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Original Research Article

The Wisdom of Crowds and Stock Price Prediction

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Technical and fundamental analysis are the two principal methods for studying financial markets. However, access to internet and social media helps investors make better decisions. Social media has turned into a source of information for investors. Surowiecki (2005) found social media can predict better than individuals, known as the Wisdom of the Crowd. In this study, we tried to evaluate the wisdom of the crowd's potential to improve stock price prediction accuracy. So, we developed a prediction model by Long Short-Term Memory based on the wisdom of the crowd. Persian users' opinions on Tehran Stock Exchange stocks were gathered for 8 months and classified as buying, sell, or neutral. During the research period, people mentioned 823 stocks and 52 stocks, which had over 100 recommendations, were chosen. Prediction model accuracy was increased for 19 stocks. While, for 33 stocks were not more accurate with the wisdom of the crowds and social media features. It is important to note that investors apply critical thinking. The wisdom of the crowd can be one input to the decision-making process, along with other related factors. The wisdom of the crowd provides an opportunity to access vast and diverse information. Getting opinions from various people can provide valuable insights into economics and investment preferences. The wisdom of the crowd can help reveal the flow of money. The combination of the wisdom of the crowd, fundamental, and technical analysis can be a useful tool for traders in detecting capital flow and profitable opportunities.

Keywords: Wisdom of Crowd, Stock Price Prediction, Long Short-Term Memory, LSTM
JEL Classification*:* A13, C53, D91, G41

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1 Introduction

Accurate stock market predictions help investors trade better and make more money while losing less (Coates, 2022), but analyzing trends is difficult because of noisy environments and market volatility (Gandhmal & Kumar, 2019). Politics, economics, and investor sentiment impact stock prices. There is no basic rule for predicting stock market prices (Shahverdiani & Khajehzadeh, 2018). In the mid-2000s, social media growth allowed predicting events like elections, public health, attendance and stock market (Bouadjenek et al., 2022). So, social media became popular for financial market analysis. Collective awareness and wisdom are key to social media (Rahjerdi et al., 2022). Investor sentiments affect the stock market beyond just pricing history (Hatefi Ghahfarrokhi & Shamsfard, 2020).Therefore, social media became a new source of data for investors to decide (Ding & Hou, 2015). According to the Wisdom of the Crowd (WoC) assumption, a larger crowd has the potential to outperform smaller groups or individuals (Surowiecki, 2005; Kumar et al., 2020). Behavioral economics considers price as perceived value (Cristescu et al., 2022), and investors' emotions impact their decision-making (Gui, 2019). The studies conducted by Hill & Ready-Campbell (2011), Woolley et al. (2010), Nofer & Hinz, (2014), Velic et al. (2013), Pan et al. (2012), Zhang et al, (2011), Hill & Ready-Campbell (2011), Saumya et al. (2016), Eickhoff & Muntermann (2016), Al-Hasan (2018), Xu et al. (2017), Sun et al. (2017), Arnes & Copenhagen (2014), Reed (2016), Bari et al. (2019), Wu et al. (2019), Li et al. (2019), Garcia-Lopez et al. (2018), Hatefi Ghahfarrokhi & Shamsfard (2020), Wu et al. (2020), Breitmayer et al. (2019), Chao et al. (2019), and Geng et al. (2022) examined how the WoC affects the stock market, and forecasting performance. According to the results, the WoC can enhance the accuracy of stock market predictions. While Lorenz et al. (2011), Antweiler & Frank (2004), Tumarkin & Whitelaw (2001), Das & Chen (2007), Raie et al. (2016),and Dewally (2000) rejected the notion of any connection between the WoC and stock price prediction. Predicting stock prices through social media input remains a challenging and disputed task. Research to improve prediction models has continued without stopping.

Technical analysis considers stock price reflects news reactions (Shah et al., 2019; Soni, 2011), while fundamental analysis looks at the economy and industry (Vargas et al, 2017). Statistical and econometric techniques are also prevalent forecasting models (Ji et al., 2021; Rajabi & Khaloozadeh, 2020). But these methods are not dynamic enough to deal with time series (Ji et al., 2021). Several machine learning approaches have become a crucial analytical tool in financial markets (Nikou et al., 2019). Their ability extends to handling data that is noisy, non-linear, and uncertain (Rajabi & Khaloozadeh, 2020). So, they are more efficient and reach more desired results than statistical methods (Nikou et al., 2019). Deep learning is becoming a powerful alternative to machine learning, according to recent studies. Deep learning algorithms are best for non-linear learning and extracting features from big data (Rajabi & Khaloozadeh, 2020). High accuracy and generalization power, and new data identification are the most important features of deep learning (Nikou et al., 2019). Sentiment analysis is a potent technique for predicting the stock market. Moreover, social media is a vital element in the sentiment analysis(Mukherjee et al., 2021). This research explored whether the WoC in SAHMETO[1] can increase the accuracy of the prediction model or not. SAHMETO is a social system which gathers the opinions of more than 500 traders in Persian about the TSE stocks. Section 2 provides a brief background and related works. Section 3 details the method and its processes. Experiment results are in Section 4. Section 5 concludes the discussion.

2 Literature Review

Recently, stock trading has become a center of attention, and acquire profit matters in the stock's prediction market (Rouf et al. 2021). Researchers and investment planners attach great importance to stock forecasting (Awan et al., 2021). The present state of the stock market is influenced by the prevailing social environment and historical pricing patterns. Daily news articles and investor sentiment play a crucial role in predicting stock prices (Awan et al., 2021). People use social media to make investment decisions. Thus, social media can be introduced as a suitable source of market sentiment measurement (Guan et al., 2022). Prices reflect all available information in an efficient market. Therefore, more information increases the accuracy. James Surowiecki (2005) wrote "The Wisdom of the Crowds" in 2004, which explains how large groups of people can be smarter than an individual (Koen, 2014). According to Surowiecki (2005), untrained people in large groups make better decisions than a few experts (Eickhoff & Muntermann, 2016). Collective judgments have been hypothesized to be accurate, while various members of a group have little knowledge relevant to a subject (Ryan, 2014). To emerge the WoC in a group, three key conditions should exist: diversity, independence, and decentralization. Diversity is the main idea of the WoC. A

[1] www.sahmeto.com

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group with informed, uninformed, and inexperienced people works better than a group of experts only. Independence prevents mass behavior (Eickhoff & Muntermann, 2016). The two most cited predictors of the WoC accuracy are independence and diversity of judgments (Ryan, 2014). A centralized group faces fewer coordinating and aggregating problems (Eickhoff & Muntermann, 2016).

Hill & Ready-Campbell (2011) showed that the online crowd outperforms more, on average, than the S&P 500. Pan et al. (2012) demonstrated that the WoC surpasses individual trades. Social influence plays a big role in trades, especially in unfamiliar decisions. Nofer & Hinz (2014) have proclaimed that the internet is a platform where the WoC phenomenon can be observed. Furthermore, the prediction outcomes based on the WoC were 0.59 percent higher than the return of analysts. The acknowledgement was made that the creation of user-generated content enhances market efficiency and overall welfare. It was concluded that a higher independence leads to improved performance among the crowd. The WoC outperforms that of experts when information is easily accessible. Eickhoff & Muntermann (2016), and Saumya et al. (2016) discovered that the online financial forum can serve as a potential data source for forecasting stock market changes. Likewise, Reed (2016) concluded conversation multiplicity of economic matters not only causes the moves in daily stock market prices but also has a substantial negative effect. Also, he concluded that individuals discuss negative events in markets rather than positive results. Thus, a growth in conversation multiplicity about economic indicators will cause individuals to sell off their stock. Sun et al. (2017) showed a significant correlation and Granger causality between the sentiment conveyed in chat-rooms and the movement of stock prices in China. Additionally, the utilization of sentiment analysis can bolster the forecast of stock price returns. Xu et al. (2017) announced detailed sentiments encompass more information about the stock market than polarity sentiments. In Li et al. (2019) introduced a new method for predicting crude oil prices using text-based data. The methods employed included deep learning techniques, sentiment analysis, and topic derivation. The proposed strategy attains the expected level of accuracy in predicting crude oil. The integration of financial market information and news text results in a substantial enhancement of the accuracy of crude oil price prediction. Wu et al. (2019), Bari et al.(2019), and Chau et al. (2020) also showed that the WoC and sensitivity analysis are effective in predicting stock prices and returns. The WoC has both positive (wisdom) and negative (irrational) effects in the search process. Geng et al.

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(2022) mentioned that crowd’s opinions increase the positive impact of internet search on returns.

In a study conducted by Khanigodarzi et al. (2019), a questionnaire was distributed among 151 investors as part of a survey research. The findings indicate that the use of negative words in written media has a significant impact on the emotional state of investors. In the same way, emotional feelings affect the market index, the market index affects the behavior of investors. Majd (2019) used text mining and machine learning to present a model. He assessed social media-active analysts' influence on stock price predictions in Iran's capital market from April 2017 to May 2019. Four stocks were investigated. The hybrid model had better accuracy for one-day predictions, but not for long-term predictions. Hatefi Ghahfarrokhi & Shamsfard (2020) collected 3-month user explanations for 3 SAHAMYAB stocks. It is demonstrated that predicting daily return is possible with volume and sentiment. Yaghoobi (2020) researched social media's impact on financial decisions. An investigation was conducted on twenty symbols for three months. Social media data decreases error rates in the predictor model. Roast et al. (2020) found that sentiment analysis improves accuracy. Mansour et al. (2021) based their work on the data from Nguyen et al. (2015), and the accuracy of stock prediction improved by 19.8% because of utilizing sentiment information extracted from social media users. Ebrahimian et al. (2021) created a model that predicts stock movement with 72.08% accuracy. User ideas and technical indicators are analyzed to predict 14 stock prices. Decision tree, Naïve Bayes, and support vector machine were used in the study. The study found a significant correlation between the trading volume of the following day and the number of opinions. Memarzadeh et al. (2022) collected data of (Cisco) and (Intel) from the social networks Twitter and Yahoo Finance for three months. Emotion indices have been effective in predicting the trend of stock market value with the least error.

The analysis of the WoC in social media and its effect on the stock market has been executed in English or translated into the English language. The process of translating messages from other languages to English carries the risk of losing information. The present article uses content from the Persian social media platform SAHMETO. Researchers in the past usually picked well-known or US stock market-related sample stocks. The research focused on chosen stocks related to the Tehran Stock Exchange (TSE) and was selected based on the most comments. Prior investigations commonly expect stock prices as a buy or sell recommendation. The research utilized regression analysis to forecast the stock price as a numerical quantity. Previous domestic

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researches have used traditional methods such as survey methods and statistical analyzes. Moreover, implementing advanced techniques such as machine learning mandates the use of a single or two stocks as a sample, not Tehran exchange stocks. Our study aimed to examine how the WoC in SAHMETO affects the accuracy of prediction models.

3 Research Methodology

The research is applied and based on the design science method. Hypothesis is not required for design science research; it can be based on a research question or problem. The main question of this research can be stated: Can Iranian users' wisdom improve the TSE stock price prediction model? Because of hardware limitation SAHMETO servers, the maximum time period which could provide was eight months. So, to extract the WoC in SAHMETO, opinions of users were gathered from 10 January 2020 to 15 August 2022, which were 177,444 records. After removing duplicated and null records, 151,274 records remained. Pre-processing is a key factor in improving classification accuracy. Preprocessing entails the processes of tokenization, stemming, and stop-word elimination. Tokenization is dividing sentences into individual words (Khedr et al., 2017). The process of stemming involves the transformation of a word into its root form. Stop words are frequently used terms in documents, such as conjunctions (Aqlan et al., 2019). The subsequent stage entails the extraction of feature sets for training the classifier. We followed the sentiment score measurement by using Equation 1 for feature extraction. Each textual data in our case, which are the SAHMETO messages, has been categorized into three values: negative, positive, or neutral. The sentiment polarity of each message was determined by adapting the following measurement (Geng et al., 2022; Gupta et al., 2019). There is no emotional dictionary and special library in the Persian language to analyze the financial market sentiment. We used a sentiment dictionary created from data by expert help for higher precision in classification.

$$\text{Sentiment score (C)} = \frac{positive_{i,t} - negative_{i,t}}{positive_{i,t} + negative_{i,t} + 2} \tag{1}$$

Where $positive_{i,t}$ represents the total number of the words, which related to buy stock i on day t; and $negative_{i,t}$ counts the words in the messages, which related to sell stock i on day t. It is represented by a separate binary variable C, which represents the sentiment class (Equation 2):

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$$C \in \{1, -1\} \quad (2)$$

The variable C can hold three distinct values because of the presence of varying thresholds (Equation 3) (Gupta et al., 2019).

$$C = \begin{cases} 1\ (buy)\ if\ sentiment\ score \geq 0.1 \\ -1\ (sell)\ if\ sentiment\ score < 0.1 \\ 0\ (neutral)\ if\ sentiment\ score = 0 \end{cases} \quad (3)$$

We have used a supervised learning algorithm, Support Vector Machine (SVM), which is widely used as a machine learning classifier (Oyland, 2015), in our work. First, we have trained our classifier with using sentiment score. After this, the trained classifier is used in predicting the test data. Also, experts tagged messages either in order to monitor SVM` results. According to (Seif et al., 2021), SVM reduces risk and has strong generalization capabilities. SVM finds a hyperplane in a space with N features to differentiate data points. Various hyperplanes may be considered separating the two classes of data points. SVM object is to find a plane that has the maximum margin. More margin distance means more reinforcement and better classification (Pisner & Schnyer, 2019). Hyperplanes serve as decision boundaries to classify data points. The occurrence of data points on either side of the hyperplane can be attributed to distinct classes. Furthermore, the hyperplane dimension depends on the number of features. If the training points are $[x_i, y_i]$, the input vector is $x_i \in R_n$, and the value of the class is $i = 1,..,J$; is defined, $y_i \in \{-1, 1\}$, then, if the data exhibits linear separability, the decision rules are established and relevant (Equation 4) by utilizing an optimal plane, the binary decision classes can be separated.

$$y = Sign(\sum_{i=1}^{n} y_i\, a_i\, (X.X_i) + b) \quad (4)$$

Where: y is the output, y_i is the value of the training sample class, and x_i indicates the internal coefficient. The vector x= $(x_1, x_2, \dots, x_n)$ presents input data, and vector x_i : 1= 1, …, nX_i , are backup vectors. In relationship (3), parameters b and a_i determined the effectiveness. If the data cannot be separated linearly, Equation (4) change to equation (5).

$$Y = Sign(\sum_{i=1}^{n} y_i\, a_i\, K(X.X_i) + b) \quad (5)$$

The $K\ (X, X_i\ )$ function serves as a kernel function which produces internal beats to form a machine with distinct nonlinear decision levels within the data

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space. The SVM regression model employs a variety of kernels, including linear, Gaussian, polynomial, Radial Basis Function (RBF), and Sigmoid (Salehi & Aminifard, 2013). In this study, RBF is used as kernel function, which is shown in Equation 6.

$$K_{RBF}(X, X_i) = exp(-\gamma|x_i - x_j|2) \tag{6}$$

Multi-classification problems are transformed into various binary classification problems. The goal is to create a mapping of data points into a high-dimensional space, which would enable linear separation between each pair of classes. One-to-one strategy is used to reduce the multiclass problem into many binary classification problems. A binary classifier will be implemented for each pair of classes. Another technique that can be employed is referred to as One-to-Rest. The approach involves setting the breakdown into a binary classifier for each class (Anzid et al., 2019). The Python library Scikit-learn provides access to SVM. Finally, 823 TSE stocks were mentioned to buy, sell or neutral during the study period. Offers here mean people's suggestions to buy or sell or being neutral about a stock. Total messages were 36,824 which including 10,107 positive (buy), 807 negative (sell), and 25,910 neutral, and as the Figure 1 shows, the number of neutral offers is higher than buy and sell offers.

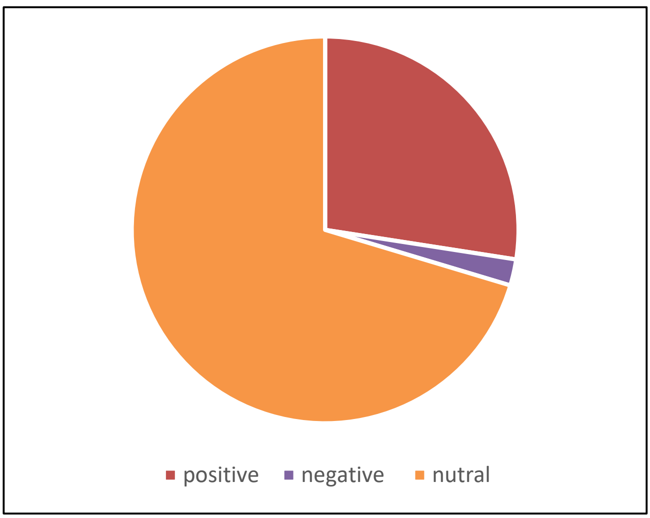

Figure 1. Offers distribution
Source: Research findings

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Sampling of research was purposeful, which was stocks had over 100 offers. Therefore, 52 TSE stocks, which had over 100 offers in the research period, were selected as the research sample. Using people's suggestions, we created a prediction model to test if it improves accuracy as an indicator for TSE stocks. Deep learning models are an effective approach for stock market prediction, as previous research has shown. Nabipour et al. (2020), Li & Bastos (2020), Bhandari et al. (2022),and Shah et al. (2022) all mentioned that deep learning is the best for building a prediction model for stock price patterns. Our paper studies the stock price prediction method based on deep learning. Deep learning approaches are classified into three categories: supervised, semi-supervised, and unsupervised. Supervised learning employs labeled data, where the algorithm receives a set of inputs and corresponding outputs.

In supervised learning, the algorithm gets inputs and labeled outputs. Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) (including LSTM and GRU) are types of supervised learning. Semi-supervised learning uses partly labeled datasets like Deep Reinforcement Learning (DRL) and Generative Adversarial Networks (GAN). Unsupervised learning seeks hidden relationships and structures without labels: Auto Encoders (AE), Restricted Boltzmann Machines (RBM), and the developed GAN (Alom et al., 2018). Research comparing deep learning algorithms showed LSTM had more accurate results than other algorithms (Chen et al., 2015; Nelson et al., 2017; Roondiwala et al., 2017; Chen & Zhang, 2018; Arora & Mani, 2019; Eapen et al., 2019; Nikou et al., 2019; Nabipour et al., 2020; Yadav et al., 2020; Shen & Shafiq, 2020; Hargreaves & Chen, 2020). Therefore, in this paper, adopt LSTM to achieve more accurate price prediction. LSTM is an algorithm that can be employed for time series forecasting because of its ability to store memory and solve the gradient vanishing problem (Moghar & Hamiche, 2020). In gradient vanishing problem, weights cannot be updated, so the network cannot learn. LSTM can recall prior states and incorporate them into prediction. The LSTM model incorporates three gates, namely the input gate, forget gate, and output gate, which facilitate the processing of information from previous states and the current input to derive the subsequent state (Shah et al., 2022). The forget gate serves to eliminate information from the cell state. The input and output gates function to determine the incorporation of information into the cell state and the utilization of information as an output, correspondingly (Hargreaves & Chen, 2020). Figure 2 below portrays the stream of information at time t. Each

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gate was associated with an activation function for calculating a weighted sum.

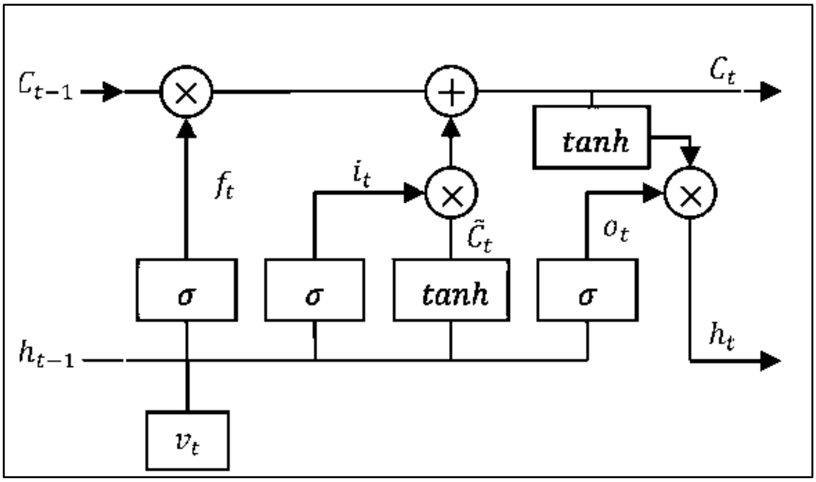

Figure 2. The Architecture of the LSTM Network
Source: (Yadav et al., 2020)

The Equations and calculations are presented below, where W denotes the weight matrix, b is the bias vector, σ represents the sigmoid function, and Tanh denotes the hyperbolic tangent function.

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \quad (7)$$
$$i_t = (W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (8)$$
$$\tilde{c}_t = \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (9)$$
$$c_t = (f_t * c_{t-1} + i_t * \tilde{c}_t) \quad (10)$$
$$o_t = \sigma\,(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (11)$$
$$h_t = o_t * \tanh(c_t) \quad (12)$$

Sigmoid, Tanh and ReLU are different activation functions which used for LSTM (Vargas et al., 2017). Also, Optimizer functions which are SGD, Adagrad, AdaDelta, RMSprop and Adam. The optimization algorithm iteratively processes training data to update the network's weights (Alom et al., 2018). Jiang (2021) pointed that Adam is the most used optimizer function for stock market prediction. The LSTM model's best architecture is based on neuron amounts and activation function. Some neurons will lead to more error

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and the network will not converge. Also, a high number of neurons will lead to over fitting and high error (Alom et al., 2018). The activation function selected was the hyperbolic tangent (Tanh). LSTM model had an input layer, two hidden layers and a dense (output) layer. The neurons in each layer were 64. Description of LSTM model is shown in Table 1, which epoch defines the number of times the entire data set has to be worked through the learning algorithm. Also, batch size defines the number of samples that will be propagated through the network.

Table 1
LSTM model parameters

parameters	**Values**
cells of each layer	64
batch size	3
hidden layers	2
activation function	Tanh
optimizer function	Adam
dense layer	1
epochs	100

Source: Research findings

Furthermore, the loss function employed was a Mean Squared Error (MSE) (Singh & Srivastava, 2017), which determines the difference between the current output of the algorithm and the expected output. We fed our LSTM model with buy, sell and neutral offers from 52 selected TSE stocks, and their close prices from www.tsetmc.com. In order to train the model, we divided the dataset into three parts, train data (70%), test data (15%) and validation data (15%), datasets details are shown in Table 2.

Table 2
Distribution of datasets

dataset	**Date**	**Number of days**
Train data	(2022-01-10) to (2022-06-12)	133 trading day
Test data	(2022-06-14) to (2022-07-15)	33 trading day
Validation data	(2022-07-16) to (2022-08-15)	30 trading day
Total	(2022-01-10) to (2022-08-15)	196 trading day

Source: Research findings

Moreover, the model is evaluated on the test dataset. In this research, the metrics of the normalized Root Mean Square Error (nRMSE), Mean Absolute

Percentage Error (MAPE) (Nikou et al., 2019), and correlation of actual and predicted values had been used. The training of the prediction model involves feature extraction. To make predictions, nine attributes are considered, which are stock price, recommendations to buy, sell, and hold, user rank and performance, risk, trend, and score. The stock price corresponds to the closing price and represents the final traded value of the stock prior to the market's daily closing. Past studies Xu et al. (2017), Geng et al. (2022),and Wu et al. (2020) only looked at buy and sell offers for stocks as the WoC index, and did not include stock holding offers. In this study, the WoC index was defined in the Equation (13) according to the studies Wu et al. (2019), Geng et al. (2022), and Kristjanpoller et al., 2021).

$$WoC = \sum \frac{buyvolum - sellvolume}{buyvolume + sellvolume + neutralvolume} \tag{13}$$

user performance using three criteria: (Sohrabi et al., 2022)

- last offer recency: time between the user's last offer and now.
- offer frequency: number of offers published by user in 1, 3, and 6 months.
- user's offers' value: ratio of correct to incorrect offers compared to total offers based on Equation (14). Where $true\ offers_{i,t}$represents the total number of the offers, which related to buy or sell stock *i* on day *t*, which lead to increase and decrease stock close price respectively; and $falseoffers_{i,t}$ represents the total number of the offers, which related to buy or sell stock *i* on day *t*, which leads to decrease and increase stock close price respectively.

$$\text{User's offers' value} = \frac{true\ offers_{i,t} - falseoffers_{i,t}}{total\ offers} \tag{14}$$

user rank using three criteria: (Sohrabi et al., 2022)

- views: User's message's average views.
- return: Calculate monthly return of user-introduced shares based on Equation (15)(Kumar et al., 2020).

$$Return = \frac{Actual\ end\ price}{Start\ price * Stock\ holding\ period} \tag{15}$$

- Growth: the user-introduced stocks' monthly yield difference.

Because of our agreement with SAHMETO, we cannot reveal how we calculate performance and rank. Standard deviation is a common risk measurement for investments. Higher standard deviation means more risk due

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to random data distribution (Gholizade et al., 2016), which is calculated based on Equation (16).

$$\text{Risk}= \sqrt{\frac{\sum(number\ of\ stock_i offers - mean\ of\ total\ offers)^2}{total\ offers-1}} \tag{16}$$

In social media, what is trending is the sufficient contents produced in social media. Similarly, a trend shows the general direction of a market or asset price (Mitchell, 2023). In this research, the stock trend is the relative frequency of offers for each stock compared to the total offers in each day, which is calculated based on Equation (17).

$$Trend= \frac{number\ of\ offers\ for\ stock_i}{total\ offers} \tag{17}$$

The stock score is calculated by three features:

- The number of users who recommended that stock.
- The rank of each user.
- The time interval between the user’s suggestion and the present time.

Because of our agreement with SAHMETO, we cannot reveal how we calculate stock score.

According to the mentioned features, five prediction models were designed. The features related to each model are shown in Table (3). In first and base prediction model, close price is the only feature used, in second model more than stock close price, WoC index which is defined before used, third model used user rank beside WoC and forth model used performance either. In fifth model beside close price and Woc index, risk, trend and score of the stock were used.

Table3
Prediction models description

Models	**M1**	**M2**	**M3**	**M4**	**M5**
features	*Close price*	*Close price* *WoC*	*Close price* *WoC× Rank*	*Close price* *WoC× Rank×* *performance*	*Close price* *WoC* *Risk* *Trend* *Score*

Source: Research findings

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4 Results

5 models applied to analyze 52 stocks using the mentioned features. The models were trained, tested, and applied to the validation set for 30 trading days. Results are from the validation set. Table 4 shows LSTM models results.

Table 4

LSTM models results

	MAPE					nRMSE					Correlation				
	M1	*M2*	*M3*	*M4*	*M5*	*M1*	*M4*	*M3*	*M4*	*M5*	*M1*	*M2*	*M3*	*M4*	*M5*
KHODRO	0.002	0.003	0.014	0.022	0.009	0.021	0.030	0.098	0.158	0.065	0.999861	0.998151	0.989688	0.988530	0.996993
KHSAPA	0.015	0.005	0.013	0.07	0.013	0.070	0.032	0.066	0.034	0.071	0.999989	0.992765	0.990754	0.998625	0.966889
KHGOSTAR	0.005	0.006	0.002	0.001	0.004	0.032	0.042	0.021	0.011	0.033	0.999931	0.998916	0.998775	0.999864	0.995359
SHAPNA	0.006	0.005	0.007	0.008	0.009	0.059	0.056	0.059	0.061	0.081	0.999146	0.998967	0.997155	0.993916	0.992468
SHATRAN	0.001	0.002	0.003	0.003	0.002	0.018	0.033	0.035	0.044	0.034	0.999923	0.999006	0.999142	0.998934	0.998586
VTEJARAT	0.005	0.005	0.006	0.010	0.011	0.037	0.040	0.040	0.075	0.080	0.999736	0.999729	0.998442	0.986105	0.986745
KHZAMYA	0.005	0.003	0.008	0.008	0.008	0.043	0.026	0.052	0.048	0.057	0.997804	0.997099	0.996365	0.995559	0.996507
VBEMELAT	0.002	0.005	0.003	0.024	0.005	0.011	0.030	0.220	0.122	0.029	0.999970	0.999353	0.999885	0.995829	0.997565
VEJAMI	0.002	0.004	0.002	0.004	0.002	0.013	0.021	0.015	0.025	0.016	0.999964	0.999182	0.999889	0.999138	0.999304
VKHARAZM	0.003	0.002	0.006	0.004	0.006	0.027	0.030	0.058	0.034	0.066	0.999879	0.999336	0.999345	0.999438	0.988814
FARABOURCE	0.002	0.003	0.006	0.010	0.009	0.015	0.023	0.032	0.050	0.048	0.999928	0.999218	0.999107	0.998971	0.993274
VRENA	0.004	0.005	0.011	0.008	0.007	0.017	0.023	0.049	0.041	0.036	0.999346	0.999218	0.997742	0.997868	0.997958
VSAPA	0.003	0.003	0.010	0.014	0.005	0.014	0.018	0.044	0.062	0.026	0.999964	0.999238	0.999011	0.996313	0.998172
ENERGY3	0.007	0.009	0.006	0.018	0.007	0.032	0.042	0.028	0.067	0.033	0.999983	0.998482	0.999117	0.999151	0.998023
PALAYESH	0.002	0.005	0.004	0.008	0.004	0.022	0.048	0.038	0.075	0.044	0.999930	0.998366	0.998100	0.995741	0.993087
LPARS	0.004	0.002	0.010	0.004	0.003	0.043	0.030	0.089	0.036	0.031	0.999959	0.996977	0.991739	0.998031	0.993459
VBSADER	0.005	0.008	0.031	0.003	0.007	0.036	0.051	0.029	0.027	0.054	0.999693	0.994318	0.973677	0.999578	0.994552
HKESHTI	0.001	0.003	0.002	0.002	0.004	0.007	0.031	0.019	0.013	0.038	0.999875	0.999533	0.999785	0.999867	0.998421
THFARS	0.004	0.002	0.009	0.022	0.009	0.018	0.008	0.037	0.010	0.043	0.999579	0.999476	0.998845	0.996392	0.988622
SHABRIZ	0.007	0.009	0.016	0.013	0.010	0.026	0.034	0.045	0.044	0.040	0.999877	0.999729	0.999493	0.999244	0.998220
FMORAD	0.005	0.005	0.009	0.005	0.009	0.029	0.024	0.046	0.039	0.041	0.998467	0.997932	0.998296	0.998183	0.996836
DARAYEKOM	0.009	0.009	0.009	0.008	0.007	0.084	0.082	0.078	0.081	0.076	0.999926	0.997794	0.995772	0.995322	0.995817
KHKAVE	0.003	0.003	0.006	0.001	0.002	0.016	0.018	0.029	0.014	0.013	0.999881	0.999873	0.999723	0.999918	0.999256
KHCHARKHESH	0.008	0.003	0.006	0.004	0.005	0.052	0.019	0.037	0.023	0.022	0.998391	0.998718	0.997345	0.998244	0.999114
FARAVAR	0.002	0.003	0.003	0.002	0.003	0.018	0.037	0.030	0.018	0.034	0.999753	0.999512	0.999592	0.999581	0.996513
GHNOOSH	0.005	0.002	0.006	0.011	0.003	0.40	0.024	0.053	0.096	0.029	0.999824	0.999809	0.999862	0.999332	0.998207
TAPKISH	0.002	0.009	0.013	0.008	0.006	0.023	0.086	0.112	0.073	0.058	0.999664	0.987098	0.981646	0.987897	0.983238
KMARJAN	0.003	0.001	0.001	0.001	0.002	0.020	0.015	0.017	0.016	0.019	0.999753	0.999696	0.999700	0.999531	0.999401
CMEGA	0.003	0.004	0.010	0.002	0.008	0.015	0.028	0.057	0.012	0.052	0.999878	0.999290	0.999282	0.999656	0.998143
BAREKAT	0.007	0.005	0.005	0.004	0.009	0.045	0.021	0.030	0.026	0.037	0.999612	0.999493	0.997541	0.997617	0.997662
FAZAR	0.003	0.002	0.004	0.003	0.001	0.028	0.017	0.045	0.038	0.013	0.999455	0.999438	0.998236	0.999088	0.998755
KDAMA	0.004	0.003	0.003	0.002	0.006	0.043	0.024	0.038	0.023	0.048	0.999508	0.999611	0.999658	0.999173	0.999418
FKHOUZ	0.003	0.004	0.013	0.010	0.009	0.012	0.017	0.062	0.045	0.040	0.999821	0.999647	0.999521	0.999467	0.997418
SIMORGH	0.002	0.004	0.004	0.005	0.004	0.029	0.042	0.040	0.052	0.050	0.999784	0.994805	0.997612	0.993119	0.992393
KERMAN	0.002	0.002	0.003	0.003	0.005	0.021	0.025	0.037	0.039	0.045	0.999507	0.998987	0.997744	0.999380	0.993116

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KHTRUCK	0.002	0.007	0.005	0.004	0.002	0.017	0.050	0.039	0.037	0.019	0.999514	0.999470	0.999504	0.994269	0.997959
FOLAY	0.005	0.006	0.005	0.003	0.008	0.037	0.044	0.027	0.030	0.043	0.998262	0.996890	0.997891	0.995133	0.994170
KHTVAGHA	0.003	0.004	0.005	0.005	0.012	0.015	0.024	0.025	0.029	0.067	0.999920	0.998691	0.999722	0.998839	0.997875
KHMOTOR	0.002	0.007	0.005	0.007	0.008	0.015	0.041	0.042	0.040	0.050	0.999632	0.999395	0.992510	0.996343	0.996449
NOORI	0.001	0.004	0.006	0.012	0.005	0.016	0.016	0.025	0.043	0.005	0.999179	0.998726	0.996167	0.995911	0.996186
BOURCE	0.002	0.007	0.007	0.007	0.005	0.011	0.035	0.047	0.046	0.005	0.999930	0.999646	0.999342	0.998240	0.996090
KAMA	0.007	0.008	0.014	0.009	0.008	0.050	0.051	0.089	0.069	0.008	0.999496	0.998881	0.987324	0.994689	0.984718
FLOULE	0.007	0.006	0.011	0.003	0.009	0.025	0.023	0.036	0.009	0.009	0.999737	0.999490	0.997848	0.999757	0.997801
THAKHT	0.002	0.002	0.002	0.006	0.002	0.020	0.021	0.025	0.062	0.002	0.999316	0.998839	0.999113	0.998903	0.998478
ZDASHT	0.001	0.003	0.001	0.004	0.002	0.007	0.033	0.012	0.051	0.002	0.999762	0.999702	0.999600	0.999322	0.999279
GHTHABET	0.001	0.009	0.027	0.025	0.011	0.007	0.045	0.014	0.107	0.011	0.999818	0.994744	0.985493	0.989665	0.995370
THABAD	0.011	0.010	0.014	0.013	0.009	0.045	0.046	0.074	0.059	0.009	0.999851	0.999327	0.997565	0.998777	0.994139
CDABIR	0.006	0.017	0.008	0.014	0.018	0.026	0.047	0.035	0.040	0.018	0.998925	0.998160	0.998360	0.999329	0.997191
MODIRIYAT	0.006	0.005	0.003	0.002	0.008	0.039	0.031	0.020	0.125	0.053	0.999526	0.999765	0.999306	0.994916	0.995977
VAZAR	0.001	0.002	0.001	0.001	0.003	0.009	0.013	0.015	0.016	0.032	0.999948	0.999619	0.998756	0.998965	0.995730
VBARGH	0.003	0.004	0.002	0.005	0.003	0.020	0.034	0.021	0.033	0.021	0.999152	0.998493	0.998333	0.999183	0.998337
CNIR	0.002	0.005	0.006	0.007	0.003	0.012	0.032	0.039	0.061	0.024	0.999632	0.999247	0.999650	0.998399	0.998563

Source: Research findings

Figures 3 and 4 show accuracy graphs for easy data understanding.

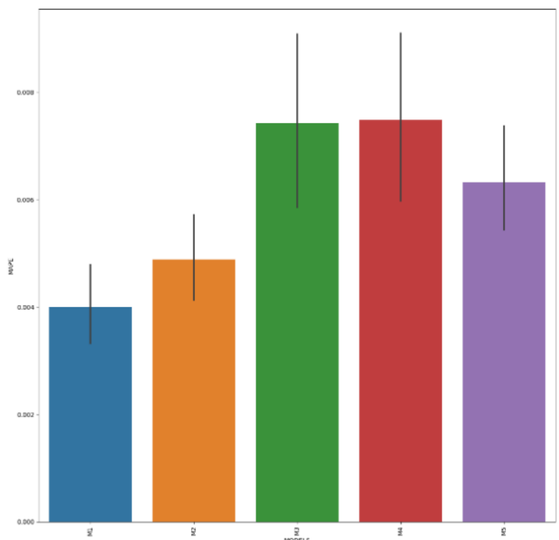

Figure 3. MAPE comparison of LSTM models
Source: Research findings

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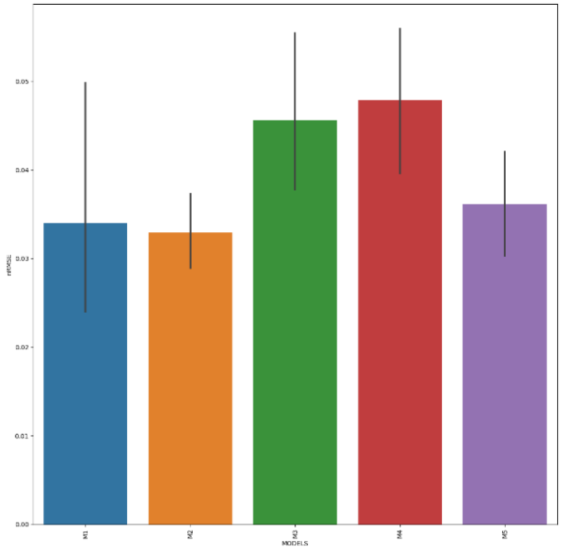

Figure 4. nRMSE comparison of LSTM model
Source: Research findings

Results vary among the five prediction models and stocks. Prediction model accuracy was increased for nineteen stocks. The stocks are KHSAPA, KHGOSTAR, SHAPNA, KHZAMYA, VKHARAZM, ENERGY, LPARS, THFARS, DARAYEKOM, KHKAVE, KHCHARKHESH, GHNOOSH, KMARJAN, CMEGA, BAREKAT, FAZAR, KDAMA, FOLAY, FLOULE. The study confirmed earlier research on 19 stocks and showed that the WoC enhances predictive models. While the prediction models for 33 stocks were not more accurate with the WoC and social media features, which was in line with the results of Raie et al. (2016), Antweiler & Frank (2004), Tumarkin & Whitelaw (2001), Nofer & Hinz (2014), Oyland (2015), Lorenz et al. (2011), Almaatouq et al. (2020). Based on Figure 3, the M1, which denotes the base model, exhibits the lowest MAPE error, while the M2, comprising WoC index, is a close second. Compared to M3 and M4, the M5, comprising WoC index, risk, trend and stock score demonstrates a lower error value. In the error diagram (nRMSE), the error of the M2, which includes the WoC feature, is lower than the base model. Incorporating users' rank and performance into the M3 and M4 models has resulted in a rise in MAPE and nRMSE. According to Lorenz et al. (2011), Oyland (2015), Nofer & Hinz, (2014),and Almaatouq et al. (2020), the social influence of opinion-givers can harm the WoC. Social influence can compel individuals to alter their beliefs and assessments. People may modify their assessments for diverse reasons upon realizing the opinions of others. Nofer & Hinz (2014) mentioned social influence decreases group diversity but does not enhance accuracy. Surowiecki (2005) believes good judgment is about independent decision making.

5 Discussion and Conclusion

Efficient market theory assumes equal information access affects prices, but disregards complex market movements. In the real world, we prefer simple and mostly accurate prediction strategies, known as bounded rationality. Limited information leads to bounded rationality, where people prioritize relative satisfaction in decision-making, resulting in a desirable decision (Noroozi et al., 2023). Investors employ accessible information to select a stock or forecast stock prices. Social media enables people with different backgrounds to share opinions on the market. Investors' opinions on social media are useful for studying market efficiency. The research focuses on diagnosis and predicting mass behavior, not judging it. Collective behavior is abundant in social networks and has been widely discussed in articles. It is uncertain whether the WoC contributes to an increase in accuracy in the stock price prediction model. Certain stocks, primarily associated with the automotive and metal sectors, experienced a decrease in prediction model error with the aid of WoC, whereas other stocks did not. The wisdom of the social media users shows the money flow, and direction of financial inflow or outflow can be inferred from the level of public attention. The optimal timing of buying or selling stocks is critical for ensuring profitability, and gaining insight into the collective behavior of investors can provide a key advantage in making informed trading decisions.

6 Limitations and Future recommendations

SAHMETO's server and technical infrastructure limited user opinion collection to less than eight months. Certain stocks (SHBANDAR, FOLAD, SHASTA, KALA, KHPARS, ZOB, DEY, KHAVAR, THNOOR, AND SHAVAN) were not available for trade and their value was stable. Persian financial market had no emotional dictionary or software for sentiment analysis. For further research, we recommend investigating different LSTM models. As what mentioned in limitations, stock trading close for some period and close price of stock will not update. Therefore, future price prediction despite price data sparseness can be an interesting research area. Investigating the digital currencies and blockchain sector, which are minor and prone to the

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impact of social media, especially Twitter. Regulatory bodies can detect fraud in the market. Trading patterns, market data, and crowd behavior analysis can detect illegal activities.

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