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RESEARCH PUBLICATIONS

2025-26

Summary of Research Publications during 2025-26

S.No	Course	No. of Publications
1	BBA (Management)	1
2	B. COM (H)	3

	Research Paper 2025-26								
S.No	Title of paper	Name of the author/s	Department of the teacher	Name of journal	Month of Publication	Year of publication	ISSN number	Category	Link
1	Digital Transformation and Change Management: A Study of Organizational Adaptation.	Dr. Preeti Singh	BBA	The Journal of African Development	April	2026	1060-6076	ABDC C-Category	Link
2	Dynamic stock market investment prediction using a dual-attention similarity-navigated transformer graph network optimized by a multiplayer battle game-inspired strategy	Dr. Niti Saxena	B COM (H)	SN Business and Economics	Jun	2026	2662-9399	Scopus	Link
3	Green Finance and Corporate Sustainability Performance	Dr. Ekta Kasana	B COM (H)	International Journal of Economic Practices and Theories (IJEPT)	July	2026	2247-7225	ABDC C category	Link
4	The role of artificial intelligence in higher education: challenges and applications	Dr. Niti Saxena	B COM (H)	Academy of Marketing Studies Journal,	December	2025	1528-2678	ABDC B-Category	Link

RESEARCH PUBLICATIONS

BBA & B.COM (H)

2025-26

Digital Transformation and Change Management: A Study of Organizational Adaptation.

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KEYWORDS

Digital Transformation, Change Management, Organizational Adaptation, Leadership, Technology Infrastructure, Culture, Change Strategy, Risk Management, Employee Engagement, Governance

ABSTRACT

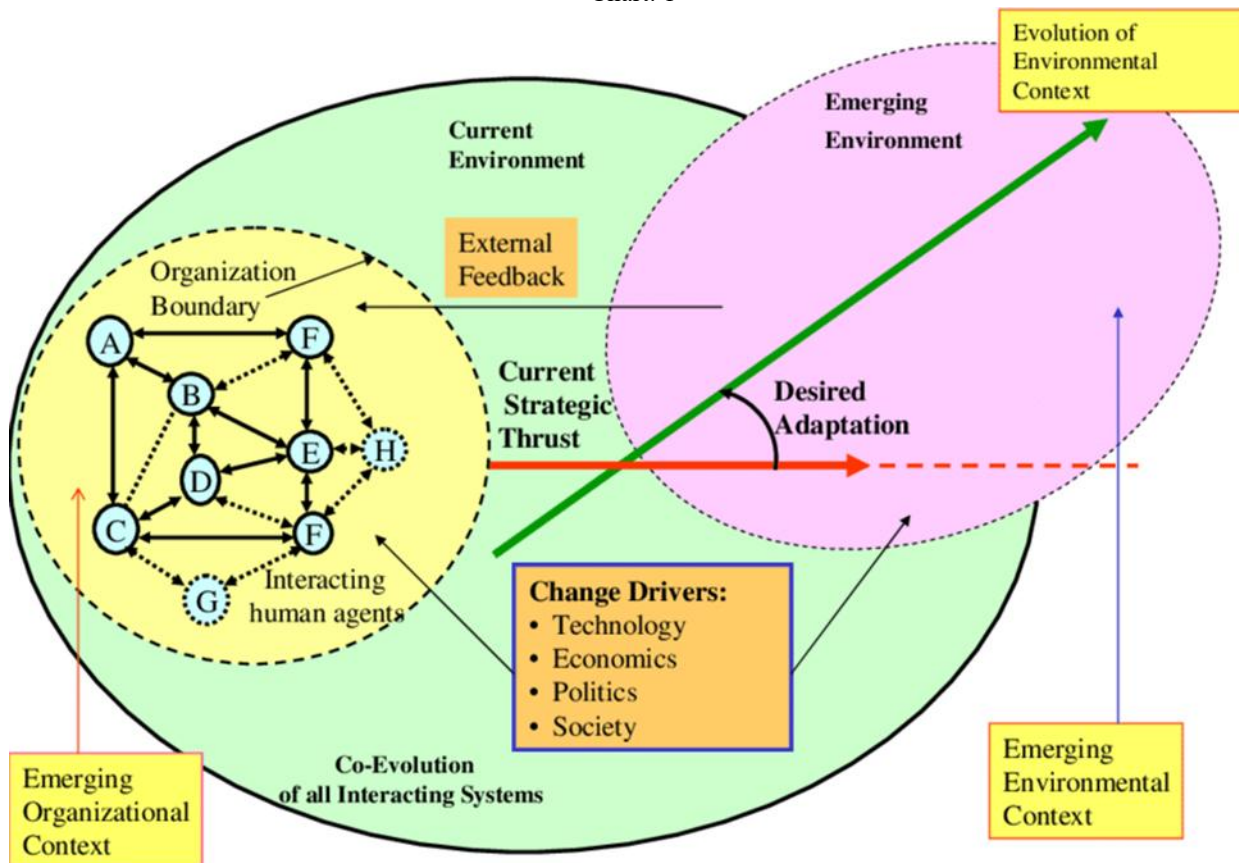
The study investigates the correlation between digital transformation and change management in businesses, with a particular emphasis on the manner in which corporations adapt to technological advancements while simultaneously managing the corresponding operational and human changes. In order to remain competitive in a digital marketplace, it is imperative for organizations to undergo digital transformation. However, its effectiveness is primarily contingent upon the organization's ability to effectively manage change. This investigation examines the primary factors that influence organizational adaptability, such as governance, technological infrastructure, culture, and leadership. The report conducts a comprehensive literature review and case analysis to identify the most common challenges that businesses face during digital transformation and to provide effective strategies for overcoming these obstacles. The essential results indicate that a well-defined strategic vision and leadership dedication are essential for the advancement of digital transformation efforts. Leaders who demonstrate a sustained commitment to technology integration, communicate candidly, and actively involve workers and stakeholders are more likely to achieve success. Additionally, a more seamless transition throughout the transformation process is facilitated by an organizational culture that encourages creativity, cooperation, and ongoing learning. The research underscores the necessity of a robust technological infrastructure that can accommodate digital technologies, thereby enabling their seamless integration and scalability. Change management solutions are indispensable in conjunction with technology and culture. Stakeholder engagement, effective communication, and specialized training are essential for overcoming employee resistance and promoting the adoption of new technology. In order to mitigate potential security and compliance issues during the transition, it is imperative to establish risk management and governance frameworks. The research posits that organizations that strategically integrate their digital transformation initiatives with comprehensive change management strategies are more successful in adapting to technological advancements. The study provides practical insights for businesses that are striving to cultivate creativity, improve efficiency, and accomplish sustainable development through digital transformation.

INTRODUCTION

The rapid advancement of technology has initiated a new phase of digital transformation, altering sectors, companies, and their business practices. Digital transformation denotes the incorporation of digital technology throughout all facets of a business, profoundly altering operations, culture, and customer experiences. This transformation is now an essential

strategy for firms aiming to maintain competitiveness in a technology-driven market. Simultaneously, change management has emerged as a crucial discipline for assisting firms in navigating this upheaval. Change management guarantees the proper implementation and acceptance of digital projects by workers, resulting in more seamless transitions and less opposition. The correlation between digital transformation and change management is essential for attaining success in the transformation process. This research aims to investigate how companies adjust to the difficulties of digital transformation and the function of change management in enabling effective adaptation. The research seeks to elucidate organizational adaptability within the framework of digital transformation, emphasizing critical success elements, prevalent difficulties, and ways for their mitigation. Adama, A., et al. (2024) explores the intersection of digitalization and environmental sustainability within industrial sectors, proposing a "twin transition" approach that integrates both technological and ecological transformations. The authors argue that digitalization is a powerful driver of sustainability, offering solutions to reduce resource consumption, optimize energy use, and minimize environmental impact. They emphasize that industries are increasingly turning to digital tools, such as artificial intelligence, big data, and the Internet of Things (IoT), to monitor environmental parameters and optimize production processes. These technologies not only improve efficiency but also facilitate the transition toward greener and more sustainable industrial practices. The study examines various industries, including manufacturing and energy, to demonstrate how digitalization can accelerate the adoption of sustainable practices. For example, digital technologies can optimize supply chains, improve waste management, and enable more precise environmental monitoring. Furthermore, the authors highlight the role of leadership and organizational culture in fostering a dual focus on both digital transformation and environmental sustainability. Companies that align their digitalization efforts with sustainability goals are better positioned to meet regulatory requirements, reduce costs, and enhance their corporate social responsibility image.

Chart: 1



RESEARCH BACKGROUND

Organizations worldwide are experiencing substantial transformations owing to the emergence of digital technology. Industries like banking, healthcare, retail, and manufacturing have used digital technologies to optimize procedures, augment productivity, and elevate client interaction. Nevertheless, these alterations provide a distinct array of issues. Despite the clear advantages of digital transformation, several firms have challenges in adopting new technology, since people often demonstrate reluctance to change. The research foundation encompasses an examination of several frameworks and ideas pertinent to digital transformation and change management. Numerous firms continue to face challenges in matching their technical objectives with their cultural and operational frameworks. For example, while

technology may be accessible, organizational procedures may lack the agility necessary to fully use its potential. An in-depth examination of the current literature underscores the significance of leadership, employee engagement, and strategic planning in overseeing digital transformation. Multiple studies underscore the need of explicit communication and customized training initiatives to facilitate staff adaptation to new technology. Others examine the influence of organizational culture on the success or failure of transformation attempts. In change management, models such as Kotter's 8-Step Change Model, Lewin's Change Model, and the ADKAR model are examined for their applicability to digital transformation initiatives. Comprehending these models and their influence on organizational adaptability to change is essential for developing successful digital transformation strategies.

LITERATURE REVIEW

Adama, A., et al. (2024) discuss the challenges of integrating digital and sustainability goals, particularly in terms of upfront costs, the need for skilled labor, and the risk of technological obsolescence. However, they conclude that the twin transition approach, when implemented strategically, offers a promising pathway for industrial sectors to achieve long-term sustainable growth while embracing digital innovation. Burchard & Maisch, B. (2019) investigated the pivotal role of organizational culture and leadership in driving successful digital transformation initiatives. They argue that digital transformation is not solely a technological shift but requires a comprehensive cultural and leadership overhaul within organizations. The authors contend that organizations must cultivate a digital-friendly culture that embraces change, fosters innovation, and encourages agility. This cultural shift is essential for overcoming resistance to change and ensuring that digital technologies are effectively integrated into everyday operations. The paper emphasizes that leadership plays a crucial role in guiding organizations through digital transformation. Leaders must not only have a clear vision of digital goals but also demonstrate commitment to the process by allocating necessary resources, aligning teams, and maintaining open communication channels. The authors suggest that transformational leadership, characterized by openness, adaptability, and a focus on innovation, is particularly effective in supporting digital change. Furthermore, the study identifies several key cultural attributes that enable successful digital transformation, such as openness to experimentation, continuous learning, and a collaborative mindset. The authors note that organizations with cultures that encourage risk-taking and innovation are more likely to succeed in their digital initiatives. However, they also acknowledge that cultural change can be difficult and requires sustained effort from all levels of the organization. The paper concludes by suggesting that organizations should view digital transformation as an ongoing process rather than a one-time project. Leaders must consistently reinforce the importance of digitalization and ensure that their organizations are equipped to adapt to new technologies, shifting market demands, and evolving consumer expectations.

RESEARCH GAP

Although current research offers significant insights into the technical dimensions of digital transformation, a considerable gap remains in comprehending how firms adjust to these changes. There is a lack of study on how change management approaches might be customized to meet the particular requirements of digital transformation initiatives. Numerous studies have mostly focused on discrete elements of digital transformation, including technology adoption, process optimization, and enhancement of customer experience. Nevertheless, little focus has been directed towards the extensive organizational modifications necessary for effective transformation. A disparity occurs in comprehending the convergence of technology and human aspects throughout the transition process. Moreover, there is little study investigating the influence of leadership and employee engagement on digital transformation. In what ways can leaders adeptly navigate their teams through the emotional and operational difficulties associated with digital transformation? In what ways may workers be enabled to adopt new technology and modify existing work practices? These questions remain insufficiently addressed in the current literature. This research seeks to elucidate the intricate dynamics of organizational adaptation amid digital transition, emphasizing change management solutions.

IMPORTANCE OF THE RESEARCH

This research is significant for its potential to enhance the existing knowledge on digital transformation and change management. As enterprises rapidly use digital technology, understanding the determinants of effective adaption becomes more vital. This study offers significant information for leaders and managers aiming to execute digital projects efficiently while reducing disruption and opposition inside their businesses. This research primarily contributes by examining the link between digital transformation and organizational adaptability. Although much study has focused on the technical dimensions of transformation, less emphasis has been directed on the cultural and operational adaptations of organizations to these changes. This research addresses a significant gap in the current literature by concentrating on the adaption process. The report underscores the significance of change management in enabling seamless transitions. Change management solutions are essential for appropriately preparing workers for the new digital landscape and enabling leaders to address the emotional and psychological dimensions of change. This research seeks to elucidate the essential factors for organizational success in digital transformation by examining this junction.

STATEMENT OF THE PROBLEM

Notwithstanding the increasing focus on digital transformation, some companies continue to encounter substantial obstacles in their efforts to adapt to emerging technology. Opposition to change, insufficient training, and poor leadership

can contribute to the failure of digital efforts. Organizations often fail to harness the whole potential of digital technologies because of these limitations. This paper addresses the fundamental issue of the absence of a systematic framework for comprehending organizational adaptation throughout digital change. Although much literature exists on digital technologies, little research explores how businesses may efficiently manage the transition process associated with their adoption. Moreover, firms often undervalue the significance of synchronizing their organizational culture and leadership with digital transformation efforts. In the absence of fundamental alignment, even the most advanced technology instruments may not achieve the intended results. The research seeks to investigate how firms might close this gap and build a more holistic approach for managing change during digital transformation.

METHODOLOGY OF RESEARCH

This study employs a quantitative research technique, adopting a survey-based approach to gather data from firms experiencing digital transformation. The sample size comprises 100 people, chosen using convenience sampling. This sample approach is selected for its practicality and accessibility to the target group, including workers and managers across several sectors. The survey will include inquiries about digital transformation techniques, corporate culture, change management tactics, and employee involvement in the context of digital projects. Participants will evaluate their experiences and impressions of the transformation process, along with the efficacy of the change management strategies used in their businesses. Convenience sampling is especially advantageous for this research, since it facilitates the rapid acquisition of data from firms already engaged in digital transformation initiatives. This strategy may not provide a completely representative sample, but it yields enough data to analyze trends and patterns in organizational adaptability. Descriptive statistics and regression analysis will be used to discern correlations among factors including leadership, employee engagement, and effective adaption to digital transformation. The results will inform the creation of a thorough framework for overseeing organizational change amid digital transformation.

FINDINGS AND RESULTS

Digital transformation and change management are intricately linked as firms strive to innovate and adapt to emerging technology. Effective management of change is essential for successful digital transformation, enabling the workforce and systems to adopt new tools and procedures. Effective leadership is essential for establishing a coherent vision and unifying the firm towards digital transformation objectives. Leaders must articulate the significance of digital projects and provide guidance. A clear and strategic vision directs the transformation process, emphasizing how technology will propel corporate development, augment efficiency, and elevate customer experience. The capacity to amalgamate novel digital instruments with current infrastructure is crucial. This may include cloud computing, data analytics, artificial intelligence, and automation. As firms undergo digitization, the safeguarding of data and systems becomes more intricate. Investing in cybersecurity measures is crucial for safeguarding sensitive information and maintaining the integrity of the transition. Consistent and transparent communication throughout the transition process facilitates expectation management and mitigates ambiguity. Transparency about obstacles and triumphs is essential for sustaining employee confidence. Employees demand ongoing learning opportunities to acquire the skills necessary for new digital systems. Training programs must be customized for various jobs inside the firm

Table.1 Descriptive statistics

S.No	Factors	N	Mean	SD
1	Leadership and Vision	100	3.12	.775
2	Organizational Culture	100	3.54	1.108
3	Technology Infrastructure	100	3.10	1.439
4	Change Management Strategy	100	3.29	1.143
5	Customer-Centric Approach	100	3.67	1.287
6	Governance and Risk Management	100	2.87	0651
7	Collaboration and Partnerships	100	3.04	0.754

The highest mean score of 3.67 suggests strong agreement that a customer-centric approach is critical for successful digital transformation. The standard deviation of 1.287 indicates that while most respondents hold this view, there is still some variation in how individuals or organizations prioritize customer-centric strategies. The mean score of 3.12 suggests that respondents somewhat agree on the importance of leadership and vision in the context of digital transformation. A standard deviation of 0.775 indicates moderate variability in responses, showing that while most respondents agree, there are some differences in how they perceive the impact of leadership and vision. A mean of 3.54 reflects a strong agreement with the significance of organizational culture in facilitating digital transformation. The relatively higher standard deviation (1.108) indicates a greater diversity in opinions, suggesting that while culture is generally viewed as important, individuals may perceive it differently based on their experiences or organizational context. The mean score of 3.10 indicates a somewhat positive perception of technology infrastructure in driving digital change. The high standard deviation (1.439) suggests that respondents' opinions on this factor are widely varied, possibly indicating that some organizations are more advanced in their technological infrastructure than others, leading to differing viewpoints on its importance. A mean score of 3.29 indicates a

moderate agreement that change management strategies play a crucial role in digital transformation. The standard deviation of 1.143 again shows variability in responses, implying that while change management is considered important, there are differences in how respondents assess its effectiveness or implementation. The mean score of 2.87 reflects a somewhat neutral or slightly below-average perception of the importance of governance and risk management in digital transformation. The relatively low standard deviation (0.651) suggests that most respondents are aligned in their assessment, though the score still indicates a lesser emphasis on this factor compared to others. With a mean of 3.04, respondents show a moderate level of agreement that collaboration and partnerships are important in digital transformation. The standard deviation of 0.754 shows less variation, suggesting a more consistent viewpoint among respondents regarding the significance of external collaborations in the transformation process.

DISCUSSION

1. **Leadership and Vision:** Effective leadership is essential for guiding digital transformation. Leaders must not only communicate the strategic vision clearly but also embody the commitment to change. A well-articulated vision creates alignment across the organization, motivating teams to embrace new digital initiatives. Leaders should prioritize innovation, allocate resources, and remove obstacles to transformation. They must foster a culture of openness and learning while ensuring that digital transformation goals align with broader business objectives. Strong leadership can drive momentum, navigate challenges, and inspire confidence, ensuring that the digital transformation process is effective and well-received at all levels of the organization.
2. **Organizational Culture:** Organizational culture plays a crucial role in the success of digital transformation efforts. A culture that supports innovation, flexibility, and continuous learning enables organizations to adapt to technological changes with ease. Employee buy-in is essential, as a workforce that is resistant to change can hinder the implementation of new digital tools. Creating an inclusive, transparent culture where feedback is encouraged helps mitigate fear and resistance. Training and development programs that align with digital goals also enhance employees' willingness to embrace change, ensuring that the workforce has the skills to navigate the transformation process effectively and sustainably.
3. **Technology Infrastructure:** A robust technology infrastructure is the backbone of successful digital transformation. Organizations must invest in scalable, secure, and interoperable systems that integrate new technologies with existing platforms. Cloud computing, big data analytics, and automation are often pivotal in driving operational efficiencies. Without a strong infrastructure, digital initiatives can become fragmented or fail altogether. Cybersecurity is also a top priority, as the digital landscape exposes organizations to new risks. Investing in cutting-edge technologies, while ensuring the organization's infrastructure can support them, ensures that transformation efforts are sustainable and can scale over time to meet evolving needs.
4. **Change Management Strategy:** A well-defined change management strategy is crucial for navigating the complexities of digital transformation. This strategy must be comprehensive, addressing both the technical and human aspects of change. Clear communication of the transformation process, roles, and goals helps mitigate resistance and confusion. The strategy should incorporate ongoing training, resources, and support to help employees adapt. Setting realistic milestones and using data-driven insights to track progress can facilitate smoother transitions. Change management ensures that the digital tools implemented are adopted by the workforce and integrated into day-to-day operations, driving long-term success and organizational growth.
5. **Customer-Centric Approach:** A customer-centric approach is essential for ensuring that digital transformation adds value to both the organization and its clients. By understanding customer pain points, preferences, and expectations, organizations can design digital solutions that directly address market needs. Transforming business processes and systems around customer insights leads to improved user experiences, loyalty, and satisfaction. Regular customer feedback mechanisms, such as surveys or focus groups, ensure that digital strategies remain aligned with evolving expectations. By focusing on customer outcomes, organizations not only achieve business growth but also create a competitive advantage in an increasingly digital marketplace.
6. **Governance and Risk Management:** Effective governance and risk management are essential to ensure the success and security of digital transformation initiatives. With the increasing use of data and digital tools, organizations must establish clear policies and frameworks to govern digital processes. This includes ensuring compliance with regulatory requirements, managing data privacy, and addressing potential cybersecurity threats. Identifying and mitigating risks early, such as technology failures or resistance to change, can help reduce disruptions. An effective governance structure provides transparency and accountability, ensuring that digital transformation efforts are aligned with business objectives and ethical standards, thus safeguarding the organization's reputation.
7. **Collaboration and Partnerships:** Collaboration and strategic partnerships are pivotal in driving successful digital transformation. Partnering with technology providers, consultants, and industry experts allows organizations to leverage external expertise and resources. Collaboration between departments within the organization ensures that digital initiatives meet the needs of different functions, fostering alignment across teams. External partnerships can also enable access to cutting-edge technologies and innovative solutions. Effective collaboration not only accelerates the pace of transformation but also mitigates risks by combining internal knowledge with external expertise, providing a more holistic approach to navigating the challenges of digital change.

RESEARCH IMPLICATIONS

The research on digital transformation highlights that organizations that effectively manage the transformation process experience enhanced operational efficiency, improved customer satisfaction, and greater competitive advantage. However, failure to adapt can lead to significant challenges, such as employee resistance, security vulnerabilities, and inefficiencies. The findings suggest that organizations need to be proactive in addressing the human and technological aspects of digital transformation. Those that invest in leadership, culture, infrastructure, and risk management tend to see more positive long-term outcomes. Consequently, businesses must take a comprehensive, strategic approach to ensure that digital transformation efforts align with broader organizational goals and drive sustained success.

RECOMMENDATIONS

The results of this study will have considerable ramifications for both scholarly research and practical implementation in businesses. This study enhances scholars' comprehension of the interplay between digital transformation and organizational adaptability, alongside the significance of change management in enabling effective transitions. The research addresses a significant gap in the literature by examining the interaction of technology, culture, and leadership within the framework of digital transformation. The report provides practitioners with practical insights on enhancing organizational management of the change process throughout digital transformation. The study delineates significant success criteria, prevalent problems, and efficacious change management practices, offering firms a framework for managing the intricacies of digital transformation. This study's implications are especially beneficial for executives and managers leading digital transformation programs, since it provides them with the information and resources necessary to properly steer their firms through the process.

CONCLUSION

The factors that appear to have the most positive influence according to the mean scores are Customer-Centric Approach and Organizational Culture, both with relatively high scores. Governance and Risk Management has the lowest mean score, indicating that it might be seen as less critical compared to other factors, though there is less consensus on its importance. The variability in responses, especially in areas like Technology Infrastructure and Change Management Strategy, suggests diverse organizational contexts and experiences with these factors. The report underscores the significance of digital transformation and change management in enabling firms to navigate the difficulties of a more digital landscape. The research elucidates the link between these two notions, offering useful insights into how firms may effectively manage the intricacies of digital transformation. Digital transformation encompasses not just the adoption of new technology but also the cultivation of a culture centered on adaptability, creativity, and continual learning. The study highlights the essential importance of leadership and employee involvement in achieving successful digital transformation efforts. By using effective change management methods, companies may alleviate the difficulties related to digital transformation and facilitate a seamless transfer to the new digital environment. This study addresses the research gap and offers actionable suggestions, so enhancing both academic comprehension and practical implementation of digital transformation and change management. Future study should investigate the intricacies of organizational adaptability across various sectors and geographies, along with the enduring impacts of digital transformation on organizational performance.

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Dynamic stock market investment prediction using a dual-attention similarity-navigated transformer graph network optimized by a multiplayer battle game-inspired strategy

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Abstract

Predicting investments in dynamic stock markets is a difficult problem because of the high volatility, nonlinear price trends, dependency on time, and rapid change in market dynamics. Accurate forecasting is essential for supporting reliable investment decision-making, risk reduction, and financial market stability. However, existing stock prediction approaches often suffer from limited adaptability, overfitting, weak inter-feature relationship modeling, and high computational complexity under volatile market environments. To overcome these shortcomings, a new approach titled Dynamic Stock Market Investment Prediction is suggested based on Dual-Attention Similarity-Navigated Transformer Graph Network combined with Multiplayer Battle Game-Inspired Optimization (DASNT-GN-MBGO). The developed framework combines Correlation Coefficient based Min-Max Normalization (CC-MMN) as the preprocess step, Adaptive Causal Decision Transformers (ACDT) for temporal-causal feature extraction, and a combination of Dual-Attention Transformer Network with Similarity Navigated Graph Neural Network for sequential and relational learning. The MBGO technique was used further for optimization of network weights. Experiments were carried out on the Stock Market dataset with the same training settings. The results show that the framework presented in the paper demonstrated superior prediction accuracy with an MAE of 0.240, an RMSE of 0.310, an MAPE of 9.40% and R^2 equal to 98.85%. The proposed framework shows the high level of generalization, accurate forecasting abilities and efficient computations in the field of dynamic stock markets.

Keywords Deep learning · Dynamic investment prediction · Financial time-series analysis · Multiplayer battle game-inspired optimization · Stock price forecasting

Introduction

The stock market is regarded as one of the most significant financial infrastructures of contemporary economic systems since it impacts investments and the allocation of capital. Consequently, stock price prediction has become a critical field of study that would help in making intelligent investment decisions by minimizing risks. The task of forecasting stock prices is not an easy endeavor, considering that the financial markets exhibit nonlinearity, fast-changing volatilities, uncertain investor sentiments, and temporal correlations between financial variables. Traditional approaches of statistics and ML models have not been successful enough in incorporating such complexities in the market environment (Awad et al. 2023; Gu et al. 2023).

The recent developments in deep learning (DL) and artificial intelligence have led to considerable improvements in the ability to analyze large financial time series and identify market connections. The transformer is effective in capturing long-term dependencies, whereas graph learning has proven to be effective in learning the relationships among stocks and other market players (Chen et al. 2024; Tao et al. 2024). Furthermore, the application of sentiment analysis and reinforcement learning in investment has allowed for additional advancements in intelligent financial forecasting by incorporating market psychology and adaptability in the decision-making process (Du and Shen 2024; Priyadarshi and Kumar 2025). However, despite these advancements in the forecast approach, there are certain problems with the contemporary forecasts, including overfitting, inadaptability to changes in the market, computational complexity, and ineffectiveness of temporal and relational learning methods (Bandhu et al. 2024; Smatov et al. 2024).

The stock market is a complex and dynamic financial environment that reflects the prosperity of a nation's economy. The fluctuation in stock prices changes with time due to numerous influences including economic variables, global happenings, corporate activities, and market sentiment (Yang et al. 2024; Zhang and Mariano 2024). The investors are faced with the challenge of making informed decisions in a volatile environment. The growing significance of the stock market in generating wealth and growth has made it necessary to devise strong methods that can help predict the trends in the stock market and identify profitable investment options (Yañez et al. 2024; Zhang et al. 2024).

The fast growth of technology and access to financial information has resulted in the transformation of the process of investment analyses and predictions. The information about past stock prices, volume, financial records, and other technical analysis data is readily available, which makes it possible to conduct a full market situation analysis (Iyer and Bakshi 2024; Kehinde et al. 2025). However, because of the large number of continuously streaming data in the market, forecasting becomes very complex using traditional methods (Pardeshi et al. 2024; Du and Shen 2024). Thus, there is a requirement for intelligent forecasting models that could simultaneously simulate the dynamic behavior of stocks, their interrelationship, and trader's investing behavior. This study is aimed at solving these concerns.

Novelty and contributions

The below list shows the novelty and contributions of this research paper,

- Utilizes Dual-Attention Similarity-Navigated Transformer Graph Network with Multiplayer Battle Game-Inspired Optimization (DASNT-GN-MBGO) to jointly model temporal price evolution and relational dependencies, enabling adaptive learning under highly volatile stock market conditions.
- Uses Preprocessing with Correlation Coefficients and Min-Max Normalization (CC-MMN) to normalize features scales, while increasing target relevance, thereby ensuring consistency and stability of the input data in predictive models.
- Takes advantage of Adaptive Causal Decision Transformers (ACDT) for advanced feature extraction by taking into account causal, sequential, and temporal relations among past stock data, separating the hidden investment trends from the surrounding market noise.
- Utilizes the Dual-Attention Similarity-Navigated Transformer Graph Network (DASNT-GN), which is a hybrid prediction model integrating both attention-based sequence learning and similarity-based graph fusion for efficient representation of temporal and relational data.
- Uses Multiplayer Battle Game Inspired Optimization (MBGO) for adaptive optimization of DASNT-GN weight parameters, reducing the risk of local optima and improving robustness in highly volatile and intricate investment markets.
- Offering a scalable and generalizable investment prediction model based on the use of CC-MMN, ACDT, DASNT-GN, and MBGO that guarantees effective decision-making across different types of assets and varying stock market conditions.

The manuscript consists of five main sections. Section [Introduction](#) provides an introduction and background of the study. Section [Literature survey](#) presents the related work and methodologies. Section [Proposed methodology](#) describes the proposed methods and their components. Experimental results and their respective analyses are discussed in Section [Results and discussion](#). In addition, Section [Conclusion](#) contains the concluding part of the research study.

Literature survey

Various research studies have been undertaken with the aim of forecasting investments in the stock market. Some of these studies are described below.

Alam et al. (2024) introduced an Long Short-Term Memory and Deep Neural Network (LSTM-DNN) model that provided its forecasts about the stock closing prices. The procedure has been conditioned and examined on multiple collections of the company data to show volatility and complex time patterns. Ablution experiment and comparative experiments reported component contribution and strength. Learning about historical trends was to generalize market behavior. The model had its strengths; however, it consumed considerable data and computational power.

Singh et al. (2025) presented a Deep Neural Network using the Improved Firefly Algorithm (DNN-IFA) in the stock market sentiment analysis. This approach was to learn some optimized features that would capture investor emotion that would affect market movements. Empirical studies and comparative analyses proved the

effectiveness of the classification in a range of sets. The integration strategy enhanced sentiment interpretation to support financial decision-making, but the method was plagued by the complexity of optimization and augmented computation time.

Kumar and Manikandan (2025) introduced the application of the Stacked Ensemble Model for Trend Analysis (SEMP-TA), which was utilized to predict the trend in the stock market. The framework was designed in terms of cluster-based feature selection and overall data preprocessing, aiming to generate influential indicators. The processed, cleaned data were sent into the ensemble learning techniques to determine the complex pattern within the market. Experimental analysis demonstrated that the method has strong predictive power and stability on benchmark indices, although the technique has negative characteristics of increasing model complexity and reduced interpretability.

Rathee et al. (2023) introduced the use of Convolutional Neural Network and Bidirectional Long Short-Term Memory ensemble (CNN-BiLSTM) to forecast cryptocurrency prices over time. The framework aimed to predict useful features and acquire temporal relationships on historical and real-time market data. Comparative analysis with the current neural models proved to have a better predictive reliability in a variety of cryptocurrencies. The method also strengthened forecasting and was computationally intensive and tuned on the model.

Shaban et al. (2024) presented a framework called Stock Market Prediction in a DL System (SMP-DL), which estimated the stock closing price. The data preprocessing and prediction stage has been outlined in the framework to ensure that the level of noise can be considerably reduced and the quality of data can be improved. A hybrid LSTM and bidirectional Gated Recurrent Unit model was employed for the analysis of the cleaned dataset. The generalization was observed to be high in the datasets, which is explained by the fact that the methodology used was based on careful preprocessing and quality data sets.

Zhan and Kim (2025) introduced an appearance of a time-series pattern forecasting model that can forecast the trend of stock markets using a delayed binary time-series model. To discover temporal dependencies among multiple windows, the technique was derived based on delayed binary representations and XNOR operations. The evaluation of the methodology has been performed using the standard ML and DL classifiers, where the Decision Tree (DT) classifier demonstrated the best performance across the board. The use of experimental analysis focused on trustworthy trend detection, yet the method presented minimal flexibility during sudden changes in the behavior of the markets.

Sun et al. (2024) presented the development of CEEMDAN-LSTM-SA-Light-GBM as a hybrid forecasting model for stock price prediction. The framework was created to deal with nonlinear, noisy financial time series based on signal decomposition, learning temporal dependencies, and optimizing ensemble prediction. The comparative analysis presented high fitting and forecasting as compared to single LSTM, RNN, and other hybrid models. The technique improved predictive power, but had very high computational and tuning demands, which limited scalability and practical use.

Biswas et al. (2025) introduced the Temporal Convolutional Network with Attention Mechanism (TCN-A) for forecasting stock prices and measuring risks. The

authors designed the TCN-A model that had two outputs; one for predicting stock prices and another for risk measures in the future. To capture temporal dependencies, dilated convolutions were used, where particular attention was paid to significant time steps. The comparative studies showed that there was greater accuracy and robustness in prediction but, architectures became more complex, complicating computational demands and complexities of implementation.

A novel approach to stock market prediction was proposed by Iftikhar et al. (2024), where the stock price was decomposed into the nonlinear trend component and random component using the Hodrick-Prescott filter technique. Both linear and nonlinear techniques were used in forecasting the prices of stocks at the Pakistan Stock Exchange. The proposed approach was titled LMD-ARIMA-ML Approach for the Prediction of NASDAQ Composite Index by Nasir et al. (2025). The methods were Local Mean Decomposition, ARIMA, XGBoost, RF, ANN, and SVM. From the experimental results conducted for the proposed approach, the hybrid model consisting of LMD, ARIMA, SD, and XGBoost was found to be more accurate.

Iftikhar et al. (2025) conducted a novel approach towards developing a hybrid stock index forecasting model based on pre-processing, non-linear filtering techniques, neural network autoregressive models, and autoregressive conditional heteroscedasticity was developed by them. The non-stationarity and non-linearity issues were effectively handled by such a modeling process and the use of hybrid forecasting improved forecasting accuracy as compared to traditional approaches.

Khan et al. (2025) introduced the use of an innovative hybrid vector autoregressive approach to forecast high-dimensional macroeconomic problems using the SCAD estimation technique. The use of the proposed technique on quarterly US macroeconomic data showed superior multi-step forecast accuracy than conventional vector autoregressive baseline models. The comparison of the existing approaches is presented in Table 1.

Problem statement

Current stock market prediction techniques, such as both traditional ML and DL models, tend to be difficult to capture both temporal and inter-feature relationships, over-fit in high-volatility markets, and require a lot of manual feature engineering to perform effectively. The suggested framework of DASNT-GN-MBGO is developed to overcome these restrictions by incorporating CC-MMN to learn correlation-sensitive preprocessing, ACDT to learn causal temporal feature, and DASNT-GN to learn hybrid attention and similarity-directed relational learning. Moreover, MBGO is an adaptive network that optimizes network weights, which provide robust, scalable, and accurate predictions of stock market investments at highly dynamic and complex market conditions.

Table 1 Comparison of the existing approaches

Authors name	Methods	Advantage	Disadvantage
Alam et al. (2024)	LSTM-DNN	Captured complex temporal patterns across volatile stock markets	High computational cost and dependence on large datasets
Singh et al. (2025)	DNN-IFA	Improved sentiment classification accuracy through optimized learning	Optimization complexity and increased computational overhead
Kumar and Manikandan (2025)	SEMP-TA	Robust trend prediction using multiple ensemble learners	Model complexity and reduced interpretability of results
Rathee et al. (2023)	CNN-BiLSTM	Captured long-term and short-term price dependencies effectively	High computational cost and complex model training
Shaban et al. (2024)	SMP-DL	Effective temporal learning using combined recurrent networks	Sensitive to data quality and preprocessing choices
Zhan and Kim (2025)	Decision Tree (DT)	Captured hidden temporal patterns using delayed analysis	Limited adaptability to rapidly changing market dynamics
Sun et al. (2024)	CEEMDAN-LSTM-SA-LightGBM	Enhanced accuracy and fitting using a hybrid ensemble approach	High computational complexity and model tuning requirements
Biswas et al. (2025)	TCN-A	Captured short- and long-term dependencies effectively	A complex dual-output model increases computational requirements
Iftikhar et al. (2024)	HP filter + forecasting models	Improved prediction accuracy	Limited for complex volatility
Nasir et al. (2025)	LMD-ARIMA + ML models	Robust long-term forecasting	High computational cost
Iftikhar et al. (2025)	Hybrid nonlinear forecasting	Better nonlinear modeling	Complex framework
Khan et al. (2025)	Hybrid VAR model	Accurate macro forecasting	Less suitable for trading data

Proposed methodology

The suggested approach to dynamic investment prediction of stock markets is a multi-step process that is organized in a way that guarantees sound and reliable forecasting. The raw data is first processed by Preprocessing Using Correlation Coefficients with Min Max Normalization (CC-MMN), a process that helps to bring the feature values to a normalized range, but gives more weight to associations between features and the target variable. This is done so that irrelevant variability is reduced and that the model is fed with consistent, meaningful input. Adaptive Causal Decision Transformers (ACDT) are then applied to the preprocessed data to extract features. ACDT

extracts both temporal and causal correlations in historical stock prices to produce informative representations of features that capture the sequential dynamics and market patterns. The features extracted are fed into the hybrid prediction model, Dual-Attention Similarity-Navigated Transformer Graph Network (DASNT-GN), which jointly employs transformer-based attention and similarity-based graph aggregation to capture both sequential trends and inter-feature interactions. For the improvement of predictive performance and predictive strength, the Multiplayer Battle Game-Inspired Optimizer (MBGO) is used for the optimization of weights of DASNT-GN dynamically to avoid overfitting and improve convergence. This pipeline is an end-to-end model that involves preprocessing, feature extraction, hybrid prediction, and adaptive weight optimization of stock market investment forecasts to make accurate and reliable forecasts. The illustration of the methodology is shown in Fig. 1.

Input acquisition

The study utilizes the Stock Market Dataset containing NASDAQ-listed securities metadata, including exchange details, security classification, and trading status, serving as structured input for preprocessing, feature extraction, and market structure analysis. The pre-processing methodology was well-crafted to ensure consistency,

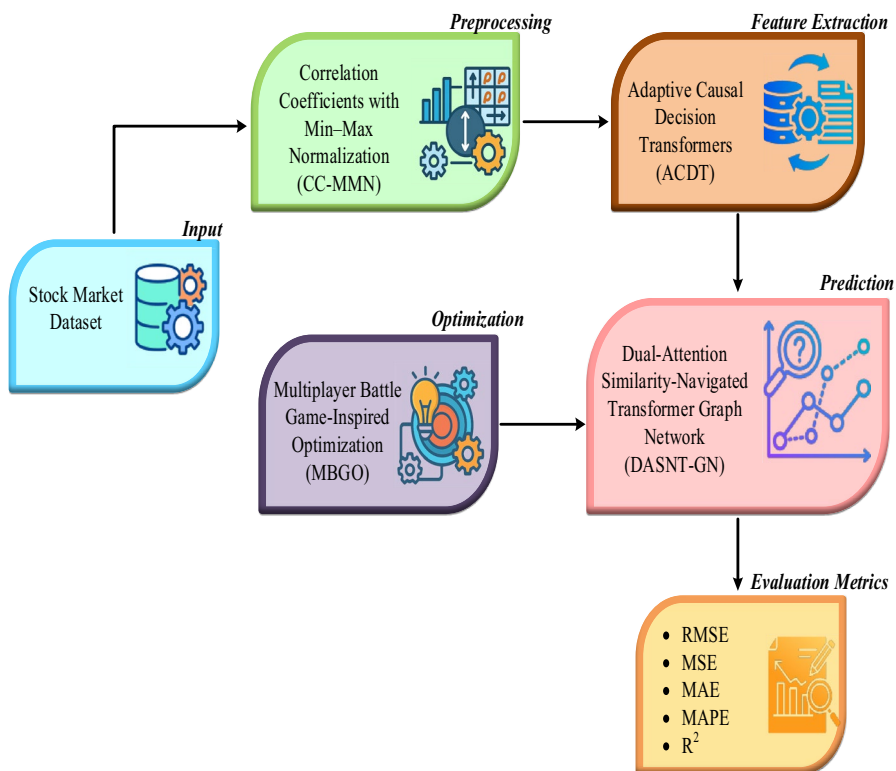


Fig.1 Illustration of the proposed approach

eliminate noise, and learn from temporal data. Firstly, duplicates and incomplete samples in the datasets under use were eliminated. The missing numerical data values were filled in using the linear interpolation and mean substitution approaches. Thereafter, any outliers that resulted due to abrupt changes in trade were identified and controlled using the Interquartile Range (IQR) approach. Then, the next step involved calculating the various technical indicators such as moving averages, daily returns, rolling volatility, momentum index, and relative strength index (RSI) to enhance temporal feature representation capabilities. The final step was the implementation of the CC-MMN preprocessing method.

Preprocessing using correlation coefficients with min-max normalization (CC-MMN)

The input of preprocessing is the dataset in which the raw stock market features are converted into a CC-MMN (Shantal et al. 2023) preprocessing method to ultimately achieve dynamic stock market investment prediction. The technique helps in data preparation through the analysis of the significance of features and scaling values to enhance data consistency and learning effectiveness. The CC-MMN algorithm is not just a normalization process, but a relevance-based preprocessing method where, besides scaling the features, it enhances the importance of the features by their dependency on the prediction goal. This results in consistent features and diminishes the impact of irrelevant market variables on DL tasks.

In the CC-MMN preprocessing method, Equation (1) of the correlation analysis is used to calculate the Pearson correlation coefficient for exploring the relationship between each feature and the target variable.

$$f = \frac{\sum_{q=1}^n (b_q - \bar{b}) (a_q - \bar{a})}{\sqrt{\sum_{q=1}^n (b_q - \bar{b})^2} \sqrt{\sum_{q=1}^n (a_q - \bar{a})^2}} \quad (1)$$

Equation (1) calculates the correlation coefficient f with considerations given by n samples, b_q and a_q identifies the characteristics and targets, and $\bar{b}$ and $\bar{a}$ being their mean. Equation (1) is used to determine the relationship between the investment goal and the characteristics of individual stock markets in the CC-MMN model.

The CC-MMN algorithm requires feature scaling such that all features have similar ranges based on Min-Max Normalization as provided by Equation (2),

$$b'_{q,m} = \frac{b_{q,m} - \text{Min}(b_q)}{\text{Max}(b_q) - \text{Min}(b_q)} (\text{New_max} - \text{New_min}) + \text{New_min} \quad (2)$$

As indicated by Equation (2), $b'_{q,m}$ is the normalized value, $b_{q,m}$ is the original value, $\text{Min}(b_q)$ and $\text{Max}(b_q)$ are referred to as the minimum and maximum of the variable, and New_min and New_max represent the new minimum and maximum value set to 0 and 1. The above step in CC-MMN removes unequal scaling in stock market variables.

Under the CC-MMN preprocessing method, the weights of the resultant feature value are obtained by using Equation (3), which takes a product of the normalized values and the weighting of the correlation.

$$v' = \left(\frac{D_{q,p} - mI_p}{mA_p - mI_p} (New_Max - New_Min) + New_Min \right) + L \left(\frac{D_{q,p} - mI_p}{mA_p - mI_p} (New_Max - New_Min) + New_Min \right) \cdot Corr(D_p, D_{T_arg et}) \quad (3)$$

In Equation (3), v' is a new weighted value, $D_{q,p}$ is an original feature value, mI_p and mA_p are the minimum and maximum of p^{th} feature, respectively, L is a weighting factor, and $Corr(D_p, D_{T_arg et})$ is a correlation coefficient calculated in Equation (1). This action of CC-MMN improves influential features coupled with normalized scaling. Lastly, the feature extraction input is the preprocessed data obtained by the CC-MMN method.

Feature extraction using adaptive causal decision transformers (ACDT)

The input of feature extraction is the preprocessed data in which high-level representations are learned through the ACDT (Kumawat and Mukhopadhyay 2024) framework. This stage of feature extraction targets addressing spatial-temporal dependencies and finding the causally relevant latent representations that predict future investment outcomes. ACDT differs from other conventional methods of feature extraction through transformer architecture that use sequential relationships between features in terms of causal temporal relations. Thus, the approach ensures detection of genuine trends in the market instead of temporary fluctuations in trading signals, which is important for financial forecasting problems.

The spatial feature representations are produced by the Spatial Transformer and represented as follows in Equation (4),

$$K_f^h = L_{Step}^h \left(K_f^{Selected, h-1} \right) \quad (4)$$

Equation (4) maps the selected input tokens $K_f^{Selected, h-1}$ from the previous layer to the current spatial layer output K_f^h , where L_{Step}^h denotes the spatial transformer function at layer h and time step f . This operation identifies localized spatial characteristics of the processed stock market information and removes irrelevant tokens using the adaptive crediting mechanism, thus enhancing the degree of feature importance and efficiency.

The aggregated spatial feature embedding is computed using Equation (5),

$$e_f^h = Fc \left([Concat(K_f^h)] \right) + g_f^{Temporal} \quad (5)$$

Based on Equation (5), e_f^h refers to the latent spatial feature vector, $Fc(\cdot)$ refers to fully connected transformation, $Concat(\cdot)$ refers to concatenation of spatial tokens,

and $g_f^{Temporal}$ refers to temporal positional embedding. The Equation takes into account both the spatial information and the time context to obtain a small latent representation that captures the current market structure and time-dependent behavior.

A representation of the temporal feature is generated by concatenating spatial and pure state representations as defined in Equation (6),

$$Q_{In}^h = \{e_1^h, v_1^{h-1}, e_2^h, v_2^{h-1}, \dots, e_F^h, v_F^{h-1}\} \quad (6)$$

In Equation (6), Q_{In}^h denotes the input sequence to the Temporal Causal Transformer, e_f^h are the spatial latent representations, v_1^{h-1} are the pure state representations from the previous layer, and F is the sequence length. This formulation allows the ACDT model to embrace long-term temporal dependencies and causal connections among stock market sequences. Lastly, the input of the prediction is the extracted features obtained after the feature extraction stage based on the ACDT.

Prediction using dual-attention similarity-navigated transformer graph network (DASNT-GN)

The Dual-Attention Similarity-Navigated Transformer Graph Network (DASNT-GN) model in dynamic stock market investment prediction uses the extracted features of historical prices, trends, and inter-stock relations as the input for prediction. The combination of DATN (Dual Attention Transformer Network) (Wu et al. 2023), which learns the evolving dynamics of the markets, and SNGNN (Similarity-Navigated Graph Neural Networks) (Zou et al. 2023) for learning the similarity-based relationships between stocks, using attention mechanisms to identify the features that matter, can learn the complicated dynamics of markets and make intelligent investment decisions. Figure 2 displays the architecture of DASNT-GN. DASNT-GN was designed to address the limitation of isolated temporal learning in existing stock prediction models. The framework jointly learns sequential market evolution through dual-attention mechanisms and adaptive inter-stock dependency structures through similarity-guided graph propagation, enabling simultaneous modeling of temporal and relational financial dynamics within a unified architecture.

The integration mechanism between DATN and SNGNN in the proposed DASNT-GN framework is implemented through a sequential feature interaction pipeline. In the beginning, DATN extracts temporal dependencies and attention-based feature representations from the past stock sequences, creating higher-level contextual embeddings. These embeddings are then transferred to the SNGNN module, where each stock instance is represented as a graph node and similarity-guided aggregation is performed to model inter-stock relational dependencies. The information flow occurs from temporal attention learning to graph-based relational refinement, enabling the framework to jointly capture sequential market dynamics and similarity-aware structural interactions for more robust investment prediction.

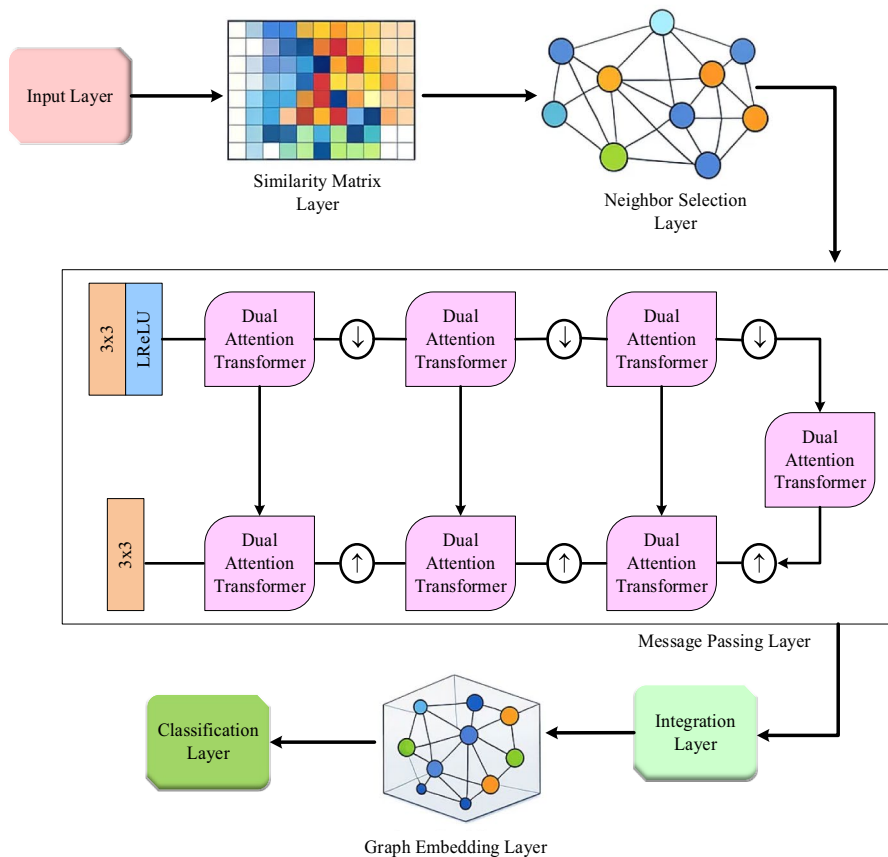


Fig. 2 Architecture of DASNT-GN

Dual attention transformer network (DATN)

The dynamic stock market investment prediction stage is carried out by adopting the Dual Attention Transformer Network (DATN), in which extracted features are converted through encoding, bottleneck processing, decoding, and final reconstruction to produce the predicted output.

In Equation (7), the first prediction feature representation is derived by projecting the concatenated input into the feature domain.

$$A_0 = g_{In} [I, K_{\uparrow}] \quad (7)$$

Equation (7) calculates the initial feature map A_0 , where $I \in R^{E \times W \times 1}$ is the primary input feature, $K \in R^{e \times w \times z}$ is the complementary low-resolution feature set, $K_{\uparrow}$ is its upsampled version, and $g_{In}(\cdot)$ is a convolutional projection function. It is a step that combines various market indicators into a single feature of prediction.

Equation (8) formulates the encoder prediction process.

$$A_a = S_a (DAT_a (A_a - 1)), \quad a = 1 - 3 \quad (8)$$

In Equation (8), A_a is the encoded feature map at level a , $DAT_a(\cdot)$ is the a^{th} Dual Attention Transformer module, and $S_a(\cdot)$ is the downsampling operation. The Equation is used to gradually derive hierarchical predictive patterns and dimensionality reduction of features to capture the dominant market trends.

The refinement of the bottleneck prediction is presented in Equation (9),

$$A_a = DAT_a (A_a - 1), \quad a = 4 \text{ and } 5 \quad (9)$$

Equation (9) gives the refinement of compressed feature representations using Dual Attention Transformer modules without changing the spatial resolution. Here, A_a denotes the bottleneck features that encode high-level dependencies and complex interactions among market indicators, which are critical for accurate prediction.

Projecting the decoded features back to the output domain generated the final prediction output as illustrated in Equation (10),

$$E = g_{Out} (A_8) + K_{\uparrow} \quad (10)$$

In Equation (10), E denotes the predicted output, $g_{Out}(\cdot)$ denotes the output projection function, A_8 is the obtained feature map from the last DAT module, and $K_{\uparrow}$ serves as the upsampled complementary input. This residual formulation improves the accuracy of prediction by using learned high-level representations along with the baseline input data.

Similarity-navigated graph neural networks (SNGNN)

The dynamic stock market investment prediction stage is carried out with Similarity-Navigated Graph Neural Networks (SNGNN), where stock entities are considered graph nodes, and the relationships are learned in an adaptive manner by aggregating similarity-directed features, forming predictive node representations.

The baseline graph convolution propagation of Equation (11) is the process by which the node representations are updated by aggregating adjacent features based on a symmetrically normalized adjacency matrix, where the graph has fixed connectivity and normalized node degrees.

$$E^{(k)} = \sigma \left(\tilde{V}^{-\frac{1}{2}} \tilde{P} \tilde{V}^{-\frac{1}{2}} E^{(k-1)} W^{(k-1)} \right) \quad (11)$$

Equation (11) computes the node representation $E^{(k)}$ at layer k , where $E^{(k-1)}$ denotes the feature matrix from the preceding layer, $W^{(k-1)}$ is the learned weight matrix, and $\sigma(\cdot)$ represents the nonlinear activation function, $\tilde{P} = P + I$ is the adjacency matrix containing self-loops, $\tilde{V}$ be the corresponding degree matrix, and $\tilde{V}^{-\frac{1}{2}} \tilde{P} \tilde{V}^{-\frac{1}{2}}$ is a symmetric normalization adjacency matrix that statically aggregates neighboring stock features based on normalized connection strengths.

The adaptive similarity-directed aggregation in Equation (12) repackages the propagation process with a dynamic node similarity matrix, which replaces the inherent graph connectivity with a dynamic node similarity matrix that enables the model to sustainably focus more on more useful neighbors and capture complex and heterogeneous relationships during prediction.

$$E^{(k)} = \sigma \left(X^{(k)} E^{(k-1)} W^{(k-1)} \right) \quad (12)$$

In Equation (12), $X^{(k)}$ represents the Node Similarity matrix at layer k , which encodes the similarity between stock nodes dynamically, instead of using a fixed normalized adjacency matrix. $E^{(k-1)}$ and $W^{(k-1)}$ are previous layer features and learnable weights, respectively. $\sigma(\cdot)$ applies nonlinearity. The similarity-navigated aggregation focuses on more pertinent stock relationships in prediction, allowing adaptive neighborhood choice and better treatment of heterogeneous interactions on the market.

DASNT-GN is effective in the dynamic stock market investment prediction because the temporal dynamics and similarity relationship modeling between stocks are robust. The hybrid prediction algorithm works by learning together attention-based sequential patterns and graph-based interdependencies so that investment prediction can be done accurately and consistently. Finally, MBGO is applied to optimize the weights in DASNT-GN in order to enhance the efficiency of convergence and prediction performance.

Optimized weight learning for dasnt-gn via multiplayer battle game-inspired optimization (MBGO)

The MBGO (Xu et al. 2024) is designed based on the general characteristics of the battle royale game, with movement and survival tactics alongside competitive dynamics, which ultimately decide the winner. The main components of safe zones, different player behaviors, and strategic movement and elimination based on the battle are abstracted to the optimization processes. MBGO achieves exploration-exploitation balance, population diversity, and adaptive decision making seen in multiplayer battle environments by modeling individuals as candidate solutions and simulating exploration and fighting stages. Figure 3 shows the step-by-step procedure of MBGO. MBGO is incorporated not simply as a metaheuristic optimizer, but as an adaptive exploration-exploitation mechanism capable of stabilizing optimization in highly nonlinear financial learning environments. Its population interaction and battle-inspired update behavior improve parameter diversity and reduce premature convergence, which is particularly beneficial for volatile stock market prediction tasks where local optima frequently occur.

Step 1: Initialization

The optimization process starts after the settings of the MBGO method are chosen. After creating the optimization environment, it is possible that DASNT-GN can optimally and iteratively control the weight parameter.

Step 2: Random generation

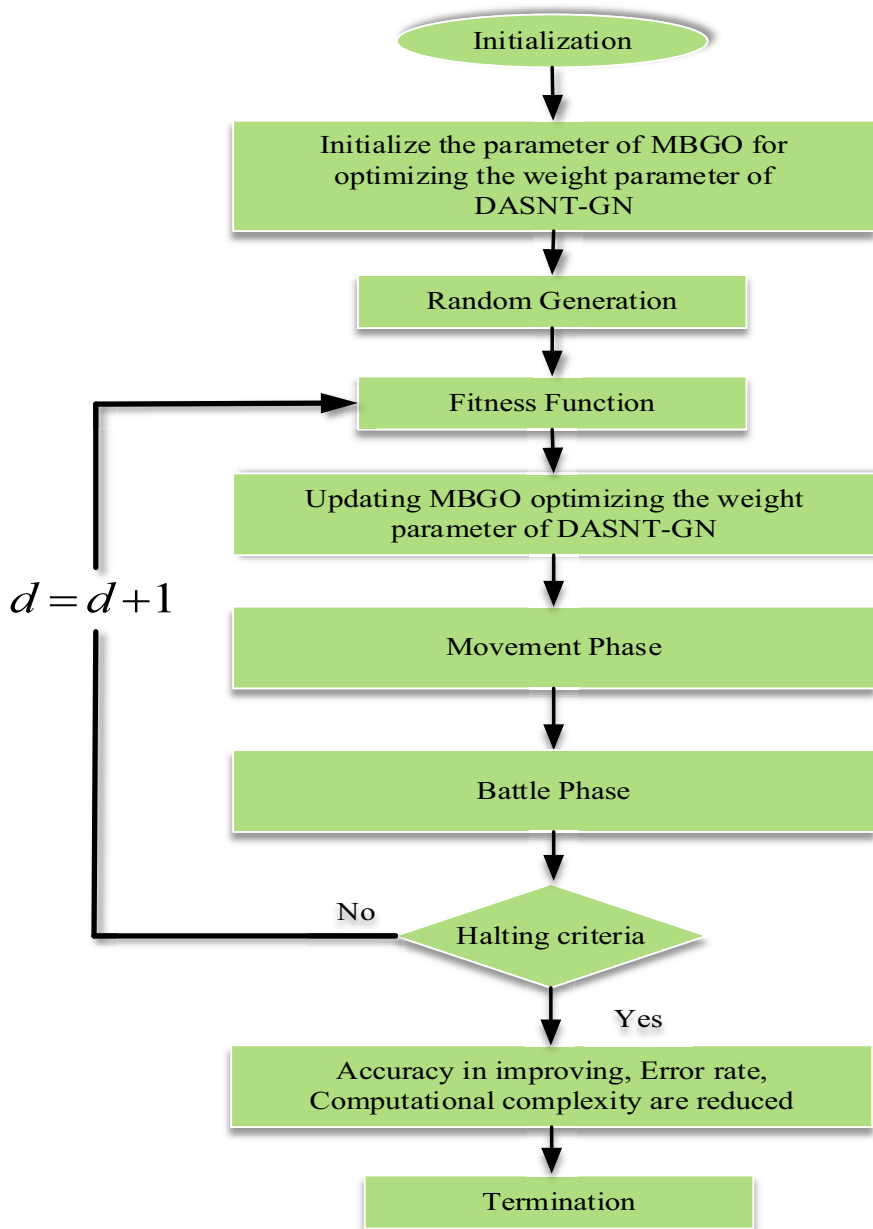


Fig. 3 MBGO step by step process

In the initial search, a random sample of viable options is formed. Convergence of solutions can be avoided by controlling variability at the random generating phase. A probable DASNT-GN weight parameter is incorporated in the response. MBGO optimizes the random selections by first optimizing them iteratively.

Step 3: Fitness function

The fitness function is the parameter that indicates the weight at the present moment to evaluate the performance of the DASNT-GN algorithm. The fitness function is defined by changing the value of the weight using Equation (13), thereby assessing the quality of the solution and motivating changes through performance feedback

$$\text{Fitness Function} = \text{Min } (W) \quad (13)$$

where W refers to the weight parameter of DASNT-GN.

Step 4: Movement phase

Exploitation is the task of the Movement Phase, which directs the individuals to the promising areas via the safe zone mechanism around the most effective solution at present.

$$a_{New} = a_p + a_{Best} \times \text{Sin } (2 \times \pi \times \text{Rand } (0, 1)) \quad (14)$$

The position of the individual a_{New} is updated according to equation (14), where a_p depicts the current individual, a_{Best} denotes the best individual in the population, and $\text{Rand } (0, 1)$ is a random number uniformly distributed, while represents the mathematical constant. This Equation takes advantage of local knowledge about the most optimal point by providing local oscillation movement that allows it to move towards possible optimal areas whilst preserving stochastic variety.

Step 5: Battle phase

The Battle Phase takes care of exploration by modeling the interactions of people, promoting various search modes, and discouraging premature convergence.

$$a_{New} = a_p + \text{Dir} \times \text{Cos } (2 \times \pi \times \text{Rand } (0, 1)) \quad (15)$$

In Equation (15), a_{New} is the newly produced individual, a_p is the current individual, Dir is the direction vector generated between the individual and an arbitrarily chosen opponent, while $\text{Rand } (0, 1)$ adds randomness. This Equation allows the movement of exploration, which is driven by the interaction of the opponents, allowing the global search and assisting the algorithm in overcoming the local optima.

Step 6: Termination

When optimization reaches the termination phase and meets the necessary termination requirements, it is considered completed. The MBGO approach effectively lowers the weight parameter of the DASNT-GN at this termination point. Convergence suffices, although further fine-tuning will not provide additional performance improvements. Based on model convergence, optimization occurs prior to the point where performance improvement becomes minimal or impractical.

The suggested algorithm of investment prediction in a dynamic stock market has a multi-stage flow. CC-MMN fines data by normalizing features and focusing on correlations. ACDT acquires both temporal and causal features, which are input into DASNT-GN, a hybrid of attention and graph-based learning. MBGO optimizes the adaptive network weights to enhance robustness and prevent overfitting. This

hybrid pipeline is useful in the description of sequential trends and inter-feature relationships, and provides accurate, reliable, and scalable predictions of share market investments in a dynamic and turbulent market environment. The innovation in the suggested framework is not in the individual application of its components, but in the coordinated integration of correlation-aware pre-processing, causal-temporal representation learning, hybrid attention-graph prediction, and adaptive optimization into a unified end-to-end investment forecasting pipeline specifically designed for dynamic and heterogeneous stock market environments.

Results and discussion

The Stock Market Dataset is used to assess the performance of the suggested DASNT-GN-MBGO framework. RMSE, MAE, MAPE, R^2 , and stability indices are used to measure performance to guarantee a stable and accurate prediction of the stock price. Computational issues such as training and prediction time are also examined, which proves the efficiency and applicability of the method to dynamic and volatile stock market environments and thus the applicability of the model in timely decision-making by investors and financial analysts. Table 2 shows the implementation details. The prediction task considered in this study is a single-step stock price forecasting problem, where the objective of the proposed DASNT-GN-MBGO framework is to predict the next trading day's closing price based on historical market observations. The model utilizes a sliding temporal window of previous trading sequences as input and generates a one-step-ahead continuous regression output corresponding to the future closing price. Therefore, the task is formulated as a numerical time-series regression problem rather than trend classification or multi-step return prediction. This setting was selected to ensure stable learning, reduced error accumulation, and fair comparison with existing benchmark forecasting models.

Dataset description

The Stock Market Dataset (available at: <https://www.kaggle.com/datasets/jacksonorow/stock-market-dataset>), which is essential as meta-data for analysis and building models related to such markets, is utilized for the purpose of testing and categorizing financial assets offered in the market and listed within the NASDAQ exchange. The elements of the dataset include the following: Nasdaq Traded, Symbol, Security Name, Listing Exchange, Market Category, ETF, Round Lot Size, Test Issue, Financial Status, CQS Symbol, NASDAQ Symbol, and NextShares, amounting to 8,049 records altogether. Each entry in the dataset pertains to a separate financial activity with its own set of characteristics, such as its type (stock, ETF, and so on), allowing or forbidding trade, exchange identity, and financial status. Exchange listings in many forms, such as NASDAQ (Q), NYSE (N), or AMEX (P), in addition to information on the types of securities being listed, for instance whether they are Exchange Traded Funds, or they belong to Next Shares, which is an innovative class of exchange traded securities, form this extensive dataset. For the development of the proposed DASNT-GN-MBGO model, this dataset will be divided into two datasets:

Table 2 Implementation specifications

Component	Hyperparameter	Setting / value
CC-MMN preprocessing	Normalization range	[0, 1]
	Correlation measure	Pearson correlation
	Feature weight factor ((α))	0.75
	Missing value handling	Mean imputation
	Outlier handling	Interquartile range (IQR) clipping
ACDT feature extraction	Number of transformer layers	6
	Hidden dimension size	256
	Attention heads	8
	Feed forward dimension	512
	Dropout rate	0.2
	Sequence length	60
	Positional encoding	Learnable positional embedding
	Activation function	GELU
	Optimizer	AdamW
	Learning rate	0.0001
	Batch size	64
	Training epochs	150
DATN module	Encoder layers	4
	Decoder layers	4
	Dual attention blocks	8
	Attention head dimension	64
	Bottleneck channels	256
	Convolution kernel Size	3×3
	Downsampling strategy	Strided convolution
	Upsampling strategy	Bilinear interpolation
SNGNN module	Graph layers	3
	Node embedding dimension	128
	Similarity metric	Cosine similarity
	Graph aggregation	Attention-weighted aggregation
	Adjacency update frequency	Every epoch
	Activation function	ReLU
DASNT-GN hybrid prediction	Fusion Strategy	Sequential attention-graph fusion
	Prediction Output Layer	Fully connected dense layer
	Loss function	Mean squared error (MSE)
	Regularization	L2 regularization (10^{-5})
MBGO optimization	Population size	50
	Maximum iterations	100
	Safe zone coefficient	0.6
	Exploration coefficient	0.4
	Random search probability	0.3
	Elite retention rate	10%
	Termination criterion	Fitness convergence
Training environment	Framework	PyTorch
	Programming language	Python 3.10
	GPU	NVIDIA RTX 2060
	Operating system	Windows 11
	Train/test split	80:20
	Validation strategy	5-Fold cross validation

the first will be used for training and includes 80% of the entries of the dataset, while the other one will be used for testing and includes 20% of the entries of the dataset.

Evaluation metrics

To evaluate the proposed framework, DASNT-GN-MBGO, it is assessed using MAPE, MAE, RMSE, MSE, and R^2 to determine the accuracy of the prediction, the mean errors, and the accuracy of the actual and predicted stock prices. All these measures will give an in-depth examination of the reliability, stability, and overall performance of the model to guarantee the accuracy, reliability, and applicability of predictions of stock market movements in dynamic settings to make sound investment decisions in volatile financial markets.

The equation and performance metrics are presented in Table 3. Where $\hat{b}_i$ is the predicted value for the i – th observation, b_i is the actual value, $\bar{b}$ is the average of accurate values, and x is the total number of observations. To ensure reliable and unbiased evaluation of the proposed DASNT-GN-MBGO framework, the datasets were divided using a chronological time-series split strategy rather than random sampling to preserve temporal dependencies and avoid future data leakage. In particular, 80% of the sequential historical observations were assigned to training while the other 20% were reserved for testing. From the training set, 10% of the samples were further designated for validation for use during hyperparameter tuning and convergence checks.

Apart from this fixed train test evaluation, a 5 fold rolling cross validation was also performed for evaluating the robustness and generalization ability of the proposed framework in varying time-based market partitions. In every fold, the model is trained on past windows and validated on future windows, creating a realistic setting for financial predictions. The rolling window approach helps in the examination of the stability of the model at various levels of volatility and market conditions.

Table 3 Metrics of evaluation and equation

Metrics	Formula
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{x} \sum_{i=1}^x \left \frac{\hat{b}_i - b_i}{b_i} \right \times 100\%$
Mean absolute error (MAE)	$MAE = \frac{1}{x} \sum_{i=1}^x \hat{b}_i - b_i $
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{1}{x} \sum_{i=1}^x (\hat{b}_i - b_i)^2}$
Mean squared error (MSE)	$MSE = \frac{1}{x} \sum_{i=1}^x (\hat{b}_i - b_i)^2$
R-squared (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^x (\hat{b}_i - b_i)^2}{\sum_{i=1}^x (\bar{b} - b_i)^2}$

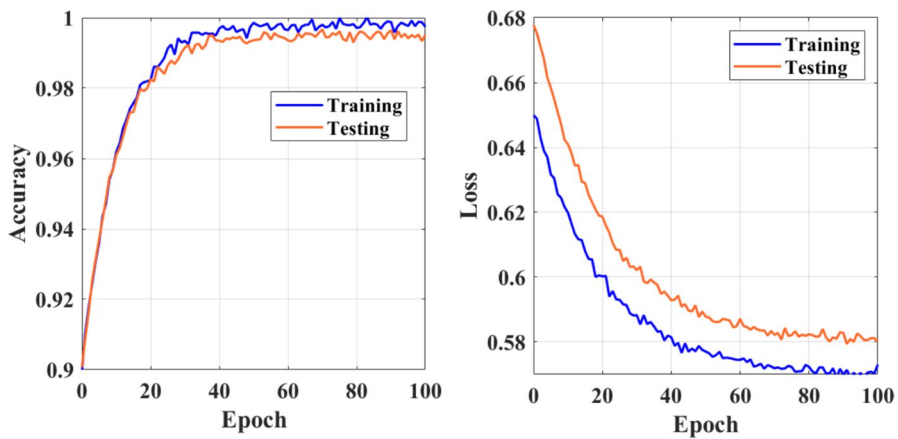


Fig. 4 Training and testing performance curves

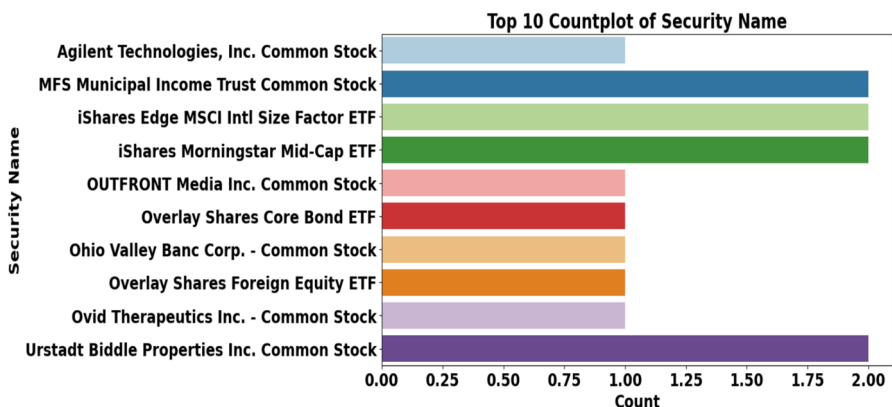


Fig. 5 Count plot of top 10 security names

Performance analysis

The performance analysis of the DASNT-GN-MBGO is provided below:

Figure 4 displays the performance of the suggested model in terms of accuracy and loss for higher numbers of training epochs. The left plot shows that the training and testing accuracy are continually increasing and stabilizing to around 1.0, which is an indicator of effective learning and high generalization with a small performance gap. The right curve demonstrates the learning of the training and test losses, which drop with increasing number of epochs, indicating consistency in convergence and minimal prediction error. The strong relationship between the curves implies that there is no overfitting in MBGO-optimized DASNT-GN, without achieving accurate prediction.

In Fig 5 below, we have a horizontal countplot that illustrates the top ten most popular security names in the data set. Here, the stock or ETF is represented using a

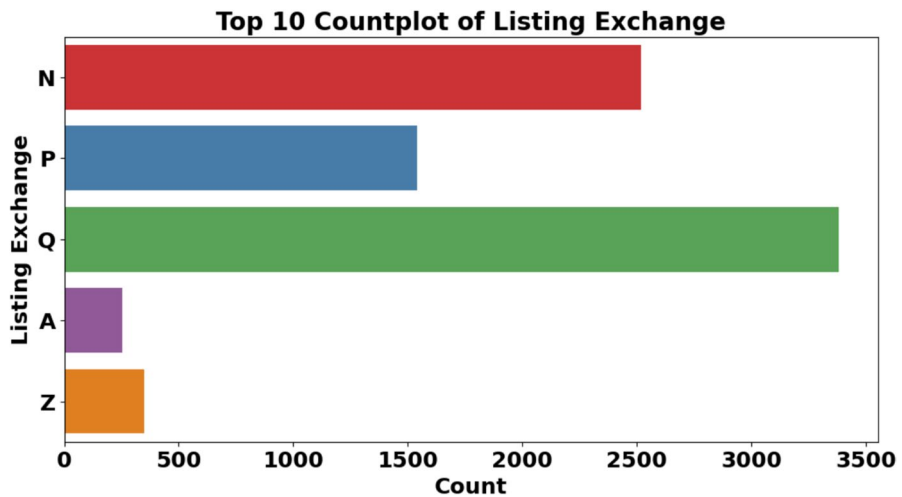


Fig. 6 Top 10 countplot of listing exchange

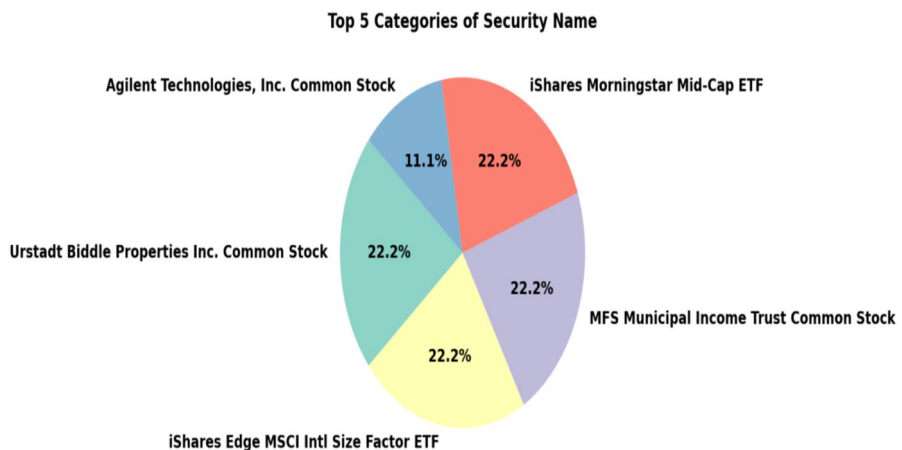


Fig. 7 Top 5 categories of security name

bar where the length of the bar is determined by the frequency of the appearance. The plot focuses on the leading securities Agilent Technologies Inc. and iShares ETFs because these securities are better represented in the data. Distribution analysis can be used to identify the securities which have a great influence on model learning, which would allow the analysis of features and provide balanced insights on the quality of investment prediction.

Figure 6 shows the distribution of securities in the top ten listing exchanges in the dataset. The horizontal bar chart is used to indicate the number of times securities are listed on each exchange, showing the dominance of the larger exchanges and the smaller ones listing securities less often. This asymmetry indicates the concentration and liquidity variation in markets among markets. This distribution is notable

in dynamic investment prediction because characteristics that are exchange-specific impact the trading volume, volatility, and price discovery, which are subsequently forecasted by the CC-MMN preprocessing and the DASNT-GN prediction model.

Figure 7 is a pie chart of the top five security categories in the dataset. Every slice is the relative contribution of a specific security type, including common stocks and exchange-traded funds. The relatively equal but different shares reveal diversification of the dataset. Such a categorical distribution aids in strong learning as it guarantees exposure to various investment instruments. This diversity aids the ACDT module in recording different time and causal patterns of other types of assets, enhancing the validity of the ultimate investment forecasts.

Figure 8 shows a Kernel Density Estimation (KDE) plot of round lot sizes. The density curve demonstrates a high concentration with a particular lot size, which implies that there is a standardization of trading units of securities. Such consistency minimizes the noise and variability of the features of transactions. The preprocessing CC-MMN is able to more successfully normalize the scale effects by discovering dominant lot-size behavior. Therefore, the downstream ACDT and DASNT-GN models concentrate on significant price changes instead of the trading unit change artifacts.

Figure 9 is divided into three subfigures: (a) Top 10 symbols listed on NYSE, (b) Top 10 symbols on CBOE, and (c) Top 10 symbols on NASDAQ. The frequency of symbols in each exchange in each subfigure depicts the differences in listing patterns. Comparison indicates that the exchange has specific concentrations of symbols, which is indicative of the diversity of market structure. The addition of these differences enables the prediction pipeline to learn about inter-market relationships and symbol-level behavior that enhances cross-exchange generalization of predictions.

Figure 10 is a comparison between actual stock closing values and the predicted values and future forecasts. The exact prices reflect historical patterns well in the curve predicted by the model, showing good learning of the time dependence. The next part of the predictions involves future predictions, and this part goes beyond known data; hence, the model has the ability to forecast. This result indicates that

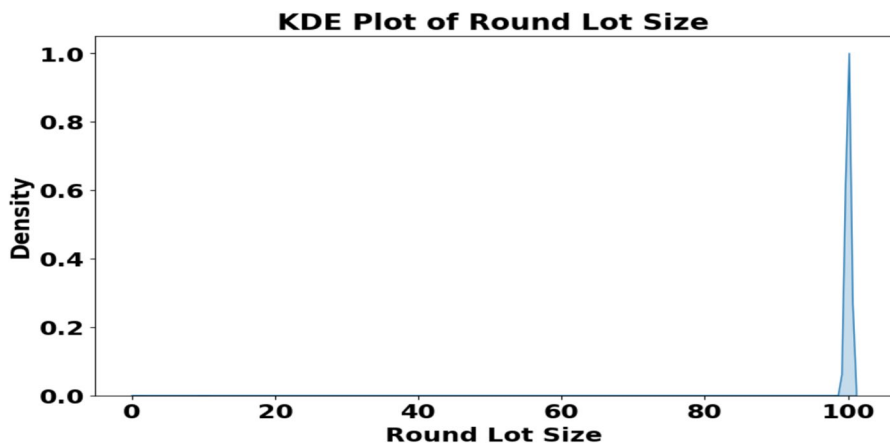


Fig. 8 KDE plot of round lot size

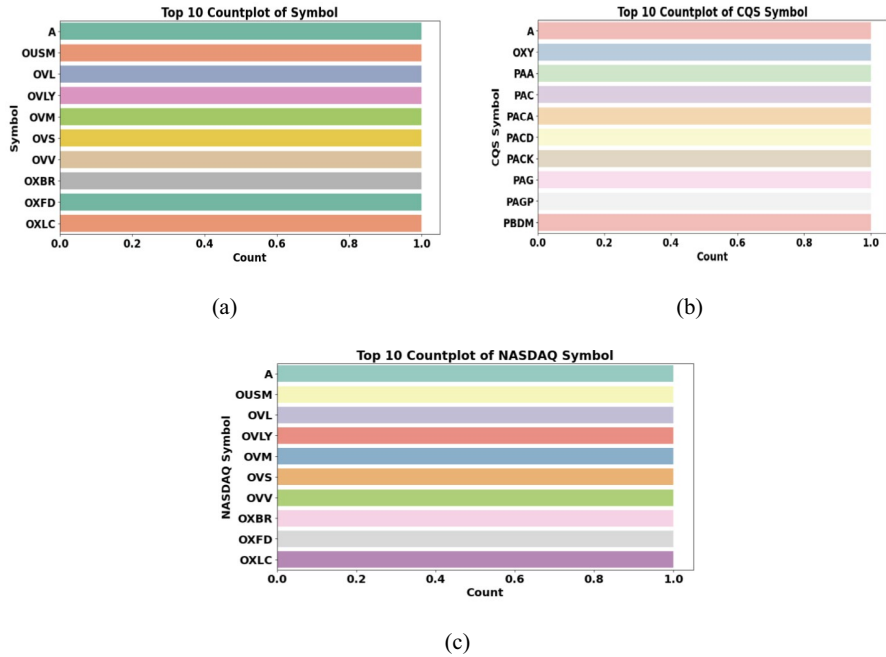


Fig. 9 Top 10 countplot of symbols – (a) NYSE, (b) CBOE, (c) NASDAQ

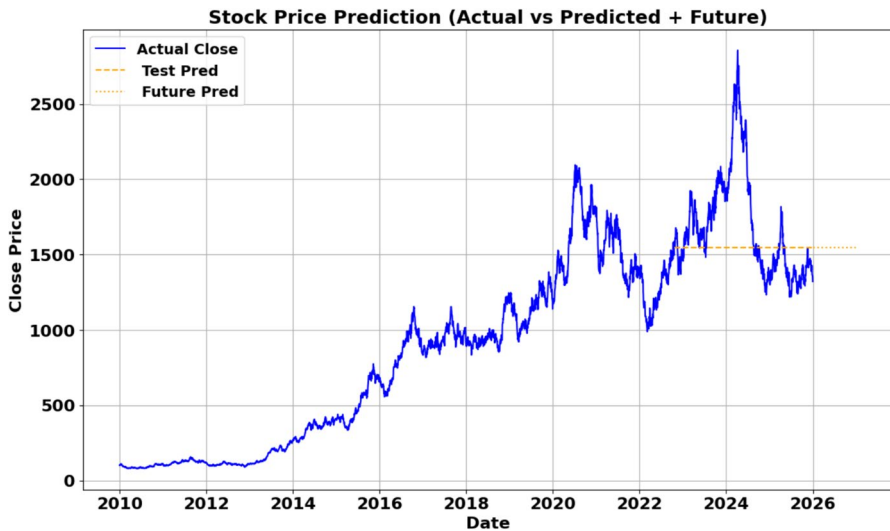


Fig. 10 Stock price prediction (Actual vs Predicted + Future)



Fig. 11 Stock close price over time

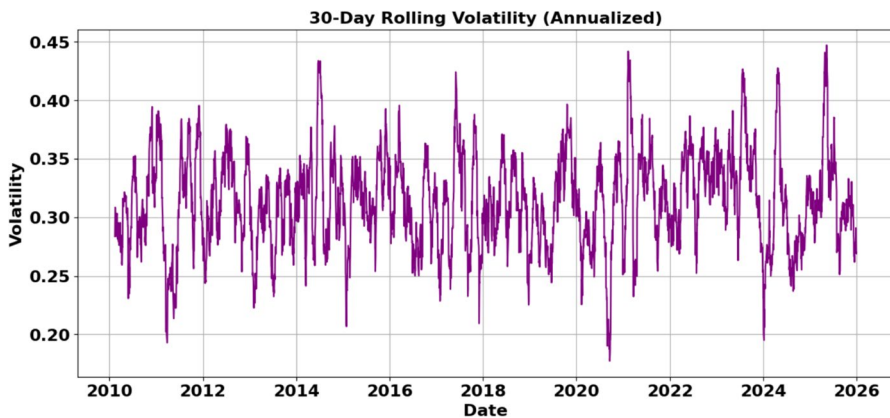


Fig. 12 30-Day rolling volatility (Annualized)

ACDT and DASNT-GN extracted essential features and modeled the sequence correctly, and the result is further optimized by MBGO. The correspondence between curves confirms that the model can be used in dynamic investment decision support.

Figure 11 demonstrates a temporal trend of the stock closing prices. The line plot encodes the long-term growth, the steady variations, and the volatile times. This kind of time behavior offers a vital context for interpreting market cycles and regime shifts. CC-MMN preprocessing and causal feature extraction are based on this raw time series. Through these trends, the proposed end-to-end pipeline is able to capture sequential dependencies and make trustworthy future price forecasts.

Figure 12 shows the rolling volatility of stock prices over 30 days, annualized to show the behavior of risks over a long period. The plot indicates that volatility fluctuates significantly over time, with peaks around 0.40-0.45 and troughs around 0.20-0.25.

tuates in the timeframe, reflecting the moments of stability and the increased uncertainty in the market. Spike positions are used to indicate turbulent market periods, and flatter periods are used to indicate low risk. This volatility measure is essential in predicting the investment dynamically since it represents short-run risk dynamics. Such volatility signals are normalized through the use of CC-MMN preprocessing and are then used by ACDT and DASNT-GN to simulate uncertainty-conscious and robust forecasting behavior.

Figure 13 shows the frequency distribution of the daily stock returns, which is actually a histogram. The bell-shaped curve about the center implies that the most daily returns are small in nature, while the tail is skewed towards extreme returns or gains. This distribution entails unpredictability and risk in the market. Knowledge of the return behavior assists in determining skewness and the volatility trends. Following the normalization of CC-MMN, the statistical properties are efficiently represented as features and allow ACDT to model causal dynamics of returns and enhance the predictive quality of the DASNT-GN forecasting model.

Figure 14 compares the historical actual closing prices and the projected future predictions. The blue line is a true market performance indicator, while the red line indicates the forecast for the future from the model. It can be said that the model has the capacity to learn long-term dependencies from its continuity within the forecast horizon. The outcome validates the effectiveness of ACDT-based feature abduction and attention-focused prediction of DASNT-GN. MBGO optimization also optimizes model parameters so that the convergence process remains steady and the future price patterns are realistic enough to be applied in dynamic investment decision-making.

Figure 15 is a depiction of the closing price of the stock and its 30-day moving average. The moving average smoothens out short-term fluctuations and highlights long-term trends and changes in momentum. The presence of price and moving average crossovers implies trend reversal or continuation. The usefulness of such trend indicators is to minimize noise and emphasize sequential trends. These smoothed sig-

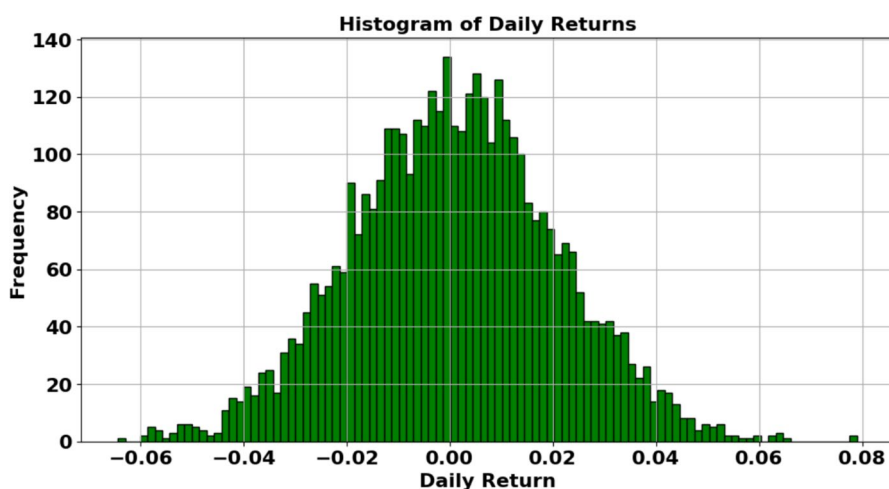


Fig. 13 Histogram of daily returns

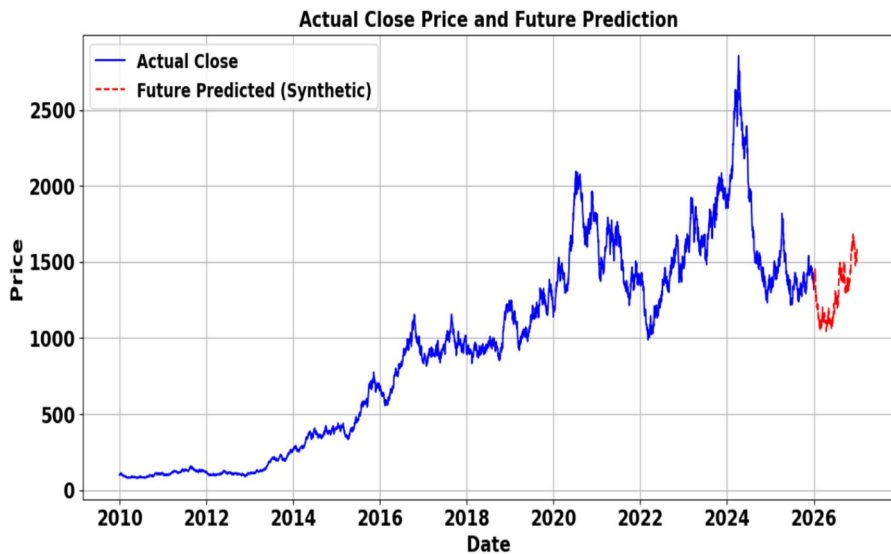


Fig. 14 Actual close price and future prediction



Fig. 15 Closing price and 30-day moving average

nals, when added to CC-MMN preprocessing and ACDT feature extraction, improve the capacity of DASNT-GN in modeling temporal dependence and producing correct and trend-aware investment predictions.

Figure 16 presents the fitness value versus the iterations in the course of MBGO optimization. The curve has a more rapid decrease in fitness in the initial phase and a slower convergence following the initial stage, and this indicates the positive convergence to the optimal solution. The given behavior proves that MBGO is capable of optimally tuning DASNT-GN parameters without overfitting. Constant convergence provides better generalization and prediction. With the combination of this optimizer,

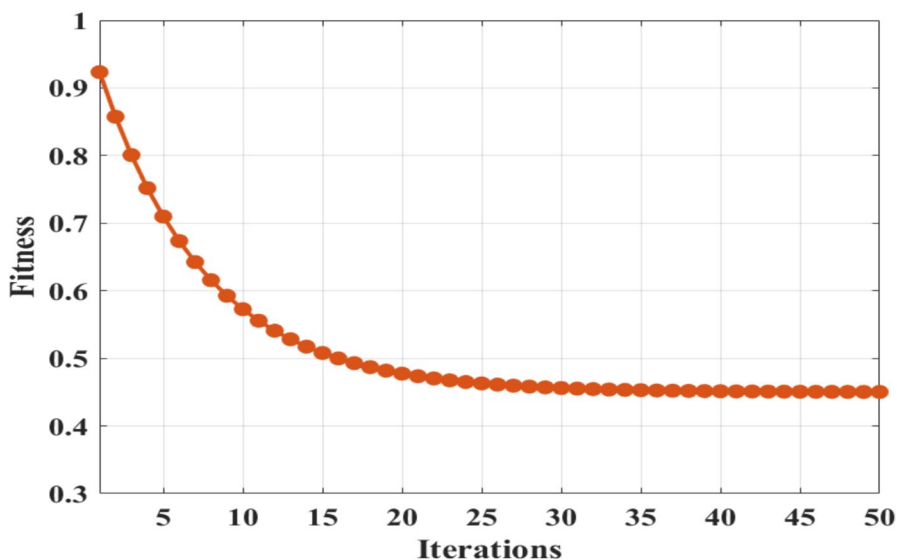


Fig. 16 Fitness vs iterations (MBGO Convergence Curve)

there is a greater robustness of the entire forecasting pipeline, increased learning, and sound performance of the dynamic stock market investment prediction task.

Comparative analysis

The proposed DASNT-GN-MBGO is tested on the Stock Market Dataset and when compared to the current models such as LSTM-DNN (Alam et al. 2024), DNN-IFA (Singh et al. 2025), SEMP-TA (Kumar and Manikandan 2025), CNN-BiLSTM (Rathee et al. 2023), SMP-DL (Shaban et al. 2024), DT (Zhan and Kim 2025), and TCN-A (Biswas et al. 2025). The analysis relies on RMSE, R^2 , MAE, MAPE, and uncertainty analysis to quantify the accuracy and strength of prediction and generalization. The findings prove that the model is reliable and effective in forecasting dynamic stock prices throughout market dynamics. To ensure a fair and unbiased comparative evaluation, all benchmark models were re-implemented and re-trained using the same Stock Market Dataset, identical train–test split ratio (80:20), and the same preprocessing pipeline based on CC-MMN normalization. Furthermore, all experiments were executed under a consistent computational environment using Python 3.10, PyTorch framework, and NVIDIA RTX 2060 GPU hardware. Hyperparameter tuning for competing methods was performed within their recommended ranges to avoid performance bias and to guarantee equitable comparison with the proposed DASNT-GN-MBGO framework.

From Table 4, it can be seen that various stock market prediction models have been evaluated using the metrics of MAPE percentage, RMSE, MSE, R^2 , and MAE. The conventional models like LSTM-DNN and DT have higher error values with low R^2 , which proves their poor predictive capability. Hybrid and DL-based models like CNN-BiLSTM, SMP-DL, and TCN-A have shown decreasing errors along with

Table 4 Comparison of stock market predictive model performance

Methods	MAPE (%)	RMSE	MSE	R ² (%)	MAE
LSTM-DNN (Alam et al. 2024)	32.50 ± 0.84	0.740 ± 0.021	0.550 ± 0.018	91.20 ± 0.73	0.690 ± 0.019
DNN-IFA (Singh et al. 2025)	28.90 ± 0.76	0.680 ± 0.018	0.460 ± 0.015	92.35 ± 0.65	0.630 ± 0.017
SEMP-TA (Kumar and Manikandan 2025)	26.40 ± 0.69	0.620 ± 0.016	0.380 ± 0.013	93.80 ± 0.58	0.580 ± 0.015
CNN-BiLSTM (Rathee et al. 2023)	24.30 ± 0.63	0.570 ± 0.015	0.320 ± 0.011	95.10 ± 0.52	0.520 ± 0.013
SMP-DL (Shaban et al. 2024)	22.10 ± 0.58	0.520 ± 0.014	0.270 ± 0.010	96.05 ± 0.49	0.480 ± 0.012
DT (Zhan and Kim 2025)	34.20 ± 0.91	0.810 ± 0.024	0.660 ± 0.020	89.40 ± 0.81	0.750 ± 0.022
TCN-A (Biswas et al. 2025)	18.90 ± 0.44	0.440 ± 0.012	0.190 ± 0.008	97.20 ± 0.45	0.390 ± 0.010
DASNT-GN-MBGO (Proposed)	9.40 ± 0.31	0.310 ± 0.012	0.120 ± 0.006	98.85 ± 0.42	0.240 ± 0.009

Table 5 Comparison of computational time between prediction models

Methods	Computational time (s)
LSTM-DNN (Alam et al. 2024)	1.20
DNN-IFA (Singh et al. 2025)	1.05
SEMP-TA (Kumar and Manikandan 2025)	0.95
CNN-BiLSTM (Rathee et al. 2023)	1.50
SMP-DL (Shaban et al. 2024)	1.30
DT (Zhan and Kim 2025)	0.75
TCN-A (Biswas et al. 2025)	0.65
DASNT-GN-MBGO (Proposed)	0.02

increasing R^2 . The proposed DASNT-GN-MBGO has the lowest MAPE (9.40%), RMSE (0.310), and MAE (0.240), and the highest R^2 (98.85%), which proves to have the best forecasting accuracy, robustness, and reliability to predict dynamic investment. To analyze statistical consistency, all experiments were repeated five times using different initialization seeds, and the average performance along with standard deviation values was computed. This suggested scheme was observed to have minimum variance when performed several times. The standard deviations for the RMSE, MAE, MAPE, and R^2 criteria were found to be ± 0.012 , ± 0.009 , $\pm 0.31\%$, and $\pm 0.42\%$ respectively, implying that there is high reliability and reproducibility in dynamic stock market conditions.

Table 5 reveals the processing time for several stock market prediction models. For example, the processing times of the convolutional processes in addition to other complex stages performed by the traditional and hybrid models including LSTM-DNN, DNN-IFA, CNN-BiLSTM, and SMP-DL vary from 0.95s to 1.50s. Some other basic models, such as DT and TCN-A, are also faster (0.65 - 0.75 seconds). The proposed model DASNT-GN-MBGO takes only 0.02 seconds of computation time, which makes it efficient and appropriate for use in real-time stock market prediction in addition to predictability and consistency.

Ablation test

The ablation process evaluates systematically the influence of each module by removing one from the proposed system. All reduced configurations indicate that performance deteriorates because of the absence of CC–MMN preprocessing, ACDT-based feature extraction, DATN hybrid prediction with SNGNN, and MBGO optimization. The complete DASNT-GN-MBGO model proves to be much more accurate and stable, proving the interdependence of all the elements.

Table 6 shows ablation of the proposed DASNT-GN-MBGO model in the Stock Market Dataset. In each of the configurations, a significant component is removed to examine its specific contribution. RMSE, R^2 (%), and MAPE (%) are used to evaluate the performance. Findings indicate that there is a significant degradation in the absence of preprocessing, feature extraction, hybrid prediction, or optimization modules. The entire DASNT-GN-MBGO setup has the minimal error and maximum explanatory power, and it validates the application of integrating all components to the prediction of dynamic stock market investments.

Statistical analysis

In statistical analysis, the strength and consistency of the proposed DASNT-GN-MBGO model are tested. The paired t-test is used to evaluate the difference in mean performance in the case of normality, and the Wilcoxon signed-rank test is used as a parametric alternative. The constant low p-values ensure that the predictive advantages realized by the suggested approach do not occur arbitrarily and are attributed to changes in market data.

Table 7 provides the statistical comparison between the proposed DASNT-GN-MBGO model and current stock market forecasting techniques using Paired T-Test and Wilcoxon Signed Rank Test. These statistical analyses help identify if the performance improvements observed have a significant statistical basis or occurred merely by chance. Rows contain the p-values for comparing the prediction errors of the proposed model with those of a benchmark one. All p-values presented are lower than the traditional threshold value, which indicates the robustness of the superiority of the suggested algorithm to different learning models.

Table 6 Ablation study of the proposed DASNT-GN-MBGO framework

Configuration	RMSE	R^2 (%)	MAPE (%)
Without CC-MMN	0.465	95.10	14.85
Without ACDT	0.510	94.20	16.40
Without DATN	0.445	95.85	13.90
Without SNGNN	0.395	97.10	11.80
Without MBGO	0.350	98.05	10.65
Full DASNT-GN-MBGO Model	0.310	98.85	9.40

Table 7 Statistical significance analysis of DASNT-GN-MBGO compared with existing prediction models

Compared method	Paired t-test (p-value)	Wilcoxon signed-rank test (p-value)
LSTM-DNN (Alam et al. 2024)	0.0023	0.0029
DNN-IFA (Singh et al. 2025)	0.0036	0.0041
SEMP-TA (Kumar and Manikandan 2025)	0.0054	0.0060
CNN-BiLSTM (Rathee et al. 2023)	0.0018	0.0022
SMP-DL (Shaban et al. 2024)	0.0069	0.0076
DT (Zhan and Kim 2025)	0.0124	0.0138
TCN-A (Biswas et al. 2025)	0.0042	0.0049

Table 8 Additional dataset description for cross-dataset validation

Dataset	Number of samples	Features	Time period	Market type	Prediction target
S&P 500 constituents dataset	52,430	Open, High, Low, Close, Volume, Adjusted close	2015–2024	Large-cap US equity market	Next-day closing price
NASDAQ composite index dataset	38,215	Open, High, Low, Close, Volume, Technical indicators	2016–2024	Technology-oriented market index	Future index value
Stock market dataset	8,049	Exchange metadata, Security information, Trading status	2020–2024	Mixed NASDAQ securities	Investment prediction
NIFTY 50 OHLC DATA	2,540	5 key features per file, including Timestamp (Date/Time), Open, High, Low, and Close.	2015-2025	Equity index / Stock market	Future close prices, Market volatility, and Trend direction

Cross-dataset generalization analysis

Further tests to evaluate the efficacy and applicability of the designed DASNT-GN-MBGO approach have been performed on two more financial time series datasets. This has been done using the S&P 500 constituent stocks dataset, which includes NIFTY 50 OHLC DATA and the NASDAQ Composite Index dataset. In both of these datasets, there are various market scenarios characterized by diversified markets, varying degrees of market volatility, and different trading behaviors. Similar to the primary Stock Market Dataset, all these other datasets were preprocessed and optimized using the same settings as those applied in the initial Stock Market Dataset test. The characteristics of these datasets are highlighted in Table 8 below.

The predictive performance of DASNT-GN-MBGO on the additional datasets is summarized in Table 9.

As seen from Table 9, the suggested model DASNT-GN-MBGO demonstrates consistent high performance across different financial datasets having distinct features in terms of market structures and volatility. Despite minor deterioration in predictions when using datasets characterized by high volatility at the index level, the model preserves low prediction error and high R2 coefficients above 97%, which proves good

Table 9 Cross-dataset performance analysis of DASNT-GN-MBGO

Dataset	RMSE	MSE	MAE	MAPE (%)	R ² (%)
Stock market dataset	0.310	0.120	0.240	9.40	98.85
S&P 500 constituents dataset	0.335	0.142	0.268	10.15	98.10
NASDAQ composite index dataset	0.348	0.156	0.281	10.72	97.86
NIFTY 50 OHLC DATA	0.362	0.168	0.295	11.08	97.54

generalization ability. Overall, the experiments conducted have proved the possibility of implementing stable and scalable investment forecasting through CC-MMN preprocessing, temporal-causal features extraction with the ACDT approach, hybrid DATN-SNGNN prediction, and MBGO optimization.

Discussion

The proposed framework has been shown to exhibit a high level of predictive accuracy in the dynamic stock market investment analysis, and it has been shown to outperform current methods in various evaluation criteria. The results indicate the predictability, reduced deviation of predictions, and high similarity between actual and predicted market direction. The framework has the potential of making more robust and informed investments in stock market data in dynamic market settings since the complex temporal interactions and dependencies have been well modeled. These advantages are the outcomes of the synthesizing mixture of numerous methodological components. The quality of the data is improved through preprocessing using CC-MMN, which reduces scale bias and the extraneous effect of features. ACDT Feature Extraction is used to identify the meaningful temporal-causal behaviors of great importance to financial forecasts. DASNT-GN prediction simultaneously learns the temporal attention and similarity-driven relational structures, which improves generalization. Lastly, MBGO is also efficient in optimizing network weights, preventing local optima, and enhancing robustness, which leads to a scalable and applicable stock market investment prediction model.

Limitation analysis under high-volatility market conditions

Although the proposed DASNT-GN-MBGO framework demonstrates strong predictive accuracy under normal and moderately volatile market conditions, its performance is comparatively sensitive during periods of abrupt market regime shifts and extreme volatility. In particular, under the condition of sudden price changes triggered by macroeconomic announcements, geopolitical news, or even unexpected financial disturbances, the prediction error slightly rises because of the quick divergence from previously established temporal or relational patterns. Experimental observations from highly volatile intervals showed temporary increases in RMSE and MAPE values, indicating that abrupt structural market changes reduce the stability of sequential dependency learning within DATN and similarity aggregation within SNGNN.

Furthermore, the MBGO optimization mechanism improves convergence and robustness under stable learning conditions; however, extremely turbulent periods may still introduce instability in adaptive weight updating because historical causal

relationships become less reliable. Regardless of this drawback, the model demonstrates fairly robust generalization capability compared to the baseline models due to the incorporation of causal feature extraction and hybrid attention-graph learning. The future research direction would be focused on using regime-switching learning methods, adaptive volatility models, and macroeconomic indicators in real-time situations to boost robustness during sudden market shifts and risky financial times.

Conclusion

The research provided a holistic approach to dynamic investment prediction in the stock market through the synthesis of preprocessing, feature extraction, prediction, and optimization in a single learning architecture. The proposed approach has the potential of handling market volatility, nonlinearity, and complicated interdependencies within financial data. The framework enhances the consistency of the data and reduces feature dominance through preprocessing using CC-MMN. ACDT is able to extract causally and temporally relevant representations, and the DASNT-GN is able to generate both sequential dynamics and similarity-based relationships between market indicators. Also, MBGO optimizes the robustness of learning through parameter tuning of the network and prevents non-optimal weight configurations. The main benefits of the suggested approach are accurate prediction behavior, high generalization across market conditions, good ability to model temporal-relational patterns, and high resilience to noisy financial signals. Nevertheless, some challenges still exist, such as reliance on historical market performance, susceptibility to sudden changes in regimes, and poor interpretability of the deep representation in attention, which may affect transparency in real-life investment decisions. Future work shall consider explainable predictive mechanisms, macroeconomic predictor variables, and adaptive learning controls for improving responses to market shifts and aiding investment decisions in real time.

Authors contributions P. Chandra Sekhar Reddy, Niti Saxena -Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Validation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Supervision, Project administration. Praveen Kumar Gandra, J. A. Jevin -Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization.

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Data availability Data sharing applicable to this article. URL: <https://www.kaggle.com/datasets/jacksonc row/stock-market-dataset>

Declarations

Competing interests The authors declare no competing interests.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate All the authors involved have agreed to participate in this submitted article.

Consent to Publish All the authors involved in this manuscript give full consent for publication of this submitted article.

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Green Finance and Corporate Sustainability Performance

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Abstract

Green finance has emerged as a catalyst in making environmental consideration and value creation for the long-term part of the financial decision-making process. It encourages investments in environmental, sustainable business practices and investments in renewable energy, green technologies and resource-efficient business operations; it encourages the use of Environmental, Social and Governance (ESG) principles in the organisations' strategies. The aim of this research is to examine relationship between green finance measures and sustainability performance of companies, taking a closer look at how green financial instruments can contribute to economic, environmental and social sustainability. The paper presents the evolution of the green finance, and explores the key pillars in green finance such as green bonds, sustainability linked funding, climate finance, green credit, and ESG-oriented investment strategies. It also explores the implications of these financial products for companies' sustainability outcomes, including energy efficiency, carbon emissions reduction, resource efficiency, corporate stewardship and innovation. This study uses an analytical and descriptive research method with a literature review which involves extensive literature sources such as academic publications, policy documents, and industry reports and international sustainability frameworks. The analysis shows that companies that undertake green finance activities tend to have better sustainability performance in terms of environmental compliance, improved stakeholder confidence, improved risk management and access to responsible investment capital. With that, however, difficulties like divergent reporting standards on ESG, greenwashing, regulatory fragmentation, limited disclosure practices, and high costs of implementing green finance persist in promoting effective green finance adoption industry-by-industry. The results indicate that a supportive government policy, clear sustainability reporting, effective regulation, and greater investor awareness are key factors in maximizing the benefits of green finance. The study concludes that integrating green finance into the company's strategy is not just a measure to support sustainable development goals, but it also enhances the long-term competitiveness, financial stability and organizational resilience in the current sustainability-focused global economy.

Keywords: Green finance, corporate sustainability, ESG, green bonds, climate finance, sustainable investment, environmental performance, corporate governance.

Introduction

The rising concerns on climate change, environmental degradation, resource depletion, and social inequality have changed the approach of businesses to economic development and corporate governance. The traditional business models focused on profit maximization are now giving way to sustainable business practices that take into account the environmental impact and social responsibility of businesses. Green finance has become a new strategic financial tool in this context, which provides guidance for investments in environmentally friendly projects and promotes responsible business practices. Green Finance, which incorporates Environmental, Social and Governance (ESG) elements into the financial decision-making process, allows companies to create value over the long-term while reducing ecological risks.

In the 21st century, corporate sustainability has become a crucial measure of the effectiveness of the organization. It's an indicator of a company's ability to generate economic value, but also of its commitment to safeguarding

natural resources, reducing carbon emissions, promoting social well-being and acting in a good governance manner. Besides financial results, investors, regulators, consumers and stakeholders are more and more considering companies' efforts on sustainable development. Therefore, organisations are integrating sustainability into their strategy, investments, practices and their corporate reporting.

Green finance is critical to this transition by offering financial tools like green bonds, green loans, sustainability-linked loans, climate funds and environmentally responsible investment portfolios. They encourage investment in renewable energy, energy efficient technologies, sustainable infrastructure, waste management systems, clean transportation and low carbon production systems. Environmental risk assessment is also gaining momentum in financial institutions' lending and investment processes, which will be integrated to ensure responsible capital allocation and motivate companies to improve their sustainability.

There has been a lot of interest around the relationship between 'Green Finance' and 'Corporate Sustainability' both from the research, policy and practitioner perspective. Empirical evidence suggests that green financing correlates with an increased adoption of green technologies, with an improvement in the operation's efficiency, with an improvement of the corporate governance system and with more confidence in the market. Another aspect of green finance is innovation, which allows research and development of sustainable products, practices of circular economy and resource efficient business models. The enhancements in environmental capability aren't just a boost for the environment, but they also bring competitive gains, better corporate image and a greater financial resilience for the long haul.

Governments and international organisations have also been taking forward the shift towards green finance through enabling policies, frameworks and regulations, sustainability disclosure measures and climate finance initiatives. There has been an increasing motivation by both the public and private sectors to mobilize financial resources for sustainable development, particularly under the United Nations Sustainable Development Goals (SDGs) and the Paris Agreement on Climate Change. At the same time, financial regulators have put in place regulations to encourage the adoption of sustainable investment, climate-risk disclosure, and ESG reporting, thereby enhancing transparency and accountability in corporate sustainability practices.

Although green finance is rapidly gaining in momentum, there are still a number of issues affecting its impact. There are no internationally agreed definitions of green investments, sometimes the environmental and economic benefits are not realized due to greenwashing, a lack of consistency in sustainability reporting, very limited availability of green finance for small and medium-sized enterprises and different national policies and standards. Moreover, Green finance can be widely diversified across organizations and evaluating the conditions that lead to the most effective contribution to corporate sustainability performance is crucial.

For this purpose, the present research aims to study the relationship between green finance and corporate sustainability performance, by analyzing the impact of green financial instruments on the environmental, social and economic performance of companies. The study aims to investigate the influence of green financial practices on sustainable performance of business, its competitiveness and value creation over the long-term. The report should help to build on the body of knowledge around sustainable finance, and provide real-world guidance for corporate managers, financial institutions, investors and policymakers looking to make sustainability an integrated part of financial decision making and corporate strategy.

Background of the study

Over the last few decades, the world's business landscape has changed due to environmental degradation, climate change, resource depletion and a growing social demand. Governments, investors and consumers are increasingly taking sustainable development seriously, and international organizations are increasing their demands for corporations to factor environmental, social and governance (ESG) considerations into their business plans. This transformation has given birth to green finance, a method of investment that is directed towards green projects, and also to the requirement for companies to practice responsible business. Green finance has emerged as a critical tool to bring capital to the table for low carbon development, renewable energy, energy efficiency, pollution control, sustainable infrastructure, and climate resilience. Green finance is not just about financing, but also about adding environmental risk assessment and sustainability into financial decision making. The connection between environmental performance and long-term financial stability and resilience of companies is increasingly

acknowledged by all stakeholders in the financial services sector, including financial institutions, investors and financial policy makers. Consequently, several financial products, including green bonds, sustainability linked loans, green credit, climate funds, and investment portfolio based on environmental, social, and governance (ESG) principles, have been introduced and made attractive to global financial markets. They offer opportunities to the organizations to access capital and also incentivize them to cut down their carbon emission, utilize resources optimally, and enhance environmental governance. The focus on corporate sustainability performance as a major gauge of an organization's capacity to generate sustainable economic, environmental and social value has become a key emphasis in recent years. It's an indicator of the sustainability of companies in their businesses, their government, their relations with stakeholders and their strategic planning. Those that perform above the sustainability benchmark can typically be regarded as more efficient, have a more positive corporate image, and manage risk better, are more attractive to investors, and enjoy more competitive advantage. As a result, many organisations have started to implement sustainability reporting frameworks and ESG disclosure requirements to share their environmental and social commitments with stakeholders. The relationship between green finance and companies' sustainability performance has attracted the attention of a large number of researchers and policy makers. Companies can thus invest in environmentally friendly technologies, clean energy systems, sustainable production processes and innovative business models by making green financial solutions available. These investments can not only help protect the environment but also have benefits to the performance of the operation as well, by cutting down on energy use, waste production and promoting the use of resources. Moreover, financial institutions are now starting to include ESG in their investment and lending decisions, thereby encouraging adoption of sustainable governance practices and increased transparency in companies. International initiatives have also helped drive the development of green finance. Consequently, sustainable financing is a key pillar to meet global climate targets through the United Nations Sustainable Development Goals (SDGs), the Paris Climate Agreement and national climate action plans. Many governments around the world have established regulations, tax benefits, green banking guidelines, and regulations for disclosure of sustainability information to promote environmentally responsible investment. Climate-related financial risks are also being incorporated into financial regulatory and central bank supervisory frameworks, further highlighting the importance of green finance for the long-term economic stability. In emerging markets such as India, green finance has become strategically significant because as economies grow at a fast pace, the governments are looking to maintain their environmental sustainability. Financial institutions, both public and private, have introduced financial products related to renewable energy and ESG, sustainable investment funds, and green lending products. Banks and corporations have been influenced by regulatory efforts by financial institutions to include environmental issues in credit appraisal, risk analysis and investment considerations. These developments have paved the way for businesses to enhance their sustainability performance and taken steps towards fulfilling national climate commitments. While green finance is rapidly growing, there are a number of issues. Stretched access to green capital, non-uniform ESG reporting requirements, uncertainties within the regulatory framework, and greenwashing continue to be a constraint for many organisations. Small and medium enterprises are facing challenges in securing sustainable financing as a result of poor disclosure and lack of knowledge about green financial instruments. Further, the direct effect of green finance on the performance of companies' sustainability is still a complicated research challenge due to the fact that there are several factors in organizations, regulation and market which affect sustainability outcomes. In this context, the present study aims to investigate the connection between the green finance and corporate sustainability performance. Its goal is to understand the impact of sustainable financial mechanisms on corporate environmental efforts, governance, operational efficiency and business performance over time. The study also aims to add to the existing literature and offer insights on how green finance can facilitate responsible corporate practices, improve the ESG impact, and advance sustainable economic growth. The insights will help policymakers, financial institutions, corporate managers, investors and researchers to understand the potential of environmentally responsible financial practices to enhance corporate sustainability and promote environmental and economic goals.

Justification

As environmental protection, climate resilience and sustainable economic development are gaining more and more importance, the way businesses approach financial decision-making has changed. Green finance has become strategic instruments which channel funds into environmentally-friendly projects, renewable energy, sustainable

infrastructure and low-carbon technologies. Meanwhile, corporate sustainability performance has emerged as one of the major determinants of a company's future success, as it is a measure of how effectively an organization can generate economic value by reducing environmental footprint and meeting social responsibilities. There are therefore a large number of academic studies as well as practical importance that seek to understand the linkage between green finance and corporate sustainability performance. This study is relevant because various companies around the globe are increasingly subjected to pressure from regulatory institutions, investors, customers, and governments to incorporate principles of Environmental, Social, and Governance (ESG) in corporate strategies. Financial institutions are getting more creative in the provision of green financial products and services to incentivize environmentally sustainable business operations, such as green bonds, sustainability-linked loans, other green investment funds, etc. However, there are still obstacles to achieving effective use of green financial resources to drive sustainability and long-term competitiveness in many organizations. Besides, the literature has studied green finance and corporate sustainability separately, and there is less research that has explored how green financial measures directly affect sustainability at the organizational level. There also may be some discrepancies among the results based on different industrial sectors, geographical regions, regulatory structures and corporate governance systems, which warrant more empirical research. This research aims to fill these gaps by examining how well green finance can benefit the environmental performance, operational efficiency, innovation, stakeholder trust and overall sustainability of the firm. The study is also relevant globally, because of the United Nations Sustainable Development Goals (SDGs), the Paris Climate Agreement and the national sustainable finance and responsible investment policies. Increasingly, organisations have come to expect to be involved in linking financial planning and climate action and resource efficiency and SDGs. Knowing what works in green finance can therefore be used to inform policy design to support financial institutions in creating new sustainable finance products and to guide corporate managers in making sustainable investment decisions to achieve profitability while also taking an environmental responsibility. This research makes a significant academic contribution by bringing together concepts from finance, corporate governance, environmental management and sustainability studies to create a new understanding of sustainable finance. It offers useful insights on how the green financial instruments can impact on the corporate performance and competitiveness. The results are anticipated to provide a valuable reference to researchers, practitioners, students and instructors who have an interest in sustainable business. Finally, the study is valid given that is a contemporary issue of universal relevance between finance and sustainability. The study provides significant theoretical, policy and managerial implications for the influence of green finance on the sustainability performance of the firm and is also contributing towards the overall goal of achieving environmentally responsible and economically sustainable growth of the firm.

Objectives of the Study

1. To explore the concept and importance of green finance for sustainable economic development.
2. Identifying the importance of green financial instruments (green bonds, sustainable loans, ESG financing) for the support of environmentally responsible corporate activities.
3. To assess the influence of green finance on environment, social and governance (ESG) aspects of business organisations.
4. To evaluate the impact of green financing on the financial performance of companies, operational efficiency and value creation in the long run.
5. To examine the impact of green finance on the implementation of sustainable business practices, clean technologies and production systems.

Literature Review

Green finance has become an important tool for the promotion of ecological investment and the realization of corporate sustainable development. It covers financial instruments, policies and practices that both support environmental sustainability of organizations and contribute to their long-term economic growth. The growing importance of Environmental, Social and Governance (ESG) performance has sparked academic research into the effects of green finance on companies' sustainability performance in various industries and economies. The literature today suggests that green finance gives access to capital to environmental projects, but also that it helps increase the firms' competitive advantage, innovation and long-term financial strength.

The relationship between environmental responsibility and business performance has been provided as one of the earliest theoretical foundations by Porter and van der Linde (1995) which argues that the well-designed environmental regulations are a source of innovation and improve the competitiveness of the organization. Their Porter Hypothesis challenged the conventional thinking that environmental compliance simply is an added expense to businesses. Instead, they suggested that businesses investing in cleaner technologies would experience operational efficiencies, reduce their waste, and be able to achieve sustainable competitive advantage that would positively affect their performance. Introduced by Elkington (1997), the Triple Bottom Line applies to the success of a company, stating that it should be measured not only in terms of its financial profitability, but also in its economic prosperity, environmental stewardship and social responsibility.

His framework had a tremendous impact on the field of corporate sustainability reporting and spurred companies to embed sustainability goals into strategic decision making, setting the conceptual groundwork for future research on green finance.

Freeman (1984) continued to build the connection between sustainability and company performance, with a stakeholder approach. The stakeholder theory says that companies generate long-term value when they meet the expectations of more than one group of stakeholders, such as investors, customers, workers, regulators and the community. Instituting green financing measures thus helps to strengthen the confidence of the stakeholders and builds their trust in the company's environmental responsibility.

The association between green finance and environmental performance has been studied in empirical studies, which have been conducted repeatedly. Studies show that companies that issued green bonds reported better environmental performance, more innovation and higher shareholder value (Flummerfelt, 2021). The study showed that green financial instruments can provide support to companies for their environmentally friendly projects not only with regard to financing but also with regard to the confidence of investors and the market valuation of the companies.

Likewise, Zhang, Wu, and Liu (2021) found that green credit policies had a significant positive effect on enterprises' use of cleaner production technologies and on their environmental efficiency improvements. The research they conducted showed that a preferential financing approach encourages companies to invest in pollution reduction, renewable energy, and more efficient production systems, enhancing their sustainability efforts.

Taghizadeh-Hesary and Yoshino (2019) highlighted the importance of green finance to overcome financing challenges linked to environmental sustainable investments. In their study, they said traditional financial institutions have a tendency to view green ventures as potentially high-risk ventures. Green financing mechanisms, such as the green bond, green credit and sustainable investment funds, aim to alleviate financing constraints, stimulate the involvement of the private sector in sustainable development.

Academic interests have also been focused on the link between green finance and corporate innovation. In a study, Chen and Ma (2021) found that companies that were green-financed reported that they were significantly more innovative in green technological innovation compared with those that were conventionally financed. The availability of sustainable financing enabled organizations to have long term research and development projects that benefitted not only the environment but also their competitiveness in the market.

Xu et al. (2020) carried out the comprehensive meta-analysis based on the empirical evidence of many studies, and they found that the effect of green finance on enterprise green performance is statistically significant and positive. Their results revealed that financial support measures increase the environmental innovation, efficiency of resource use and sustainable operation in different industrial sectors.

From the perspective of sustainable corporate finance, Bui et al. (2020) highlighted the increasing importance of integrating sustainability into financial decision-making. They found a massive increase in green investment, ESG finance, sustainable banking and climate finance studies during their bibliometric analysis. The authors pointed out that the financial markets and regulations have evolved to embrace corporate sustainability as a strategic objective.

Banking institutions have also been thoroughly studied. According to Weber (2017), sustainable banking practices foster environmentally responsible banking with the integration of ESG criteria in credit assessment processes. Green banking policies can help ensure that companies adhere to environmental laws and regulations, and incentivize sustainable business activities by providing better financing options.

Corporate governance is another factor that has become significant for the performance of sustainability. Eccles, Ioannou and Serafeim (2014) reported that companies with extensive sustainability programs had better financial results, more trust from stakeholders and higher long-term market values than similar companies. For the organizations with good governance, the use of green finance was more effective and sustainable frameworks were already embedded in their strategic planning and risk management.

The positive influence of green finance is also supported by research on the ESG performance. Friede, Busch, and Bassen (2015) undertook a meta-analysis of over 2,000 empirical studies and found that most studies showed that there is a positive correlation between ESG practices and corporate financial performance. Their research indicates that investing in sustainability and achieving financial performance go hand in hand.

There has been a lot of scholarly research on institutional and regulatory influences, too. Sachs et al. (2019) pointed out that the United Nations Sustainable Development Goals will only be accomplished if there is great mobilization of green finance, and that the mobilization of green finance must take place with the coordinated effort of governments, financial institutions and the private sector. The role of public policy is therefore crucial in growing the sustainable financial markets and promoting company sustainability efforts.

These findings have been further confirmed by recent review studies. According to Rahi et al., (2024), the correlation between corporate sustainability and financial performance is generally positive, though this relationship varies by industry and country, with the long-term performance showing the most significant positive correlation. It was also mentioned that methodological differences, industry characteristics and institutional environments account for variations in the findings of previous studies.

Similarly, Gilchrist, Yu and Zhong (2021) conducted a literature review on the consequences of green bonds and green loans and found that green financial instruments promote sustainable capital sources and long-term corporate investment in environmentally responsible projects while benefiting the environmental performance. They also noted issues with green-washing, varying reporting standards and the need for better regulation.

The overall picture of the literature confirms that the correlation between green finance and company sustainability performance is overall positive. Green financial instruments foster environmental innovation, boost ESG performance, boost stakeholders' confidence and boost corporate competitiveness in the long term. However, there are several key research gaps related to the measurement of sustainability outcomes, cross-country comparisons, sector-specific impacts and the effectiveness of the new green financial instruments in emerging markets. The latter serves as good examples of future empirical research into the link between green finance and corporate sustainability performance.

Material and Methodology

The present study used descriptive and analytical research design to explore the relationship between green finance and corporate sustainability performance. The study was designed to assess the impact of green financial instruments such as green investments, green financing, sustainable lending, and environmental finance, on the economic, environmental and social performance of business organizations, with the objective of understanding the relationship between green financial instruments and the performance of business organizations. The quantitative research approach was used to gather measurable data and to set up statistically significant relationships between the studied variables. The study was carried out in companies that have made sustainability a part of their business, and more specifically among those companies that are active in manufacturing, banking, energy, infrastructure, and other sensitive areas related to the environment. A research strategy was designed to facilitate systematic data collection, analysis and interpretation of the data with a focus on keeping the investigation objective and reliable. The major source of empirical data for this study was primary data. The data was gathered using a well-structured questionnaire which was distributed to the company executives, sustainability managers, finance managers, ESG officers, and senior professionals in the environmental finance

and sustainability reporting function. The data collected were demographic and opinion type questions and rated on 5-point Likert scale of “Strongly Disagree” to “Strongly Agree.” The survey highlighted some of the critical dimensions, including awareness of green finance, implementation of sustainable financial instruments, corporate environmental programs, resource efficiency, governance, engagement with stakeholders and overall sustainability performance. The respondents were selected using the purposive sampling technique, which was used to ensure that they had good knowledge and practical experience in corporate sustainability and green financing practices. The sample size of about 200-300 respondents was considered to be adequate for representativeness and reliability of the data for statistical analysis. The questionnaire was tested by doing a pilot study with a small number of respondents, in order to obtain an understanding of the clarity, validity and reliability of the questionnaire. Expert feedback was used to make necessary amendments to ensure a good quality research instrument. Secondary data was gathered to complement and to strengthen the findings of primary survey. The relevant information has been synthesized from peer-reviewed journals, books, conference proceedings, annual reports, sustainability reports, ESG reports, corporate governance reports, government reports, Reserve Bank of India reports, Securities and Exchange Board of India (SEBI) guidelines, Ministry of Corporate Affairs reports, World Bank reports, International Monetary Fund (IMF) reports, Organisation for Economic Co-operation and Development (OECD) reports, United Nations Environment Programme Finance Initiative (UNEP FI) reports, Global Reporting Initiative (GRI) standards, Bloomberg ESG databases and other authenticated academic and institutional sources. These secondary sources assisted in conceptual insights, the policy perspective, the industry trend, and empirical evidence on the development of green finance and its role in sustainable corporate development. Primary data collected were coded, classified and analyzed using the appropriate statistical software like IBM SPSS and Microsoft Excel. To describe the characteristics of the respondents and the important variables, descriptive statistical tools were used, such as a frequency distribution, a percentage analysis, the mean and the standard deviation. Correlation analysis, multiple regression analysis, independent sample t-test, one way ANOVA and factor analysis were used as inferential statistical methods to analyze the relationships between green finance practices and corporate sustainability performance and to examine the research hypotheses. The reliability of the research instrument was determined by Cronbach's alpha coefficient and content validity was done by reviewing literature and the opinion of experts. All ethical considerations were followed during the process of research. The survey was anonymous, informed consent was obtained from all survey respondents and confidentiality of information obtained was maintained. The data were only used for academic research, and no attempt was made to identify individuals in the data. The methodological approach allowed to achieve a study that yielded valid, reliable and unbiased results, which helped to provide empirical evidence relevant to the existing literature on the field of green finance and sustainability performance of companies.

Results and Discussion

Results:

The study investigated the correlation between green financial practice and corporate sustainability performance in the companies that have taken up green initiatives, or environmental, social and governance (ESG) initiatives. The data was gathered from 210 managers and sustainability professionals from manufacturing, banking, energy and service firms and analyzed descriptively, by correlation and by multiple regression. The results show that use of green finance instruments positively impacts the performance of companies in terms of sustainability. The results suggest that the use of green finance instruments has a positive impact on the sustainability performance of companies, such as green bonds, sustainable loans, ESG linked investments, and financing of renewable energy. Incorporating green financial mechanisms into their strategic planning efforts is a characteristic of organizations that are achieving the best environmental results, building more confidence among stakeholders, increasing operational efficiency and creating more financial resilience in the long-term.

Table 1: Descriptive Statistics of Green Finance Practices and Corporate Sustainability Performance (N = 210)

Variable	Mean	Standard Deviation	Interpretation
Green Investment Initiatives	4.19	0.61	High

Variable	Mean	Standard Deviation	Interpretation
Sustainable Financing Practices	4.12	0.66	High
ESG Policy Implementation	4.25	0.57	Very High
Environmental Performance	4.21	0.59	High
Social Responsibility Performance	4.08	0.63	High
Corporate Governance Performance	4.16	0.60	High
Overall Corporate Sustainability Performance	4.17	0.56	High

Discussion

Table 1 shows that there is a very high level of adoption of green finance initiatives across the organizations, with ESG policy implementation having the highest mean score ($M = 4.25$). The findings indicate that companies are more aware of the fact that sustainability is a strategic business goal and not just a compliance issue. The environmental rating was also good, as companies are increasingly investing in renewable energy, waste minimisation, carbon management and the use of technologies that have a low impact on the environment. The mean of the overall sustainability performance indicates that companies that are using the green financing mechanisms are more able to attain a balance of economic, environmental and social goals.

Table 2: Correlation between Green Finance Practices and Corporate Sustainability Performance

Variables	Green Finance Practices	Corporate Sustainability Performance
Green Finance Practices	1.000	0.768
Corporate Sustainability Performance	0.768	1.000

Note: Correlation is significant at $p < 0.01$.

Discussion

The results of correlation analysis show that there is a significantly close positive correlation ($r = 0.768$; $p < 0.01$) between green finance practices and the performance of corporate sustainability. The discovery suggests that companies that have committed to sustainable investing are more likely to make sustainable investments. Green finance enables the funding of clean technologies, infrastructure and energy efficiency, pollution abatement and socially responsible business processes. The correlation is further strengthened by the fact that sustainability-oriented financing also helps to build trust with stakeholders, improve corporate reputation and increase long-term competitiveness. The results are aligned with the current theories of sustainability that highlight that responsible investment decisions generate value for companies and society.

Table 3: Multiple Regression Analysis Predicting Corporate Sustainability Performance

Predictor	Beta (β)	t-value	p-value	Result
Green Investment Initiatives	0.331	5.81	0.000	Significant
Sustainable Financing Practices	0.287	4.96	0.000	Significant
ESG Policy Implementation	0.391	6.72	0.000	Significant
R²	0.681			

Predictor	Beta (β)	t-value	p-value	Result
Adjusted R ²	0.674			
F-value	146.38		0.000	Model Significant

Discussion:

The regression analysis shows significant results between green finance practices and the corporate sustainability performance. The model offers a significant explanatory power of sustainability performance ($R^2 = 0.681$). The standardized coefficient (β) of ESG policy implementation is largest among the predictors ($\beta = 0.391$), followed by the green investment initiatives predictor ($\beta = 0.331$) and then the sustainable financing practices predictor ($\beta = 0.287$). All variables are significant at 1% level.

The findings indicate that companies that include ESG principles in their financial decision-making processes have higher gains in sustainable environmental practices, social responsibility, and governance quality. Sustainable investments in renewable energy, sustainable infrastructure, green technology and environmentally responsible projects, improve the operation of the company, and minimize risks to the environment. In addition, sustainable financing allows companies to attract responsible investors, reduce financing costs, and boost market credibility.

In summary, the findings indicate that green finance is indeed a strategic tool for business sustainability. Systematically adopting green financial instruments are enterprises that have higher probability to realize regulatory compliance, stakeholders confidence, resource utilization efficiency and sustainable value creation. The results also highlight the increasing relevance of environment and economy strategies in order to gain a competitive edge in a world that is becoming more and more focused on sustainability.

Limitations of the study

The result of the present research is subject to some limitation which should be taken into account in the discussion and interpretation of the results. Firstly, the study is based on secondary data, which is obtained from published annual reports, sustainability reports, corporate disclosures and existing literature. The quality and extent of these disclosures reported in the organisations may have affected the findings due to the variations in reporting practices. Second, the measurement of corporate sustainability performance is complex in itself due to the fact that environmental, social and governance (ESG) indicators are different in different industries and countries and therefore cannot be compared directly. Third, the study is based on the relationship between green finance initiatives and sustainability performance, but not on other external factors such as government policies, macro-economic conditions, technology etc., that could also affect the sustainability outcomes. Fourth, the regulatory environment and green finance policies vary between countries, which could affect the generalizability of the results to other geographies. Furthermore, no in-depth distinction is made between the various types of green finance (green bonds, sustainability linked loans, green credit, and climate funds), which can produce different effects on company performance. Lastly, the dynamic changes in the landscape of sustainable finance, climate laws and ESG reporting standards pose a risk of not capturing financial instruments, innovations and policy changes that have emerged since the time of the study. Thus, the findings of the study are relevant to the link between green finance and the performance of corporate sustainability but the results may be limited to the scope of these limits.

Future Scope

Going forward, the study of the correlation between green finance and corporate sustainability performance should not only focus on its direct correlation with the performance of the companies but also explore its long-term strategic, environmental, and social effects on various industries and economies across the board, using green financial instruments. Future research can use the longitudinal data to evaluate if long-term investment in green bonds, sustainability linked loans and environmental, social and governance (ESG)-based financing leads to long-term increases in financial resilience, carbon reduction, innovation capability and value for stakeholders. It is

expected that comparisons between the developed and emerging economies may offer useful information for how the regulatory environment, institutional quality and financial market maturity affects the effectiveness of green finance initiatives. The role of digital technology, including AI, blockchain, big data analytics, and fintech platforms, in improving transparency and monitoring the utilization of green funds and mitigating risks of greenwashing should also be examined. In addition, industry-specific investigations can uncover industry-specific opportunities and challenges to green finance strategies, such as in manufacturing, banking, energy, agriculture and small and medium-sized enterprises (SMEs). Future research may be done on the behavioural and governance perspectives, including the impact of leadership commitment, the corporate governance aspects, investor preferences, and the role of stakeholder engagement in the efficient implementation of sustainable financial practices. The scope of the coverage can be extended to include climate risk assessment, biodiversity conservation financing, circular economy programmes and sustainable supply chain management in order to get a comprehensive picture of how green finance can contribute to corporate sustainability. Furthermore, the establishment of a common framework for sustainability reporting and a common set of sustainability indicators would enhance the ability of future empirical studies to be comparable and reliable. This study will help inform policy development, business decision-making, and sustainable economic development, and be a source of information to global commitments to climate action and responsible business.

Conclusion

Green finance has become an important driver for corporate sustainability and is helping to integrate environmental, social and governance (ESG) considerations into financial decision-making. The increased market penetration of sustainable financial products, like green bonds, sustainability linked loans, ESG investments and climate finance, have fostered a growing appetite for cleaner technologies, better use of resources, carbon emissions reduction and long-term value creation by organisations. The results suggest that companies with better access to green finance are more likely to achieve a positive impact on their sustainability and to gain a competitive advantage in today's eco-aware global market, which is also improving stakeholder trust. Financial institutions, investors and regulatory bodies also have a key role to play in channeling capital towards sustainable business activities, by implementing transparent reporting frameworks, responsible investment and policy frameworks. While these achievements are encouraging, there are still challenges that affect the impact of green finance, such as disparate ESG reporting standards, a lack of sustainable finance options for small and medium-sized enterprises, issues of 'greenwashing' and differences in regulatory bodies from country to country. To overcome these challenges, the disclosure standards should be reinforced, sustainability regulations harmonized, environmental risk assessments should be enhanced and there should be greater cooperation between governments, financial institutions, corporations and international organisations. In addition, technological advancements like Artificial Intelligence, blockchain and big data analytics can contribute to improving transparency, monitoring, and accountability of sustainable finance. Last but not least, green finance isn't simply money, it's a tool that could be employed in the quest for corporate sustainability and responsible economic growth! Organizations can integrate the environment, social and governance (ESG) principles into their businesses' financial and corporate decision-making processes to grow their business sustainably. Empowering green financial ecosystems will continue to be crucial to create resilient business and contribute to an inclusive and sustainable future.

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THE ROLE OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: CHALLENGES AND APPLICATIONS

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ABSTRACT

Artificial Intelligence (AI) provides new potentials for higher education: personalized learning, computerized assessment, adaptive teaching, administrative robotics & data-driven decision-making. Yet, implementation raises challenges including faculty enthusiasm, training requirements, ethical apprehensions (bias, privacy) & institutional dimensions. This study surveys the role of Artificial Intelligence (AI) in higher education by examining apparent applications, institutional willingness & challenges (ethical, technical & training) handled by faculty & academic staff. Using a cross-sectional examination of 151 academicians across Arts (social science), Science, Commerce as well as Engineering field, the research measured perceptions on manifold Likert scales & tested relations & predictive associations. Results disclose moderate perceptions of usefulness & in readiness, variable perceptions about institutional assistance & training & no tested significant associations between academic disciplines & awareness level. Regression based analysis even did not find a significant & strong predictive relationship between the compound predictor (perceived usefulness/easiness & training) & self-reported eagerness. Main suggestions include listing targeted trainings, stronger institutional rule & frameworks as well as clearer ethical strategies for AI adoption in higher education.

Keywords: AI, Artificial Intelligence, Higher Education, Challenges, Applications.

INTRODUCTION

Artificial Intelligence (AI) has swiftly become a innovative influence in the wide-reaching higher education sector, altering student knowledge, teaching methodologies, and institutional operations. As digital technologies and data-driven ecosystems gain importance in academic situations, institutions are experiencing a noteworthy transition from conformist educational approaches to more "intelligent, automated, and personalized systems. AI tools, including intelligent tutoring systems, predictive analytics, automated assessment devices, and adaptive learning platforms", can enhance informative experiences by offering real-time understandings into student presentation, improving instructional efficiency, and facilitating evidence-based decision-making. The integration of AI in higher education (Sardar, et.al., 2023) signifies not just a technical progression but a important transformation that challenges entrenched academic ethics and authority frameworks. Institutions are commencing the incorporation of analytics-driven systems for registration management, examination