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SPECIAL FOCUS PAPER

Volatility Risk Prediction in Healthcare Sector Using Hybrid Neural Networks with Gradient Descent Learning Model

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ABSTRACT

This study enhances prediction of the AM-healthcare services index (AMHCSX) in Jordan's Amman Stock Exchange (ASE). It takes daily stock price data from the healthcare sector for 2014–2026 (1,865 observations). We propose a hybrid model by combining the gradient descent learning (FIR.DM) and the maximum overlapping discrete wavelet transform (MODWT) with five wavelet functions (Haar, d4, la8, bl14, c6). The model uses new input variables such as government spending freedom (GSF), political risk freedom (PRF), normalized insurance weighted price index (N.AMINS) and normalized Brent crude oil prices (N.Brent Oil) determined on the basis of OLS regression and multicollinearity diagnostics. The output is the normalized volatility of the AMHCSX closing prices (Volatility-N. AMHCSX). The optimal model was the Haar wavelet with ARIMA (5,1,0) with drift, which had the lowest RMSE, MAE and MAPE. Within FIR.DM, the Haar hybrid performed better in terms of RMSE and MAE. The OLS results show the GSF ($\beta = -0.5810$) and PRF ($\beta = -0.5310$) as the most significant predictors followed by N.Brent Oil ($\beta = -0.1780$) and N.AMINS ($\beta = 0.1050$) explaining 59.80% of the volatility. Study effectively confirms politics and fiscal policy drive volatility; forecasts outperform naive models.

KEYWORDS

volatility risk, healthcare, neural network

1 INTRODUCTION

The Amman Stock Exchange has demonstrated a remarkable resilience in the last years. It is a primary financial market in a small open and geopolitically exposed economy. These kinds of markets, the sectoral vulnerability to different types of crises is not sufficiently quantified [1]. The present study measures the performance of healthcare services sector. The ASE has absorbed several large global and regional financial shocks in the period 2008–2026, including the global financial crisis of 2008,

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the Arab Spring of 2011, the COVID-19 pandemic and the Iran war of 2026. Each of these crises tested the resiliency of the Jordanian market [2–4]. The 2008 global financial crisis, which originated in developed economies and spread globally through financial channels, caused the ASE to suffer significantly negative abnormal returns [5]. Subsequently, the 2011 Arab Spring events had a heavy influence on the liquidity commonality on the ASE. The market suffered from the regional instability, trading volumes decreased, and the market capitalization was set to end the year below $30 billion for the first time since 2006 [2].

Volatility of closing prices – the degree of variation of stock prices over time, usually measured by the standard deviation of returns or closing prices. In stock-market research, volatility is commonly used as a quantitative proxy for risk and uncertainty [6]. A traditional proxy based on closing prices uses the standard deviation of daily returns as a measure of volatility [7]. Other common proxies include squared daily returns [8], absolute returns [9], and rolling standard deviations based on daily closing values [10, 11]. Studies also note that measures based only on closing prices are practical and widely available. Other uses of machine learning models in different area [12–14].

Government spending freedom measures the size of government expenditure relative to GDP within the Heritage Foundation's Index of Economic Freedom [15, 16]. Spending in excess of 30% of GDP is penalized in the scoring, with zero spending being the theoretical benchmark. Supporters say that too much government spending strains the economy, misdirects resources and causes deficits. But critics say low-spending countries can achieve high scores without delivering the necessary public goods. [17] mention that GSF specifically has been linked to a positive effect on bank stock returns in MENA markets.

The degree to which a country's political situation is transparent, stable, and predictable is known as PRF. This means that businesses and investors are less vulnerable to risks from arbitrary government action, shoddy institutions, censorship, or sudden policy changes. Political risk is generally regarded in the literature to be the potential for political events or governmental acts to change the economic climate that investors face [18]. This matters for stock markets because higher political uncertainty tends to raise volatility and risk premium [19], depress equity returns across countries [20], and reduce market liquidity at the firm level [21]. Conversely, institutional freedoms such as press freedom can mitigate stock-market instability by lowering country-level idiosyncratic volatility [22, 23].

By creating a predictive model for volatility risk in Jordan's healthcare services sector utilizing a hybrid neural networks with gradient descent learning (FIR.DM) technique, this study contributes to the body of literature. Although earlier studies have highlighted the significance of oil shocks for Jordan's sectoral volatility, especially during times such as COVID-19 [24, 25], little is known about how GSF and PRF interact with sector-specific indices. The FIR.DM model overcomes the shortcomings of the standard models in Jordan's specific geopolitical context by the inclusion of these institutional factors with the AMINS index and Brent Oil prices to capture complex non-linear interactions.

2 RESEARCH METHODOLOGY

This section shows the statistical models and key concepts that form the basis of the study.

2.1 Wavelet transform models

The WT is an essential mathematical tool to decompose original time series data into time-scale representations when examining non-stationary financial time series, such as stock market data [26]. The WT can be broken down into three main types: Discrete wavelet transform (DWT), continuous wavelet transform (CWT) and maximum overlap discrete wavelet transform (MODWT). These transforms have essentially the same underlying mechanics but differ in their practical use. One important difference is in the data length requirement: the DWT requires the number of observations to be a power of two (2^J) whereas the MODWT does not have such a restriction and can be used on datasets of arbitrary size. Given the flexibility and practical advantages of the MODWT, we adopt this variant in the present study [27].

The WT is an extension of the Fourier transform [28]. The Fourier transform is based on sine and cosine functions. The WT, however, satisfies the admissibility condition [29].

$$C_{\varphi} = \int_{0}^{\infty} \varphi(f) V \frac{\varphi(t)}{f} df < \infty \tag{1}$$

Where $\varphi(f)$ represents the Fourier transforms as a function of frequency. The WT is applied in image analysis and signal processing. It addresses the shortcomings of the Fourier transform. These shortcomings arise when handling time, space, or frequency.

There are two types of wavelet functions. The father wavelet captures low-frequency components. These correspond to smooth features in the data. The mother wavelet captures high-frequency components. These correspond to detailed features. The mathematical representations are shown in Equation (2). Here $j = 1, 2, 3, \ldots, J$ denotes the decomposition level. The wavelet decomposition is performed at J levels.

$$\phi_{jk} = 2^{-\left(\frac{j}{2}\right)} \phi\left(t - \frac{2^j k}{2^j}\right) \tag{2}$$

$$\varphi_{jk} = 2^{-\left(\frac{j}{2}\right)} \varphi\left(t - \frac{2^j k}{2^j}\right)$$

It satisfies the following conditions:

$$\int \phi(t) dt = 1 \text{ and } \int \varphi(t) dt = 0 \tag{3}$$

The general mathematical model is denoted in equation (4)

$$S_{jk} = \int \phi_{jk} f(t) dt, \quad d_{jk} = \int \varphi_{jk} f(t) dt, \tag{4}$$

In other form,

$$X(t) = \sum S_{jk} \phi_{jk}(t) + \sum d_{jk} \varphi_{jk}(t) + \sum d_{j-1,k} \varphi_{j-1,k}(t) + \cdots + \sum d_{1,k} \varphi_{1,k}(t) \tag{5}$$

$$S_j(t) = \sum S_{jk} \phi_{jk}(t) \text{ and } D_j(t) = \sum d_{jk} \varphi_{jk}(t) \tag{6}$$

The WT computes the approximation coefficient shown in equation (6). The smooth coefficients are denoted by S. The detailed coefficients are denoted by D.

Several popular wavelets transform functions exist. These include Haar, Daubechies (d4), Coiflet (c6), Least Asymmetric (LA8), and Best-Localized (bl14) [27]. These wavelet functions share four main characteristics. First, they are arbitrary regular except for the Haar model. Second, they lack explicit expressions except for the Haar model. Third, they use real numbers. Fourth, they possess several important properties. These properties include orthogonality, compact support, and an arbitrary number of zero moments. They also include the existence of a scale function, orthogonal and bio-orthogonal analysis, and continuous or discrete transformation. Additionally, they support exact reconstruction and fast algorithms. The Haar model is symmetric. The LA8 and d4 models are asymmetric. Near symmetry is associated with C6 and bl14.

2.2 Fuzzy inference rules by descent method model

In order to overcome the shortcomings of neural-network-driven fuzzy reasoning, [30] developed the fuzzy inference rules by descent method (FIR.DM) model, which combines gradient-based descent optimization for automatic parameter tuning from input-output data with simplified fuzzy inference rules [30].

The FIR.DM model is estimated as a multi-input-single-output (MISO) fuzzy system with an input vector $x = [x_1, x_2, x_3, x_4]^T \in \mathbb{R}^4$, comprising four financial indicators: GSF, PRF, N.AMINS, and N.Brent Oil. The single output variable $y \in \mathbb{R}$ represents the normalized volatility of AMHCSX closing prices (Volatility-N. AMHCSX), capturing the inherent uncertainty in financial markets. The fuzzy system maps four variables. It captures complex non-linear patterns. Linguistic rules make things interpretable. This allows for transparent market risk forecasts. However, the rule of simplified fuzzy inference model is expressed as [29, 30]

$$\textit{Rule } i\textit{: IF } x_1 \textit{ is } A_{i,1} \textit{ AND } x_2 \textit{ is } A_{i,2} \textit{ AND } x_3 \textit{ is } A_{i,3} \textit{ AND } x_4 \textit{ is } A_{i,4} \textit{ THEN } y = \omega_i$$

where $i (i = 1, 2, \ldots, n)$ is a rule number, A_{ij} is a fuzzy set for the j-the unput variable in the i-the rule, A_{ij} is a membership function of the antecedent part (x_1, x_2, x_3, x_4), and $\omega_i \in \mathbb{R}$ is a real number of the consequent part (y). If Gaussian membership function is used, then A_{ij} is expressed as [29]

$$A_{ij}(x_j) = \exp\left(\frac{-1}{2}\left(\frac{x_j - c_{ij}}{b_{ij}}\right)^2\right) \tag{7}$$

Where c_{ij} and b_{ij} denote the center and the width value of A_{ij}, respectively [29]. The firing strength $\mu_i(x)$ of rule i is computed using the t-norm over all four input variables [29]:

$$\mu_i(x) = \prod_{j=1}^{4} A_{ij}(x_j) \tag{8}$$

The overall inferred output y (predicted normalized volatility) is obtained via center-of-gravity defuzzification [30]:

$$y = \frac{\sum_{i=1}^{n} \mu_i(x) * \omega_i}{S(x)} \tag{9}$$

Where $S(x) = \sum_{i=1}^{n} \mu_i(x) > 0$ is the total firing strength. Then, all parameters are updated using the steepest descent method. For a given training sample (x, y^r), the update rules of consequent parameters (ω_i), antecedent centers (a_{ij}), and antecedent widths (b_{ij}) are [30]:

$$\omega_i(t+1) = \omega_i(t) - K_\omega * \frac{\mu_i(x)}{S(x)}(y - y^r) \tag{10}$$

$$a_{ij}(t+1) = a_{ij}(t) - K_a * \frac{\mu_i(x)}{S(x)} * (y - y^r) * (\omega_i - y) * \frac{2}{b_{ij}(t) * A_{ij}(x_j)} * sgn(x_j - a_{ij}(t)) \tag{11}$$

$$b_{ij}(t+1) = b_{ij}(t) - K_b * \frac{\mu_i(x)}{S(x)} * (y - y^r) * (\omega_i - y) * \frac{1 - A_{ij}(x_j)}{A_{ij}(x_j)} * \frac{1}{b_{ij}(t)} \tag{12}$$

Where $K_\omega, K_a, K_b > 0$ are the learning rate, and $sgn(.)$ is the sign function.

2.3 Accuracy error criteria

To comprehensively evaluate the forecasting performance of the proposed MODWT and FIR.DM models, we employ a diverse set of accuracy error criteria, including the mean absolute percentage error (MAPE), mean percentage error (MPE), mean error (ME), mean absolute error (MAE), root mean squared error (RMSE), and mean absolute scaled error (MASE). The MAPE, also referred to as the mean absolute percentage deviation (MAPD), is a widely used statistical measure of prediction accuracy that expresses forecast error as a percentage, making it intuitively interpretable across different scales. It is formally defined as:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{X_t - X_t^*}{X_t} \right| \tag{13}$$

$$MPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{X_t - X}{X_t} \tag{14}$$

$$ME = \frac{1}{n} \sum_{t=1}^{n} \left(X_t - X_t^* \right) \tag{15}$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| X_t - X_t^* \right| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(X_t - X_t^* \right)^2} \tag{17}$$

$$MASE = \frac{\frac{1}{n} \sum_{t=1}^{n} \left| X_t - X_t^* \right|}{\frac{1}{n-1} \sum_{t=2}^{n} \left| X_t - X_{t-1}^* \right|} \tag{18}$$

Where X_t^* is the forecasted value, X_t is the actual value, and n is the sample size [31].

2.4 Study design

The methodology used in the study uses a systematic multi-stage approach to develop and evaluate hybrid forecasting models in the healthcare sector volatility. Figure 1 shows the overall structure of the study design.

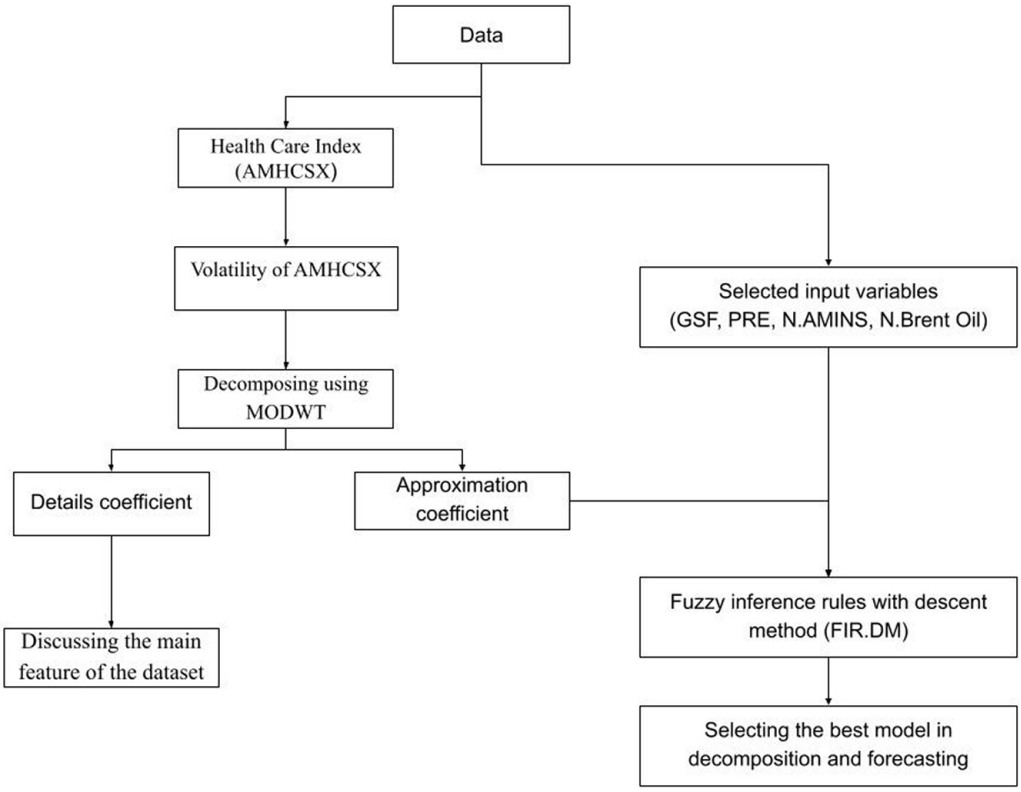


Fig. 1. The flowchart of the study

First, we collected data for the input and output variables on a daily basis. AMHCSX is the output variable for ASE healthcare firms. GSF, PRF, AMIN, and Brent Oil are among the input variables. Second, the volatility of the healthcare services sector was calculated using the standard deviation of closing prices for the AMHCSX $\left(\sigma = \sqrt{\Sigma \frac{(x-\overline{x})^2}{n-1}}\right)$. Volatility serves as the output variable in the study, reflecting the uncertainty and risk inherent in the healthcare services sector. Third, all variables were normalized by min-max scaling method to transform data to a common scale between [0, 1]. Four, multicollinearity and OLS regression were employed to identify the input variables. Five, MODWT was used to decompose the normalized output variable (volatility of AMHCSX). Then approximation coefficients, which capture the smooth data, were used as the output for the FIR.DM models. Six, the FIR.DM was combined with a variety of wavelet functions to produce hybrid models. The model was chosen based on its performance on different training/testing data splits (80/20 and 90/10). R-program version 4.4.3 was used to run statistical analyses.

3 RESULTS

3.1 Data

A daily time-series dataset is used in this study. The sample has 1,865 observations. It covers period between January 5, 2014 and June 28, 2026. The output variable is the AMHCSX index. This index works as a proxy for Jordan's stock performance in the healthcare sector. Data collected from Investing.com. Political risk is the main input variable. GSF is a crucial macroeconomic variable. Both came from the Euromoney Country Risk database (www.euromoneycountryrisk.com). The dynamics of the financial sector are captured by AMINS indicator. The ASE (www.ase.com.jo) provided financial information. Brent crude oil prices were obtained from Investing.com. All variables were matched by date. This produced a balanced dataset. Only days with complete data were retained. The empirical analysis was conducted using R-program version 4.4.3, which was employed to estimate all statistical models.

3.2 Descriptive statistics

Summary data for 1,865 daily observations (January 2014–June 2026) are shown in Table 1. The AMHCSX ranges from 684.0300 to 2871.9000, with a mean of 898.2422 (SD = 115.5330). PRF (mean = 48.8780, SD = 2.0634) varies from 45.0000 to 50.0000, suggesting moderate political risk, whereas GSF (mean = 59.9230, SD = 4.1722) ranges from 54.0000 to 67.0000. With a range of 1212.2542 to 1954.4200 and a maximum 43% above the mean, AMINS records a higher mean of 1365.4184 (SD = 110.2774). With a range of 28.4000 to 127.9800, the average price of Brent oil is 67.4362 USD/barrel (SD = 19.6564), indicating considerable volatility.

Table 1. Descriptive statistics for input and output variables

	Sample Size (N)	Mean	Standard Deviation	Minimum	Maximum
AMHCSX	1865	898.2422	115.5330	684.0300	2871.9000
GSF	1865	59.9230	4.1722	54.0000	67.0000
PRF	1865	48.8780	2.0634	45.0000	50.0000
AMINS	1865	1365.4184	110.2774	1212.2542	1954.4200
Brent Oil	1865	67.4362	19.6564	28.4000	127.9800

3.3 Multicollinearity tests

The volatility measures of AMHCSX, AMINS, and Brent oil were normalized using (X – Min)/(Max – Min) to scale data between [0, 1] for FIR.DM requirements, while GSF and PRF were divided by 100 for percentage form. Multicollinearity diagnostics in Table 2 confirm no substantial multicollinearity, as all input variable correlations are below the 50% threshold, with tolerance values ranging from 0.7120 to 0.8970 and VIF scores ranging from 1.1140 to 1.4050, all well below the conventional thresholds of 5 and 10. The correlation matrix reveals strong negative correlations between AMHCSX volatility and GSF (r = –0.5600) and PRF (r = –0.5410), while weak positive correlations exist with N.AMINS (r = 0.2290) and N.Brent Oil (r = 0.2120), with GSF and PRF showing a very weak relationship (r = 0.0830), confirming that each predictor captures unique information without significant overlap.

Table 2. Multicollinearity tests (Correlations, Tolerance, VIF)

	Volatility-N. AMHCSX	GSF	PRF	N.AMINS	N.Brent Oil	Tolerance	VIF
Volatility-N. AMHCSX	1.0000		–0.5410	0.2290	0.2120		
GSF		1.0000	0.0830	0.1010	–0.3090	0.8970	1.1140
PRF			1.0000	–0.3260	–0.4080	0.7120	1.4050
N.AMINS				1.0000	–0.0550	0.8470	1.1810
N.Brent Oil					1.0000	0.7310	1.3680

3.4 Regression results

All variables are statistically significant at the 5% level, according to the OLS regression model using normalized AMHCSX volatility as the dependent variable and GSF, N.AMINS, and N.Brent Oil as predictors. When all predictors are zero, the baseline volatility is 6.9040, as indicated by the constant term of 6.9040 ($t = 45.1380$, $p < 0.05$). The greatest predictor is GSF ($\beta = –0.5810$, $B = –4.1360$, $t = –37.4410$, $p < 0.05$), which rejects H01 by lowering volatility by 4.1360 units for every unit increase. The second-strongest predictor, PRF ($\beta = –0.5310$, $B = –7.6400$, $t = –30.4690$, $p < 0.05$), shows that a one-unit increase (reduced political risk) reduces volatility by 7.6400 units, rejecting H02. N.AMINS shows a weaker positive relationship ($\beta = 0.1050$, $B = 0.2430$, $t = 6.5940$, $p < 0.05$), rejecting H03, while N.Brent Oil exhibits a moderate negative relationship ($\beta = –0.1780$, $B = –0.2740$, $t = –10.3580$, $p < 0.05$), rejecting H04. With a regression sum of squares of 98.4770 and a residual sum of squares of 66.1090, The ANOVA demonstrates that the regression model is statistically significant ($F = 692.6770$, $p < 0.05$). With $R = 0.7740$, $R^2 = 0.5980$, and adjusted $R^2 = 0.5970$, Table 3 shows a high overall fit, meaning that the four predictors together account for around 59.80% of the variation in the volatility of the healthcare sector, with an estimate standard error of 0.1885.

Table 3. Ordinary least squares (OLS) regression results

	Unstandardized Coefficients		Standardized Coefficients	T-stat	
	B	**Std. Error**	**Beta**		**F-stat** = 692.6770**
(Constant)	6.9040	0.1530		45.1380**	**R** = 0.7740
GSF	–4.1360	0.1100	–0.5810	–37.4410**	**R Square** = 0.5980
PRF	–7.6400	0.2510	–0.5310	–30.4690**	**Adj. R Square** = 0.5970
N.AMINS	0.2430	0.0370	0.1050	6.5940**	**S.E of the Estimate** = 0.1885
N.Brent Oil	–0.2740	0.0260	–0.1780	–10.3580**	

3.5 Maximum overlapping discrete wavelet transform results

To determine the most appropriate forecasting model for healthcare services sector volatility, we compared the performance of various MODWT wavelet filters combined with ARIMA models. The selection criteria were based on multiple error metrics. Lower values across these error metrics indicate better forecasting

performance. Table 4 presents the comparative results for both training data splits (80% and 90%).

The Haar wavelet in conjunction with the ARIMA (5,1,0) model with drift consistently performs better than all other wavelet models (d4, la8, bl14, and c6) across all error metrics for both the 80% training sample (1,492 observations) and the 90% training sample (1,679 observations). With the lowest RMSE (0.0140), MAE (0.0015), MAPE (2.5028%), and MASE (0.0409) in the 80% sample, the Haar model is around 96% more accurate than the naïve forecast with the least amount of bias (ME = 0.0003, MPE = 0.7058%). With the lowest RMSE (0.0158), MAE (0.0015), MAPE (2.1052%), and MASE (0.0605) for the 90% sample, the Haar model continues to perform better, exhibiting negligible bias (ME = 0.0003, MPE = 0.5171%). These results confirm that the Haar wavelet with ARIMA (5,1,0) with drift is the superior forecasting model regardless of the training sample size.

Table 4. MODWT models for output based on training data (80% and 90%)

(a) Percentage/Sample Size: 80%/1492 (Observation)					
MODWT	**Haar**	**d4**	**la8**	**bl14**	**c6**
ARIMA models	(5,1,0) with drift	(3,1,3) with drift	(1,1,0) with drift	(1,1,0) with drift	(3,1,2) with drift
ME	0.000318006	0.000071410	0.000001133	0.000001735	0.000020248
RMSE	0.014023753	0.015497178	0.038493369	0.049175328	0.036114632
MAE	0.001532091	0.002197109	0.005583895	0.008672807	0.005400755
MPE	0.705825980	0.210427630	2.979349340	12.114768060	1.256446270
MAPE	2.502833000	3.494273000	7.464135000	18.124874000	4.524321000
MASE	0.040938351	0.250594354	0.760627391	0.859723938	0.755659481
(b) Percentage/Size of Sample: 90%/1679 (Observation)					
MODWT	**Haar**	**d4**	**la8**	**bl14**	**c6**
ARIMA models	(5,1,0)	(5,1,0) with drift	(1,1,0) with drift	(1,1,0) with drift	(4,1,2) with drift
ME	0.000261297	0.000278913	0.000001156	0.000001873	0.000153800
RMSE	0.015820041	0.017794587	0.043879191	0.055736740	0.041105126
MAE	0.001548861	0.001820802	0.005730437	0.008868868	0.005558438
MPE	0.517076400	1.945763400	2.487841200	10.644313500	1.091011500
MAPE	2.105184000	3.865378000	6.548685000	15.971206000	4.120589000
MASE	0.060525572	0.163541402	0.755920853	0.856166118	0.745493005

3.6 Fuzzy inference rules by descent method results

To enhance the forecasting accuracy of health care services sector volatility, we employed the FIR.DM and its hybrid variants combined with wavelet transformations. The FIR.DM models were evaluated on their predictive performance using the testing data splits (20% and 10%). The hybrid models use different wavelet functions (Haar, d4, la8, bl14 and c6) to decompose the data before FIR.DM estimation.

Model selection was based on multiple error criteria including ME, RMSE, MAE, MPE, and MAPE. Lower values across these metrics indicate superior forecasting performance. Table 5 presents the comparative results for both testing data splits.

For the 20% test sample (373 observations), the FIR.DM + WT (Haar) model presents the best performance in terms of forecasting, showing the best performance in the main error metrics. The Haar hybrid model achieves the lowest RMSE of 0.9508125, compared to FIR.DM (0.9519802), FIR.DM + WT(d4) (0.9511207), FIR.DM + WT (la8) (0.9552963), FIR.DM + WT (bl14) (0.9536342), and FIR.DM + WT(c6) (0.9533191). The Haar-wavelet hybrid model demonstrably achieved the highest overall forecast accuracy due to its minimized prediction errors. The MAE of FIR.DM + WT(Haar) is 0.9486283 which is slightly lower than the stand-alone FIR.DM (0.9497986) and FIR.DM + WT(d4) (0.9489372) indicating that Haar hybrid has better point forecasts. The ME of FIR.DM + WT(Haar) is 0.9486283 showing there is little bias in the forecasts which means the models predictions are not systematically over or under predicting actual values. Since FIR. DM + WT(Haar) ranks first in RMSE, MAE, and ME we can determine that this model had the best model overall forecast accuracy.

Table 5. FIR.DM models for prediction of output using testing data (20% and 10%)

(a) Percentage/Sample: 20%/373 (Observations)						
Models	**FIR.DM**	**FIR.DM + WT (Haar)**	**FIR.DM + WT (d4)**	**FIR.DM + WT (la8)**	**FIR.DM + WT (bl14)**	**FIR.DM + WT (c6)**
ME	0.9497986	0.9486283	0.9489372	0.9531223	0.9514563	0.9511406
RMSE	0.9519802	0.9508125	0.9511207	0.9552963	0.9536342	0.9533191
MAE	0.9497986	0.9486283	0.9489372	0.9531223	0.9514563	0.9511406
MPE	Inf	81054.32349	110155.4482	28677.09194	57395.145	70877.58351
MAPE	Inf	81054.32349	110155.4482	28677.09194	57395.145	70877.58351
(b) Percentage/Sample: 10%/186 (Observations)						
Models	**FIR.DM**	**FIR.DM + WT (Haar)**	**FIR.DM + WT (d4)**	**FIR.DM + WT (la8)**	**FIR.DM + WT (bl14)**	**FIR.DM + WT (c6)**
ME	0.995567361	0.994396999	0.994705908	0.998890997	0.99722509	0.996909309
RMSE	0.995570394	0.994400036	0.994708944	0.99889402	0.997228118	0.996912338
MAE	0.995567361	0.994396999	0.994705908	0.998890997	0.99722509	0.996909309
MPE	Inf	84964.97	115468.4	30054.16023	60156.07419	74288.20227
MAPE	Inf	84964.97	115468.4	30054.16000	60156.0700	74288.2000

The FIR.DM + WT(Haar) model continues to show better predicting performance for the 10% testing sample (186 observations), with the lowest RMSE (0.994400036), MAE (0.994396999), and ME (0.994396999) when compared to solo FIR.DM and every other variation of the wavelet (d4, la8, bl14, and c6). This indicates that although it has a lower testing sample size, the Haar wavelet ensemble maintains higher predictive accuracy. Also, the forecast bias being nearly zero indicates there is no evidence of biased forecasts that have systematic errors. Despite its superior performance in percentage-based criteria, FIR.DM + WT (la8) has limited practical usefulness because to its extraordinarily high MAPE values.

4 DISCUSSION

The results give strong statistical evidence that volatility in Jordan's healthcare sector responds to changes in politics and macroeconomic policy regimes. Both OLS coefficient estimates, GSF (β = –0.5810) and PRF (β = –0.5310) are large relative to the rest. There coefficients are strongly negative implying that increases in AMHCSX volatility are related to decreases in these variables. This supports the conjecture in the literature review. Sound fiscal policy and political stability decrease uncertainty. Sound macroeconomic variables will also increase investor confidence in a country. This increases certainty and stability in that sectors performance. The negative relationship between GSF and volatility suggests that fiscal discipline improves market predictability. Lower political risk contributes to a more stable investment climate. It reduces uncertainty that typically drives volatility in emerging markets. [32, 33] found similar impacts of political risk.

Healthcare volatility and insurance sector index present a positive effect (β = 0.1050) meaning that inter-sectoral links exist where volatility is transmitted by positive shocks [34, 35], Brent oil prices show a somewhat negative influence (β = –0.1780), illustrating the dual function of oil prices in Jordan's economy: higher prices raise operating expenses but may also indicate greater global activity and better fiscal circumstances. 59.80% of the variation is explained by the model (R^2 = 0.5980). With Haar-ARIMA (5,1,0) appearing as the best model (RMSE = 0.0140, MAE = 0.0015, MAPE = 2.5028%, MASE < 0.06) and demonstrating greater accuracy within FIR.DM, forecasting study demonstrates that wavelet-based hybrid models outperform conventional approaches (MAE = 0.9486, RMSE = 0.9508), providing a thorough framework for forecasting volatility in the healthcare sector.

5 CONCLUSION

This study used wavelet-based hybrid models and OLS regression to investigate the factors influencing the volatility of Jordan's health care services industry from January 2014 to June 2026. GSF (β = –0.5810) and PRF (β = –0.5310) emerged as the dominant negative predictors, while the insurance sector (β = 0.1050) showed a weaker positive effect and Brent oil prices (β = –0.1780) exhibited a moderate negative effect, with the OLS model explaining 59.80% of the variance. The Haar wavelet with ARIMA (5,1,0) with drift achieved the lowest RMSE (0.0140), MAE (0.0015), and MAPE (2.5028%), demonstrating superior forecasting performance. Simpler wavelet filters proved more effective than higher-order wavelets. Policymakers should prioritize political stability and institutional transparency, while investors should incorporate political risk indicators into their decisions. Future research should explore additional macroeconomic variables and apply machine learning techniques with wavelet decomposition. This study provides a comprehensive framework for understanding and forecasting volatility in emerging market healthcare sectors.

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