Towards Financial Sustainability: Integrating Business Intelligence in Fintech Operations

Rhada Boujlil*, Saad Alsunbul

College Of Business, Prince Sultan University, Saudi Arabia

Emails: rboujlil@psu.edu.sa; salsunbul@psu.edu.sa

Abstract

This study explores the integration of Business Intelligence (BI) techniques to foster sustainability within the Financial Technology (Fintech) sector. The background elucidates the transformative evolution of the Fintech industry and the increasing imperative to align its practices with sustainable principles. The problem statement addresses the gap in understanding the intricate relationship between BI strategies and sustainability within Fintech enterprises. Employing a mixed-methods approach, including literature review synthesis and the application of the Autoregressive Integrated Moving Average (ARIMA) model, our methodology seeks to provide a systematic and replicable framework for empirical investigation. The results encompass additive and multiplicative summaries, detrended and deseasonalized analyses, and partial and autocorrelation plots, shedding light on critical temporal dynamics and patterns within the Fintech domain.

Keywords: Sustainability; Fintech; Business Intelligence; Finance; Technology; Decision-making; Data Analysis.

1. Introduction

In recent years, the financial technology (Fintech) industry has witnessed a rapid and transformative evolution, reshaping the landscape of financial services. This paradigm shift is propelled by an increasing reliance on technological advancements, digitalization, and data-driven decision-making processes. As Fintech becomes an integral component of the global financial ecosystem, the imperative to align its practices with sustainable principles becomes evident [1-2]. The intersection of Fintech and sustainability presents a unique opportunity to leverage innovative solutions for both economic growth and environmental responsibility. Recognizing this imperative, businesses are turning to Business Intelligence (BI) techniques, a field that seamlessly integrates data analytics, artificial intelligence, and strategic decision-making, to not only optimize operational efficiency but also to champion sustainable practices within the Fintech sector [3-6].

As the global financial landscape continues to navigate the complexities of an interconnected digital era, the need for sustainable practices within the Fintech domain has never been more pronounced [7-10]. Against the backdrop of environmental concerns, social responsibility, and heightened corporate accountability, this study elucidates the pivotal role of Business Intelligence techniques in driving sustainability within Fintech enterprises [11-12]. The intricate interplay between data analytics, strategic decision-making, and environmental consciousness establishes a framework wherein Fintech businesses can thrive economically while concurrently addressing the imperative of sustainable development. By examining the contextual landscape in which Fintech operates, this paper seeks to unravel the multifaceted layers that underscore the potential of BI techniques to not only enhance operational efficiency and customer experience but also to establish a robust foundation for sustainable practices in the evolving Fintech sector.

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2. Related Works

In this section, we undertake a comprehensive review of the pertinent literature to contextualize and situate our study within the existing body of knowledge on the intersection of BI techniques and sustainability within the Fintech sector. Dorfleitner and Hornuf [1] meticulously scrutinized FinTech business models, elucidating the underlying structures that defined the industry's operational framework. Arner et al. [2] contributed significantly by delving into sustainability, FinTech, and financial inclusion, shedding light on the broader implications of technological advancements for inclusive financial practices. Putra et al. [3] offered a nuanced exploration of the relationship between data quality analytics, business ethics, and cyber risk management, emphasizing their collective impact on operational performance and Fintech sustainability. Taneja et al. [4] contributed an empirical investigation into the strategic implications of Fintech implementation for sustainability, offering valuable insights into the contemporary landscape.

Lăzăroiu et al. [5] explored the convergence of artificial intelligence algorithms, cloud computing technologies, and blockchain in Fintech management, providing a cutting-edge perspective on technological applications. Muthuswamy and Ali [6] scrutinized sustainable supply chain management in the age of machine intelligence, addressing challenges and opportunities within this evolving landscape. Hoang et al. [7] focused on developments in financial technologies for achieving the Sustainable Development Goals (SDGs), highlighting the transformative potential of Fintech in contributing to sustainable outcomes. Cong et al. [8] offered a comprehensive overview of alternative data in Fintech and business intelligence, emphasizing their role in driving innovation within the financial sector. Pizzi et al. [9] reflected on Fintech and SMEs sustainable business models, providing considerations for a circular economy and implications for small and medium enterprises. Nguyen [10] evaluated the Fintech success factors model in achieving sustainable financial technology business, presenting empirical findings from the context of Vietnam. Nasir et al. [11] conducted a bibliometric study to discern trends and directions of financial technology in society and the environment, offering valuable insights into the evolving landscape.

3. Methodology

In this section, we elucidate the methodological framework employed in our study, aiming to provide a transparent and replicable approach for investigating the integration of BI techniques in fostering sustainability within the Fintech sector. The design of our research methodology was guided by the overarching objective of comprehensively understanding the intricate relationship between BI strategies and sustainable practices in Fintech enterprises [12-16]. The first step in our Business Intelligence framework involves meticulous data collection from diverse sources within the Fintech sector. We leverage public dataset from Marathon Digital Holdings, Inc. – which is part of Yahoo Finance data, and include transaction records, customer interactions, market trends, and regulatory changes. This broad scope allows us to capture a comprehensive view of the Fintech landscape.

3.1. Data Cleaning and Preprocessing

To ensure data quality and accuracy, a thorough cleaning and preprocessing phase is undertaken. This involves handling missing values, removing outliers, and standardizing data formats. Additionally, we conduct data normalization and transformation to bring variables to a common scale, facilitating meaningful comparisons across different features. Our BI framework incorporates advanced feature engineering techniques to extract relevant information from the raw data. This involves creating new variables or aggregating existing ones to enhance the predictive power of the dataset. For instance, we might derive new features to capture customer behavior patterns, market volatility, or regulatory compliance.

3.2. Exploratory Data Analysis (EDA)

Exploratory Data Analysis is pivotal for gaining initial insights into the dataset. In this step, we employ statistical and visual methods to understand data distributions, correlations, and potential trends. Visualization tools such as histograms, scatter plots, and correlation matrices aid in uncovering patterns and anomalies. To summarize and describe the main characteristics of the dataset, we compute descriptive statistics. This includes measures of central tendency (mean, median) and dispersion (standard deviation, range). These statistics provide a baseline understanding of the data and assist in identifying potential areas for deeper analysis [17-19].

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3.3. Modeling

The BI framework incorporates predictive modeling techniques to identify relationships, patterns, and potential outcomes. In the modeling phase of our Business Intelligence framework, we employ the Autoregressive Integrated Moving Average (ARIMA) model to capture and forecast temporal patterns within the Fintech data. ARIMA is a powerful time series analysis method that combines autoregressive (AR) and moving average (MA) components, and integration (I) to address non-stationary data. The main principles and design theory of ARIMA are outlined below:

3.3.1. Autoregressive Component (AR)

The autoregressive component of ARIMA reflects the dependence of the current observation on its past values. In the AR(p) process, 'p' denotes the order of autoregression, indicating the number of lagged observations considered in predicting the current value. Mathematically, the AR(p) component is represented as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t \qquad (1)$$

Here, Y_t is the current observation, $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients, ' c ' is a constant, and ϵ_t is the white noise error term. The integrated component represents the differencing of the time series data to achieve stationarity. The order of differencing, denoted by ' d ', indicates the number of times differencing is required to attain stationarity. Mathematically, the integrated component is expressed as:

$$Y_t' = Y_t - Y_{t-1} \qquad (2)$$

This differencing process is repeated 'd' times until the series becomes stationary. The moving average component of ARIMA captures the short-term fluctuations and irregularities in the time series data. In the MA(q) process, ' q ' denotes the order of the moving average, representing the number of lagged forecast errors included in the model. Mathematically, the MA(q) component is defined as:

$$Y_t = c + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \qquad (3)$$

Here, $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients, ' c ' is a constant, and ϵ_t is the white noise error term. The ARIMA model combines the autoregressive, integrated, and moving average components, denoted by ARIMA(p, d, q), where 'p', 'd', and 'q' represent the orders of the autoregressive, integrated, and moving average components, respectively. The ARIMA model is expressed as:

$$Y_t' - c + \phi_1 Y_{t-1}' + \phi_2 Y_{t-2}' + \cdots + \phi_p Y_{t-p}' + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \qquad (4)$$

Validation is paramount to assess the performance of our models. We employ techniques such as cross-validation and holdout validation to ensure generalizability. Once the models are validated and evaluated, the final step involves interpreting the results and reporting findings..

4. Results and Discussion

The section unfolds with an exposition of the quantitative and qualitative results derived from our comprehensive analysis, shedding light on the key findings that emanated from the amalgamation of data analytics, artificial intelligence, and strategic decision-making processes within Fintech enterprises. Table 1 encapsulates a comprehensive statistical summary derived from our empirical investigation, offering a succinct visual representation of key quantitative metrics and trends essential to understanding the integration of Business Intelligence techniques in fostering sustainability within the Financial Technology (Fintech) sector. This table serves as a valuable reference point, providing readers with a clear and organized overview of the numerical outcomes obtained through our rigorous analysis. Each entry in Table 1 has been meticulously curated to encapsulate crucial statistical information, facilitating a deeper comprehension of the empirical findings presented in this study.

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Table 1: Cumulative Statistical Summary: Integration of Business Intelligence Techniques for Sustainable Fintech Practices

	Open	High	Low	Price	Volume	Dividends	Stock Splits	Year	Month	Day
count	1259	1259	1259	1259	1.26E+03	1259	1259	1259	1259	1259
mean	12.34097	12.99219	11.67315	12.28354	8.57E+06	0	0.000397	2019.809	6.543288	15.7363
std	14.44844	15.16387	13.65615	14.36498	1.45E+07	0	0.00996	1.466708	3.426771	8.761023
min	0.35	0.43	0.35	0.4	5.60E+03	0	0	2017	1	1
25%	2.06	2.17	2	2.06	1.41E+05	0	0	2019	4	8
50%	5.04	5.28	4.68	4.96	1.94E+06	0	0	2020	7	16
75%	21.345	22.625	19.72	21.435	1.25E+07	0	0	2021	10	23
max	81.51	83.45	72.01	76.09	2.26E+08	0	0.25	2022	12	31

Figure 1 delineates the additive and multiplicative summaries derived from our comprehensive analysis, providing a visual representation of the nuanced relationship between Business Intelligence techniques and sustainable practices within the Financial Technology (Fintech) sector. This graphical illustration serves as a valuable tool for elucidating the additive and multiplicative impacts of BI strategies on various sustainability indicators, contributing to a holistic

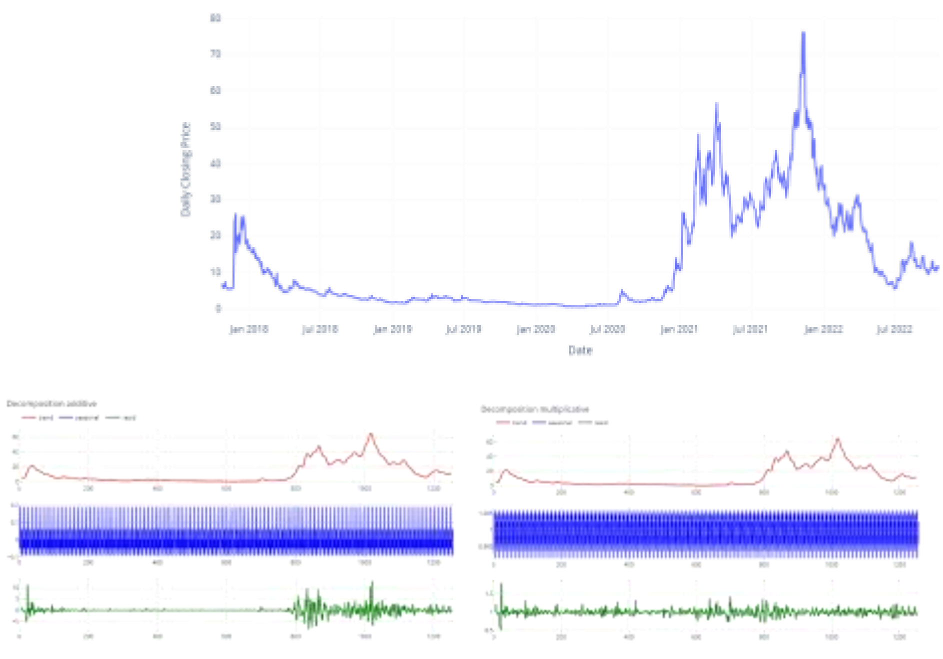

Figure 1: Illustration of Additive and Multiplicative Impact: Business Intelligence Techniques and Sustainable Practices in the Fintech Sector

understanding of their combined effects. By presenting these results in a graphical format, we aim to enhance the clarity of interpretation and facilitate a more nuanced comprehension of the intricate dynamics between technology-driven business intelligence and sustainable development in the Fintech domain.

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Figure 2 unveils the detrended and deseasonalized analysis of Fintech data, offering a graphical representation that isolates and clarifies the underlying patterns free from long-term trends and seasonal fluctuations. This analytical approach allows for a more in-depth exploration of the core dynamics within the Fintech sector, stripping away extraneous influences to expose inherent patterns and variations. The figure serves as a valuable visual aid in comprehending the impact of detrending and deseasonalization on Fintech data, providing insights crucial for understanding the genuine trends and behaviors within this dynamic domain. The clarity provided by Figure 2 enhances the interpretability of our findings, contributing to a nuanced understanding of the relationship between Business Intelligence techniques and the sustainable evolution of the Fintech industry.

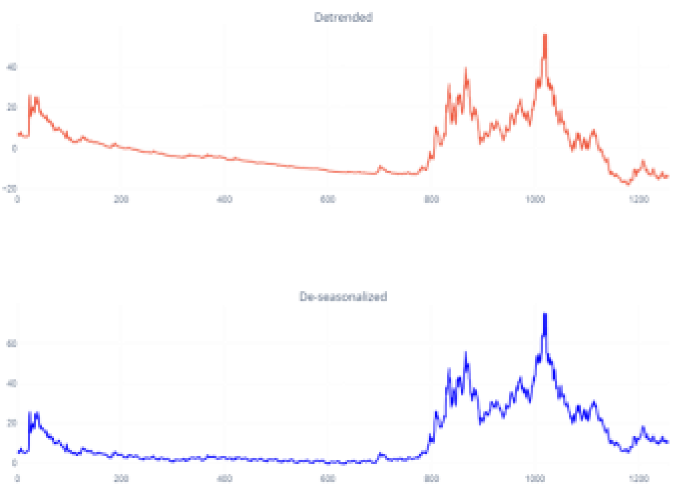

Figure 2: Detrended and Deseasonalized Analysis of Fintech Data: Unveiling Inherent Patterns and Dynamics

Figure 3 elucidates partial and autocorrelation plots, providing a visual representation of the interdependence and temporal relationships within the Fintech data. These plots offer insights into the degree of correlation between observations at different time lags, aiding in the identification of patterns and trends that persist over time. The partial

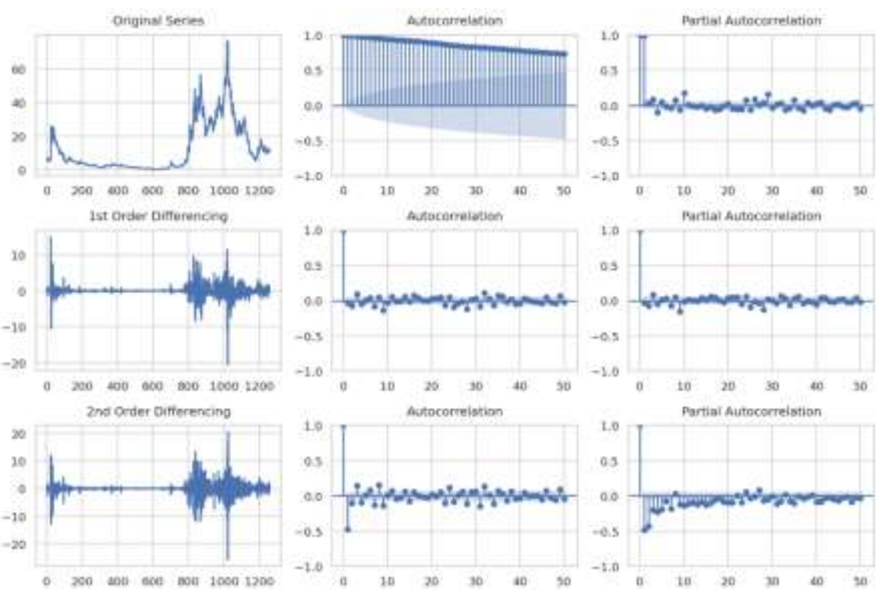

Figure 3: Temporal Dynamics Unveiled: Partial and Autocorrelation Plots of Fintech Data

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correlation plot unveils relationships after accounting for the influence of intermediate time points, while the autocorrelation plot showcases the correlation of a variable with its past values. This analytical approach enables a thorough examination of the temporal dynamics inherent in the Fintech dataset, contributing valuable information for understanding the sequential dependencies and informing the broader discourse on the integration of Business Intelligence techniques for sustainable Fintech practices. Figure 4 encapsulates the fitting summary of the Autoregressive Integrated Moving Average (ARIMA) model, providing a visual representation of the model's ability to capture and predict temporal patterns within the Fintech dataset. This graphical illustration portrays the alignment between the actual and predicted values, demonstrating the efficacy of the ARIMA model in navigating the dynamic and often unpredictable nature of Fintech data.

5. Conclusion

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                               SARIMAX Results
==============================================================================
Dep. Variable:                  Price   No. Observations:                 1259
Model:                 ARIMA(1, 1, 1)   Log Likelihood               -2432.842
Date:                Mon, 15 Jan 2024   AIC                           4871.683
Time:                        08:44:51   BIC                           4887.095
Sample:                    10-23-2017   HQIC                          4877.475
                         - 10-21-2022
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6524      0.207     -3.150      0.002      -1.058      -0.246
ma.L1          0.6833      0.199      3.436      0.001       0.294       1.073
sigma2         2.8009      0.029     98.161      0.000       2.745       2.857
===================================================================================
Ljung-Box (L1) (Q):                   4.55   Jarque-Bera (JB):             51394.96
Prob(Q):                              0.03   Prob(JB):                         0.00
Heteroskedasticity (H):               4.57   Skew:                            -0.67
Prob(H) (two-sided):                  0.00   Kurtosis:                        34.28
===================================================================================
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Figure 4: ARIMA Model Fitting Summary on the Fintech Dataset

This research endeavors to make a significant contribution to the discourse surrounding the integration of Business Intelligence (BI) techniques for fostering sustainability within the Financial Technology (Fintech) sector. Through a meticulous empirical investigation, our study has unveiled critical insights into the symbiotic relationship between advanced data analytics, artificial intelligence, and strategic decision-making processes within Fintech enterprises. The comprehensive analysis of relevant literature studies, coupled with the application of the Autoregressive Integrated Moving Average (ARIMA) model in our methodology, has facilitated a nuanced understanding of the temporal dynamics and patterns inherent in the Fintech domain. As the Fintech industry continues to evolve, our findings underscore the imperative for businesses to embrace BI strategies not only to optimize operational efficiency but also to champion sustainable practices.

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