Utilising AI Models to Analyse the Relationship between Battlefield Developments in the Russian-Ukrainian War and Fluctuations in Stock Market Values

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Abstract

This study examines the impact of battlefield developments in the ongoing Russian–Ukrainian war, which to date has lasted over 1000 days, on the stock prices of defence corporations such as BAE Systems, Booz Allen Hamilton, Huntington Ingalls, and Rheinmetall AG. Stock prices were analysed alongside sentiment data extracted from news articles, and processed using machine learning models leveraging natural language processing (NLP). Although the main hypothesis was not confirmed due to methodological and data limitations, the study demonstrated that neural network-based models, specifically long short-term memory (LSTM) networks, effectively captured hidden temporal patterns. The model's performance was evaluated using root mean squared error (RMSE). Alternative models, including XGBoost, ARIMA, and VAR, were also tested but did not yield accurate forecasts. The findings highlight nonlinear patterns in the data and emphasise the importance of hyperparameter optimisation, such as tuning the number of epochs and LSTM layer sizes. Techniques such as Grid Search and Random Search significantly enhanced forecasting performance, resulting in stock price predictions with low RMSE. The full-scale war between Russia and Ukraine, which has been ongoing for more than 1000 days on European soil, triggered market reactions with the first shots fired on the Russian–Ukrainian border on 24 February 2022. Since then, Europe and other countries around the world have supported Ukraine militarily, humanitarianly, and economically while revising their defence doctrines and strategies, as well as increasing and modernising their military capabilities. News of Russian aggression and new orders for military products sparked market reactions, particularly changes in the stock prices of defence companies that ramped up production and continue to expand it. This study selected several of the largest defence corporations, whose stock prices showed significant responses to the full-scale Russian invasion of Ukraine, to examine whether other battlefield events elicit similar stock price reactions as the first reports. To investigate this, artificial intelligence tools, including several machine learning methods, were employed. The purpose of this article is to examine the impact of battlefield developments in the Russian–Ukrainian war on stock volatility among major players in the global defence industry, while also identifying the most effective method for forecasting stock prices by testing various machine learning (ML) models. NLP was used to capture sentiment and analyse news about the Russian–Ukrainian war. Vector AutoRegression, the XGBRegressor, the Long Short-Term Memory (LSTM) neural network, and the ARIMA model were used for stock price forecasting. The main hypothesis that stock price changes are influenced by battlefield developments in the Russian–Ukrainian war was not confirmed due to methodological and data limitations. However, the research results indicate that, in this case, the Long Short-Term Memory (LSTM) model is well-suited for time series forecasting, effectively capturing nonlinear time patterns and long-term dependencies for major defence corporations.

Key words

Russian–Ukrainian war, machine learning, sentiment, forecasting.

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Introduction

Russian aggression against Ukraine has significantly impacted financial markets, particularly the stock prices of companies specialising in systems for the security industry. An initial analysis of major defence corporations, including the U.S.-based Boeing Co., Booz Allen Hamilton, Esterline Technologies Corporation, General Dynamics, Huntington Ingalls, Harris Corporation, L-3 Communications, and Rockwell Collins Inc.; the U.K.-based Babcock International Group, Lockheed Martin, Northrop Grumman, OSI Systems Inc., Textron Inc., United Technologies, and BAE Systems; the German-based Rheinmetall AG; and Israel's Elbit Systems Ltd., reveals that some of these companies experienced a significant increase (>3%) in stock prices following the Russian invasion (Fig. 1).

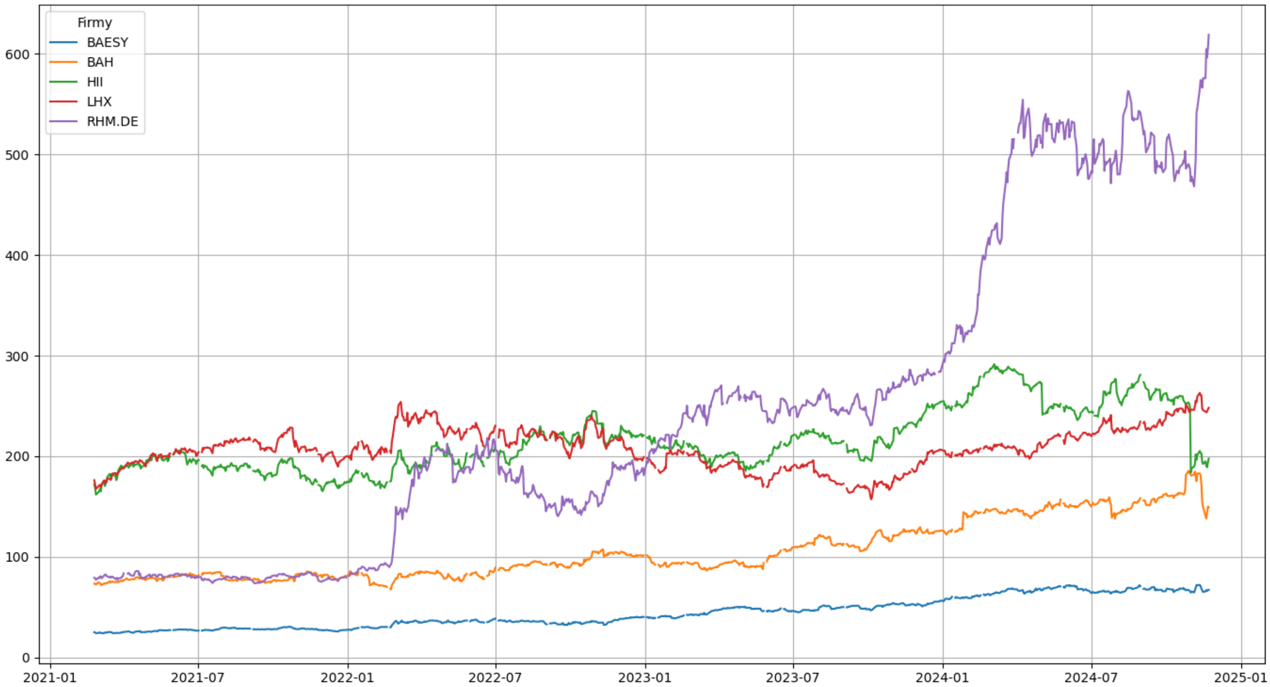

Figure 1. Stock prices (in EUR) of BAE Systems (BAESY), Booz Allen Hamilton (BAH), Huntington Ingalls (HII), Harris Corporation (LHX), and Rheinmetall AG (RHM.DE) from February 24, 2021 to November 25, 2024.
Source: Author's development based on (Yahoo Finance).

On 24 February 2022, when Russian troops and tanks crossed the Ukrainian border, stock prices fluctuated initially but soon exhibited an upward trend that continues to this day.

For Rheinmetall AG, the full-scale war in Ukraine also served as a catalyst for growth. As of 20 March 2023, Rheinmetall AG joined the DAX, Germany's benchmark index of 40 blue-chip companies.

In Figure 1, we observe changes in stock prices during February 2022, a time when the reality of war in Europe became evident, emphasising the urgent need to strengthen the EU's defence position.

The subsequent fluctuations in stock prices were influenced by various factors. However, this study focuses on predicting stock prices by analysing time series data and the sentiment of news related to Ukraine in the context of Russian aggression, using machine learning methods.

The hypothesis proposed in this study is that stock price changes are influenced by battlefield developments in the Russian–Ukrainian war. To test this hypothesis, the author analysed stock price data in conjunction with specific events related to the conflict. By leveraging artificial intelligence methods, the author aims to evaluate the significance of these events in shaping stock price movements.

1. Literature Review

Financial markets have historically reacted to geopolitical and military events, often showing significant abnormal returns on event days and the day following such events (Chen & Siems, 2004). Previous studies highlight the positive impact of war-related geopolitical events on stock returns for defence companies (Apergis & Apergis, 2016) and the negative impact of peace-related news (Shapiro et al., 1999). These findings underscore the influence of geopolitical risks on stock returns and market volatility (Alqahtani & Klein, 2021; Apergis et al., 2017; Umar et al., 2022; Klein, 2024).

Recent analyses, such as those employing Google Trends data (Halousková et al., 2022), have explored the impact of investor attention on asset price volatility during Russia's full-scale invasion of Ukraine, demonstrating significant index volatility and evidence of volatility spillover between different stock markets (Beraich et al., 2022). Notably, it is often not the event itself but the availability and dissemination of information online that significantly influences stock price changes and returns for defence companies (Klomp, 2020). This highlights the critical role of news feeds and the subjective reactions of investors to updates, such as the successes of the Ukrainian army supported by Western allies (Chowdhury & Humaira, 2023).

Earlier research on the impact of military, geopolitical (Nygaard & Sørensen, 2024; Alqahtani & Klein, 2021), and terrorist events (Papakyriakou et al., 2019) on defence stock prices and profitability focused primarily on the events as a whole. For example, studies examined the financial market reactions to the terrorist attacks of September 11 (Charles & Darné, 2006), the invasion of Iraq (Fernandez, 2009), and the Paris terrorist attacks (Apergis & Apergis, 2016; 2017), assessing their effects on market performance and specific financial instruments. Russia's ongoing war against Ukraine has drawn worldwide attention, as critical global issues related to world order, trade, and security are being decided on the battlefield (Melnychenko et al., 2022a; Melnychenko et al., 2022b). The growing interest in machine learning (ML) and artificial intelligence (AI) methods (see Figure 2) is particularly notable due to their broad applicability across various fields of science and practice. This interest is fuelled by modern computational capabilities and the rapid changes occurring in the global landscape (Melnychenko, 2019; 2020; 2021; Dabrock, 2024)).

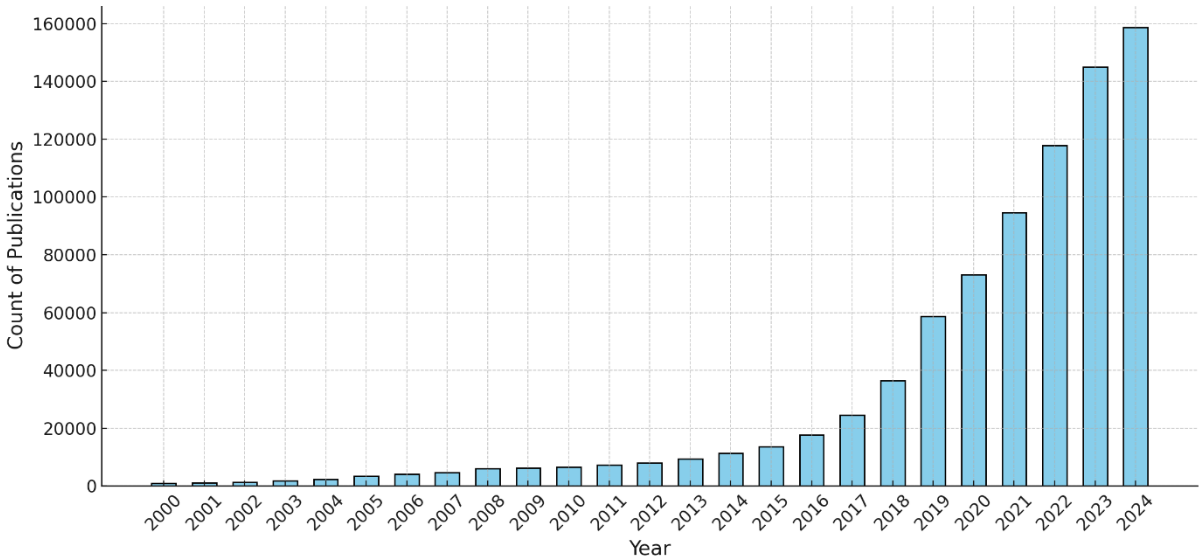

Figure 2. Scopus search results for the query "machine AND learning".
Source: Author's development based on (Scopus).

Furthermore, contemporary trends in the optimisation of cognitive functions across various methodological aspects of foresighting are comprehensively described in numerous scholarly works. These include studies on sustainability (Kharazishvili et al., 2020; Kwilinski, 2024b; Kwilinski & Vysochyna, 2024; Kwilinski et al., 2023b; 2023c; 2024b; 2024e), the interplay of factors influencing entrepreneurial reflexivity (Berg & Spicka, 2023; Dacko-Pikiewicz, 2019b; Gigauri et al., 2024; Kwilinski et al., 2022; 2024f; Kyrylov et al., 2020; Lyulyov et al., 2020; Payonk et al., 2015; Surya et al., 2024; Zimbroff, 2023), energy management (Karpenko et al., 2018; Kharazishvili et al., 2021; Kwilinski, 2024a; Kwilinski et al., 2024a; Mlaabdal et al., 2024; Ziabina et al., 2023) and the correlation between the digitalisation process and various input and output indicators (Ayala-Mora et al., 2023; Boyko et al., 2024; Dementyev et al., 2021; Infante-Moro et al., 2022a; 2022b; Kharazishvili et al., 2022; Kwilinski, 2019; 2023; Kwilinski & Kardas, 2024a; Kwilinski et al., 2023a; 2023d; 2024c; 2024d; Labudova & Fodranova, 2024; Lyulyov et al., 2024b).

Thus, the purpose of this article is to examine the impact of battlefield developments in the Russia-Ukraine war on stock volatility among major players in the global defence industry, while also identifying the most effective method for forecasting stock prices by testing various machine learning (ML) models.

The remainder of the article is structured as follows: The next section outlines the methodology employed in this study, including a description of the data and their sources. The Research Results section presents the findings from evaluations, analyses and forecasts conducted using different machine learning models to identify the optimal approach for the dataset. Finally, the article concludes with a summary of the findings and a discussion of their implications.

2. Data and Methodology

In the absence of military intelligence data, publicly available information serves as the primary resource for analysing the relationship between stock prices and events related to the Russia-Ukraine war. One major challenge in identifying correlations between events and price fluctuations lies in the lack of data that numerically represent these events. A good solution to this issue is the application of machine learning methods, particularly those based on natural language processing (NLP), which have demonstrated great progress (Supriyono et al., 2024). NLP analyses text to determine sentiment on a scale from -1 to +1, where +1 represents positive sentiment, -1 represents negative sentiment, and 0 indicates neutrality. NLP-based sentiment analysis has been successfully applied in numerous disciplines, including financial market analysis (Rahman Jim et al., 2024), financial sentiment analysis (Du et al., 2025), accounting and auditing (Fisher et al., 2016), and more. Although the development of a domain-specific lexicon can enhance sentiment analysis in financial contexts (Yekrangi & Abdolvand, 2021), general sentiment analysis approaches have also proven effective (Nemes & Kiss, 2021).

Given the impracticality of analysing all individual articles from multiple sources, this study focuses on publications from *The Voice of America* (English version) and *The Guardian*. These sources frequently draw from reliable providers like Reuters and the BBC and are widely recognised for their credibility (Lewis & Cushion, 2017; Walsh, 2020; Nelson, 2018). Both outlets compile summaries of key events related to the Russian invasion of Ukraine under headings such as "Latest Developments in Ukraine", "Russia-Ukraine War Live: What We Know on Day ..." and "Ukraine War Briefing: ...", consolidating significant events on a single page. This structured presentation enables NLP tools to analyse major events daily and calculate sentiment scores for each trading day within the context of relevant developments. For sentiment analysis and related tasks, the Python programming language was employed, utilising libraries such as BeautifulSoup, NLTK (featuring the VADER tool, an unsupervised sentiment analysis algorithm), Pandas, ydata-profiling, and others. To improve the accuracy of sentiment calculations, common stopwords – such as "it", "they", "them", "what", "which", "while", "of", "at", "by", "for", "with" and "about" – were removed, as these words contribute little to the contextual meaning of the text (Chanda & Pal, 2023). Additionally, stock price data were retrieved using the *yfinance* library from Yahoo Finance.

The sentiment analysis of articles describing significant events in Ukraine related to Russian military aggression revealed predominantly negative tones, as expected given the nature of the subject. Reports frequently highlighted war casualties, infrastructure destruction, and civilian suffering. However, on certain trading days, publications exhibited positive sentiment, occasionally reaching high scores (e.g. +0.9), often reflecting military successes or diplomatic achievements.

For this study, 705 articles from the selected sources were analysed, corresponding to 705 trading days and spanning 1000 days of the Russia-Ukraine war. Descriptive statistics for the sentiment analysis are presented in Table 1.

Table 1. Descriptive statistics of sentiment scores for publications from The Guardian and The Voice of America websites during the period from February 24, 2022 to November 25, 2024.

Parameters	Values	Parameters	Values
count	705	25%	-0.9980
mean	-0.8345	50%	-0.9946
std	0.4769	75%	-0.9795
min	-0.9999	max	0.9985

Source: Author's development based on (Guardian; VOA).

The author also utilises daily stock price data from major defence system suppliers, including BAE Systems (BAESY), Booz Allen Hamilton (BAH), Huntington Ingalls (HII), and Rheinmetall AG (RHM.DE), all of which experienced significant stock price increases on 24 February 2022, following the onset of the Russian invasion of Ukraine. Harris Corporation (LHX), however, did not exhibit price increases in alignment with the trends observed in other defence stocks (Figure 3).

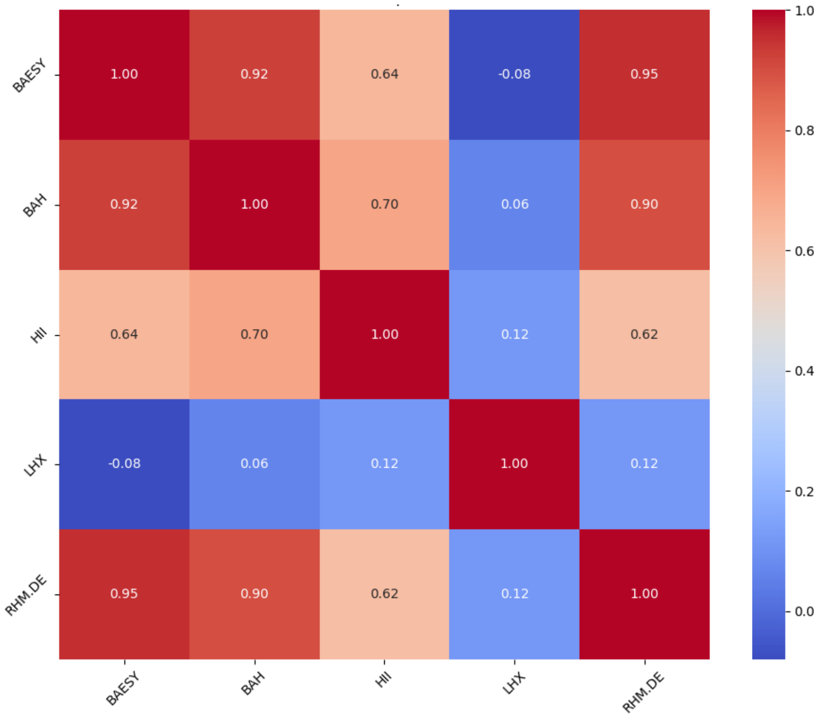

Figure 3. Correlation Heatmap of Stock Prices of BAE Systems (BAESY), Booz Allen Hamilton (BAH), Huntington Ingalls (HII), Harris Corporation (LHX), Rheinmetall AG (RHM.DE); Closing Share Price from February 24, 2022 to November 25, 2024

Source: Author's development based on (Yahoo Finance).

The data, sourced from the Yahoo Finance website, span the period from 24 February 2022 to 25 November 2024, and include share prices for each trading day. This timeframe captures the early stages of Russian military aggression against Ukraine and subsequent key events, resulting in 692 to 705 daily observations, depending on the stock exchange. To ensure data consistency, the study utilised 685 trading sessions for subsequent calculations to exclude gaps in the dataset. Descriptive statistics for these data are presented in Table 2.

Table 2. Descriptive Statistics of BAE Systems (BAESY), Booz Allen Hamilton (BAH), Huntington Ingalls (HII), Harris Corporation (LHX), Rheinmetall AG (RHM.DE); Closing Share Price for Each Trading Day from February 24, 2022 to November 25, 2024.

Parameters	BAESY	BAH	HII	RHM.DE	Parameters	BAESY	BAH	HII	RHM.DE
count	692.00	692.00	692.00	705.00	**25%**	39.48	95.12	212.35	200.50
mean	51.59	117.82	233.50	305.36	**50%**	50.19	111.46	228.49	257.20
std	12.03	26.63	25.87	133.00	**75%**	64.98	145.13	253.77	468.30
min	33.97	75.14	184.96	100.05	**max**	72.46	186.00	296.43	619.00

Source: Author's development based on (Yahoo Finance).

For stock price forecasting of BAE Systems, Booz Allen Hamilton, Huntington Ingalls, Harris Corporation, and Rheinmetall AG, this study evaluated four methods: the VAR (Vector AutoRegression) model for multivariate time series, the XGBRegressor model for machine learning, the LSTM (Long Short-Term Memory) neural network model (utilising the tensorflow.keras library), and the ARIMA model. The results of these methods are presented in the Research Results section. To assess model performance, the study used RMSE (Root Mean Squared Error) as the primary evaluation metric (Braiek, Khomh, 2020).

3. Research Results

The correlation analysis of the stock prices of the selected companies indicates a low level of correlation. To ensure greater confidence in the findings, the correlation analysis was performed using the Pearson, Spearman, and Kendall methods, with the results presented in Tables 3–5.

Table 3. Correlation matrix (Pearson).

	BAESY	BAH	HII	RHM.DE	compound
BAESY	1	0.925213	0.641138	0.953614	-0.00078
BAH	0.925213	1	0.696697	0.901562	-0.00925
HII	0.641138	0.696697	1	0.619472	-0.01430
RHM.DE	0.953614	0.901562	0.619472	1	-0.01277
compound	-0.00078	-0.00925	-0.01430	-0.012770	1

Source: Author's development based on (Yahoo Finance).

Table 4. Correlation matrix (Spearman).

	BAESY	BAH	HII	RHM.DE	compound
BAESY	1	0.871084	0.542130	0.967084	0.4238580
BAH	0.871084	1	0.714909	0.826880	0.3766550
HII	0.54213	0.714909	1	0.512402	0.2097430
RHM.DE	0.967084	0.826880	0.512402	1	0.3984420
compound	0.423858	0.376655	0.209743	0.398442	1

Source: Author's development based on (Yahoo Finance).

Table 5. Correlation matrix (Kendall).

	BAESY	BAH	HII	RHM.DE	compound
BAESY	1	0.686842	0.356146	0.843057	0.286991
BAH	0.686842	1	0.534106	0.628106	0.248954
HII	0.356146	0.534106	1	0.337931	0.139066
RHM.DE	0.843057	0.628106	0.337931	1	0.267462
compound	0.286991	0.248954	0.139066	0.267462	1

Source: Author's development based on (Yahoo Finance).

Although the results of the Spearman correlation analysis indicated a moderate correlation with stock prices, further modelling of Rheinmetall AG (RHM.DE) revealed a very high RMSE level (Table 6), disproving the hypothesis of stock price dependency on battlefield events in the Russia-Ukraine war. This finding persists despite the significant price surge observed following initial reports of the onset of the war.

Among the tested models, only ARIMA (SARIMAX) demonstrated moderate accuracy. However, due to feasibility constraints, further research will not focus on improving this model or exploring additional connections.

Table 6. Root Mean Squared Error for each model was tested using Rheinmetall AG stock price with sentiment (compound) as an additional parameter.

Model	RMSE	Model	RMSE
ARIMA (SARIMAX)	37.2960	XGBoost	214.2886
VAR	196.6667	LSTM	254.6767

Source: Author's development.

During the search for the optimal model for forecasting the stock prices of the selected companies, it was observed that excluding sentiment (compound) as an explanatory variable still allowed the models to produce decent results when applied to time series data. This was particularly evident with the Long Short-Term Memory (LSTM) model, which is well-suited for capturing nonlinear time patterns and long-term dependencies. Each model was tested using the stock data of Rheinmetall AG to determine the most suitable approach for time series analysis without incorporating sentiment (compound) as a variable (Table 7).

Table 7. Root Mean Squared Error for each model was tested using Rheinmetall AG stock price.

Model	RMSE	Model	RMSE
LSTM	23.4788	ARIMA	37.0979
XGBoost	27.4883	VAR	96.8055

Source: Author's development.

In this case, the linear models (ARIMA and VAR) failed to forecast the RHM.DE variable effectively, suggesting the presence of nonlinear and more complex patterns in the data. The LSTM model outperformed both ARIMA and VAR, indicating that the data for RHM.DE contain nonlinear patterns that require advanced models, such as neural networks. The LSTM model effectively captured hidden temporal patterns in the data.

During the initial stage of running the LSTM model, the RMSE value obtained was 23.4788, which, despite being relatively high, was considered attractive for several reasons. First, it was the lowest RMSE value among the tested models. Second, the result was achieved despite the limited amount of data and the consideration of only one explanatory factor for the complex mechanism of stock price formation. Third, the testing was conducted on a stock with prices fluctuating between 100.05 and 619.

To improve these results further, the hyperparameters of the LSTM model were optimised. This involved adjusting the number of epochs, the size of the LSTM layers, and the lookback parameter, as well as employing Grid Search and Random Search for parameter tuning. After optimisation, the RMSE value for the RHM.DE stock forecast using the LSTM model improved to 17.8862.

Based on these improved results, a decision was made to apply the optimised LSTM model to the stock prices of the remaining companies in the dataset: BAE Systems, Booz Allen Hamilton, Huntington Ingalls, and Harris Corporation. The results are presented in Table 8 and Figure 4.

Table 8. Root Mean Squared Error for the LSTM model with optimising the hyperparameters of defence corporation stock prices.

Corporation	RMSE	Corporation	RMSE
BAESY	1.4648	HII	7.5409
BAH	5.4675	RHM.DE	17.8862

Source: Author's development.

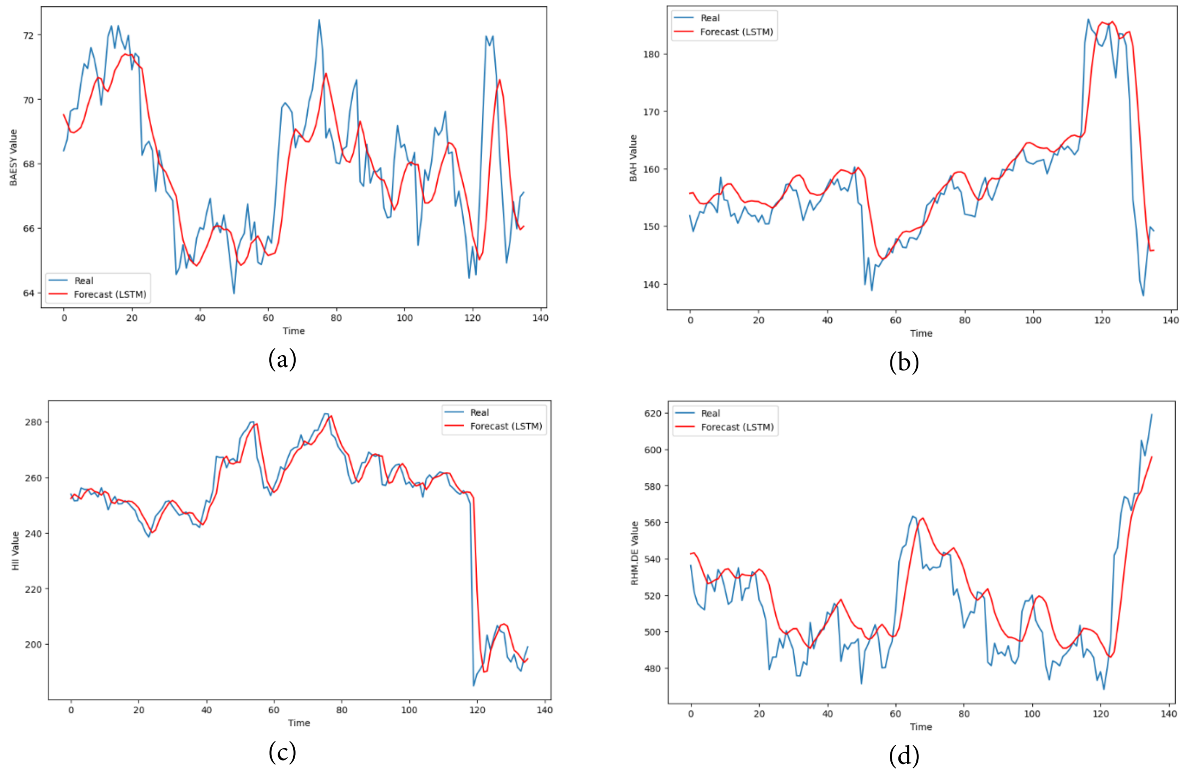

Figure 4. Visualisation of the results from running the optimised LSTM model for (a) BAESY, (b) BAH, (c) HII, (d) RHM.DE.
Source: Author's development.

4. Discussion

This study demonstrates the potential of applying artificial intelligence at every stage of evaluating factors influencing stock prices. The analysis of news articles concerning the evolving situation in the Russia-Ukraine war was enabled by natural language processing (NLP) methods. Although, in this specific case, sentiment did not play a significant role in the changes in the stock prices of defence companies, the study presented an approach that can be utilised in other contexts where the sentiment level of publications shows a sufficient correlation with stock prices. Taking that into acount, Caldara and Iacoviello (2022) demonstrated that the attention of "newspapers' to geopolitical events is an accurate measure of the perceptions of investors", underscoring the relevance of sentiment analysis as a tool for understanding market dynamics in geopolitically influenced scenarios. Using an extensive reading of news coverage over 120 years and a dictionary-based method, they developed the Geopolitical Risk (GPR) Index, which quantifies "the threat, realisation and escalation of adverse geopolitical events". Applying the news analysis methods used in this study could improve the speed and reliability of GPR calculations, leveraging AI capabilities for rapid information retrieval.

The testing of machine learning methods in this study identified an approach that is optimally suited for time series analysis. The tested methods have been widely applied in scientific literature, including:

- VAR (Vector AutoRegression): Utilised for the analysis of green equity indices (Cummins, Garry, Kearney, 2014), economic policy uncertainty, and stock market returns (Christou et al., 2017; Padhy et al., 2024).

- XGBRegressor Model: Applied for the accurate forecasting of corporate financial distress (Kristanti et al., 2024), stock market and price predictions (Lavanya, Gnanasekaran, 2023), and efficient portfolio management (Dezhkam, Manzuri, 2023).
- LSTM (Long Short-Term Memory) Neural Network Model: Implemented using the TensorFlow Keras library (Mohapatra et al., 2023), described as "offering robust and flexible tools for the design, training and evaluation of deep neural networks" (Villegas-Ch, Navarro, Sanchez-Viteri, 2024).
- ARIMA Model: Highlighted in many studies as an example of "advanced algorithmic forecasting techniques" (Kissell, 2014).

This research contributes to the growing body of knowledge by applying these well-established methods to time series data, demonstrating their strengths and potential use cases in various financial and economic contexts.

As previously highlighted, the Long Short-Term Memory (LSTM) method proved to be the best-performing approach. This is not the first instance where the model has demonstrated significantly lower root mean squared error (RMSE) values in stock market data forecasting (Dioubi et al., 2024).

Another study, by Li et al. (2024), examined the spillover effects of yields and volatility across 26 asset classes grouped into six markets: Stock, Gold, Energy, Food, Currency and Bond. Their analysis focused on the invasion of Ukraine by Russian troops on February 24, 2022, which they referenced 44 times. However, their focus did not extend to individual battlefield events nor subsequent impacts on the market.

It is important to note that Russia's invasion of Ukraine began earlier, in 2014, with the annexation of Crimea and incursions into Donetsk and Luhansk. The focus on February 24, 2022, as the starting point likely influences how researchers interpret the importance of events in the ongoing war. Consequently, events before the February 2022 invasion are often overlooked in the scientific literature.

While the findings of this study suggest a relationship between battlefield developments and stock price fluctuations in major defence corporations, it is important to acknowledge several limitations that constrain the scope of the conclusions. Firstly, it would be overly simplistic to assume that the stock prices of large defence companies are influenced solely by a single indicator, such as sentiment derived from news reports. Stock prices are inherently multifactorial and can be impacted by a myriad of variables, including macroeconomic conditions, defence budgets, interest rates, geopolitical alliances, and broader market trends.

The sharp price surge observed following Russia's full-scale invasion of Ukraine on 24 February 2022 is a notable market reaction that underscores the significance of immediate news. However, attributing this reaction solely to the sentiment of battlefield developments may overlook other influencing factors. For instance, market participants may also have been responding to anticipated government policy shifts, projected increases in defence spending, or speculative investment behaviours prompted by geopolitical instability.

Furthermore, this study's reliance on sentiment analysis derived from the Python VADER module introduces methodological constraints. While VADER is a widely-used and practical tool for text sentiment analysis, it may not fully capture the nuanced and context-specific language often found in geopolitical news. The complexity of interpreting sentiment in articles that describe dynamic and multifaceted battlefield events may lead to inaccuracies or oversimplifications. Additionally, sentiment scores generated by such tools do not account for the subjective interpretations of news by different market actors.

Another limitation lies in the scope of this study, which primarily examined sentiment related to a single geopolitical event. This approach may not adequately generalise to other contexts or conflicts, as the market's response to battlefield developments may vary depending on the scale, stakeholders involved, and global economic conditions at the time.

Lastly, while the study focuses on major defence corporations, the findings do not account for smaller defence companies or adjacent industries, which may exhibit different patterns of stock price movement. This could lead to a partial understanding of the overall impact of battlefield developments on the broader defence sector.

To address these limitations, future research should consider incorporating a wider array of variables, employing advanced sentiment analysis tools that leverage deep learning, and expanding the scope to include comparative analyses of different geopolitical events. By doing so, subsequent studies can provide a more holistic understanding of the intricate relationships between geopolitical developments, market sentiment and financial performance in the defence industry.

Conclusions

This study aimed to identify a model capable of predicting stock prices based on the battlefield developments during the Russia-Ukraine war. Sentiment data extracted from news articles describing the conflict in Ukraine were collected and analysed. The market reaction – specifically, the stock prices of some of the largest defence companies – to Russia's full-scale invasion of Ukraine in February 2022 was immediate and significant.

The study sought to investigate whether the market, and the same stocks, reacted as strongly to subsequent individual battlefield events in Ukraine, such as the successes or setbacks of the Ukrainian army. However, the applied methodology did not confirm the hypothesis of a correlation between stock prices and these events.

Nevertheless, success was achieved in testing various machine learning methods for forecasting stock prices of specific defence industry companies. The results demonstrate that for BAE Systems, Booz Allen Hamilton, Huntington Ingalls, and Rheinmetall AG, LSTM neural networks provide the best solution based on time series data. This was particularly evident after optimising hyperparameters, including the number of epochs and the size of the LSTM layers.

The findings of this study underline the robustness of LSTM models in capturing complex patterns in time series data, making them particularly effective in highly volatile and event-driven industries such as defence. However, the variations in model performance across different companies highlight the importance of tailoring machine learning models to the specific characteristics of individual stock behaviours and market dynamics.

In this study, the Python VADER module was used to assess the sentiment of news articles. While VADER is a practical tool, it is neither universal nor the most advanced option for text sentiment analysis. Future research should therefore explore alternative tools and methods for text analysis, with a particular emphasis on identifying the most effective approaches among machine learning models for analysing sentiment in geopolitically sensitive contexts.

Additionally, future studies should aim to identify other markers that reflect battlefield developments and demonstrate a clear correlation with stock prices. Expanding the range of indicators could provide deeper insights into the relationship between geopolitical events and financial market dynamics, enhancing the understanding of how specific events influence market reactions.

Further research should also focus on the integration of additional variables, such as macroeconomic indicators, defence budgets and international policy shifts, to enhance the predictive capabilities of machine learning models. Incorporating such factors could offer a more comprehensive understanding of the interplay between geopolitical events and financial markets, enabling more accurate and nuanced forecasts.

Finally, the study underscores the potential of machine learning in supporting investment decision-making and risk management in defence-related sectors. By leveraging AI-driven insights, stakeholders can better navigate the uncertainties of geopolitically sensitive industries, refine their strategic approaches to investment, and optimise policy formulation in response to rapidly changing global dynamics.

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Conflicts of Interest: The author declares no conflicts of interest related to this study.

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