also referred to as the fear index or fear gauge in both national and international theoretical and empirical studies, is a risk perception indicator that provides investors with insights into market expectations of downturns and upturns (Sağlam & Kargın, 2023; Jung, 2016; Osterrieder et al., 2019). The Consumer Confidence Index, on the other hand, offers information about the economic tendencies of individuals and society, providing a foundation to assess the potential future direction of these tendencies (Islam & Mumtaz, 2016). Numerous studies examine the effects of the volatility index and consumer confidence index on stock market indices. These studies can be grouped into those analyzing the relationship between the volatility index and stock indices (Kula & Baykut, 2017; Kaya & Coşkun, 2015; Bayramoğlu & Abasız, 2017; Ögel & Fındık, 2020; Tuncay, 2021; Bayrakdaroğlu & Kaya, 2021; Önem, 2021; Tunçel & Gürsoy, 2020; Başarır, 2018; Münyas, 2022; Bouri, Graddeojevic & Nekhili, 2024; Shah, 2024; İlter & Aksoy, 2024), the relationship between the

Consumer Confidence Index and stock indices (Emre & Dinara, 2024; Gül, Yıldırım & Hattapoğlu, 2024), and the relationship among volatility, the consumer confidence ındex, and stock indices (Sadeghzadeh, 2018; Tayar & Aktaş, 2024; Kumar & Bouri, 2024; Çetinoğlu, Koç & Çapraz, 2024; Han, 2024).

The relationship between volatility and stock markets has been a prominent area of research in the finance literature. Krein & Fernandez (2012) have highlighted the risk-reducing effects of volatility index products. Sarwar (2012) has stated that there is a strong negative correlation between the VIX and stock returns in BRIC countries. Chang, Hsieh & McAleer (2016) identified the adverse short-term effects of the VIX on European ETF returns. Kula & Baykut (2017) showed a long-term relationship between the XKURY and VIX indices using the ARDL method. Kaya & Coşkun (2015) and Kaya (2015) found that the VIX index negatively affected the BIST 100 index using cointegration and error correction models. Bayramoğlu & Abasız (2017) and Ögel & Fındık (2020) analyzed volatility spillovers using VAR-EGARCH models and demonstrated the effects of the VIX on stock market indices. Studies using the DCC GARCH method, such as Kutlu & Türkoğlu (2023), identified both short- and long-term relationships between stock indices of fragile five countries, excluding IDX, and the VIX, while Önem (2021) found time-varying, positive, and strong relationships between most BIST indices and VIX returns. İltaş & Güzel (2021) found that the VIX and CDS spreads have an impact on stock market indices using the Fourier Toda-Yamamoto causality test. These studies show that there are robust and reliable outcomes from the several approaches taken to explain how volatility and confidence indicators affect financial markets.

Conversely, the relationship between the consumer confidence index and stock market performance has significant outcomes. Ottoo (1999) found a positive relationship between the Wilshire 5000 index and the consumer confidence index, while Fisher & Statman (2003) noted that an increase in confidence could reduce stock returns. Brown & Cliff (2004) stated that there is a positive relationship between trust and stock returns. Singal (2012) argued that confidence is successful in predicting future returns, while Liu (2015) found that an increase in confidence makes the market more liquid. Barışık & Dursun (2021) examined the relationships between the economic confidence index, stock, exchange rate, and gold, revealing both symmetric and asymmetric relationships with the BIST100 index. Kamışlı & Meriç (2024) investigated the interplay between the economic confidence index, consumer confidence index, real sector confidence index, and BIST sector indices through the application of the Fourier Toda-Yamamoto causality test. Their findings revealed that only a few sector indices displayed causal relationships with the economic, consumer, and real sector confidence indices.

There are also a few studies that investigate both the impact of the consumer confidence index and volatility on stock market indices. Sadeghzadeh (2018) argued that in the short term, the effects of fear and confidence indices on the stock market were in line with theoretical expectations, while in the long term, the fear index had a reducing effect and the confidence index was more effective in the short term. Tayar & Aktaş (2024) examined the impact of confidence and expectation indices, which are factors of investor confidence, on investment decisions in Turkey and the U.S. According to volatility models, while expectation and confidence variables did not have a significant impact on BIST100 investments, they observed significant effects on other investment vehicles. Kumar & Bouri (2024) studied the effects of changes in consumer confidence, economic policy, financial market uncertainty, and oil market uncertainty on the returns and risks of the United Kingdom's travel and leisure stock index. The canonical regression and CoVaR measurements showed that consumer confidence and uncertainties had a stronger effect on the left tail of travel and leisure index returns. Additionally, they observed significant upward and downward extreme risk spillovers from excessive movements in consumer confidence and uncertainty indices. Han (2024) investigated the impact of fear and confidence factors on investor behavior in Turkey's financial markets. The study revealed long-term relationships between the consumer confidence index, VIX fear index, and the BIST100 index.

Prasad et al. (2023), Dixit et al. (2013), Prasad et al. (2022), and Campisi, Muzzioli, and De Baets (2024) modeled the directions of indices using machine learning algorithms. Prasad et al. (2023), in various machine learning models, predicted the daily movement of the India VIX with 63% to 65% accuracy. Campisi et al. (2024) applied machine learning algorithms to forecast the information content of volatility indices, achieving over 60% accuracy in predicting the future direction of the stock market.

Prasad et al. (2022) modeled the impact of macroeconomic variables on the CBOE VIX using machine learning, achieving an accuracy score of 62%. Dixit et al. (2013) used an artificial neural network (multilayer perceptron) on a dataset of only four years to train and forecast the India VIX, producing models with accuracy scores ranging from 57% to 61%. Overall, studies in the field show that accuracy values of 57% and above are generally accepted when using machine learning algorithms.

In conclusion, a review of the existing literature reveals that while there is evidence supporting the relationship between volatility and consumer confidence indices in capital markets, studies that model the direction of the capital market index using these indicators are limited. Current research predominantly analyzes the effects of the volatility index or the consumer confidence index through econometric methods. Although recent studies have incorporated machine learning models such as logistic regression and random forest (Gupta, Nel & Pierdzioch, 2023; Campisi, Muzzioli & De Baets, 2024), these investigations primarily focus on the US stock markets and emphasize comparing model applicability. This study offers a novel perspective by examining the relationship between the volatility index, the consumer confidence index, and the MSCI World Healthcare Index. By employing the IBk, K-Star, and LWL algorithms, which are rooted in the lazy learning method, this research provides a comprehensive evaluation of the interplay between these factors. Furthermore, it explores whether psychological factors and market actors' expectations play a pivotal role in the financial analysis of the healthcare sector. Consequently, this study significantly contributes to the literature by emphasizing the importance of not only macroeconomic indicators but also psychological factors in financial forecasting.

2. MODEL AND FINDINGS

The Lucas Critique argues that the behavior and expectations of economic actors change over time, and therefore, basing economic analyses solely on past data can be misleading. The healthcare sector, especially during uncertain periods like the COVID-19 pandemic, provides a suitable domain for adopting this approach due to the changing expectations and risk perceptions. This study aims to enhance the accuracy of financial analyses in the healthcare sector by evaluating not only macroeconomic indicators but also the impact of market actors' expectations and psychological factors. In this context, the MSCI World Healthcare Index (MSCI, 2025a) has been modeled using lazy learning-based algorithms, namely K-Star, IBk, and LWL, in data mining, incorporating variables including the MSCI Volatility Index (MSCI, 2025b) and the Consumer Confidence Index (OECD, 2025).

Lazy learning is a machine learning method that delays the generalization of training data until it is needed (Hormozi et al., 2012). This approach offers advantages such as lower training costs, increased efficiency through reuse of solutions, and the ability to produce abstract explanations. Additionally, lazy learning, also known as instance-based learning, is well-suited to dynamic datasets and increasing learning tasks due to its ability to adapt to new data (Aha, 1992; Wilson & Martinez, 2000; Kartal, 2020; Birattari, 1999). Instance-based learning models have the capability to adapt to previously unseen data. In other words, instance-based learning models can either store a new instance or discard existing old instances. Models like lazy learning perform classification by comparing an instance to previously classified examples. The lazy learning algorithm called IBk (Instance-Based k) is a k-nearest neighbor classifier (Fentie, Alemu, & Shankar, 2014; Vijayarani & Muthulakshmi, 2013). It is one of the most commonly used methods in example-based learning. IBk evaluates the k nearest neighbors to determine the class or value of a new instance, typically using Euclidean distance or other similarity measures (Vijayarani & Muthulakshmi, 2013). The flexibility of the IBk algorithm, which allows for varying values of k and different distance measures, enhances its adaptability. IBk is particularly effective when working with large datasets and has a wide range of applications (Aydemir, 2019). The K-Star algorithm, in particular, is an instance-based learning algorithm designed to classify each instance into the class with the nearest average (Vijayarani & Muthulakshmi, 2013). Unlike other classifiers, this algorithm uses an entropy-based distance function that calculates the average complexity of the transformation between instances (Cleary & Trig, 1995; Shannon, 1948; Kartal, 2020). When classifying, K-Star considers the sum of the probabilities of all elements within a class and selects the one with the highest probability (Piramuthu & Sikora, 2009; Painuli, 2014). LWL (Locally Weighted Learning) is a lazy learning method that constructs a local regression model for each new prediction. This algorithm focuses only on the observations within a specific region rather than the entire dataset when making predictions, applying weighted linear regression in that region (Schneider & Moore, 2000; Atkeson, Moore &

Schaal, 1997). LWL is particularly effective in modeling nonlinear relationships, offering a more flexible model by conducting separate calculations for different subsets of the data.

In this study, the MSCI Volatility Index and the Consumer Confidence Index were used as independent variables for the lazy learning algorithms. The dependent variable is the increase and decrease signals of the MSCI World Healthcare Index, calculated based on the previous day's data. The dataset consists of 1,239 daily observations from January 1, 2020, to September 30, 2024, covering the broadest available range that encompasses the uncertainty caused by Covid-19. The data is secondary data published by MSCI and OECD. Of the observations, 1,177 (95%) were used for training the algorithm, while 62 (5%) were reserved for testing. The analysis was carried out using the IBk, K-Star, and LWL algorithms, all based on the lazy learning method.

The IBk, K-Star, and LWL algorithms were assessed using performance criteria such as accuracy, precision, sensitivity, and F-score. Accuracy, a measure of the model's overall performance, is calculated by dividing the sum of true positive and true negative predictions by the total number of observations (Aydemir, 2019; Noutfia & Ropelewska, 2024; Sabancı, Aslan, Ropelewska, & Unlersen, 2022). A high accuracy rate indicates that the model generally makes successful predictions. Precision is calculated by dividing the number of true positive predictions by the sum of true positive and false positive predictions. It evaluates the percentage of correctly identified positive events among those predicted to be positive. This metric helps reduce the impact of false positive forecasts. A high precision rate indicates that the model generates more reliable results by minimizing false positive errors (Aydemir, 2019; Noutfia & Ropelewska, 2024; Sabancı, Aslan, Ropelewska, & Unlersen, 2022). The number of true positive predictions divided by the sum of true positives and false negatives gives the sensitivity, often referred to as recall. This metric evaluates how effectively the model identifies actual positive cases. Sensitivity is particularly important in imbalanced datasets, where false negatives can significantly impact model performance. A high sensitivity rate indicates that the model successfully detects positive class occurrences (Aydemir, 2019; Noutfia & Ropelewska, 2024; Sabancı, Aslan, Ropelewska, & Unlersen, 2022). The F-score is derived by computing the harmonic mean of precision and sensitivity (Aydemir, 2019; Noutfia & Ropelewska, 2024; Sabancı, Aslan, Ropelewska, & Unlersen, 2022). By considering the trade-offs between sensitivity and precision, this metric provides a fair assessment of model performance and ensures a more comprehensive analysis, especially when addressing false positive and false negative predictions. In this context, Table 1 presents the performance metrics of the models developed to predict the direction of the MSCI World Healthcare Index, based on the MSCI Volatility Index and the Consumer Confidence Index, using the IBk, K-Star, and LWL algorithms.

Table 1. Model performance metrics*

Algorithm	Comparison Matrix			Performance Metrics				
		Decrease	Increase	Class Accuracy	Accuracy	Precision	Sensitivity	F-score
IBk	**Decrease**	15	7	68%	57%	68%	42%	52%
	Increase	20	20	50%				
K-Star	**Decrease**	31	5	86%	65%	86%	65%	74%
	Increase	17	9	35%				
LWL	**Decrease**	21	1	95%	48%	95%	40%	57%
	Increase	31	9	23%				

* The data presented in the table were calculated by the authors based on secondary data sourced from MSCI (2025a), MSCI (2025b), and OECD (2025).

According to the findings from the IBk algorithm presented in Table 1, the overall accuracy of the model was determined to be 57%. This accuracy rate represents the proportion of correct predictions made by the model across all classifications. Given that an accuracy value above 57% is considered acceptable in the literature, the model developed using the IBk algorithm can be regarded as acceptable (Campisi, Muzzioli & De Baets, 2024; Prasad, Bakhshi & Guha, 2023; Bai & Cai, 2024; Prasad et al., 2022; Kartal, 2020; Shyam & Vinayak, 2020; Dixit et al., 2013). The model's precision was calculated to be 68%, indicating that it is relatively reliable in predicting positive classes with a low number of false positives. The sensitivity was determined to be 42%, which measures how well the model identifies true positive examples. A sensitivity rate of 42% suggests that the model misses some positive examples. The F-score of the model is 52%. When examining the comparison matrix, the accuracy rate in the decrease class is reported as 68%, reflecting the model's moderate success in correctly classifying positive examples within this class. In contrast, the accuracy rate in the increase class is 50%, indicating that the model performs moderately in this class as well.

When examining the performance metrics of the K-Star algorithm presented in Table 1, the overall model accuracy was found to be 65%. This accuracy rate is considered acceptable according to the literature. The model's precision was reported as 86%, indicating that it is reliable in predicting positive classes, with a low number of false positives. The sensitivity was determined to be 65%, which suggests that the model has a strong ability to recognize positive classes. The F-score of the model was calculated as 74%. Additionally, when the comparison matrix is examined, it is observed that the model achieves an accuracy rate of 86% in the decrease class. This high accuracy indicates that the model performs well in the decrease class. However, the accuracy rate in the increase class is lower, at 35%, suggesting that the model does not perform adequately in this class.

Finally, when evaluating the performance metrics of the LWL algorithm, as presented in Table 1, the overall model accuracy is determined to be 48%. This accuracy rate represents the proportion of correct predictions made by the model across all classifications, and it is well below the 57% threshold considered acceptable in the literature. The precision value is 95%, which is relatively high, indicating that the model is reliable in predicting positive classes with a low number of false positives. The sensitivity is determined to be 40%, revealing that the model tends to miss some positive examples. The F-score of the model is calculated to be 57%. When examining the comparison matrix results, it is observed that the accuracy rate of the model in the decrease class is 95%, indicating that the model performs very well in this class. However, the accuracy rate in the increase class is quite low at 23%, suggesting that the model does not perform adequately in this class.

The performance of the models is directly related to the number of examples correctly or incorrectly assigned to a class. In this study, the classification success of the IBk, K-Star, and LWL algorithms was evaluated using the mean absolute error, mean squared error and Kappa statistic.

Mean Absolute Error (MAE) is calculated by averaging the absolute differences between the predicted values and the true values. It is a statistical metric used to assess the accuracy of a model's predictions, and its formula is given in Eq. 1 (Küçükönder, Vursavuş & Üçkardeş, 2015; Ogunsanwo, Kuti, Aiyelokun, & Alaba, 2024; Chicco, Warrens & Jurman, 2021).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \dot{y}_i| \qquad (1)$$

where N is the number of data points, y_i is the true values, and $\dot{y}_i$ is the predicted values.

Mean Squared Error (MSE) is a widely used measure to evaluate the performance of a model and measures the average of the squared differences between the predicted values and the actual values. The formula for MSE is given in Eq. 2 (Chicco, Warrens & Jurman, 2021).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \dot{y}_i)^2 \qquad (2)$$

where N is the number of data points, y_i is the true values, and $\dot{y}_i$ is the predicted values.

The Kappa statistic is a measure that evaluates the agreement between the model's predictions and the actual results, ranging from -1 to 1. A Kappa statistic value calculated using Eq. 3 that is close to 1 indicates a high level of agreement between the model's predictions and the actual values, whereas a value close to 0 suggests that the agreement is due to chance (Cohen, 1960; Kılıç, 2015; İspir & Aybek, 2022; Bitek, Uludağ & Kurban, 2024; Landis & Koch, 1977).

$$\kappa = \frac{P_0 - P_e}{1 - P_e} \qquad (3)$$

where, P_0 represents the observed agreement rate between the predicted and actual values, while P_e denotes the expected agreement rate based on chance.

Landis & Koch (1977) divided the range $[-1,1]$ into sections to interpret the Kappa statistic. Accordingly, a Kappa statistic less than 0 indicates worse agreement than expected by chance. A value in the range [0.01,0.20] signifies insignificant agreement, [0.21,0.40] indicates poor agreement, [0.41,0.60] represents moderate agreement, [0.61,0.80] corresponds to good agreement, and [0.81,1] denotes very good agreement. Accordingly, the error statistics of the models developed to predict the direction of the MSCI World Healthcare Index, based on the MSCI Volatility Index and the Consumer Confidence Index, using the IBk, K-Star, and LWL algorithms, are presented in Table 2.

Table 2. Error statistics

Algorithm	Kappa Statistic	MAE	MSE
IBk	-17%	57%	75%
K-Star	15%	49%	49%
LWL	-20%	50%	50%

The Kappa statistic for the IBk algorithm is -17%, indicating that the model performs worse than random guesses. The MAE is 57%, and the MSE is 75%. These values suggest significant errors in the model's predictions, reflecting its low performance. The Kappa statistic for the K-Star algorithm is 15%, indicating a minimal level of agreement. The MAE is 49%, and the MSE is also 49%, suggesting moderate errors in the model's predictions. Finally, the Kappa statistic for the LWL algorithm is -20%, indicating that the model performs worse than random guesses. The MAE is 50%, and the MSE is 50%, which also indicates moderate errors in the model's predictions.

CONCLUSIONS

The healthcare sector is significantly influenced by global economic changes and crises. Events like the COVID-19 pandemic have disrupted the sector's financial stability. During such periods, it became evident that healthcare sector participants must be aware not only of health-related economic data but also of changes in financial markets and their psychological impact on market actors.

The Lucas Critique emphasizes that economic analyses based solely on historical data can be misleading, as market participants' expectations evolve. This view suggests that traditional economic modeling methods are limited, and more dynamic analytical approaches are needed. Particularly during crises, considering the interactions between financial and psychological factors within the healthcare sector can lead to more accurate results. The goal of this study is to give a more in-depth look by looking at how psychological factors, market expectations, and macroeconomic indicators affect changes in the healthcare sector's finances. In this context, the independent variables used in this study are the MSCI Volatility Index and the Consumer Confidence Index. The dependent variable consists of the increase or decrease signals of the MSCI World Healthcare Index, calculated based on the previous day's performance. The dataset includes 1,239 daily observations of both dependent and independent variables, spanning from January 1, 2020, to September 30, 2024. This period covers the broadest available range, including the uncertainty caused by the Covid-19 pandemic. The data used in this study are secondary data published by MSCI (2025a), MSCI (2025b), and the OECD (2025). Of the 1,239 observations, 1,177 (95%) were used for training the algorithm, while 62 (5%) were used for testing. The analysis was conducted using the IBk, K-Star, and LWL algorithms, a lazy learning method.

When examining the performance metrics of the lazy algorithm models, the K-Star algorithm demonstrates the highest overall performance with an accuracy rate of 65%. The IBk algorithm shows medium-level performance, with an accuracy rate of 57%, while the LWL algorithm has the lowest overall accuracy at 48%. An examination of similar studies in the literature reveals that machine learning models used to predict stock market indices are generally considered acceptable if their accuracy rates are 57% or higher (Campisi, Muzzioli & De Baets, 2024; Prasad, Bakhshi & Guha, 2023; Bai & Cai, 2024; Prasad et al., 2022; Kartal, 2020; Shyam & Vinayak, 2020; Dixit et al., 2013). In this context, the overall classification accuracy of the IBk and K-Star models aligns with the average performance accepted in the literature, suggesting that both models have an acceptable level of accuracy. However, the accuracy of the LWL algorithm falls below the accepted threshold. Despite this, relying solely on accuracy to assess the model's performance may be misleading, as accuracy alone may fail to account for class imbalances, which can skew the results. The model's performance rate may have been influenced by performance differences between the two classes and the class imbalance. In terms of precision, the LWL algorithm achieves the highest value at 95%, followed by K-Star with 86%. The IBk algorithm performs relatively lower, with a precision value of 68%. Regarding sensitivity, K-Star leads with the highest value of 65%, while IBk ranks second with 42%. The LWL algorithm exhibits the lowest sensitivity at 40%. For the F-score, K-Star again leads with a score of 74%, while both LWL and IBk show lower performance, with F-scores of 57% and 52%, respectively.

The IBk algorithm demonstrates moderate success with an accuracy of 68% in the decrease class and 50% in the increase class. While the model is somewhat capable of identifying market downturns, it struggles to accurately predict upturns. The overall performance metrics, such as a Kappa value of -17%, MAE of 57%, and MSE of 75%, reveal that the model is unreliable for financial decision-making, especially in predicting positive movements in the healthcare sector. Due to these significant error rates, investors should be cautious and refrain from relying solely on this model for their financial decisions.

The LWL algorithm shows a high accuracy rate of 95% in the decrease class but performs poorly in the increase class, with an accuracy of just 23%. Its high error metrics, including a Kappa value of -20%, MAE of 50%, and MSE of 50%, indicate similar limitations to the IBk algorithm. Therefore, investors should be careful and avoid relying solely on the LWL algorithm, as is the case with the IBk algorithm, in their financial decision-making processes. Both models have high error rates in predicting upward market movements, making them unreliable for making sound financial decisions.

The K-Star algorithm demonstrates an overall strong performance with a Kappa value of 15%, MAE of 49%, and MSE of 49%, reflecting its consideration of not only macroeconomic indicators but also the psychological factors and market expectations that influence the healthcare sector. These performance metrics, which are better than those of other models, make the K-Star algorithm more reliable for making accurate financial forecasts in the healthcare sector, with reduced error. However, the algorithm's ability to predict positive market movements is somewhat limited, as evidenced by its 35% accuracy rate in the increase class. This highlights a weakness in forecasting upward trends, which is critical for investors looking to make sound decisions during periods of growth. In dynamic and crisis-sensitive markets like the healthcare sector, failing to predict upward movements could lead to missed opportunities or reduced returns. On the other hand, the K-Star algorithm performs very well in predicting downturns, with an accuracy rate of 86% in the decrease class. This strong performance in forecasting negative market conditions—such as crises or financial collapses—provides a key advantage for investors. Accurately predicting downturns allows for better risk management and helps to minimize potential losses, ensuring more effective decision-making in uncertain market environments. Therefore, while the K-Star algorithm excels in anticipating market declines, its limited ability to predict rises means it should be used with caution when forecasting market growth.

The models' main results show how important psychological factors like volatility and consumer confidence indices are for understanding how complex markets like the MSCI World Healthcare Index change over time. These results align with studies in the literature that employ structural econometric models, which recognize the influence of such factors in financial forecasting (Krein & Fernandez, 2012; Sarwar, 2012; Kula & Baykut, 2017; Ottoo, 1999; Kumar & Bouri, 2024). This study fills a gap in the literature concerning the healthcare index, offering a new perspective on how machine learning techniques can be applied to financial predictions. However, the results also emphasize the importance of investors conducting a more comprehensive and cautious analysis rather than relying solely on these algorithms. Although the lazy learning algorithms are particularly effective in predicting downtrends in the MSCI World Healthcare Index, caution is advised in using it for predicting uptrends due to its limitations in that regard. Therefore, while the lazy learning algorithms can be a reliable tool, its performance should be carefully evaluated, especially when applied to uptrend predictions.

The models highlight a discrepancy between the low accuracy rate for the increase class and the high accuracy rate for the decrease class. Although the model meets the accuracy threshold generally accepted in the literature, future studies could explore advanced machine learning techniques to mitigate this class imbalance. For instance, applying methods like SMOTE could improve the model's performance in predicting the increase class. This would enable the models to provide investors and market participants with predictions not only for downturns but also for periods of growth, enhancing their practical value for comprehensive financial decision-making.

REFERENCES

Aha, D. W. (1992). Tolerating noisy, irrelevant and novel attributes in instance-based learning algorithms. *International Journal of Man-Machine Studies, 36*(2), 267–287.

Akbal, H. (2020). The whip effect of the COVID-19 pandemic on the healthcare supply chain. *Kesit Akademi Journal,* 6*(25*), 181–192.

Atkeson, C. G., Moore, A. W., & Schaal, S. (1997). Locally weighted learning for control. *Lazy learning*, 75-113.

Aydemir, E. (2019). Predicting Authors and Newspapers in Turkish Columns with Artificial Neural Networks. *DUMF Engineering Journal,* 10(1), 45-56

Bai, Y., & Cai, C. X. (2024). Predicting VIX with adaptive machine learning. *Quantitative Finance*, 1–17.

Barışık, S., & Dursun, E. (2021). Impact of gold, stock, and foreign exchange markets on the economic confidence index: The case of Turkey. *Cumhuriyet University Journal of Economics and Administrative Sciences, 22*(1), 253–280.

Başarır, Ç. (2018). The relationship between the fear index (VIX) and BIST 100: Frequency domain causality analysis. *Dokuz Eylül University Journal of Business Administration, 19*(2), 177–191.

Bayrakdaroğlu, A., & Kaya, B. T. (2021). Testing the relationship between stock market index and market volatility-fear index in BRICS-T countries using panel data analysis. *Electronic Journal of Social Sciences,* 20*(*77), 313–328.

Bayramoğlu, M. F., & Abasız, T. (2017). Analysis of the volatility spillover effect between emerging market indices. *Accounting and Finance Journal*, (74), 183–200.

Birattari, M., Bontempi, G., & Bersini, H. (1999). Lazy learning meets the recursive least squares algorithm. In *Advances in Neural Information Processing Systems*, 375–381.

Bitek, D., Uludağ, M., & Kurban, E. A. (2024). Determination of water surface change areas of gala and pamuklu lakes by using remote sensing techniques and monitoring of environmental impacts. *Trakya University Journal of Social Sciences*, 26(2), 461-486.

Bouri, E., Gradojevic, N., & Nekhili, R. (2024). Fear, extreme fear and US stock market returns. *Physica A: Statistical Mechanics and its Applications, 656*, 130212.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance,* 11*,* 1–27.

Campisi, G., Muzzioli, S., & De Baets, B. (2024). A comparison of machine learning methods for predicting the direction of the US stock market on the basis of volatility indices. *International Journal of Forecasting, 40*(3), 869–880.

Chang, C. L., Hsieh, T. L., & McAleer, M. (2016). How are VIX and stock index ETF related? *Tinbergen Institute Discussion Paper, 16-010/III.*

Choi, C., & Jung, H. (2022). COVID-19's impacts on the Korean stock market. *Applied Economics Letters,* 29(11), 974–978.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *Peerj computer science*, 7, e623.

Cleary, J. G., & Trigg, L. E. (1995). K*: An instance-based learner using an entropic distance measure. *Proceedings of the 12th International Conference on Machine Learning*, Tahoe City, California, USA, 108–114.

Cohen, J. (1960). A coefficient of agreement for nominal scales, *Educational and Psychological Measurement*, 20, 37-46.

Çetinoğlu, S., Koç, Y. D., & Çapraz, S. (2024). The relationship between macroeconomic indices: The case of the fragile five countries. *Dumlupınar University Journal of Social Sciences, 82*, 1–10.

Dixit, G., Roy, D., & Uppal, N. (2013). Predicting India's volatility index: An application of artificial neural network. *International Journal of Computer Applications,* 70*(4).*

Dranove, D., Garthwaite, C., & Ody, C. (2013). How do hospitals respond to negative financial shocks? The impact of the 2008 stock market crash (No. w18853). *National Bureau of Economic Research*.

Emre, T. Y., & Dinara, Z. (2024). The relationship between financial services confidence index and stock returns: Toda-Yamamoto and asymmetric causality analysis. *EKOIST Journal of Econometrics and Statistics, 41*, 97–108.

Fentie, S. G., Alemu, A. D. & Shankar, B. (2014). A Comparative Study on Performance Evalution of Eager versus Lazy Learning Methods. International journal of computer science and mobile computing, 3(3), 562-568.

Fisher, K. L., & Statman, M. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management,* 30(1), 115–127.

Gupta, R., Nel, J., & Pierdzioch, C. (2023). Investor confidence and forecastability of US stock market realized volatility: Evidence from machine learning. *Journal of Behavioral Finance,* 24*(*1), 111–122.

Gül, S., Yıldırım, S., & Hattapoğlu, M. (2024). The relationship between investor sentiment and the BIST 100 index: A Toda-Yamamoto causality approach. *Anadolu University Journal of Social Sciences, 24*(4), 1589–1616.

Han, A. (2024). The impact of fear and confidence on investor behavior: Evidence from break tests. *Kastamonu University Journal of Economics and Administrative Sciences,* 26*(2*), 344–369.

Hormozi, H., Hormozi, E., & Nohooji, H. R. (2012). The classification of applicable machine learning methods in robot manipulators. *International Journal of Machine Learning and Computing*, 2(5), 560–563.

IMF (International Monetary Fund). (2020). *COVID-19 crisis poses threat to financial stability.* https://www.imf.org/en/Blogs/Articles/2020/04/14/blog-gfsr-covid-19-crisis-poses-threat-to-financial-stability

Islam, T. U., & Mumtaz, M. N. (2016). Consumer confidence index and economic growth: An empirical analysis of EU countries. *EuroEconomica, 35*(2).

İltaş, Y., & Güzel, F. (2021). The causal relationship between stock index and uncertainty indicators: The case of Turkey. *Hacettepe University Journal of Economics and Administrative Sciences*, 39*(*3), 411–424.

İlter, H. İ., & Aksoy, B. (2024). VIX volatility (fear) index and its impact on the BIST participation index in the context of behavioral finance: An ARDL bounds testing model. *Islamic Economics and Finance Journal, 10*(2), 308–337.

İspir, M. A., & Aybek, A. (2022). Product Classification in Kahramanmaraş Province Kartalkaya Left Bank Irrigation Union Area Using Remote Sensing (RS) and Geographic Information Systems (GIS) Techniques. *International Journal of Eastern Mediterranean Agricultural Research*, 5(1), 37-57.

Jung, Y. C. (2016). A portfolio insurance strategy for volatility index (VIX) futures. *The Quarterly Review of Economics and Finance*, 60*,* 189–200.

Kamışlı, S., & Meriç, E. (2024). The relationship between confidence indices and stock markets: A sectoral approach. *Anadolu University Journal of Social Sciences, 24*(2), 797–816.

Kartal, C. (2020). Modeling Bitcoin prices using the K-Star algorithm. *BMIJ, 8*(1), 213–231.

Kaya, E. (2015). Cointegration and Granger causality between the Borsa Istanbul (BIST) 100 Index and implied volatility (VIX) index. *KMÜ Journal of Social and Economic Research,* 17*(28*), 1–6.

Kaya, A., & Çoşkun, A. (2015). Is the VIX index a cause for securities markets? The case of Borsa İstanbul. *Cumhuriyet University Journal of Economics and Administrative Sciences, 16*(1), 175–186.

Kılıç, S. (2015). Kappa Testi, *Journal of Mood Disorders*, 5(3), 142-144.

Krein, D., & Fernandez, J. (2012). Volatility risk control. *Journal of Index Investing,* 3*(2),* 62–75.

Kula, V., & Baykut, E. (2017). An analysis of the relationship between the Borsa Istanbul Corporate Governance Index (XKURY) and the Fear Index (Chicago Board Options Exchange Volatility Index - VIX). *Afyon Kocatepe University Journal of Economics and Administrative Sciences, 19*(2), 27–37.

Kumar, D., & Bouri, E. (2024). Consumer confidence, uncertainties, and risks in the UK travel and leisure industry. *Tourism Analysis, 29*(2), 205–220.

Kutlu, M., & Türkoğlu, D. (2023). Volatility index (VIX) and volatility interaction among the stock indices of fragile five countries. *Aksaray University Journal of Economics and Administrative Sciences*, 15*(*2), 125–136.

Küçükönder, H., Vursavuş, K. K., & Üçkardeş, F. (2015). Determining The Effect of Some Mechanical Properties on Color Maturity of Tomato with K-Star, Random Forest and Decision Tree (C4.5) Classification Algorithms. *Turkish Journal of Agriculture-Food Science and Technology*, 3(5), 300–306.

Landis, J.R. & Koch, G.G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33, 159-74.

Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance*, *16*(1), 51–67.

Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy,* 1*,* 19–46.

MSCI. (2025a). https://www.msci.com/indexes/index/106801

MSCI. (2025b). https://www.msci.com/indexes/index/716003

Münyas, T. (2022). An empirical analysis of the VIX fear index and emerging market stock exchanges. *Istanbul Commerce University Social Sciences Journal,* 21(43), 1–19.

Noutfia, Y., & Ropelewska, E. (2024). Exploration of Convective and Infrared Drying Effect on Image Texture Parameters of ‘Mejhoul’ and ‘Boufeggous’ Date Palm Fruit Using Machine Learning Models. *Foods*, 13(11), 1602.

OECD. (2025). https://www.oecd.org/en/data/indicators/consumer-confidence-index-cci.html?oecdcontrol-b2a0dbca4d-var3=2019-11&oecdcontrol-b2a0dbca4d-var4=2024-01&oecdcontrol-cf46a27224-var1=G20

Ogunsanwo, G.O, Kuti. A.A, Aiyelokun O.O., & Alaba, O.B. (2024). Application of machine learning techniques for stock price prediction. *FNAS Journal of Computing and Applications*, 2(1), 38-50.

Osterrieder, J., Vetter, L., & Röschli, K. (2019). The VIX volatility index - A very thorough look at it. Available at SSRN 3311727.

Ottoo, M. W. (1999). Consumer sentiment and stock market. *Finance and Economics Discussion Series* from the Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/pubs/feds/1999/199960/199960pap.pdf

Ögel, S., & Fındık, M. (2020). The relationship between stock indexes from different continents and the VIX (fear) index. *Afyon Kocatepe University Faculty of Economics and Administrative Sciences Journal,* 22(1), 127–140.

Önem, H. B. (2021). The volatility interaction between the VIX (fear index) and BIST indexes analyzed with the DCC-GARCH model. *Business Research Journal,* 13*(*3), 2084–2095.

Piramuthu, S., & Sikora, R. T. (2009). Iterative feature construction for improving inductive learning algorithms. *Expert Systems with Applications,* 36*(*2), 3401–3406.

Prasad, A., Bakhshi, P., & Guha, D. (2023). Forecasting the direction of daily changes in the India VIX index using deep learning. *IIMB Management Review,* 35*(*2), 149–163.

Prasad, A., Bakhshi, P., & Seetharaman, A. (2022). The impact of the US macroeconomic variables on the CBOE VIX Index. *Journal of Risk and Financial Management,* 15*(*3), 126.

Sabancı, K., Aslan, M. F., Ropelewska, E., & Unlersen, M. F. (2022). A convolutional neural network-based comparative study for pepper seed classification: Analysis of selected deep features with support vector machine. *Journal of Food Process Engineering*, 45(6), e13955.

Sadeghzadeh, K. (2018). Sensitivity of the stock market to psychological factors: The relationship between the VIX volatility index, the Consumer Confidence Index (CCI), and the BIST 100 index. *Cumhuriyet University Faculty of Economics and Administrative Sciences Journal,* 19(2), 238–253.

Sağlam, K., & Karğın, M. (2023). Measuring the volatility spillover effect of the VIX index on Borsa Istanbul. *Management and Economics Journal,* 30(3), 493–509.

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets?. *Journal of Multinational Financial Management, 22*(3), 55–65.

Schneider, J., & Moore, A. W. (2000). A locally weighted learning tutorial using vizier 1.0. *Carnegie Mellon University, the Robotics Institute*. 1 (1), 1-9.

Shah, J. (2024). The relationship between the volatility of the S&P 500 and the CBOE Volatility Index (VIX). *International Journal of Social Science and Economic Research*, 9(9), 3840–3851.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal,* 27*,* 379–423.

Shyam, R., & Vinayak, P. (2020). Stock prediction overview and a simple LSTM based prediction model. *International Research Journal of Engineering and Technology (IRJET)*, 7(4), 5935-5940.

Singal, M. (2012). Effect of consumer sentiment on hospitality expenditures and stock returns. *International Journal of Hospitality Management*, 31(4), 511–521.

Şıklar, İ. (1992). The inefficiency of expected economic policy and developing countries. *Anadolu University Faculty of Economics and Administrative Sciences Journal,* 10(1), 65–85.

Tayar, T., & Aktaş, R. (2024). Investigation of investor sentiment through confidence and expectation indices: A behavioral approach. *Öneri Journal,* 19(61), 95-122.

Tuncay, M. (2021). Investigating the volatility interaction between the VIX fear index and BIST sector indices with CCC-GARCH: The 2013-2020 period. *Dicle University Journal of Economics and Administrative Sciences,* 11(21), 126-146.

Tunçel, M. B., & Gürsoy, S. (2020). An empirical analysis of the causality relationship between the VIX (fear index), Bitcoin prices, and the BIST100 index. *Electronic Journal of Social Sciences,* 19(76), 1999-2011.

Uçakkuş, P., & Arslan Çilhoroz, İ. (2022). Financial performance of hospitals during the COVID-19 pandemic. *International Journal of Health Management and Strategies,* 8(2), 257-271.

Vijayarani, S., & Muthulakshmi, M. (2013). Comparative analysis of Bayes and lazy classification algorithms. *International Journal of Advanced Research in Computer and Communication Engineering,* 2(8), 3118–3124.

Wilson, D. R., & Martinez, T. R. (2000). Reduction techniques for instance-based learning algorithms. *Machine Learning,* 38(3), 257-286.