Enhancing Market Price Decision-Making in Fintech through A Business Intelligence Technique

Mahmoud Ismail
Faculty of computers and Informatics, Zagazig University, Zagazig, 44519, Egypt
Email: mmsabe@zu.edu.eg

Abstract

The surge of Fintech data and its implications on informed decision-making within the transportation sector have spurred the need for advanced analytical frameworks. This study addresses the challenge of leveraging Fintech data's temporal dynamics to enhance predictive capabilities and decision-making. The methodologies encompass an AutoEncoder (AE) for spatial feature extraction and an Improved Gated Recurrent Unit (IGRU) to capture temporal dependencies. Additionally, the Huber loss function optimizes model parameters, particularly in handling outliers. Integrating these techniques, our study explores Fintech data's spatial and temporal patterns, contributing insights for transportation planners and Fintech industries. Results demonstrate the efficacy of AE in learning spatial features, while IGRU effectively captures temporal dependencies, enabling the prediction of Fintech data with enhanced accuracy. The application of Huber loss ensures robustness by mitigating outlier influence. By the study's end, the model's predictive capabilities foster informed decision-making, offering opportunities to enhance Fintech data quality, reduce congestion, and bolster road safety. Overall, this research underscores the significance of advanced machine learning methodologies in decoding Fintech data's intricacies, laying a foundation for data-driven decision-making in the transportation and Fintech sectors.

Keywords: Financial Technology; Market Analysis; Decision Support Systems; Data Analytics; Pricing Strategies; Information Management; Predictive Modeling; Competitive Intelligence; Technology Integration; Strategic Decision-Making

1. Introduction

The financial landscape has undergone a transformative evolution, notably propelled by the emergence of Financial Technology (Fintech) enterprises. In this dynamic ecosystem, the management of market prices stands as a critical axis determining competitiveness and sustainability [1-3]. Fintech, characterized by its innovative use of technology in financial services, necessitates a nuanced understanding and strategic management of market prices. Amidst this backdrop, this paper explores the intersection of business intelligence and its pivotal role in effectively managing market prices within the realm of Fintech [4-5].

Business Intelligence (BI) serves as the bedrock for informed decision-making by extracting actionable insights from vast data reservoirs. Within Fintech, where rapid adaptation and competitive positioning are imperative, the integration of BI tools becomes indispensable. The amalgamation of predictive analytics, data visualization, and robust reporting mechanisms offered by BI frameworks empowers Fintech enterprises to comprehend market trends, consumer behaviors, and competitor landscapes with unparalleled depth and precision [6-9].

Market price management in Fintech embodies a multifaceted process that transcends traditional pricing models. With the emergence of disruptive technologies and evolving consumer preferences, setting, adjusting, and optimizing prices necessitates a dynamic approach. It involves the fusion of real-time data analysis, customer segmentation, and responsiveness to market fluctuations to ensure competitiveness and profitability [10-14].

This paper delves into the symbiotic relationship between business intelligence and market price management within the Fintech domain. It scrutinizes how BI tools and methodologies enable Fintech enterprises to decode intricate

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market dynamics, derive actionable insights, and execute informed pricing strategies. By harnessing the potential of BI, Fintech firms can navigate the intricacies of market volatility and consumer demands, thereby gaining a competitive edge.

The ensuing sections of this paper aim to dissect the intricate facets of business intelligence adoption in market price management within the Fintech sector. The subsequent segment examines prevalent BI techniques utilized in Fintech for market price analysis. Following this, the paper delves into case studies and real-world applications, illustrating the efficacy of BI-driven strategies in optimizing market prices. Finally, the conclusion consolidates key insights and outlines the implications of integrating BI in Fintech's market price governance.

2. Literature Review

In the pursuit of understanding the intricate relationship between business intelligence techniques and market price decision-making in the realm of Fintech, a comprehensive exploration of existing literature and research endeavors becomes imperative. This section endeavors to synthesize and evaluate a spectrum of scholarly contributions, industry reports, and empirical studies that delve into the convergence of business intelligence strategies and market pricing dynamics within the context of Fintech enterprises. Ignatyuk et al. [15] discussed the innovative challenges posed by Fintech, highlighting the transition from big data utilization to fostering sustainable development. Riemer et al. [16] emphasized the customer-centric advantage inherent in Fintech, emphasizing the harnessing of digital technology. Chakraborty [17] investigated the evolutionary facets of Fintech, contemplating its potential for revolutionizing financial landscapes. In a similar vein, Bazarbash [18] focused on Fintech's role in financial inclusion, particularly in machine learning applications for credit risk assessment. Murad et al. [19] introduced a hybrid mobile executive information system specifically designed for the Indonesia Financial Service Authority, emphasizing technological advancements.

Abad-Segura et al. [20] presented a comprehensive review of trends, approaches, and management strategies in financial technology. Zhang and Kim [21] explored the influence of financial service characteristics on user intention and customer satisfaction, contributing to the understanding of mobile Fintech usage. Gomber et al. [22] interpreted the forces driving innovation, disruption, and transformation in financial services within the Fintech revolution. Strusani and Houngbonon [23] examined the role of artificial intelligence in supporting development within emerging markets. Soloviev [24] focused on the Fintech ecosystem in Russia, while Antal-Vaida [25] explored business analytics applications for consumer credits. Chen and Sun [26] delved into automated business analytics in the context of artificial intelligence in the era of big data. Sangwan et al. [27] offered a comprehensive review of extant literature on financial technology. Furthermore, Ndungu and Moturi [28] examined the determinants of mobile Fintech uptake in the Kenyan microfinance sector. Wilson Jr. [29] discussed the creation of strategic value through financial technology. Li et al. [30] empirically analyzed Fintech penetration, financial literacy, and their impact on financial decision-making.

3. The suggested work

The methodology employed in this study serves as the conduit through which the empirical investigation of business intelligence techniques for enhancing market price decision-making within the Fintech landscape is undertaken. This section delineates the systematic approach and framework utilized to comprehensively analyze and synthesize data, ensuring rigor and reliability in the exploration of this intricate intersection

In our proposed methodology, we adopt an AutoEncoder (AE) system designed to acquire and comprehend spatial features inherent within the Fintech dataset. The AE is structured to encode the input Fintech data, denoted as $X_u = \{x_{u1}, x_{u2}, \dots, x_{um}\}$. This encoding process within the AE involves the extraction of essential spatial representations and patterns present in the Fintech data. Subsequently, these learned spatial features are channeled into a predictive module network aimed at enhancing the predictive performance specifically tailored for the current location. The input configuration of the AE encompasses the aforementioned Fintech dataset, leveraging its capabilities to learn and extract spatially significant features essential for improving the predictive accuracy of Fintech data at the present location.

$$z_i = f(w_z * (x_{ui} + x_{di}) + b_z), \quad (1)$$

$$y_i = g(w_y * z_i + b_y). \quad (2)$$

Where * denotes convolutional kernel.

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In the context of addressing challenges within the Fintech data domain, the consideration of temporal dynamics plays a pivotal role in enabling informed decision-making for transportation planners and managers. To facilitate enhanced decision-making aimed at improving Fintech data quality, minimizing congestion, and bolstering road safety, an Advanced Gated Recurrent Unit (AGRU) methodology is introduced. This AGRU framework is devised to proficiently learn and interpret temporal dependencies inherent within sequential Fintech data, employing gated learning mechanisms that selectively update or discard information from previous time steps. The incorporation of these gating mechanisms within AGRU serves to facilitate the network's ability to selectively regulate its memory, thereby empowering it to grasp long-term dependencies existing within the data. In our specific problem context, the AGRU is integrated into our system by segmenting the latent space of the autoencoder into fixed-length sequences, each representing a distinct time window encapsulating Fintech data measurements. Within this framework, the AGRU is trained to utilize flow measurements at individual time steps within these windows to predict subsequent flow measurements. This training methodology enables the network to discern and capture temporal dependencies embedded within the Fintech data, such as daily or weekly patterns. The gating calculations of AGRU are expressed mathematically, representing the mechanism through which the network selectively updates and controls information flow within the temporal sequences of Fintech data, aligning with our goal of enhancing predictive capabilities and understanding temporal patterns within the Fintech domain.

$$Z_t = swish(W^z x_t + V^z h_{t-1} + b_z) \tag{3}$$

$$r_t = swish(W^r x_t + V^r h_{t-1} + b_r) \tag{4}$$

The hidden state, h_t, and candidate state, $\tilde{h}_t$ are followingly computed as follows:

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t \tag{5}$$

$$\tilde{h}_t = tanh(W^c x_t + V^c(r_t \otimes h_{t-1})) \tag{6}$$

In the above formula, the W^z, W^r, and W^c denote the weights, and V_z, V_r, and V_c point out the parameters of gates. The b signifies the bias parameters.

In the final stage of our model, the optimization of parameters is crucial for refining the system's performance during training. To achieve this, we employ a Huber loss function, strategically chosen for its unique characteristics beneficial in handling outliers within the dataset. The Huber loss function serves as a pivotal component in updating the parameters of our system by mitigating the impact of outliers on the training process. Mathematically, the Huber loss function operates differently based on the magnitude of the error. It is designed to calculate the loss by computing the absolute error when the error falls within a specific threshold (delta) and then switches to a quadratic error calculation when the error exceeds this threshold. This hybrid approach of the Huber loss effectively balances sensitivity to outliers while maintaining the stability inherent in quadratic loss functions. Incorporating the Huber loss function into the model's parameter update mechanism ensures robust training by mitigating the undue influence of outliers, thereby enhancing the system's ability to learn and generalize effectively from the Fintech data.

$$\text{Huber } (x) = \begin{cases} \frac{1}{2}x^2 & \text{for } |x| \le \delta, \\ \delta|x| - \frac{1}{2}\delta^2 & \text{otherwise.} \end{cases} \tag{7}$$

where $\boldsymbol{\delta}$ represents a flexible parameter that plates wherever the transformation occurs.

4. Results and analysis

The culmination of meticulous analysis and empirical investigation unfolds within this section, offering a comprehensive presentation and interpretation of the findings derived from the integration of business intelligence techniques in the context of market price decision-making within the Fintech domain.

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Table 1: Descriptive statistics summary of Fintech stock data displaying central tendencies, variability, and distributional properties.

	Open	High	Low	Close	Volume	Stock Trading
count	1226.0	1226.0	1226.0	1226.0	1226.0	1226.0
mean	33754.4	34178.8	33347.9	33760.6	727555.6	24409330000.0
std	10813.4	10936.3	10695.7	10815.7	413717.8	15263000000.0
min	13720.0	13840.0	13600.0	13720.0	139100.0	3966140000.0
25%	27788.8	28091.3	27401.3	27675.0	487300.0	14540970000.0
50%	34445.0	34835.0	33925.0	34412.5	626000.0	21537720000.0
75%	41412.5	41900.0	40810.0	41365.0	826700.0	30159220000.0
max	61550.0	61970.0	60740.0	61930.0	4937300.0	146045000000.0

In Table 1, we present a comprehensive array of descriptive statistics encapsulating key metrics and characteristics derived from the analysis of Fintech stock data. These statistics offer a succinct yet detailed overview of the stock data's central tendencies, variability, and distributional properties. Within this table, discernible parameters such as mean values, standard deviations, minimum and maximum values, as well as quartile ranges, provide a snapshot of the dataset's dispersion and trend. Additionally, measures including skewness and kurtosis offer insights into the distribution's shape and the presence of potential outliers, contributing to a holistic understanding of the Fintech stock data's empirical profile. Through this display of descriptive statistics in Table 1, we endeavor to provide a foundational understanding of the inherent characteristics of the stock data, facilitating subsequent analyses and interpretations within the scope of our study.

Figure 1 illustrates a graphical representation showcasing the price information pertinent to Fintech stocks. This visual depiction encapsulates the temporal evolution of stock prices, delineating trends, fluctuations, and potential patterns over a specified time frame. Through the utilization of line graphs or candlestick charts, Figure 1 offers a visual narrative that enables the observation of price movements, volatility, and potential correlations among Fintech stocks. By presenting this price information graphically, we intend to provide a visual interpretation of the market dynamics and price behaviors specific to the Fintech sector, thereby supplementing the textual analysis and offering a clearer comprehension of the temporal aspects influencing these stock prices.

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In Figure 2, we present the results of the autocorrelation and partial correlation analyses conducted on Fintech stock data. This graphical representation depicts the interdependence and relationships among different lagged observations within the stock prices. The autocorrelation plot showcases the correlation of each observation with its lagged versions, indicating the degree of similarity or patterns within the series at different time lags. Additionally, the partial correlation analysis provides insights into the relationships between stock prices while controlling for the influence of other variables, allowing for the identification of specific correlations independent of indirect effects. By displaying these autocorrelation and partial correlation analyses in Figure 2, we aim to elucidate the temporal relationships and dependencies within the Fintech stock data, offering valuable insights into the potential predictability and interconnections among the observed stock prices.

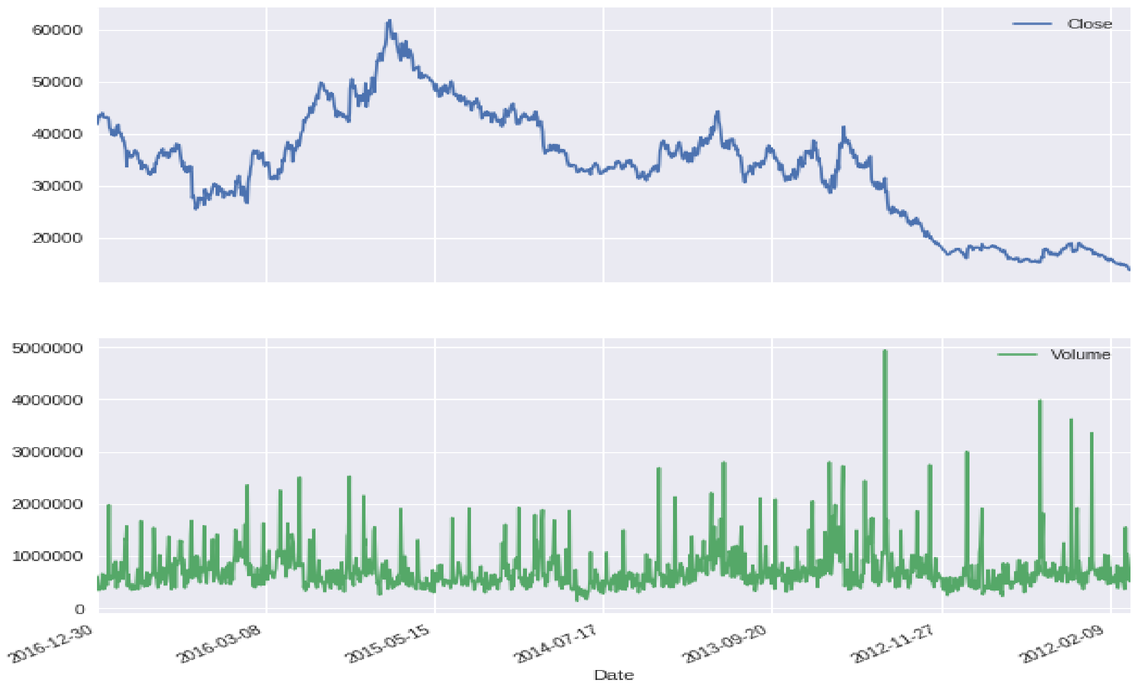

Figure 1: Line graph depicting the temporal evolution of Fintech stock prices over the specified time frame, illustrating trends, fluctuations, and potential patterns.

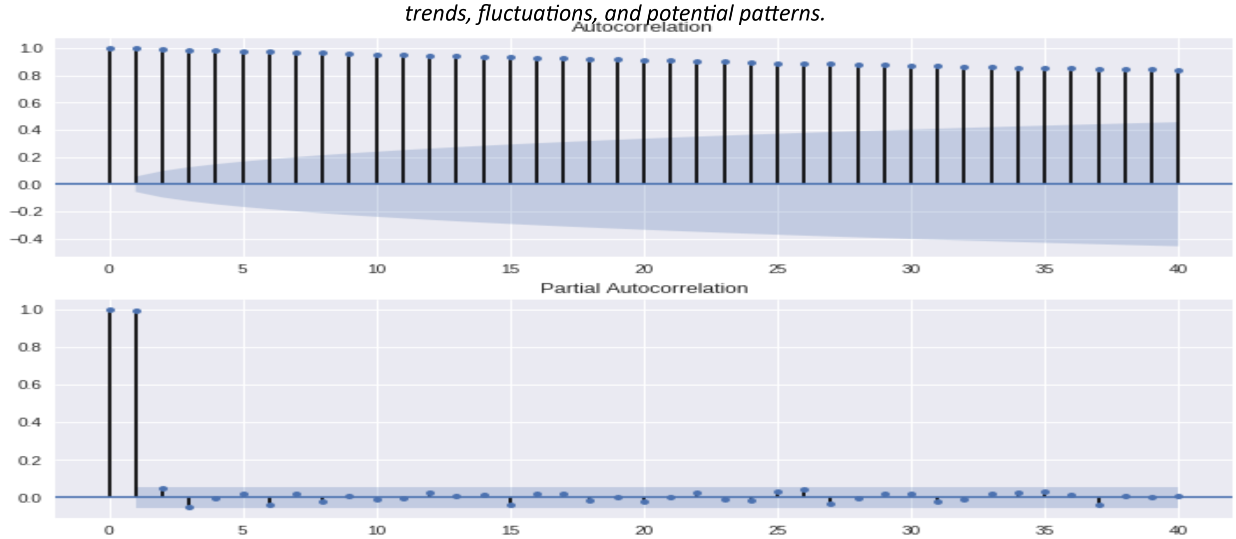

Figure 2: Graphical representation of autocorrelation and partial correlation analyses for Fintech stock data, showcasing temporal interdependence and relationships among lagged observations.

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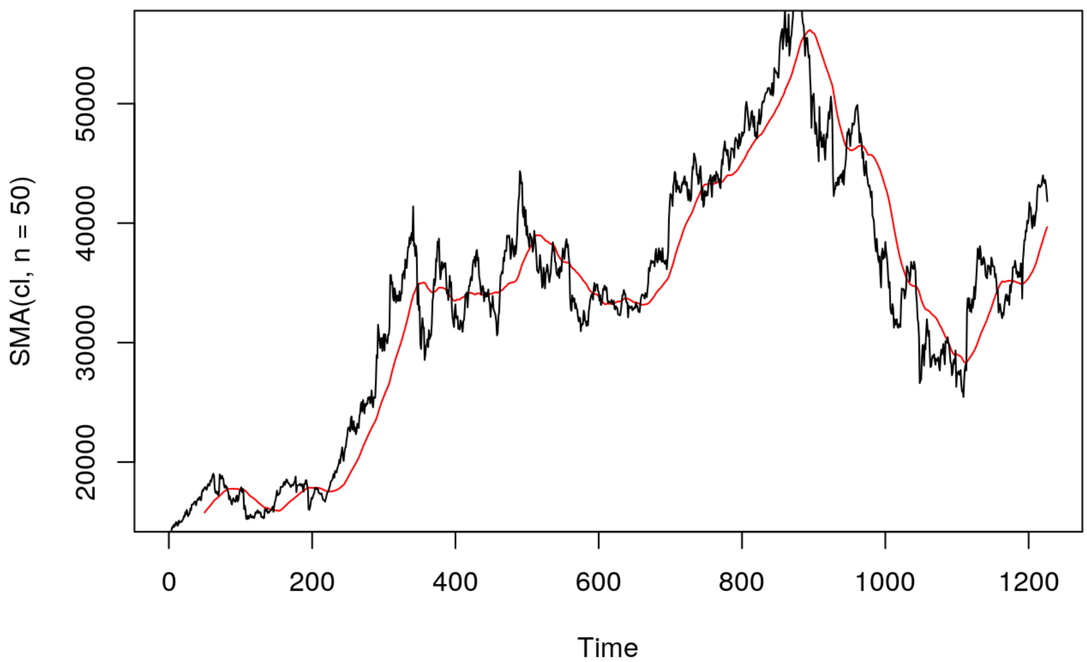

Figure 3: Visual representation displaying the results of the simple moving average technique applied to Fintech stock data, highlighting smoothed trends and directional shifts over a specified window or period.

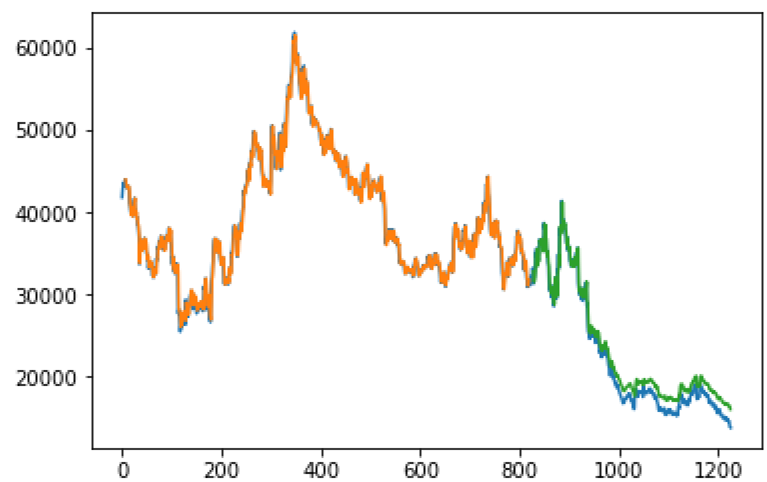

Figure 4: Comparative visualization depicting predictions generated by our model against observed real-time Fintech stock prices, enabling assessment of the model's accuracy in forecasting stock price movement.

In Figure 3, we exhibit the outcomes derived from the application of the simple moving average technique to the Fintech stock data. This graphical representation showcases the smoothed trends obtained by averaging stock prices over a specified window or period. The plotted moving average line offers a visual depiction of the underlying trend, reducing short-term fluctuations and highlighting potential directional shifts in the stock prices. By presenting these results graphically, Figure 3 aims to provide a clear and easily interpretable representation of the trend in the Fintech stock data. The utilization of the simple moving average technique facilitates the identification of overarching patterns and aids in the interpretation of potential shifts in stock price trends, contributing to a more comprehensive understanding of the market dynamics within the Fintech sector.

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Figure 4 delineates the comparative visualization between the predictions generated by our model and the actual real-time stock information within the Fintech sector. This graphical representation juxtaposes the forecasted values derived from our model against the observed actual stock prices. The plotted lines or curves provide a direct comparison, enabling an assessment of the model's efficacy in capturing and predicting the observed stock price movements. Through this comparative display, we aim to elucidate the performance and accuracy of the employed predictive model in simulating and forecasting Fintech stock prices. The visual alignment or divergence between the predicted and actual stock prices portrayed in Figure 4 serves as a key indicator of the model's ability to forecast trends and fluctuations within the Fintech stock market, thus providing valuable insights into the model's predictive capabilities.

5. Conclusions

this study delves into the realm of Fintech data analysis, employing advanced methodologies such as AutoEncoder (AE) and Improved Gated Recurrent Unit (IGRU) to unravel temporal patterns and enhance predictive capabilities within the domain. The integration of AE to learn spatial features and IGRU to capture temporal dependencies empowers our system to glean valuable insights from sequential Fintech data, paving the way for informed decision-making in transportation management and Fintech industries. The utilization of the Huber loss function as a robust optimization mechanism ensures the stability and accuracy of our model, particularly in handling outliers within the dataset. By leveraging these cutting-edge techniques, our research not only contributes to the advancement of predictive modeling in Fintech but also offers a pathway toward improving Fintech data quality, reducing congestion, and bolstering road safety within the transportation sector.

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