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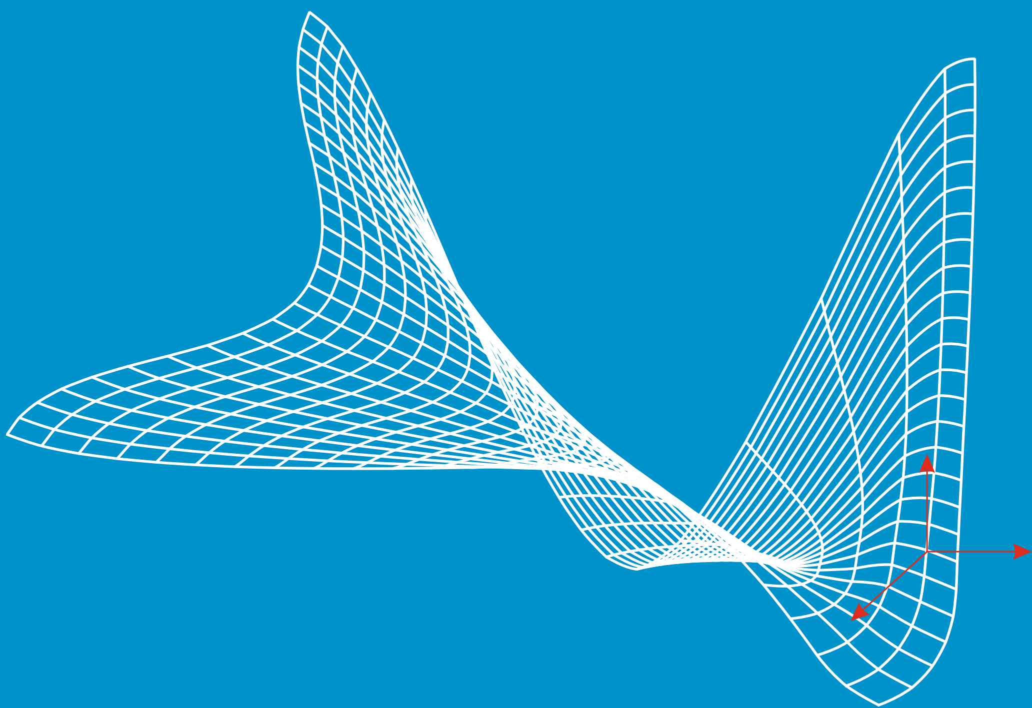
OF ECONOMICS AND MANAGEMENT



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Green finance and renewable energy investments: a comparative analysis of successes, challenges, and policy implications across regions

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Aim: This study examines recent green finance developments to evaluate how institutional, economic, and policy factors affect renewable energy investments globally. It employs a comparative approach to identify key success drivers and barriers influencing the effectiveness of green finance in promoting renewable energy across different national contexts.

Research Methods: The study systematically examines green finance impacts on renewable energy investments through a literature review, thematic analysis, and case studies. It reviews peer-reviewed articles (2015–2025). Prioritizing qualitative research, it analyzes policies, institutional frameworks, and outcomes. Comparing successful cases (e.g., Singapore, China) with failures (e.g., Middle East & Central Asia, Latin America) provides key insights.

Findings: The findings depict a varied global scenario for green finance. Successes like Singapore's Green Bond Grant Scheme and China's Green Finance Pilot Zones showcase how strong regulations and blended financing boost renewable energy. In contrast, challenges in Africa (weak policies), Southeast Asia (high costs), and Latin America (political instability) emphasize the importance of tailored strategies to overcome structural obstacles.

Originality: This study provides a unique comparative analysis of regional green finance initiatives, examining successes and failures. Unlike previous research, it identifies key factors and barriers, offering practical recommendations for policymakers. Addressing region-specific challenges enhances understanding of global green finance and supports sustainable development.

Implications: The study underscores the necessity of strong regulations, blended finance, and regional collaboration for green finance success. Addressing weak governance, financing gaps, and political instability is crucial to scaling renewable energy investments and achieving sustainability goals globally.

Limitations: Limited quantitative analysis; future research should explore hybrid financing models.

Keywords: Green finance, renewable energy investments, sustainable development, Climate Finance.
JEL: G23, Q01, Q42, Q56.

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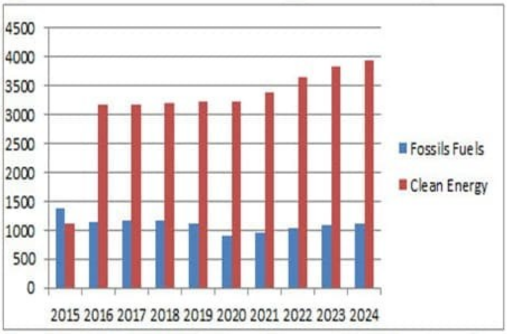
1. Introduction

Green finance has emerged as a transformative tool for addressing the substantial global renewable energy investment gap, estimated at $4.5 trillion annually. Instruments such as green bonds, loans, and climate funds are pivotal in channelling financial resources toward renewable energy projects, essential to achieving net-zero emissions by 2050. Despite their potential, significant disparities persist across countries due to unequal access to capital and inconsistent policy frameworks. These disparities hinder the uniform adoption of green finance mechanisms, creating a divide between nations effectively leveraging these instruments and those struggling to attract investments. For example, while developed economies benefit from mature financial markets that facilitate green finance initiatives, emerging and developing economies (EMDEs) face structural barriers such as high capital costs and limited long-term financing options, particularly for solar energy projects (Sareen, Prakash Jena 2022; Akash, Atharva 2022; Cian et al. 2024). As seen in the Figure 1 which illustrates a significant shift in global investment trends between 2015 and 2024, showcasing a growing divergence between clean energy and fossil fuel investments. While clean energy investments have demonstrated a robust and consistent upward trajectory, nearly doubling from $2200 billion in 2015 to $4000 billion by 2024, fossil fuel investments have shown only marginal growth, increasing from $1100 billion to $1200 billion over the same period. This stark contrast has led to a widening gap between the two sectors, with clean energy investments more than tripling their fossil fuel counterparts by 2024, compared to being just double in 2015. This trend underscores a major reorientation of global investment priorities towards clean energy technologies and infrastructure, reflecting an increasing focus on sustainable and renewable energy sources.

Figure 1: Global Investment in clean energy and fossil fuels (in Billion USD), 2015-2024



SourceFigure1 to 4: IEA, World Energy Investment 2024, https://www.iea.org/reports/world-energy-investment-2024/overview-and-key-findings.

Existing research highlights success stories in green finance implementation, such as in China and Singapore. China has established green finance pilot zones and implemented feed-in tariffs to attract private investments. At the same time, Singapore has introduced targeted financial mechanisms like green bonds and government-backed guarantees to support renewable energy development. These cases demonstrate how effective policy frameworks and institutional support can drive renewable energy investments. However, this narrow focus on successful examples neglects the systemic challenges developing economies face. For instance, many African nations with significant solar potential cannot secure adequate financing due to fragmented market structures, regulatory uncertainties, and the high cost of capital (Akash, Atharva 2022; Pradnyaswari et al. 2024; Cian et al. 2024).

This study aims to synthesize recent advancements in green finance research by evaluating how institutional, economic, and policy factors influence renewable energy investment outcomes across different national contexts. By adopting a comparative approach, the research seeks to identify the drivers of success and the barriers contributing to failures in leveraging green finance for renewable energy development. This comprehensive analysis aims to provide a more nuanced understanding of the global green finance landscape and offer actionable insights for policymakers and stakeholders (World Bank 2024; Henry, North 2024; Segal et al. 2024).

Green finance has emerged as a crucial mechanism for promoting sustainable development and addressing environmental challenges. It aims to increase financial flows from various sectors towards sustainable development priorities, focusing on better management of environmental and social risks while seeking opportunities that provide both financial returns and environmental benefits (UNEP 2025).

Recent research highlights the growing role of investment funds in financing green companies in emerging markets (EMs). Despite a global surge in sustainable investing, companies involved in carbon solutions in EMs still make up a small portion of reported sustainable investments. Key characteristics driving green investments include younger funds, retail investor funds, funds with domestic mandates, and sustainable funds, which are more inclined to invest in green companies and less in fossil fuels (Lepers, De Crescenzio 2024).

The field of green finance research has seen significant growth, with a surge in publications from 2018 to 2023. This increase reflects the growing academic interest and the global momentum of investing in green finance as an economic driver. Environmental activists' demand and the availability of information to capitalize on ecological and sustainability opportunities have contributed to this rise in interest (Ali et al. 2024).

While emerging markets and developing economies (EMDEs) currently rely mainly on domestic public sector financing for green investments, private financing will need to cover a large share of future needs due to shrinking fiscal space in both EMDEs and advanced economies. Cross-border private capital flows, including foreign direct investment, bank lending, and portfolio equity and debt flows, will be significant for markets with few domestic investors (Lepers, De Crescenzio 2024).

However, EMDEs face unique challenges in implementing green and sustainable finance initiatives. These include higher reliance on fossil fuels for domestic energy consumption and financial, institutional, and capacity gaps compared to advanced economies. These factors create higher hurdles for financial firms in moving toward green and sustainable finance, while climate policy frameworks in EMDEs are generally less advanced (World Bank 2023).

Despite these challenges, green finance is crucial in harmonizing economic and environmental objectives. For instance, studies examining the relationship between green finance and sustainable development in countries like Morocco have focused on its dual impact on economic growth and environmental protection (Dahhou et al. 2024). As the field of green finance continues to evolve, addressing the specific needs and characteristics of emerging markets will be essential for its successful implementation and contribution to global sustainability goals.

2.Theoretical framework

The theoretical foundation linking green finance to renewable energy investments is anchored in interdisciplinary frameworks integrating financial mechanisms with environmental objectives. The innovative approach of the Data-Driven Sustainable Finance Framework integrates sustainable finance principles with advanced analytics to optimize renewable energy investments. It employs a multifaceted strategy encompassing comprehensive risk assessment, considering financial and non-financial factors to evaluate project viability (Adeyoe et al. 2024). The method also quantifies positive impacts, such as carbon reduction and job creation, to ensure alignment with sustainability goals (Adeyoe et al. 2024). Furthermore, it harnesses the power of artificial intelligence and machine learning to analyze extensive datasets spanning energy production, environmental metrics, and geopolitical factors. This data-driven approach enables the identification of high-potential projects (Ali et al. 2024) ultimately enhancing the effectiveness and sustainability of investments in the renewable energy sector.

Building on this data-driven approach, the Institutional-Policy Synergy Theory emphasizes the role of policy frameworks in facilitating private sector participation in renewable energy investments. This theory highlights how green finance policies, such as China's green bond guidelines, lower investment barriers through tax incentives and risk-sharing mechanisms. It also incorporates the double dividend hypothesis, which suggests that environmental taxes and green investments can simultaneously drive economic growth and reduce emissions, as demonstrated by initiatives like the European Union's carbon markets (Schöb 2003; Bayer, Aklin

2020). These institutional arrangements create an ecosystem that channels capital into sustainable energy initiatives.

Complementing these policy-focused insights is the STIRPAT Environmental Impact Model, which examines how societal factors and technological advancements interact to drive renewable energy adoption. This model identifies two primary pathways: the technology channel, where green finance accelerates R&D and deployment of wind and solar technologies (Yunpeng et al. 2023; Bingfeng, Zhihao 2024; Subramaniam, Loganathan 2024) (2) and affluence modulation, where wealthier economies use green financing to decouple economic growth from emissions (Yunpeng et al. 2023; Zhao, Ellisha 2024). These pathways illustrate how financial mechanisms can align technological progress with economic development patterns.

The risk-return optimization theory further advances this discussion, exploring how structured financial instruments balance profitability and sustainability in renewable energy projects. Tools like green bonds and blended finance demonstrate how public and private resources can be strategically combined to reduce risks while ensuring measurable returns. For example, Peru's $164M green bond for hydroelectric grid upgrades exemplifies how these instruments achieve financial viability and environmental impact (Adeoye et al. 2024; UNEP and the People's Bank of China 2015).

Finally, the Ecological-Economic Harmonization Theory bridges economic growth with environmental protection by emphasizing circular investment flows and social cost internalization. Circular flows reinvest profits from renewable projects into further innovations (Dahhou et al. 2024; Hailiang 2023), while mechanisms like carbon credits make renewables more competitive by accounting for environmental externalities (Xing et al. 2024). Together with earlier frameworks, this theory underscores how green finance catalyses renewable energy transitions by addressing scalability challenges through policy coordination and financial innovation.

Collectively, these interconnected theories present a comprehensive perspective on how green finance fosters a sustainable energy landscape by aligning economic incentives with environmental goals.

3. Methodology

The methodology for this study is structured to systematically evaluate the impact of green finance on renewable energy investments across successful and failed cases. It employs a literature review strategy, thematic analysis, and case study selection to ensure comprehensive insights into the factors influencing project outcomes.

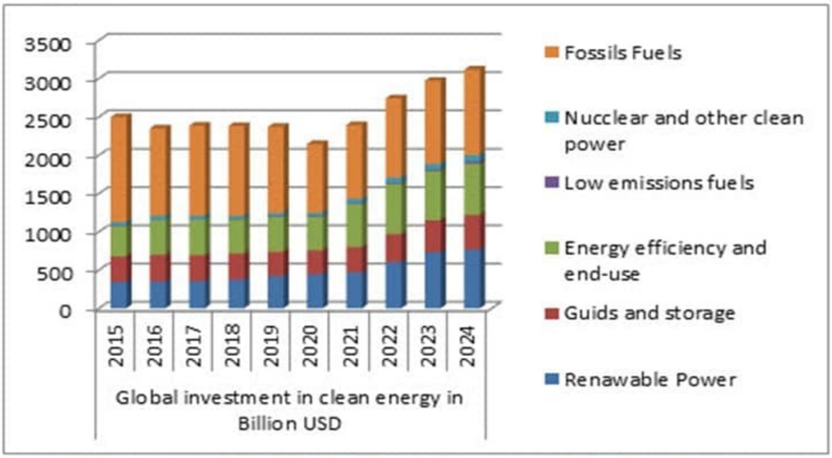
3.1. Literature review strategy

The field of green finance has seen significant growth, driven by its potential to address environmental challenges and promote sustainable development. Investments in clean energy have become a cornerstone of global decarbonization strategies, with renewable power emerging as a dominant focus. Figure 2 comprehensively summarizes global investments in clean energy and fossil fuels by sectors from 2015 to 2024. The data reveals that renewable power consistently attracts the largest share of clean energy investments, underscoring its pivotal role in reducing carbon emissions. Additionally, significant growth is observed in investments in grids and storage infrastructure, which are crucial for integrating renewable energy sources into existing power systems.

The diversification of clean energy investments is evident, with funding allocated to energy efficiency, low-emission fuels, and nuclear power. This diversified approach highlights the multifaceted nature of green finance, aiming to build a sustainable and varied energy landscape. In contrast, fossil fuel investments remain relatively consistent but are overshadowed by the rapid expansion of clean energy sectors, particularly renewable power.

Existing research supports these trends by emphasizing the importance of robust regulatory frameworks and institutional support in driving sectoral investments. For example, countries like China have implemented green finance pilot zones to attract private-sector participation in renewable energy projects. At the same time, Singapore’s Green Bond Grant Scheme has incentivized issuers to adopt sustainable financing.

Figure 2: Global Investment in clean energy and fossil fuels by Sectors (in Billion USD), 2015-2024



SourceFigure1 to 4: IEA, World Energy Investment 2024, https://www.iea.org/reports/world-energy-investment-2024/overview-and-key-findings.

The research methodology for this study on green finance and renewable energy investments employs a systematic approach to literature review, ensuring a comprehensive and up-to-date analysis of the field.

The search criteria focus on peer-reviewed articles published between 2015 and 2025, using keywords such as “green finance,” “renewable energy investments,” and “case studies.” This timeframe captures recent developments in green finance mechanisms and their global application to renewable energy projects (Betul, Yaşar 2024; Subramaniam, Loganathan 2024). By concentrating on this period, the study ensures relevance to current market conditions and policy landscapes.

Regarding inclusion and exclusion criteria, the research prioritizes non-econometric studies that qualitatively assess national policies, institutional frameworks, and project outcomes. This approach allows a deeper understanding of contextual factors influencing success and barriers in green finance initiatives. Conversely, articles emphasizing econometric modelling or purely quantitative analyses were excluded to maintain focus on rich, contextual insights (Betul, Yaşar 2024; Chang 2019).

The study employs thematic coding to analyze the selected literature and identify recurring patterns in success factors and barriers. This method enables a structured approach to synthesizing diverse case studies and policy analyses.

Success factors identified through this process include robust regulatory support (e.g., feed-in tariffs, green bond standards), effective risk mitigation strategies (such as government-backed guarantees), and institutional partnerships that foster private-sector involvement (Subramaniam, Loganathan 2024; Chang 2019). For instance, Singapore's Renewable Energy Funding Scheme exemplifies how targeted policies can reduce financial risks while attracting investments in the renewable energy sector.

Conversely, the analysis highlights common barriers to green finance and renewable energy investments. These challenges include high capital costs, weak regulatory environments, political instability, and limited institutional capacity. African nations, for example, often face significant financing barriers due to fragmented markets and geopolitical instability, which deter private investment in renewable energy projects (Africa Policy Research Institute 2025; Khoffash, Subhi Awwad 2024; Cai et al. 2024). This research methodology provides a comprehensive framework for understanding the complex landscape of green finance in renewable energy investments by systematically examining success factors and barriers across diverse contexts. This approach enables policymakers and investors to draw valuable lessons from global experiences, potentially informing more effective strategies for accelerating the transition to sustainable energy systems.

3.2. Successful cases of green finance by regions

Analysing successful green finance initiatives across various regions reveals innovative approaches to promoting renewable energy investments and sustainable development. These cases demonstrate how tailored strategies can effectively address regional challenges while accelerating global progress toward sustainable energy transitions.

In Asia, Singapore has emerged as a leader in green finance through its Green Bond Grant Scheme and regional energy partnerships. The scheme, introduced by the Monetary Authority of Singapore (MAS), subsidizes external review costs for green bonds, encouraging sustainable financing practices. For example, Sunseap Group secured a $50 million green loan for rooftop solar installations, significantly boosting the country's solar energy capacity. Singapore's participation in the Laos-Thailand-Malaysia-Singapore Power Integration Project further diversified its energy sources and reduced carbon emissions (Zhang et al. 2023; IFC 2017).

China's implementation of Green Finance Pilot Zones in provinces like Jiangsu, Zhejiang, and Guangdong has been equally impactful. These zones offer concessional loans, tax incentives, and land-use benefits to attract private-sector participation in clean energy projects. By 2024, China had mobilized approximately $4.5 trillion in green loans, enabling it to meet its renewable energy targets ahead of schedule (Zhang et al. 2023).

Kenya has leveraged innovative financing models in Africa to expand renewable energy access. The M-KOPA Solar initiative uses a pay-as-you-go model to provide affordable solar home systems to over one million households. Additionally, the Lake Turkana Wind Power Project, Africa's largest wind farm, supplies 17% of Kenya's electricity needs (CIF 2024; IFC 2017). South Africa's Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) has attracted over $13 billion in investments and added 6 GW of renewable energy capacity to the national grid (IFC 2017).

Europe showcases successful initiatives such as Germany's KfW Renewable Energy Programme, which has financed thousands of solar photovoltaic systems and wind turbines through low-interest loans. Croatia's Citizen-Led Energy Renovation Fund demonstrates the power of community engagement in financing energy-efficient building renovations (IFC 2017). Croatia has implemented a crowdfunding initiative for energy-efficient building renovations through its Citizen-Led Energy Renovation Fund. This fund supports approximately 250 households annually, reducing thermal and electrical usage by up to 1,300 kWh per year per household. Croatia has successfully scaled up small-scale renewable energy adoption by engaging local communities directly in financing efforts while fostering public participation in sustainability initiatives (Mestri-CE 2024).

In Latin America, Chile's Cerro Dominador Solar Thermal Plant, financed through blended finance, generates 580,000 MWh annually while avoiding 235,000 tons of CO_2 emissions (Groves et al. 2020; UNFCCC 2018). Costa Rica's National

Decarbonization Plan (NDP) aims to achieve net-zero emissions by 2050 through transportation, agriculture, and forestry sectoral reforms. The plan attracted nearly $1 billion in international funding from institutions like the International Monetary Fund (IMF) and Inter-American Development Bank (IDB). Early achievements include deploying electric buses and reducing agricultural emissions through composting initiatives. The NDP demonstrates how robust policy frameworks can attract large-scale investments while ensuring long-term sustainability goals are met (Elliott et al. 2024; Groves et al., 2020).

These successful cases highlight key lessons for effective green finance strategies: strong regulatory frameworks, public-private partnerships, blended finance models, community engagement, and regional collaboration. By adapting these approaches to local contexts, countries can overcome barriers and leverage green finance to achieve sustainability goals.

3.3. Failure cases of green finance by regions

The failure cases of green finance across various regions highlight significant challenges in implementing sustainable financial practices and reveal systemic vulnerabilities that hinder progress toward environmental goals.

The Middle East and Central Asia (ME&CA) region faces significant challenges in implementing green finance due to climate-related risks and systemic vulnerabilities in its financial sectors. Countries like Afghanistan, Pakistan, and Iran are particularly susceptible to climate-induced financial risks, as they heavily rely on climate-sensitive industries such as agriculture and tourism. Climate disasters amplify these vulnerabilities, causing substantial credit losses and increasing systemic risks for banks. The region also grapples with transition risks, especially for oil-exporting nations, as the global shift towards renewable energy threatens to create stranded assets. Low carbon pricing and continued reliance on subsidies for energy-intensive sectors exacerbate these challenges. Furthermore, the ME&CA region suffers from significant insurance gaps, with only 16% of insurance protection needs met between 2005 and 2019. This lack of coverage has resulted in a mere $2 billion of the $44 billion in climate-related economic losses being insured during this period, placing a substantial financial burden on governments and impeding the adoption of green finance initiatives (Radzewicz-Bak et al. 2024).

Despite its significant renewable energy potential, Latin America faces substantial hurdles in scaling up green finance initiatives due to limited access to long-term financing and insufficient technical capacity. A European Investment Bank survey revealed that 55% of the region's Public Development Banks (PDBs) identified inadequate green investment knowledge among clients as a significant obstacle. In comparison, 45% cited clients' lack of awareness of green finance opportunities. Funding constraints compound these challenges as PDBs struggle to secure the long-term capital necessary for climate investments (European Investment Bank 2025). The region requires an estimated \$2.1–\$2.8 trillion by 2030 to address climate change effectively, but persistent financing gaps stemming from insufficient international cooperation and weak domestic financial systems hinder progress (Omori 2024).

Furthermore, the vulnerability of critical sectors like agriculture to climate change impacts exacerbates food insecurity and economic instability, further impeding the adoption of green finance solutions in Latin America (European Investment Bank 2025; Omori 2024).

Southeast Asian countries face significant challenges in implementing green finance initiatives due to regulatory uncertainty, resource constraints, and greenwashing concerns. In Indonesia, for example, unclear power purchase agreement (PPA) regulations have led to delays in renewable energy projects, with investors struggling to navigate inconsistent policies that fail to provide long-term stability for green investments (World Bank 2023). Across the region, allegations of companies misrepresenting their environmental credentials have eroded trust and deterred private-sector participation in green bond markets. Additionally, the high upfront costs associated with renewable energy projects pose a substantial barrier for local companies, particularly those without access to concessional financing or government support. These interrelated factors collectively undermine investor confidence and hinder the growth of green finance in Southeast Asia despite the region's significant potential for sustainable development (World Bank 2023).

Although Europe has historically been a global leader in green finance, recent developments reveal mounting challenges driven by political resistance, economic pressures, and unequal financing distribution. Opposition to the European Green Deal has introduced uncertainty about long-term sustainability commitments, with countries like Poland continuing to rely heavily on coal subsidies despite receiving EU funding for renewable energy transitions. Economic pressures, including rising inflation and higher interest rates, have further increased the debt issuance cost for renewable energy projects, making green bonds less appealing to investors. Additionally, financing remains disproportionately allocated, with fossil fuel companies receiving five times more funding than green initiatives, undermining efforts to meet net-zero targets. These factors collectively hinder Europe's progress in maintaining its leadership in green finance and achieving its climate goals (IFC 2017).

The failure cases in green finance across various regions reveal several key contributing factors hindering sustainable investment progress. Weak regulatory frameworks, exemplified by inconsistent policies like Southeast Asia's power purchase agreements, discourage private-sector participation. Limited access to long-term financing creates funding gaps that prevent large-scale investments, particularly in regions like Latin America. A lack of technical capacity, especially among financial institutions in the Middle East, Central Asia, and Latin America, impedes the development and implementation of green finance initiatives. Political instability, such as resistance to sustainability policies in Eastern Europe, creates uncertainty and undermines long-term commitments. Additionally, insurance gaps, particularly evident in the Middle East and Central Asia, amplify financial risks associated with climate disasters. These interconnected challenges underscore the critical need to address structural barriers, enhance regulatory clarity, promote international cooperation, and build institutional capacity to scale up green finance on a global scale effectively.

4. Results

4.1. Results: successful cases of green finance by regions

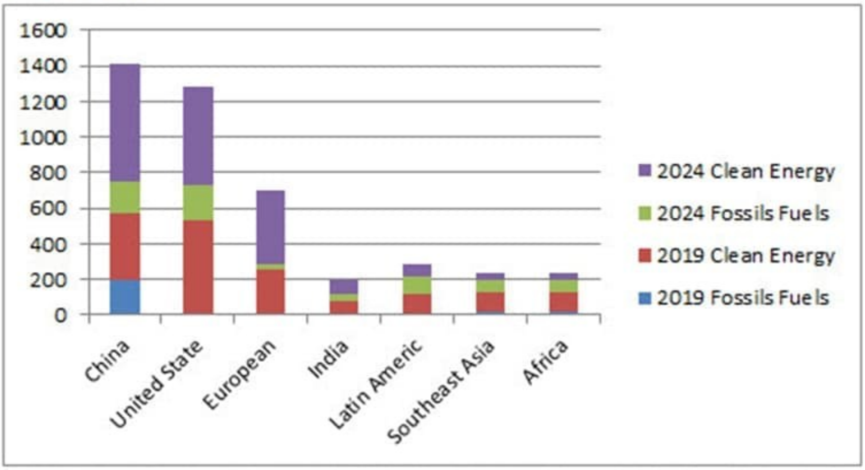
The analysis of green finance initiatives reveals significant regional disparities in clean energy investments between 2019 and 2024. Figure 3 illustrates the global landscape of clean energy investments during this period, highlighting China's leadership in renewable energy funding. China consistently maintains its dominant position due to strong policy support, such as its Green Finance Pilot Zones and extensive renewable energy projects. The United States also shows notable growth in clean energy investments, driven by federal incentives and private-sector participation.

In contrast, Europe experienced a decline in clean energy investment between 2019 and 2024, reflecting challenges such as political resistance to sustainability policies and unequal financing allocation. Other regions, including India, Latin America, Southeast Asia, and Africa, demonstrate modest but consistent increases in clean energy funding. These trends underscore varying levels of commitment and progress across different regions.

Notably, fossil fuel investments remain relatively stable across all regions but are significantly overshadowed by the growing clean energy sector. This shift highlights a global reorientation toward renewable energy technologies and infrastructure, particularly in leading economies like China and the United States.

Singapore has established itself as a regional leader in green finance, mainly through the Green Bond Grant Scheme, which subsidizes the costs of external reviews for green bonds. This initiative has encouraged issuers to adopt sustainable financing practices, resulting in significant investments in renewable energy projects. Between 2016 and 2020, Singapore led the ASEAN region with 47 green finance deals, amounting to approximately $9.6 billion in green loans. The country's leadership is further reflected in its Singapore Green Plan 2030, which integrates green finance as a key pillar to achieve sustainable development goals (Climate Bonds Initiative 2021).

Figure 3: Annual investment in clean energy by selected country and region (in Billion USD), 2019 and 2024



SourceFigure1 to 4: IEA, World Energy Investment 2024, https://www.iea.org/reports/world-energy-investment-2024/overview-and-key-findings.

China's success in green finance is exemplified by its Green Finance Pilot Zones, particularly in cities like Huzhou. These zones allow local governments to test innovative green finance policies and products before scaling them nationwide. Huzhou developed its green finance taxonomy, focused on industries such as textiles and batteries, and introduced financial products to support small and medium-sized enterprises (SMEs) in adopting sustainable practices. By 2024, China had mobilized $4.5 trillion in green loans, accelerating renewable energy adoption (Eiff 2025).

Chile has emerged as a leader in Latin America's green finance landscape, being the first country to issue sovereign green bonds. By 2021, Chile had issued $3.8 billion worth of sovereign green bonds, which have been used to fund large-scale renewable energy projects such as solar and wind farms. These efforts have positioned Chile as a key player in advancing sustainable energy transitions (Climate Bonds Initiative, 2021; European Investment Bank 2024).

Brazil has leveraged green finance to support sustainable agriculture and renewable energy projects. In 2023, Brazil issued $2 billion in national sustainable bonds to fund initiatives to reduce deforestation and promote clean energy solutions. Corporate issuers such as Klabin have also utilized green bonds to finance biomass energy production and other eco-friendly industrial practices (Climate Bonds Initiative 2021; European Investment Bank 2024; Climate Investment Funds 2024).

Colombia issued its first domestic green bond worth $70 million to fund renewable energy projects and later launched a biodiversity-focused bond of similar value.

These initiatives highlight Colombia's efforts to integrate environmental sustainability into its financial markets (Climate Bonds Initiative 2021; European Investment Bank 2024).

Germany's success in green finance is primarily attributed to the KfW Renewable Energy Programme, which provides low-interest loans for renewable energy projects. Through this program, thousands of small-scale solar photovoltaic (PV) systems and wind turbines have been installed across Germany, significantly contributing to the country's transition toward a low-carbon economy (Ecofy Finance Private Limited 2023).

Croatia has implemented a citizen-led crowdfunding initiative for energy-efficient building renovations through its Citizen-Led Energy Renovation Fund. This fund supports approximately 250 households annually, significantly reducing thermal and electrical energy usage—up to 1,300 kWh per household per year (Ecofy Finance Private Limited 2023).

The analysis of successful green finance cases across various regions reveals several key lessons for effective implementation. Strong regulatory frameworks, exemplified by China's pilot zones, are crucial for attracting private-sector investments. Public-private partnerships, such as Singapore's Green Bond Grant Scheme, have proven effective in reducing risks for investors while scaling up renewable energy projects. Blended finance models, combining public subsidies with private capital as seen in Chile's sovereign green bonds, ensure financial viability for large-scale initiatives. Community engagement through localized approaches, like Croatia's citizen-led fund, fosters trust and encourages public participation in sustainable projects. Additionally, regional leadership, demonstrated by countries like Singapore and Chile, shows how proactive policies can position nations as hubs for sustainable finance. These diverse strategies illustrate how tailored approaches can address specific regional challenges while contributing to global sustainability goals, offering valuable insights for policymakers and investors worldwide.

4.2. Results: failure cases of green finance by regions

The Middle East and Central Asia (ME&CA) region faces significant obstacles in implementing green finance due to systemic vulnerabilities, limited institutional capacity, and climate-induced risks. Many countries in the region, particularly low-income and developing economies like Afghanistan, Pakistan, and Iran, rely heavily on climate-sensitive industries such as agriculture, fishing, and tourism. These sectors are highly susceptible to climate disasters, exacerbating poverty, unemployment, and food insecurity. Notably, seven of the region's ten most significant climate disasters since 2000 occurred in low-income countries, highlighting the fragility of their economic drivers and limiting investments in climate-resilient infrastructure. Additionally, oil-exporting nations face transition risks as the global shift toward renewable energy reduces demand for fossil fuels. This challenge is compounded by low carbon pricing and reliance on fossil fuel subsidies, with the banking sector in 30 ME&CA countries projected to incur cumulative loan losses of $11 billion by 2030 and over $50 billion by 2050 due to stranded assets.

Furthermore, the region has one of the lowest levels of insurance resilience globally; only 16% of insurance protection needs were met between 2005 and 2019. Climate-related disasters caused $44 billion in economic losses during this period, but only $2 billion was insured. This lack of coverage increases financial burdens on governments and deters private-sector investments in green finance initiatives (Radzewicz-Bak et al. 2024).

Despite its growing energy demand and vast renewable potential, Southeast Asia faces significant challenges in implementing green finance initiatives. The region grapples with regulatory uncertainty, exemplified by unclear power purchase agreement (PPA) regulations in countries like Indonesia, which have delayed renewable energy projects and created an unstable environment for long-term green investments (IFC 2023). However, current sustainable financing levels meet only one-sixth of this requirement. Greenwashing concerns have further eroded investor confidence, with allegations of companies misrepresenting their environmental credentials undermining trust in green bonds across the region (Cai 2023). Small and medium-sized enterprises (SMEs), which form a significant portion of Southeast Asia's economy, face additional barriers, including high costs, limited knowledge of sustainability practices, and restricted access to concessional financing. Despite recognizing the importance of sustainability, only 40% of SMEs in the region have adopted such measures, highlighting the need for targeted support and capacity building to drive green finance adoption across all sectors of the economy.

Latin America faces significant challenges in scaling green finance due to its dependence on fossil fuel revenues, weak financial systems, and sectoral vulnerabilities. Many countries, such as Brazil, rely heavily on fossil fuel exports, making the transition to renewable energy difficult. For instance, Brazil's Amazon Fund experienced setbacks due to political changes that eroded international donor confidence (Climate Investment Funds 2024). Public Development Banks (PDBs) in the region also struggle with limited access to long-term capital, essential for financing renewable energy projects. A survey revealed that 55% of PDBs identified inadequate client awareness about green finance opportunities as a significant barrier, further hindering progress (IFC 2023). Additionally, agriculture—a critical sector for many Latin American economies—is highly vulnerable to climate change impacts. The lack of adaptation investments exacerbates food insecurity and economic instability across the region, further constraining efforts to implement effective green finance initiatives.

Although Europe has long been a global leader in green finance, it now faces mounting challenges from political resistance, economic pressures, and unequal financing distribution. Countries like Poland depend heavily on coal subsidies in Eastern Europe despite receiving EU funding for renewable energy transitions. Political opposition to the European Green Deal has further created uncertainty about long-term commitments to sustainability goals (IFC 2023, 2017). Economic pressures, including rising inflation and higher interest rates, have increased the debt issuance cost for renewable energy projects, making green bonds less appealing to investors (IFC 2017). Additionally, financing remains disproportionately allocated, with fossil fuel companies receiving five times more funding than green initiatives, undermining Europe's efforts to meet its net-zero targets and maintain its leadership in global green finance (IFC 2023).

Analysing failure cases in green finance reveals several critical lessons highlighting the structural barriers impeding progress globally. Weak regulatory frameworks, such as inconsistent power purchase agreements (PPAs) in Southeast Asia, discourage private-sector participation. At the same time, limited access to long-term financing creates significant funding gaps, particularly in regions like Latin America. A lack of institutional capacity, especially among financial institutions in the Middle East, Central Asia, and Latin America, further hinders the effective implementation of green finance initiatives. Political instability, including resistance to sustainability policies in regions like Eastern Europe, generates uncertainty and undermines long-term commitments. Additionally, insurance gaps, particularly in the Middle East and Central Asia, exacerbate financial risks from climate disasters and deter private-sector investments. These challenges underscore the urgent need for stronger regulatory frameworks, expanded concessional financing, enhanced institutional capacity building, and increased international cooperation to overcome these barriers and scale green finance globally. Table 1 summarizes and compares the key metrics across several countries to highlight influential factors in green finance and renewable energy investments:

The analysis of green finance and renewable energy investments across various countries reveals several key factors driving success in this sector. Robust policy frameworks and regulatory support, exemplified by initiatives like China's Green Finance Pilot Zones and Singapore's Green Bond Grant Scheme, are crucial in attracting investments. Government-led programs, such as Germany's KfW Renewable Energy Programme and Chile's sovereign green bonds, significantly contribute to project implementation and investment growth. International collaboration and adherence to global standards, as demonstrated by France's partnership with Sweden and the adoption of EU initiatives, further enhance a nation's green finance ecosystem. Countries focusing on specific sectors, like Brazil's emphasis on sustainable agriculture and deforestation, can channel investments more effectively. Developing innovative financial instruments, including green bonds and sustainability-linked loans, also increases investment volumes and diversifies projects. Collectively, these factors underscore the importance of combining strong policy support, innovative financial mechanisms, and targeted sector approaches to create successful green finance and renewable energy investment strategies across different national contexts.

Table 1. Comparative analysis of green finance initiatives and renewable energy investments across selected countries

Country	Total Investment (USD)	Policy Frameworks	Outcomes
China	4.5 trillion	Green Finance Pilot Zones, strong regulations	Mobilized $4.5 trillion in green loans, 35.75 trillion yuan in outstanding green loans by Q3 2024
Singapore	9.6 billion	Green Bond Grant Scheme, subsidies for green bonds	47 green finance deals, significant solar capacity increase
Germany	13 billion	KfW Renewable Energy Programme, low-interest loans	Thousands of solar PV systems installed
Chile	3.8 billion	Sovereign green bonds, National Decarbonization Plan	Large-scale renewable energy projects funded
Brazil	2 billion	National sustainable bonds, focus on deforestation	Support for sustainable agriculture and clean energy
United Arab Emirates	Not specified	Dubai Declaration on Sustainable Finance	Framework for identifying contributions to green economy
France	Not specified	EU-level initiatives, partnership with Sweden	Stronger disclosure obligations, climate stress testing for banks, new green bonds

Source: prepared by the researcher based on the data in paragraph number 4.1.

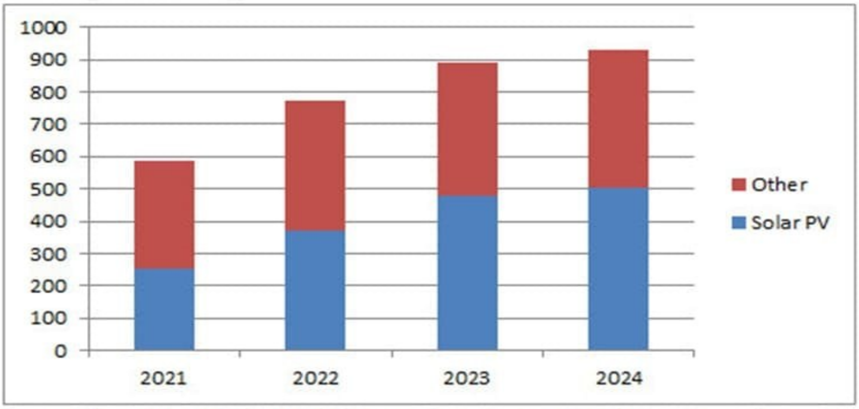
5. Discussion

The theoretical analysis of green finance and renewable energy investments reveals a complex interplay of frameworks that explain successes and challenges across different regions. The Data-Driven Sustainable Finance Framework has proven effective in countries like China and Singapore, where comprehensive risk assessment and impact quantification have optimized renewable energy investments. China’s Green Finance Pilot Zones exemplify how data-driven approaches can identify high-potential projects. However, this framework’s efficacy is limited in regions with systemic vulnerabilities, such as the Middle East and Central Asia, where inadequate data infrastructure and climate risk modelling capabilities hinder advanced analytics applications.

The Institutional-Policy Synergy Theory supports successful initiatives like Germany's KfW Renewable Energy Programme, demonstrating how well-crafted policies can encourage private investment in renewable energy. Conversely, this theory helps explain setbacks in Southeast Asia, where regulatory uncertainty has deterred private sector participation. The STIRPAT Environmental Impact Model offers insights into regional variations, highlighting China's strong technology channel effect in accelerating renewable technology R&D and deployment while revealing challenges in Latin America, where fossil fuel dependence impedes the renewable transition.

Risk-Return Optimization Theory is evident in successful blended finance models, such as Chile's sovereign green bonds, which effectively balance profitability and sustainability. However, this theory also illuminates challenges in regions like Africa, where high perceived risks and limited risk mitigation tools hinder investment. The Ecological-Economic Harmonization Theory is exemplified by initiatives like Croatia's Citizen-Led Energy Renovation Fund, which creates circular investment flows at the community level while also highlighting the persistent challenges in fossil fuel-dependent regions.

Figure 4: Global annual investment in Solar PV and other generation technologies from 2021 to 2024 (Billion USD)



SourceFigure1 to 4: IEA, World Energy Investment 2024, https://www.iea.org/reports/world-energy-investment-2024/overview-and-key-findings.

In the global context, a stark divide exists between regions successfully leveraging green finance and those struggling with structural barriers. This disparity is evident in the concentration of clean energy investments in countries like China and the United States, contrasting with the lag in Africa and Southeast Asia. As seen in the figure 4, the global shift towards renewable energy, particularly in solar PV investments, underscores green finance's potential to drive sustainable development. However, persistent challenges in scaling up these investments in developing economies highlight the need for targeted international cooperation and capacity-building efforts.

Critical examination of successes and failures raises questions about the replicability and scalability of green finance initiatives. China's success in mobilizing green loans, partly due to its unique political and economic structure, may not be easily replicated elsewhere. Failures in regions like the Middle East and Central Asia underscore the critical role of underlying economic structures and institutional capacities in determining the effectiveness of green finance initiatives.

This analysis reveals several areas for future research and policy development, including tailoring green finance strategies for resource-dependent economies, enhancing climate risk modelling and data infrastructure in vulnerable regions, designing innovative risk mitigation tools for high-risk environments, and accelerating technology transfer and capacity building in developing economies. By addressing these areas, policymakers and researchers can work towards more effective and equitable green finance solutions that drive global progress in renewable energy investments.

6. Policy implications and recommendations

Analysing green finance initiatives and their impact on renewable energy investments yields several critical policy implications and recommendations. These strategies aim to create a more favourable environment for green finance and accelerate the global transition to renewable energy.

Strengthening regulatory frameworks should be a primary focus. This involves implementing robust and consistent policies that provide long-term certainty for investors (Azhgaliyeva et al. 2018), developing sector-specific decarbonization roadmaps (Griffa 2025), and establishing transparent accountability mechanisms. These measures will help maintain integrity in green finance markets and clarify pathways for different industries.

Enhancing financing mechanisms is equally crucial. Policymakers should prioritize blended finance models that combine public and private capital, expand access to concessional financing (especially for emerging markets and developing economies) (Criscuolo et al. 2014), and promote innovative financial instruments like green bonds (Griffa 2025). These strategies can effectively mobilize capital for renewable projects.

Supportive legal frameworks for research and development in renewable energy should be created to foster innovation and technology advancement. Collaboration with international organizations can accelerate technological progress and reduce costs. Additionally, implementing differentiated support for emerging versus near-competitive renewable technologies can drive further advancements (Criscuolo et al. 2014).

Improving policy design is another key area. This includes designing feed-in tariffs to compensate for cost differences between renewables and fossil fuels, using renewable energy certificates to incentivize innovation in near-competitive technologies, and considering upstream R&D support alongside output-based incentives (Criscuolo et al. 2014).

Promoting international cooperation is vital for sustainable development. Establishing bilateral and multilateral agreements can mobilize resources while harmonizing green finance standards and practices across jurisdictions and facilitate cross-border investments in renewable energy projects (Criscuolo et al. 2014).

Addressing regional challenges requires tailored strategies to overcome structural barriers such as high capital costs and weak governance. Providing targeted support and capacity building for small and medium enterprises and developing region-specific risk mitigation tools can attract private investment.

By implementing these recommendations, policymakers can create a more conducive environment for green finance and accelerate the transition to renewable energy globally. Success will depend on consistent political commitment, innovative financing approaches, and international collaboration to overcome persistent barriers and scale up sustainable investments.

7. Conclusion

The comprehensive analysis of green finance initiatives for renewable energy reveals a nuanced global landscape with promising successes and persistent challenges. The study highlights that effective implementation of green finance mechanisms depends on tailored strategies addressing specific regional contexts. Key success factors include strong regulatory frameworks, innovative blended finance models, and community engagement, which have proven effective in driving renewable energy adoption, particularly in Asia, Europe, and Latin America. However, persistent barriers such as weak regulations, limited access to long-term financing, political instability, and insufficient institutional capacity impede progress in regions like Africa, Southeast Asia, and parts of Europe. The analysis underscores the critical importance of addressing these structural barriers through enhanced international cooperation, capacity building, and policy innovation to achieve a sustainable, low-carbon future globally. Moving forward, concerted efforts from governments, financial institutions, and the private sector will be essential to develop context-specific solutions that can effectively mobilize green finance for renewable energy across all regions, ultimately accelerating the transition to a more sustainable energy landscape worldwide.

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Analysis of Value-at-Risk (VaR) of Naira against BRICS Currencies

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Aim: This study investigates foreign exchange market dynamics by forecasting and analyzing the Value-at-Risk (VaR) for the Nigerian Naira against BRICS currencies utilizing daily data from January 1, 2010 to December 31, 2024.

Design/Research methods: The five BRICS currencies (BRL, RUB, INR, CNY, and ZAR), were analyzed to explore the impact of foreign exchange market dynamics on the Nigerian Naira against BRICS currencies. The value-at-risk methodology was implemented plus the Monte Carlo simulation. The calculated VaR95% quantifies potential losses, emphasizing the importance of managing downside currency exchange risks in a volatile financial market at both the 95% and 99% confidence thresholds. The robustness of the Monte-Carlo simulation (MCS) and historical simulation (H-S) results validates the conditional variances and the corresponding value-at-risk estimates for the Naira exchange rate in relation to each currency of the BRICS derived from the variance-covariance model. GJR-GARCH model reveals critical insights into the valuation and volatility risk associated with the Naira exchange rate against BRICS currencies.

Findings: The valuation of the Naira/Real rate has significant vulnerabilities to changes in oil prices, external debt, and changes in money supply; the results show that the Naira/Rubble exchange rate had significant and negative responsiveness to changes in output growth, crude oil prices and external debt levels; valuation of the Naira/Rupee exchange rate is significantly responsive to the vulnerability of trade balance, external reserves, foreign debt, monetary policy rate, and crude oil prices; valuation of the Naira/Yuan exchange rate has significant vulnerabilities to changes in oil prices, output growth, external debt, and CBN policy rate; valuation of the Naira/Rand has significant vulnerabilities to changes in external reserves, financial healthiness and external debt levels.

Originality / value of the article: The study findings are robust explanation of asymmetric risk identified by VaR with policy advice for the CBN to strategically rebalance its exposure to BRICS currencies by using risk-weighted analysis instead of just trading volumes. Also, the study contributed to prediction of possible losses associated with unfavorable Naira currency fluctuations when trading particularly with

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the BRICS, and so emphasized the necessity for the adoption of VaR-based stress testing to national foreign exchange reserves and financial institutions. Conclusion: Given the asymmetric risk, the CBN should intentionally rebalance its exposure to BRICS currencies by using risk-weighted analysis instead of just trading volumes. For example, the CBN ought to look at establishing more local currency settlement agreements with the BRICS countries. This could reduce exposure to the volatility of the US dollar and dependence on it.

Keywords: Variance-Covariance methodology, Monte-Carlo Simulation (MCS), Historical-Simulation (H-S), BRICS currencies, VaR, Naira Exchange Rate
JEL: B23, D25, C17.

1. Introduction

The performance of the Nigerian Naira in the foreign exchange market has been marked by substantial volatility, particularly when compared to other global currencies. This volatility is primarily driven by Nigeria's heavy reliance on oil exports, which leaves the Naira vulnerable to fluctuations in global oil prices. Between 2014 and 2016, a significant decline in oil prices contributed to the weakening of the Naira as Nigeria’s foreign reserves dwindled, forcing the Central Bank of Nigeria (CBN) to adopt measures aimed at stabilizing the currency (FEWS NET 2016). Thus, to address this issue, in 2017, the CBN introduced the Investors and Exporters (I&E) window to facilitate a market-driven exchange rate, thereby improving liquidity and reducing the pressure on the official exchange rate. Despite these efforts, the Naira continues to experience substantial fluctuations, driven by domestic policy and external factors, such as global economic conditions and speculative market activities (Chinwe 2024). Additionally, the continued presence of the parallel market, where exchange rates often reflect a more accurate market-driven value of the Naira, has exacerbated the discrepancies between official and market rates, complicating the management of the Naira’s value (Bamidele 2024). So, the Naira’s ongoing volatility remains a critical challenge for businesses and consumers in Nigeria, influencing inflation, trade, and investment decisions. The complexities of managing the Naira’s value in this dynamic environment state the importance of consistent and adaptive economic policies (Olu, Anu 2019).

This research centers on understanding the Value-at-Risk (VaR) of the Naira exchange rate vis-à-vis the currencies of the BRICS countries. This is crucial for policymakers, investors, and businesses in those nations engaged in international trade and investment. Among the BRICS nations, the Brazilian Real (BRL) has limited direct impact on Nigeria's economy but plays a role through trade in commodities like agriculture and raw materials. Additionally, Brazilian investments in Nigeria's infrastructure and mining sectors create indirect linkages between the BRL and the Naira (Fernandes 2024). The Russian Ruble (RUB) influences Nigeria primarily through energy, defense, and mining industries. While its direct economic linkages are small, fluctuations in the RUB-Naira exchange rate impact the cost of Russian imports, including oil and military equipment (Ezinwa, Anyanwu 2019). The Indian Rupee (INR) influences Nigeria's economy through trade in pharmaceuticals, technology, and other manufacturing sectors. Economic or currency fluctuations in India can affect Nigeria's import costs and capital flows, while India's growing investments in Nigeria in sectors like technology and education further connect the two economies (Oseni 2020).

Moreover, the Chinese Yuan (CNY) is perhaps the most significant BRICS currency for Nigeria. China's status as one of Nigeria's largest trade partners, especially in non-oil goods like electronics, machinery, and manufactured products, means that fluctuations in the CNY-Naira exchange rate have substantial impacts on Nigeria's trade dynamics. China's investment in infrastructure projects across Africa, including Nigeria, also links the Yuan directly to Nigeria's investment landscape (Adeniran, Popoola 2020). The South African Rand (ZAR) affects Nigeria's trade relations within Africa. As Nigeria's trade partner in sectors like energy and retail, the ZAR's fluctuations can influence the costs of cross-border trade, with potential effects on Nigeria's business environment and inflation rates (Olawale, Garwe 2021). Thus, these key global and BRICS currencies play significant roles in shaping Nigeria's economic interactions. From trade and investment flows to the management of Nigeria's foreign reserves, these currencies directly influence the Naira's exchange rate, inflation, and overall economic stability.

Empirical literature highlights these gaps, emphasizing the need for tailored methodologies that account for Nigeria's unique economic and policy environment. The estimation of VaR for the Nigerian Naira further underscores the complexities of managing financial risks where exchange rates can exhibit sudden and extreme fluctuations. This challenge is particularly pronounced in Nigeria, where currency depreciation and speculative activities in the parallel market exacerbate volatility. The relevant research question is: What is the Value-at-Risk (VaR) for the Naira exchange rate in relation to the Brazilian Real, Russian Ruble, Indian Rupee, Chinese Yuan, and South African Rand using the VaR estimation method? Against the backdrop of the research question, the study seeks to forecast the exchange rate of the Naira and estimate its VaR in relation to emerging market currencies (Real, Rubles, Rupee, Yuan, Rand).

The significance of this research lies in its potential to advance knowledge in the fields of foreign exchange forecasting and risk estimation, particularly within the unique context of Nigeria's economy. As an emerging market, Nigeria faces persistent challenges in managing exchange rate volatility, which impacts macroeconomic stability and financial decision-making. Besides, foreign exchange forecasting and VaR analysis are pivotal in addressing the complexities of currency dynamics, particularly for the Nigerian Naira, which is prone to volatility due to factors such as oil price fluctuations, inflation, and macroeconomic instability. VaR, widely regarded as a cornerstone in risk management, quantifies the maximum potential loss of assets under adverse conditions within a defined time horizon. The V-C, MCS, and H-S add value by estimating various potential losses under conditions of uncertainty, making them particularly useful for addressing the risk of forex markets (Sun et al. 2019; Ren et al. 2021). Together, by evaluating risk assessment techniques like V-C, MCS, and H-S; these tools help mitigate the challenges posed by forex volatility, enabling stakeholders to navigate uncertainties more effectively.

The study contributes to existing literature by exploring the applicability of modern forecasting and risk estimation techniques in an emerging economy like Nigeria. Policymakers will benefit significantly from this research, as it provides empirical evidence on currency fluctuations and their effects on the Naira. Nigeria's dependence on oil exports, fluctuating foreign reserves, and exposure to external shocks make currency stability a crucial policy objective. By understanding the dynamics of how global currencies, including the USD, EUR, and CNY, interact with the Naira, policymakers can develop robust strategies to minimize economic vulnerabilities and ensure sustainable growth (Ibrahim et al. 2020).

The present research builds on this historical foundation to explore contemporary forecasting and risk management issues, bridging gaps in the empirical understanding of Nigeria's foreign exchange market (Ibekwe et al. 2022). This follows from the fact that the Nigeria's foreign exchange landscape has undergone significant shifts. From a fixed exchange rate regime in the 1960s to various forms of managed float systems, the Naira has experienced periods of stability and extreme volatility. Structural reforms in the 1980s, such as the Structural Adjustment Program (SAP), initiated the liberalization of the foreign exchange market, but the lack of consistent implementation has often led to instability. More recently, policy responses to external shocks, such as oil price declines and global financial crises, have further highlighted the challenges of managing exchange rate volatility in an open economy.

The research's contributions extend beyond its immediate findings. It addresses methodological gaps by exploring the suitability of advanced models like Monte Carlo (MCS) simulations and historical simulation (H-S) and the variance-Covariance (V-C) methods for evaluating risk of exchange rates of emerging market economies. This validates the effectiveness of these models and provides a framework for future studies in similar contexts, enhancing the academic discourse on financial risk estimation and exchange rate dynamics (Oyetade et al. 2019). This study is structured into five comprehensive sections to ensure a logical progression from the research problem to actionable insights. The first section introduces the study; it establishes the context and relevance of the study, particularly in the field of exchange rate forecasting and risk estimation for the Nigerian Naira. The second section provides a critical review of existing literature, focusing on exchange rate risk based on Value-at-Risk (VaR) estimation techniques. The third section details the research methodology, explaining the data collection, modeling, and analysis procedures. The fourth section presents the results of the analysis, offering a detailed interpretation of the findings. Section five concludes the research by highlighting some findings that contribute meaningfully to literature and practical applications while also emphasizing the study's limitations and propose directions for future research.

2. Previous scientific research findings

The VaR estimation has evolved to address exchange rate volatility challenges. Singh & Kumar (2024) employed the wavelet transform theory to estimate the VaR for the INR/USD exchange rate. Using daily exchange rate data from 2015 to 2023, the study demonstrated that wavelet-based models effectively captured multi-scale volatility dynamics, which are critical during rapid market shifts. The research highlighted the capability to identify localized spikes in volatility while maintaining accuracy over extended horizons. Johnson & Roberts (2024) applied the ensemble learning theory method to estimate the VaR for the GBP/USD exchange rate. The study demonstrated that ensemble methods, particularly boosting algorithms, excelled in improving predictive accuracy across various market conditions. The study emphasized that ensemble learning's adaptability to diverse conditions makes it essential for precise risk estimation. The study suggested that financial institutions adopt ensemble frameworks to enhance VaR accuracy and mitigate losses in dynamic currency markets.

Dlamini et al. (2024) combined GARCH and extreme value theory (EVT) to estimate the VaR for the ZAR/USD exchange rate, basing their approach in the hybrid model theory. Using daily exchange rate data from 2010 to 2023, the study demonstrated that the GARCH-EVT hybrid model provided superior estimates of extreme losses. This approach was particularly effective during high-volatility periods, accurately capturing rare but impactful events in the currency market. The findings stated the hybrid model's utility in managing currency risk, particularly for emerging markets with high exposure to external shocks.

Zhao et al. (2024) advanced Monte-Carlo historical simulation (MCS) by integrating agent-based models that capture behavioral and systemic feedback loops. For VaR estimation across market regimes, reliance on GARCH-family models dominates, with Ofori & Mensah (2023) highlighting their strengths during stable periods but limitations during crises. The authors applied the historical simulation theory to estimate the VaR for the NGN/USD exchange rate, emphasizing its reliance on past market behavior as a predictor of future risks. Using exchange rate data from 2015 to 2022, the study found that MCS produced reliable VaR estimates during periods of market stability. It suggested integrating extreme value theory (EVT) with historical simulation to enhance its capability in modeling extreme tail risks. The study resolved that such hybrid approaches would improve VaR accuracy in highly volatile markets like Nigeria's. Nonetheless, its accuracy declined during crises when market dynamics significantly deviated from historical norms. Besides, their focus on developed economies limits applicability to Nigeria's diverse volatility drivers.

Ali et al. (2023) explored the use of machine learning algorithms, including decision trees and random forests, for VaR estimation of the PKR/USD exchange rate, basing their work on ensemble learning theory. Using data spanning 2010 to 2022, the study demonstrated that ensemble methods provided more accurate and stable risk estimates, particularly in volatile settings. The findings highlighted the robustness of ensemble approaches in adapting to diverse market conditions and managing uncertainty. López & Martinez (2022) relied on Quantile Regression (QR) method to estimate the VaR for the MXN/USD exchange rate, emphasizing QR's suitability for analyzing the tails of return distributions. The study utilized daily exchange rate data from 2015 to 2021, focusing on the lower quantiles to estimate downside risks during periods of market volatility. Results showed that QR outperformed traditional linear regression models by providing more accurate and tailored risk estimates under extreme conditions. The findings underlined QR's ability to adapt to market regimes and its theoretical relevance for asymmetric risk analysis. The resolved that incorporating QR into risk management practices could enhance the precision of VaR estimates, particularly for currencies prone to high volatility, such as the MXN/USD pair.

Müller et al. (2022) employed the Component GARCH (CGARCH) model, rooted in volatility decomposition theory, to estimate the VaR of the CHF/USD exchange rate. Using daily data spanning 2010 to 2020, the study revealed that the CGARCH model effectively captured persistent volatility trends and transitory fluctuations. The results showed that the model provided superior VaR estimates compared to standard GARCH models, particularly during periods of sustained volatility. It established that CGARCH aligns with the theoretical framework of volatility decomposition, offering a valuable approach for improving currency risk forecasts in stable and volatile market settings.

Zhang et al. (2022), drawing from the support vector machine (SVM) theory, examined the integration of SVM with MCS (SVM-MCS) for estimating the VaR of the JPY/USD exchange rate. The SVM theory posits that the algorithm captures complex, non-linear relationships by finding optimal boundaries between data points in high-dimensional spaces. Utilizing exchange rate data from 2011 to 2021, the study demonstrated that the hybrid SVM-MCS approach outperformed standalone SVM and traditional parametric models in accurately estimating tail risks. The study endorsed adopting SVM-MCS frameworks for financial institutions to improve risk modeling and mitigate potential losses during volatile market phases.

Kim & Choi (2021) applied deep learning models rooted specifically long short-term memory (LSTM) networks, to estimate the VaR for the USD/KRW exchange rate. The study utilized exchange rate data from 2010 to 2020, finding that LSTM models significantly outperformed traditional GARCH models in predictive accuracy and computational efficiency. The research established that LSTM models offer a superior approach for VaR estimation in volatile markets, recommending their adoption in modern financial risk assessment practices.

Silva et al. (2021) assessed the combination of GARCH and Artificial Neural Networks (ANN) for estimating the VaR of the BRL/USD exchange rate. Using data spanning 2010 to 2020, the study found that the hybrid GARCH-ANN model effectively captured non-linear volatility patterns and offered superior risk estimates compared to standalone GARCH models. The research highlighted that the hybrid model's ability to adapt to changing market dynamics and volatility made it an essential tool for financial risk management in emerging markets. Silva et al. suggested further exploration of hybrid frameworks to enhance VaR estimation accuracy in complex financial systems. Wang et al. (2020) utilized Copula theory to estimate VaR for the CNY/USD exchange rate, highlighting the theory's capability to model dependency structures between variables independent of their marginal distributions. Analyzing high-frequency data from 2010 to 2018, demonstrated that copula-based models effectively captured joint dependencies and tail behaviors, outperforming traditional approaches in volatile market conditions. The findings underscored the theoretical significance of copulas in addressing the complexities of exchange rate dynamics, particularly during periods of heightened uncertainty.

The reviewed studies on exchange rate forecasting and VaR estimation reveal gaps remain that necessitate additional research, particularly in the context of emerging markets such as Nigeria. These include the integration of advanced forecasting methods, such as MCS, H-S, and V-C methods for robust VaR estimation of the Naira exchange rate in volatile markets. The MCS has shown success in forecasting exchange rate volatility in advanced and emerging economies, as demonstrated by Chen & Zhang (2019) and Williams et al. (2020). Nonetheless, its application to African currencies, particularly the Nigerian Naira (NGN), remains limited. Ahmed et al. (2021) and Okafor & Adeyemi (2022) explored Nigeria's context but lacked comprehensive modeling of external shocks and non-linearities, emphasizing short-term horizons. While Ahmed et al. (2021) applied MCS to the NGN/USD exchange rate considering oil price fluctuations; their focus on oil-related shocks overlooks other significant drivers, such as market sentiment and behavioral dynamics. Besides, the hybrid approaches utilized by Zhao et al. (2024) have not yet been extended to the Naira exchange rate.

Existing researches are less relevant to the specific obstacles faced by emerging economies since the majority of research focuses on advanced economies with reliable financial systems and easily accessible data. The evaluation of African currencies, such as the NGN, which is impacted by changes in the price of oil, trade imbalances, and political unrest, is seriously lacking. Nigeria's major trading currencies, including regional rivals and new partners like the CNY, are mostly ignored in research that focusses on international currency pairs like USD/EUR or USD/JPY. This omission restricts the findings' relevance to the economic environment of Nigeria. There is a dearth of thorough comparisons between the MCS and V-C methods of predicting the VaR of the Naira exchange rate. While evaluating the advantages and disadvantages of MCS and ARIMA, Okafor & Adeyemi (2022) neglected to take exogenous shocks or medium- to long-term forecasting into account. This present work provides a thorough analysis of these approaches and their consequences for estimating VaR in the economic setting of Nigeria. By measuring VaR using the MCS and H-C methodologies for currencies essential to Nigeria's trade and investment landscape, this study closes this gap. Furthermore, there is a lack of a comprehensive framework that integrates risk estimation and forecasting techniques; instead, research have addressed them separately (e.g., Ahmed et al. 2021; Chen et al. 2019).

Another population gap lies in the narrow temporal scope of many studies, which frequently exclude data from periods of economic instability, such as the Covid-19 pandemic and sectoral analyses of critical areas like agriculture and informal trade. These omissions limit understanding of how exchange rate volatility affects diverse economic actors. This study addresses these gaps by focusing on the Naira, key trading currencies, and a broader range of stakeholders, including SMEs and individuals. It also incorporates data from periods of instability and examines sectoral impacts to provide a more inclusive and context-specific analysis of exchange rate forecasting and risk estimation for Nigeria. By integrating advanced forecasting techniques, external variables, and systematic comparisons, this research aims to address the gaps identified and contribute meaningfully to the fields of exchange rate forecasting and risk management. Thus, this study addresses these gaps by applying MCS to forecast exchange rates of selected currencies against the Nigerian Naira, incorporating external variables such as interest rate differentials and inflation rate differentials. This study addresses these gaps by extending MCS and ARIMA applications to multiple currencies, incorporating advanced VaR estimation technique, and integrating forecasting and risk frameworks. This will provide actionable insights for policymakers and financial stakeholders managing Nigeria's volatile exchange rate environment.

3. Methodology

In foreign exchange markets, Modern Portfolio Theory (MPT) provides a framework for assessing risk-return trade-offs in currency investments. The MPT, developed by Markowitz (1952), emphasizes the importance of diversification in portfolio construction to optimize the Naira exchange rate returns against the currencies of the BRICS for a given level of risk. Besides, Obi et al. (2022) utilized MPT to optimize currency portfolios under volatile conditions. These unpredictable circumstances inform the methodological approach of this study, particularly the integration of VaR models and MCS for risk assessment and forecasting. Since MPT provides a robust framework for assessing and quantifying risk associated with exchange rate movements through VaR, VaR analysis is useful for implementing risk management measures, such as adjusting currency positions or hedging instruments like options and forwards, to mitigate the risks of adverse currency movements. The VaR was estimated using the V-C method, sometimes referred to as the parametric method, which accounts for the exchange rate's sensitivity to changes in price. 5,110 days of historical data for the daily exchange rate returns and losses of the Naira and the currencies of the BRICS nations were used to estimate the V-C matrices displayed below.

$$Var-Cov=\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/BRL}\\ \sigma_{NGN/BRL} & \sigma^2_{NGN}\end{bmatrix}, Var-Cov=\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/RUB}\\ \sigma_{NGN/RUB} & \sigma^2_{NGN}\end{bmatrix}$$

$$Var-Cov=\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/INR}\\ \sigma_{NGN/INR} & \sigma^2_{NGN}\end{bmatrix}, Var-Cov=\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/CNY}\\ \sigma_{NGN/CNY} & \sigma^2_{NGN}\end{bmatrix}, Var-Cov=\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/ZAR}\\ \sigma_{NGN/ZAR} & \sigma^2_{NGN}\end{bmatrix}$$

The volatility of the aggregate changes in exchange rate losses was articulated as a function of the vector of market-price sensitivities, the standard deviations of the exchange rate returns between the Naira and the BRICS currency as well as the covariance between the two currencies. Thus, the standard deviation of changes in the exchange rate between the Naira and each of the BRICS currencies is given as:

$$S_{NGN/BRL}=\sqrt{\begin{bmatrix}\delta_{NGN} & \delta_{BRL}\end{bmatrix}\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/BRL}\\ \sigma_{NGN/BRL} & \sigma^2_{NGN}\end{bmatrix}\begin{bmatrix}\delta_{NGN}\\ \delta_{BRL}\end{bmatrix}}, S_{NGN/RUB}=\sqrt{\begin{bmatrix}\delta_{NGN} & \delta_{RUB}\end{bmatrix}\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/RUB}\\ \sigma_{NGN/RUB} & \sigma^2_{NGN}\end{bmatrix}\begin{bmatrix}\delta_{NGN}\\ \delta_{RUB}\end{bmatrix}}$$

$$S_{NGN/INR}=\sqrt{\begin{bmatrix}\delta_{NGN} & \delta_{INR}\end{bmatrix}\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/INR}\\ \sigma_{NGN/INR} & \sigma^2_{NGN}\end{bmatrix}\begin{bmatrix}\delta_{NGN}\\ \delta_{INR}\end{bmatrix}}, S_{NGN/CNY}=\sqrt{\begin{bmatrix}\delta_{NGN} & \delta_{CNY}\end{bmatrix}\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/CNY}\\ \sigma_{NGN/CNY} & \sigma^2_{NGN}\end{bmatrix}\begin{bmatrix}\delta_{NGN}\\ \delta_{CNY}\end{bmatrix}}$$

$$S_{NGN/ZAR}=\sqrt{\begin{bmatrix}\delta_{NGN} & \delta_{ZAR}\end{bmatrix}\begin{bmatrix}\sigma^2_{NGN} & \sigma_{NGN/ZAR}\\ \sigma_{NGN/ZAR} & \sigma^2_{NGN}\end{bmatrix}\begin{bmatrix}\delta_{NGN}\\ \delta_{ZAR}\end{bmatrix}}$$

Under this methodology, VaR was estimated by calculating the mean return and standard deviation of returns. Using these parameters, the potential losses over a given time period was estimated. The estimation of the VaR for the exchange rate between the Naira and any of the BRICS currencies for a given threshold of confidence was such that the standard deviation was scaled by the standard normal threshold factor. Considering that financial-asset returns and, consequently, exchange rate returns and losses are normally distributed that financial-asset returns and hence, exchange rate returns and losses are normally distributed. The appropriate scaling factors for the 99% and 95% levels of confidence are 2.33 and 1.645. As a robustness check, the MCS and Historical-Simulation (H-S) methods were used in addition to the V-C otherwise parametric method. The MCS is an advanced method that simulates several possible future events by using samples at random from a probability distribution. The MCS technique generates VaR in the FX context by determining the worst loss in the distribution and producing a range of potential future currency price movements. MCS's adaptability makes it possible to incorporate non-linearities which make it suitable for portfolios with intricate structures.

The core theory of the MCS method was the replication of numerous potential future price fluctuations that would have an impact on the value of the Naira relative to the BRICS currencies. The bivariate t-distribution with a correlation coefficient of 0.7955 was used to extract the exchange-rate returns and losses for currency pairs. A t-distribution was chosen for being able to measure the fat-tails characteristic observed in the data. The MCS generated series of pseudo-random figures to simulate macroeconomic factors and the financial variables of the study. One hundred thousand (100,000) simulations of the currency exchange rates were performed. For every currency pair, the Naira exchange rate was recalculated. Following a revaluation of the Naira exchange rate for every currency pair of simulated exchange rates, the differences between the current and the revalued return/losses were calculated for the NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, and NGN/ZAR exchange rate. Simulation of the effects of variables and market events that were not observed during the historical era but have the potential to occur is made possible by the MCS. A unique VaR estimate was obtained by analyzing the changes in exchange rate values.

Also, using historical data on the daily exchange rate of the Naira versus the BRICS currencies, the historical-simulation (H-S) approach calculates the VaR estimate by first applying each of the 5,110 currency pairs of the daily exchange rate changes that would have occurred if the current currency exchange rate had remained constant over those 5,110 trading days. This is followed by a revaluation of the exchange rates using the previous exchange rates of each nation, and then sorting the 5110 changes (losses/returns) in the value of the Naira exchange rate in order of magnitude to arrive at an observed distribution of changes in the exchange rates of the

Naira and BRICS currencies. This is because the H-S does not offer an underlying statistical assumption for the distribution of exchange rate losses and returns. So, the VaR estimate equals the percentile linked to the threshold of confidence.

Accordingly, the VaR framework which provides information into the forecasting dynamics between exchange rate losses and the implications for risk management fits so nicely with the objectives of the study. The VaR is a crucial risk management tool that measures possible losses at different confidence levels, which is consistent with MPT theories. This study estimates the VaR associated with the Naira exchange rate vis-à-vis the BRICS currencies by calculating the VaR for the chosen currency pairs. The MPT strengthens estimation of risk or losses particularly in dynamic markets. The VaR is a vital instrument in financial risk management since it measures the possible loss of the value of an asset or portfolio over a certain time period at a specific confidence level.

In foreign exchange (FX), VaR measures the greatest possible loss in a currency portfolio by taking into account the likelihood of unfavourable market changes over a predetermined period of time. The value of the VaR resides in its capacity to give financial organizations a tangible indicator of risk, allowing them to evaluate probable losses from exchange rate swings, allocate capital efficiently, and maintain adequate reserves to cover future losses. Regulators also utilize VaR to assess the solvency of financial organizations, establishing capital adequacy standards based on anticipated exchange rate losses (Bank for International Settlements 2022). By fusing the techniques of V-C, the MCS and H-S methods with the GJR-GARCH regression model, the VaR approach becomes a powerful tool for evaluating currency exchange risk, allowing analysts to quantify the potential losses associated with exchange rate fluctuations based on historical data and economic factors. Moreover, by analyzing how macroeconomic and financial factors influence exchange rate changes, this approach offers a valuable framework for risk management in currency portfolios. This helps to guarantee that possible losses remain within manageable bounds. The regression model can be expressed as follows:

$$EXCRAT = \alpha + \beta_1(m2/gdp) + \beta_2(Opr) + \beta_3(Ogr) + \beta_4(ERev) + \beta_5(Mpor) + \beta_6(Tbal) + \epsilon_t \quad (1)$$

Where EXCRAT is the exchange rate (dependent variable) for the selected currency pairs (NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, NGN/ZAR), financial healthiness measured as changes in broad money supply as a percentage of output (m2/gdp), trade balance-deficit or surplus (Tbal), external reserves (ERev), monetary policy rate (Mpor), changes in BRENT oil prices (Opr), output growth rate (OgR), α is constant term, β_1, β_2, β_3, β_4, β_5, β_6 are coefficients measuring the impact of each independent variable on the exchange rate of the Naira in relation to each of the BRICS currencies, ε is error term capturing unobserved factors affecting the exchange rate. The model is further enhanced using advanced econometric techniques to ensure robustness and predictive accuracy. The model offers an additional layer of risk quantification by incorporating volatility measures and macroeconomic indicators into the VaR estimation, making it a more comprehensive tool for risk management.

VaR is frequently used in the management of foreign exchange portfolios of currencies since it aids in evaluating and controlling the risks related to changes in currency prices. VaR can be used to calculate the overall risk of a multi-currency portfolio by adding the exchange rate risk of each individual currency holding. This makes it possible for financial firms to establish risk thresholds, distribute funds efficiently, and create hedging plans to reduce any losses. The study examines the exchange rate changes of the Naira in relation to five emerging market currencies: the South African Rand, the Indian Rupee, the Chinese Yuan, the Russian Ruble, and the Brazilian Real. A number of important international and emerging market currencies have an impact on the Nigerian economy, which is reflected in the Nigerian Naira (NGN), the country's currency. A specific time frame, from January 1, 2010 to December 31, 2024, was covered for the analysis, which makes use of daily exchange rate data. The m2/gdp ratio was calculated by adding up the currency outside the banking system, demand deposits, time, savings, and foreign currency deposits, as well as bank and traveler's checks and other securities like commercial paper. The m2/gdp ratio measures the healthiness of the financial industry of the countries in the study. Then sources of these data were the databases of the World Bank (https://data.worldbank.org/indicator).

4. Results

This section systematically addresses the study objectives by presenting the empirical findings and providing an in-depth discussion of the implications for services trade policies in the examined regions. Results are analyzed in light of theoretical expectations and prior empirical studies to draw meaningful conclusions. All of the variables are integrated of order I(1), according to the results in the Appendix; the results of the co-integration test for the Russian Ruble (RUB) vs the Nigerian Naira (NGN) point to an extended equilibrium connection between the independent variables and the exchange rate (EXCRAT). The VaR of NGN/BRL exchange rate based on V-C in Table 1 provides insights into potential risks associated with exchange rate fluctuations. In this model, the mean return (μ) is 2.77050, which represents the expected return based on historical data. The Z-value ($Z_{0.05}$) and Z-value ($Z_{0.01}$) are 1.645 and 2.33 corresponding to 95% and 99% confidence levels, indicating the likelihood that the losses will not exceed the estimated VaR. The conditional variance (σ^2) of 308.64587 is calculated using a V-C model, which accounts for time-varying volatility, while the conditional standard deviation (σ) is 17.56832. The VaR at the 95% and 99% confidence level are 28.89989, and 40.93419 giving the maximum expected losses over one day, with 5% and 1% probabilities that losses will exceed the VaR values.

Table 2 summarizes the VaR of NGN/BRL exchange rate based on H-S while Table 3 presents the VaR results of NGN/BRL exchange rate using the MCS. The MCS VaR estimates of NGN/BRL exchange rate at the 95% and 99% threshold levels include 126.1792 and 425.3150; while the H-S method, the VaR estimates for the 95% and 99% levels of thresholds are 26.34855 and 37.33921 respectively.

Table 1. Value-at-Risk (VaR) of NGN/BRL exchange rate based on variance-covariance

Parameter	Value	Narration
Mean Return (μ)	2.77050	The constant term from the mean equation represents the expected return
Z-Value ($Z_{0.05}$)	1.645	Z-score for a 95% confidence level
Z-Value ($Z_{0.01}$)	2.33	Z-score for a 99% confidence level
Conditional Variance (σ2)	308.6587	Variance estimate
Conditional Std. Dev. (σ)	17.5632	Standard deviation, σ2
VaR ($VaR_{95\%}$)	28.89989	Maximum expected loss at 95% confidence for one day
VaR ($VaR_{99\%}$)	40.93419	Maximum expected loss at 99% confidence for one day
Confidence Level	95%	Indicates that losses will not exceed the VaR in 95% of the cases
Confidence Level	99%	Indicates that losses will not exceed the VaR in 99% of the cases
Time Frame	Daily	Each VaR result applies to a single day from January 1, 2010 – December 31, 2024)

Source: authors' estimation results (2025).

Table 2. Value-at-Risk (VaR) of NGN/BRL exchange rate based on historical simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	26.34855	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	37.33921	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 3: Value-at-Riks (VaR) of NGN/BRL exchange rate based on Monte-Carlo simulation

Parameter	**Value**	**Narration**
VaR ($VaR_{95\%}$)	126.1792	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	425.3150	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 4. Value-at-Risk (VaR) of NGN/RUB exchange rate based on variance-covariance

Parameter	**Value**	**Narration**
Mean Return (μ)	60.94285	The constant term from the mean equation represents the expected return.
Z-Value ($Z_{0.05}$)	1.645	Z-score for a 95% confidence level
Z-Value (Z0.01)	2.330	Z-score for a 99% confidence level
Conditional Variance (σ2)	434.9352	Variance estimate
Conditional Std. Dev. (σ)	20.8551	Standard deviation, σ2
VaR ($VaR_{95\%}$)	34.30664	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	48.59238	Maximum expected losses at 99% confidence for one day
Confidence Level	95%	Indicates that losses will not exceed the VaR in 95% of the cases
Confidence Level	99%	Indicates that losses will not exceed the VaR in 99% of the cases
Time Frame	Daily	Each VaR result applies to a single day from January 1, 2010 – December 31, 2024).

Source: authors' estimation results (2025).

The potential risks in exchange rate changes between RUB and NGN are evaluated by the VaR of the NGN/RUB exchange rate using the V-C approach. The estimates are shown in Table 4. The expected return is indicated by the mean return (μ), which is 60.94285. With 95% and 99% confidence thresholds, respectively, the $Z_{0.05}$ and $Z_{0.01}$ are 1.645 and 2.330, indicating 5% and 1% likelihood that losses will surpass the estimated VaR. In order to account for time-varying volatility, the V-C model yields a conditional variance (σ^2) of 434.9352, and the conditional standard deviation (σ) of 20.8551, which shows the degree of variation in returns. The VaR, which represents the maximum projected losses per day with 95% and 99% probabilities that losses will not surpass these values, are 34.30664 and 48.59238, respectively.

Table 5. Value-at-Risk of NGN/RUB exchange rate based on historical simulation

Parameter	**Value**	**Narration**
VaR ($VaR_{95\%}$)	30.18745	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	42.19378	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 6 presents the VaR estimates of the NGN/RUB exchange rate using the H-S method for both the 95% and 99% threshold of confidence. These estimates—30.18745 and 42.19378, respectively—compare closely with the estimates derived from the V-C method. Table 6 displays the VaR of the NGN/RUB exchange rate using the MCS, which are comparatively larger, at 192.0134 and 317.1595, respectively.

Table 6: Value-at-Risk (VaR) of NGN/RUB exchange rate based on Monte-Carlo simulation

Parameter	**Value**	**Narration**
VaR ($VaR_{95\%}$)	192.0134	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	317.1595	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 7 shows that the projected mean return (μ) of 57.36302. This serves as a baseline for future forecasts using the Indian Rupee's exchange rate against the Nigerian Naira. For 95% and 99% confidence levels, the Z-values of 1.645 and 2.330 represent the critical value, indicating that the odds of losses surpassing the computed VaR are just 5% and 1%, respectively. To account for variabilities, the V-C model was used to calculate the conditional variance (σ^2), which came out to be 228.87454. The average fluctuation in returns is measured by the conditional standard deviation (σ), which is 0.9186 and is calculated as the square root of variance. The highest projected losses per day are represented by the estimated VaR at 95% confidence, which is 24.88655 and 35.24964, guaranteeing that these losses only happen by 5% and 1%.

Table 7. Value-at-Riks (VaR) of NGN/INR exchange rate based on variance-covariance

Parameter	Value	Narration
Mean Return (μ)	57.36302	The constant term from the mean equation represents the expected return.
Z-Value ($Z_{0.05}$)	1.645	Z-score for a 95% confidence level
Z-Value ($Z_{0.01}$)	2.330	Z-score for a 99% confidence level
Conditional Variance (σ2)	228.87454	Variance from Variance-Covariance model
Conditional Std. Dev. (σ)	15.1286	Standard deviation, derived as σ2
VaR ($VaR_{95\%}$)	24.88655	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	35.24964	Maximum expected losses at 99% confidence for one day
Confidence Level	95%	Indicates that losses will not exceed the VaR in 95% of the cases
Time Frame	Daily	Each VaR result applies to a single day from January 1, 2010 – December 31, 2024).

Source: authors' estimation results (2025).

Table 8. Value-at-Risk of NGN/INR exchange rate based on historical simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	19.28794	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	31.29475	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 8 shows the VaR estimates of the NGN/INR exchange rate for both the 95% and 99% threshold of confidence using the H-S method. These estimates 19.28794 and 31.29475 respectively are closely related in magnitude with the VaR estimates computed with the V-C method. On the contrary, the VaR of NGN/INR exchange rate given by 113.4809 and 225.3975 for the 95% and 99% threshold of confidence using the MCS are relatively larger. These are reported in Table 9 below.

Table 9. Value-at-Risk (VaR) of NGN/INR exchange rate based on Monte-Carlo simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	113.4809	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	225.3975	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

The VaR estimates of the NGN to CNY exchange rate are shown in Table 10 from the V-C method. The projected average return is represented by the mean return (μ) of 5.565377. The 95% and 99% confidence thresholds are represented by the Z-values ($Z_{0.05}$) of 1.645 and Z-values ($Z_{0.01}$) of 2.33, respectively, which indicate that the likelihood of losses exceeding the estimated VaR is only 5% and 1%. Time-varying volatility is taken into account by the conditional variance (σ^2) of 100.79457, and the degree of return fluctuation is reflected by the conditional standard deviation (σ), which is 10.03965. In terms of 95% and 99% probability that losses will not surpass these values, the VaR at 95% and 99% confidence thresholds are 16.51522 and 23.39238, which represent the maximum expected loss for a day.

Table 10. Value-at-Risk (VaR) of NGN/CNY exchange rate based on variance-covariance

Parameter	Value	Narration
Mean Return (μ)	5.565377	The constant term from the mean equation represents the expected return.
Z-Value ($Z_{0.05}$)	1.645	Z-score for a 95% confidence level.
Z-Value ($Z_{0.05}$)	2.330	Z-score for a 99% confidence level.
Conditional Variance (σ2)	100.79457	Variance computed using the Variance-Covariance model
Conditional Std. Dev. (σ)	10.03965	Standard deviation, σ2
VaR ($VaR_{95\%}$)	16.51522	Maximum expected loss at 95% confidence for one day
VaR ($VaR_{99\%}$)	23.39238	Maximum expected loss at 95% confidence for one day
Confidence Level	95%	Indicates that losses will not exceed the VaR in 95% of the cases.
Confidence Level	99%	Indicates that losses will not exceed the VaR in 99% of the cases.
Time Frame	Daily	Each VaR result applies to a single day from January 1, 2010 – December 31, 2024)

Source: authors' estimation results (2025).

Table 11. Value-at-Risk (VaR) of NGN/CNY exchange rate based on historical simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	13.49751	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	22.10389	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

As shown in Table 11, the VaR estimates of the NGN/CNY exchange rate for both the 95% and 99% threshold of confidence using the H-S method are 13.49751 and 22.10389 respectively as against 106.8091 and 314.1256 estimated with the MCS method. A critical examination of these VaR estimates shows that the VaR of NGN/CNY exchange rate given by MCS as presented in Table 12 are relatively larger.

Table 12. Value-at-Risk (VaR) f NGN/CNY exchange rate based on Monte-Carlo simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	106.8091	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	314.1256	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

Table 13 presents the VaR estimates of the NGN/ZAR exchange rate derived from the V-C method. The predicted return for the exchange rate is 9.35823, and the thresholds for substantial deviations are shown by the Z-values of 1.645 and 2.330, and both defines the 95% and 99% confidence levels, respectively. The exchange rate return variability is represented by the conditional variance of 338.54197. The exchange rate risks are represented by the conditional standard deviation of 18.39951. The VaR estimates, which represent the entire projected loss for a single day, are 30.26719 and 42.87086 at 95% and 99% confidence thresholds respectively. These indicate that the NGN/ZAR currency rate will not drop by more than N30.3 and N42.9 during the day, with 95% and 99% confidence levels.

Table 13. Value-at-Risk (VaR) NGN/ZAR exchange rate based on variance-covariance

Parameter	Value	Narration
Mean Return (μ)	9.35823	The constant term from the mean equation represents the expected return
Z-Value ($Z_{0.05}$)	1.645	Z-score for a 95% confidence level
Z-Value ($Z_{0.01}$)	2.330	Z-score for a 99% confidence level
Conditional Variance (σ2)	338.54197	Variance estimate
Conditional Std. Dev. (σ)	18.39951	Standard deviation, σ2
VaR ($VaR_{95\%}$)	30.26719	Maximum expected loss at 95% confidence for one day
VaR ($VaR_{99\%}$)	42.87086	Maximum expected loss at 99% confidence for one day
Confidence Level	95%	Indicates that losses will not exceed the VaR in 95% of the cases
Confidence Level	99%	Indicates that losses will not exceed the VaR in 99% of the cases
Time Frame	Daily	Each VaR result applies to a single day from January 1, 2010 – December 31, 2024)

Source: authors' estimation results (2025).

Table 14. Value-at-Risk (VaR) of NGN/ZAR exchange rate based on historical-simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	25.38914	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	35.29847	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

As shown in Table 14, the VaR estimates of the NGN/ZAR exchange rate for both the 95% and 99% threshold of confidence using the H-S method are 25.38914 and 35.29847 respectively as against 137.1293 and 339.5163 estimated with the MCS method. A statistical comparison of these VaR estimates shows that the VaR of NGN/ZAR exchange rate given by MCS as presented in Table 15 are relatively larger while those of H-S are strictly related in size with the estimates obtained from the V-C method.

Table 15. Value-at-Risk (VaR) of NGN/ZAR exchange rate based on Monte-Carlo simulation

Parameter	Value	Narration
VaR ($VaR_{95\%}$)	137.1293	Maximum expected losses at 95% confidence for one day
VaR ($VaR_{99\%}$)	339.5163	Maximum expected losses at 99% confidence for one day

Source: authors' estimation results (2025).

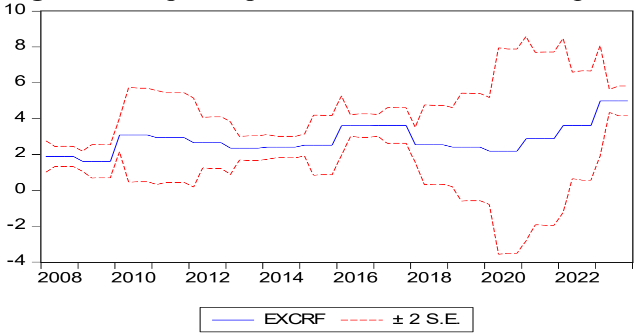
Graphical plots of forecast results are crucial for evaluating the accuracy and reliability of predictive models. These plots compare actual values with forecasted ones, offering insights into how well the model captures trends and patterns. The time series forecast plot displays the actual and predicted values with confidence intervals, illustrating the uncertainty around predictions. Residual plots show the differences between actual and forecasted values, with random distribution around zero indicating a well-fitted model. A cumulative forecast error plot highlights potential biases, while forecast error density plots help assess whether errors follow a normal distribution. Close alignment between actual and predicted values, minimal deviations, and unbiased residual patterns indicate robust forecasts. These visual analyses enhance the understanding of model performance and provide a foundation for improving predictive accuracy where necessary.

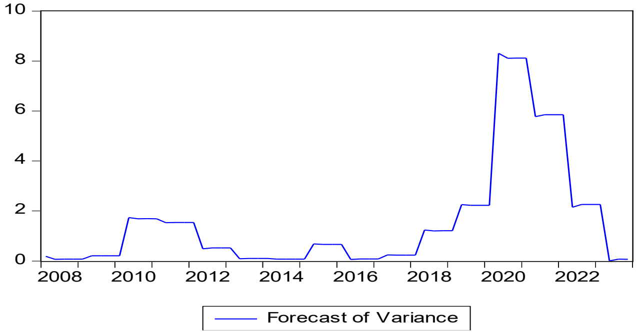
The NGN/BRL exchange rate's actual and predicted values, including ±2 standard error (S.E.) bands, are displayed in the top graph of Figure 1. Whereas the dashed red lines show uncertainty, the blue line shows the forecast. The exchange rate fluctuated within the confidence interval but stayed comparatively constant between 2008 and

2018. The period from 2019 to 2022 had a substantial rise in volatility, and this is when the exchange rate peaked. Although rates are still high in comparison to previous years, the prognosis indicates stabilization starting in late 2022. Predictions for the NGN/BRL exchange rate show a decreasing uncertainty range, suggesting less volatility. The bottom graph shows the exchange rate variation, which increased after 2018 due to either policy changes or increased economic volatility. After 2022, there appears to be less uncertainty in future rates, according to the variance trends.

Model accuracy is reasonable, as confirmed by the RMSE of 1.28 and MAE of 0.93. A moderate level of predictive performance is shown by Theil's IC of 0.197. The model appears to be able to represent dynamic patterns well, that is, capable of accurately capturing dynamic patterns. As indicated by the variance (16.37%) and covariance proportion (72.77%). Although forecast trends indicate stabilization, they also emphasize the necessity of aggressive economic actions to maintain stability. According to the findings, it is important to keep an eye on changes in the money supply, external debt, and oil prices.

Figure 1. Graphical plots for NGN/BRL exchange rate

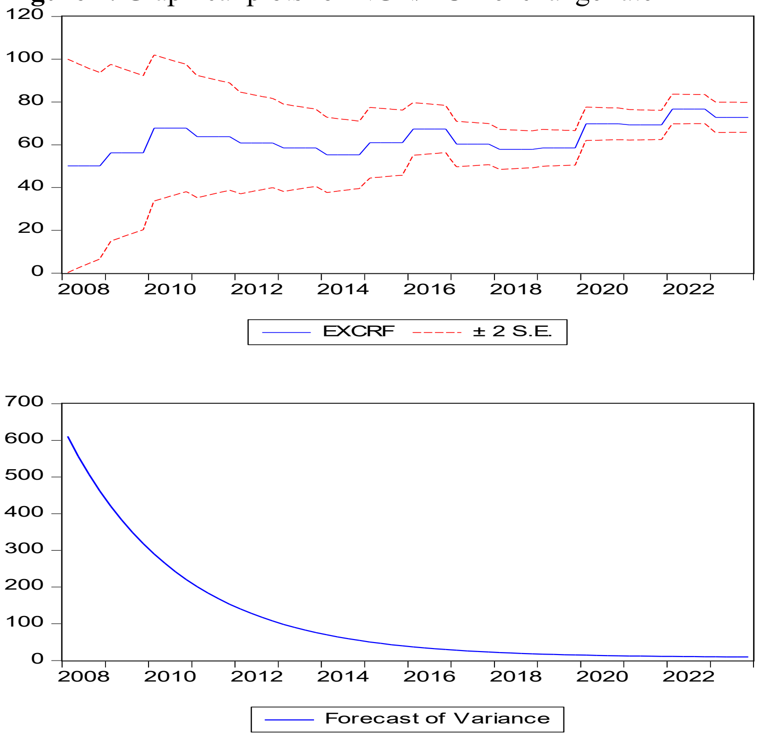




Source: authors' estimation results (2025).

According to Figure 2, the forecast indicates gradual growth in the NGN/RUB exchange rate over time, with occasional fluctuations but staying within the confidence intervals. The exchange rate showed moderate variability between 2008 and 2018, followed by more consistent trends from 2020 onwards. The bottom graph, depicting forecast variance, shows a steep decline in uncertainty from 2008 to 2015, after which volatility remained minimal. The RMSE of 19.41 and MAE of 14.73 reflect the model's predictive performance, with a moderate MAPE of 43.80%. Theil's IC of 0.163 suggests reasonable forecasting accuracy. The variance proportion of 41.49% and bias proportion given by 31.90% indicate a balanced contribution of factors, while the covariance proportion (26.61%) highlights effective dynamic modeling. The reduced forecast variance implies growing confidence in predicting NGN/RUB exchange rates, emphasizing the importance of observing key drivers like changes in output growth, BRENT crude oil prices and external debt levels.

Figure 2. Graphical plots for NGN/RUB exchange rate



Source: authors' estimation results (2025).

The forecast results as reported in Figure 3 reveals a steady upward trend in the NGN/INR exchange rate over time, particularly from 2014 to 2022, with values mostly staying within the confidence bounds. The exchange rate displayed significant variability before 2015 but stabilized in later years. Forecasts indicate continued growth with narrowing uncertainty, reflecting greater stability. The bottom graph, which highlights forecast variance, shows high volatility between 2008 and 2012, declining sharply afterward and remaining minimal from 2015 onward. The RMSE of 11.03 and MAE of 7.41 demonstrate the model's strong predictive performance, with a moderate MAPE of 14.82%. Theil's IC of 0.082 signals high forecasting accuracy. Considering the variance and covariance proportions of 28.59% and 32.31% respectively; there is evidence to show that the model captures dynamics in NGN/INR effectively, while the bias proportion (39.09%) suggests some forecasting lag. Consistent trends and a lower forecast variance point to increased NGN/INR exchange rate predictability. Observing indicators such as trade balance, monetary policy rate, and BRENT crude oil prices remains vital for NGN/INR exchange rate management.

Figure 3. Graphical plots for NGN/INR exchange rate

Source: authors' estimation results (2025).

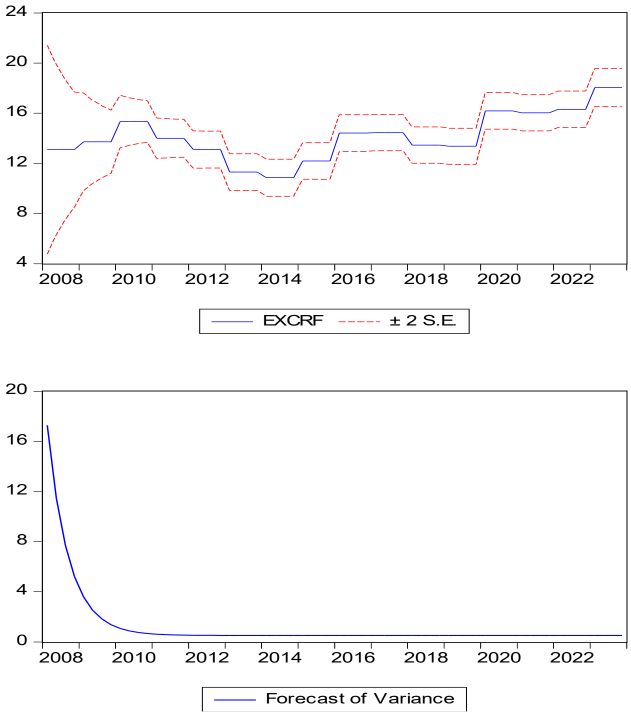
Figure 4 shows the graphical analysis of the NGN/CNY exchange rate. The upper plot illustrates the actual and forecasted exchange rate (blue line) with ±2 standard error bounds (red dashed lines). The exchange rate shows a stable trend from 2008 to 2023, with minor fluctuations and a slight upward movement in recent years, indicating a potential mild depreciation of the Yuan against the Naira. Accuracy metrics reveal strong model performance, with a RMSE of 0.21, MAE of 0.17, and a low MAPE of 2.55%. The Theil IC of 0.02 suggests minimal forecasting errors, with most of the error attributed to the covariance proportion (0.89), reflecting a strong alignment between actual and forecasted values. The variance plot shows stability in the forecast except for a temporary spike around 2018, indicating unusual volatility during that period. According to the estimate, the Yuan would continue to move gradually in relation to the Naira, impacted by the interaction of economic variables including inflation and interest rates. When making decisions on trade and investment using these currencies, these findings are essential.

Figure 4. Graphical plots for NGN/CNY exchange rate

Source: authors' estimation results (2025).

The topmost plot for the NGN/ZAR exchange rate as reported in Figure 5 shows plot shows the actual and forecasted exchange rate as a blue line, while the red dashed lines represent the ±2 standard error bounds, indicating forecast uncertainty. A gradual upward trend from 2008 to 2023 suggests consistent depreciation of the Rand against the Naira over the forecast period. The model's accuracy is indicated by metrics such as RMSE of 3.46, MAE of 2.29, and MAPE of 27.24%, which suggest moderate reliability. The Theil IC of 0.13 signifies a relatively good fit, while the bias proportion (0.32), variance proportion (0.23), and covariance proportion (0.45) explain the forecasting errors. The bottom plot highlights a declining forecast variance over time, signifying improved stability from 2010 onward. These results point to a continued depreciation of the ZAR against the NGN, influenced by the interplay of economic factors. This forecast offers valuable insights for understanding future exchange rate movements and potential financial implications.

Figure 5. Graphical plots for NGN/ZAR exchange rate



Source: authors' estimation results (2025).

Table 16. GJR-GARCH results of NGN/BRL exchange rate

Equation Type: Mean		
Variable	Coefficient	P-Value
NGN/BRL(-1)	0.15429	0.0000
Dgdpr	-0.47293	0.0020
OPr	-0.21936	0.0000
m2/gdp	1.92653	0.0001
Ogr	0.14793	0.1567
Tbal	-0.30982	0.1945
ERev	0.28919	0.1789
Mpor	-0.54911	0.0457
C	1.17505	0.0011
Equation Type: Variance		
Variable	Coefficient	P-Value
C	0.75722	0.0033
ARCH(-1)^2, α	-0.15598	0.0000
RESID(-1)^2*(RESID(-1)<0), γ	0.17290	0.0000
GARCH(-1), β	0.69376	0.0000
R-squared = 0.85621; Adjusted R-squared 0.73289		

Source: authors' estimation results (2025).

Table 17. GJR-GARCH results of NGN/RUB exchange rate

Equation Type: Mean		
Variable	Coefficient	p-value
NGN/RUB(-1)	-0.26439	0.0000
Dgdpr	-0.17956	0.0000
OPr	-0.32750	0.0245
m2/gdp	1.03792	0.2651
Ogr	-0.14623	0.0000
Tbal	-0.15479	0.2571
Erev	0.23879	0.2193
Mpor	0.42157	0.0184
C	0.94285	0.0000
Equation Type: Variance		
Variable	Coefficient	P-value
C	0.25791	0.2921
ARCH(-1)^2, α	-0.13495	0.0001
RESID(-1)^2*(RESID(-1)<0), γ	0.18562	0.0000
GARCH(-1), β	0.89256	0.0000
R-squared =0.78132; Adjusted R-squared = 0.61375		

Source: authors' estimation results (2025).

Table 18. GJR-GARCH results of NGN/INR exchange rate

Equation Type: Mean		
Variable	Coefficient	P-value
NGN/INR(-1)	-0.41879	0.1161
Dgdpr	-0.25763	0.0004
OPr	-1.15042	0.0000
m2/gdp	0.16728	0.1672
Ogr	0.03576	0.2389
Tbal	-1.02798	0.0000
ERev	0.14735	0.2861
Mpor	-0.18725	0.0000
C	5.16302	0.0000
Equation Type: Variance		
Variable	Coefficient	P-value
C	0.72355	0.2921
ARCH(-1)^2, α	-0.10932	0.0001
RESID(-1)^2*(RESID(-1)<0), γ	0.14246	0.0000
GARCH(-1), β	0.66307	0.0052
R-squared =0.657114; Adjusted R-squared 0.509970		

Source: authors' estimation results (2025).

Table 19. GJR-GARCH results of NGN/CNY exchange rate

Equation Type: Mean		
Variable	Coefficient	P-value
NGN/CNY(-1)	0.63215	0.0093
Dgdpr	-0.12691	0.0006
OPr	-0.34562	0.0022
m2/gdp	1.0387	0.1467
Ogr	0.102861	0.0000
Tbal	0.18735	0.1672
ERev	0.13910	0.0001
Mpor	-0.25617	0.0000
C	5.565377	0.0000
Equation Type: Variance		
Variable	Coefficient	P-value
C	0.23597	0.3243
ARCH(-1)^2, α	0.14623	0.0000
RESID(-1)^2*(RESID(-1)<0), γ	0.15294	0.0000
GARCH(-1), β	0.76315	0.0006
R-squared = 0.58931; Adjusted R-squared 0.509970		

Source: authors' estimation results (2025).

Table 20. GJR-GARCH results of NGN/ZAR exchange rate

Equation Type: Mean		
Variable	Coefficient	P-value
NGN/ZAR(-1)	0.31986	0.0000
Dgdpr	-0.11256	0.0000
OPr	0.07834	0.0000
m2/gdp	0.15612	0.0000
Ogr	-0.14520	0.1863
Tbal	-0.01892	0.2579
ERev	1.03265	0.0000
Mpor	-0.01893	0.1772
C	1.35250	0.0000
Equation Type: Variance		
C	0.17426	0.0040
ARCH(-1)^2, α	0.11519	0.0141
RESID(-1)^2*(RESID(-1)<0), γ	0.13346	0.0000
GARCH(-1), β	0.59123	0.0001
R-squared = 0.82371; Adjusted R-squared 0.791544		

Source: authors' estimation results (2025).

5. Discussion

Results from an evaluation of the three VaR estimation techniques vary greatly. The strategy that produces the lowest risk estimations is the H-S method, which considers the actual shape of the observed distribution of losses and returns. According to the H-S technique, the VaR estimates of 26.34855, 30.18745, 19.28794, 13.49751, and 25.38914, respectively, correspond to the fifth percentile of the distribution of changes in the exchange rate values (profit or losses) of NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, and NGN/ZAR at a 95% threshold level. Relatively, for a 99% level of threshold the VaR estimates are 37.33921; 42.19378; 31.29475; 22.10389; and 35.29847 all equals the first percentile of the NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, NGN/ZAR exchange rate returns/losses.

The NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, and NGN/ZAR exchange rates have MCS VaR estimates of 126.1792 and 425.3150, 192.0134 and 317.1595, 113.4809 and 225.3975, 106.8091 and 314.1256, and 137.1293 and 339.5163 at the 95% and 99% threshold levels, respectively. Earnings and losses are given the same weight in the V-C estimates, which produces VaR estimates that are only slightly consistent with the VaR estimates of the H-S approach. This does, in fact, establish how stable the VaR of the Naira exchange rates is in respect to the BRICS countries' currencies. The MCS VaR estimates were significantly higher than the VaR estimates provided by the V-C and H-S methods. The probability of tail events is the main focus of a VaR model, the t-distribution upon which the MCS simulation was done, with a few exceptions, showed longer tails than the normal distribution, which has a higher proportion of its probability mass in the distribution's tails. Hence, the VaR estimates emanating from the MCS became much larger than those given by V-C and H-S methods. Noticeably, this effect becomes remarkable (the larger the VaR estimate) the higher the threshold of confidence.

The V-C VaR estimates of the Naira's exchange rate against the BRICS currencies are 28.89989 and 40.93419; 34.30664 and 48.59238; 24.88655 and 35.24964; 16.51522 and 23.39238; and 30.26719 and 42.87086 for the NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, and NGN/ZAR values, at the 95% and 99% threshold levels respectively. The VaR estimate clearly increases with the degree of confidence. There is a 5% chance that the NGN/BRL currency rate will lose more than 28.89989 Naira, according to statistical inference, and a 1% chance that the NGN/BRL exchange rate will lose more than 40.93419 Naira. Comparatively, the estimates show that the NGN/RUB currency rate will lose more than 34.30664 Naira at a 5% chance level and more than 48.59238 Naira at a 1% probability level. Additionally, there is a 5% chance that the NGN/INR currency rate will lose more than 24.88655 Naira, and a 1% chance that the NGN/RUB exchange rate will lose more than 35.24964 Naira. The likelihood that the NGN/CNY exchange rate will lose more than 16.51522 Naira is 5%, and at the 1% probability threshold, the loss will exceed 23.39238 Naira. There is a 5% probability that the loss on the NGN/ZAR currency exchange rate is above 30.26719 Naira but at 1% probability, the loss on the NGN/ZAR will be larger than 42.87086 Naira.

The study's results agree with those of Ahmed et al. (2021), and Gupta & Patel (2020). Ahmed et al. (2021) used extreme value theory (EVT) to estimate the VaR of the NGN/USD exchange rate, highlighting EVT's theoretical focus on modeling the tails of return distributions where extreme losses occur. By examining exchange rate data from 2012 to 2020, Ahmed et al. (2021) showed that EVT is superior in identifying extreme market risks, particularly during financial crises when traditional models tend to underestimate risks. The study concluded that EVT provides a crucial tool for precise risk estimation in extremely volatile markets and suggested incorporating it into risk management frameworks for emerging economies like Nigeria. Gupta & Patel (2020) investigated the VaR estimation for the INR/USD exchange rate, building on the MCS theory as a foundation. The study simulated exchange rate movements using historical data from 2014 to 2019 and estimated VaR under various market conditions. The results showed that, in comparison to conventional parametric techniques, MCS provided more accurate risk estimations during extreme market occurrences and successfully captured tail risks. In stress-testing scenarios, which are crucial for emerging markets with volatile currencies, the study underlined that MCS's ability to model non-normal distributions offered a notable benefit. It emphasized MCS's resilience and flexibility in unpredictable economic conditions and pushed for its inclusion in risk management frameworks for financial firms and central banks.

Table 16 presents the findings of the conditional volatility of the BRL/NGN exchange rate. The estimations shed light on the variables that influence exchange rate volatility. With a coefficient of -0.15598 and a probability value of 0.0000, the ARCH(-1)^2 term, which represents lagged squared residuals, shows that historical shocks (residuals) have a substantial impact on the current volatility of the NGN/BRL exchange rate. This finding implies that recent disruptions significantly influence how volatile the currency pair is. The GJR-GARCH(1,1) model's persistence in volatility was determined by -0.15598 + 0.17290 + 0.69376/2 = 0.35534 < 1. For a leverage effect, we examined the sign, magnitude, and statistical significance of γ. The sign of $\gamma > 0$ (0.17290> 0). The magnitude of γ |0.17290| is positive and the zero p-value indicates significance. fulfilling the requirements for non-negativity of variance equation coefficients, 0.75722 > 0; $\alpha > 0$ (i.e., coefficient of RESID(-1)^2); $\beta >= 0$

(i.e., coefficient of GARCH(-1)); $\alpha + \gamma >= 0$. In other words, the variance equation results are valid as long as -0.15598 + 0.17290 = 0.01692 >= 0. The findings show that volatility persists. This suggests that times of high volatility may not always be followed by periods of lower volatility to reflect a natural adjustment process in the foreign currency market, and it does not imply mean-reverting behaviour in the NGN/BRL exchange rate volatility. Also, the model's adjusted R-squared value of 0.73289 indicates 73% of the variation in the NGN/BRL exchange rate is explained by the conditional variations of the model as well as the fluctuations in the independent variables.

The conditional volatility results of the NGN/RUB exchange rate are reported in Table 17. The ARCH(-1)^2 term, which represents lagged squared residuals, has a coefficient of -0.13495 with a probability value of 0.0001, indicating a significant positive association. This means that past shocks to the exchange rate have a substantial impact on current volatility, reflecting the persistence of volatility over time. In essence, the exchange rate experiences continued fluctuations as a result of previous disturbances in the market, highlighting the long-lasting effects of these shocks. The persistence in volatility is -0.13495 + 0.18562 + 0.89256/2 = 0.47162 < 1. This is an indication of the high level of volatility persistence in the exchange rate of NGN/RUB. There is presence of leverage effect based on the sign, magnitude, and statistical significance of γ. This follows from the fact that the sign of 0.18562 is positive, that is, > 0; the magnitude |0.18562| is positive and also it has a p-value of zero. The conditions for non-negativity of variance equation coefficients, c > 0; $\alpha > 0$, $\beta >= 0$ are satisfactory. The validity of the variance model was measured by 0.05067 which is >= 0. Accordingly, the variance model is valid. Together, these results highlight the dynamic interplay between past market conditions and the current volatility of the NGN/RUB exchange rate. Also, the model fit statistics demonstrate a concrete capacity to explain the NGN/RUB exchange rate movements as made evident by the adjusted $R^2$of 61% having accounted for the number of predictors.

Table 18 provides the estimates of the conditional volatility of the NGN/INR exchange rate. The ARCH(-1)^2 term, representing lagged squared residuals, has a coefficient of 0.704221 with a probability value of 0.0111. This indicates a significant and positive relationship, meaning past shocks to the exchange rate contribute strongly to its current volatility. The persistence of volatility, as captured by this term, highlights the importance of recent market disturbances in shaping exchange rate fluctuations. Additionally, the GARCH(-1) term, which accounts for the lagged conditional variance, has a coefficient of 0.010364 and a probability value of 0.0001, indicating a highly significant effect. The degree of volatility persistence was estimated at 0.34811. This value is < 1 with the implication of the incidence of volatility persistence in the exchange rate of NGN/INR. Additionally, the statistical significance of 0.14246 indicates the impact of leverage. The conditions for non-negativity of variance results are confirmed despite the negative α since 0.72355 > 0; 0.66307 >= 0, and -0.10932 + 0.14246 = 0.03314 > 0. Collectively, these results highlight the dynamic interplay between past shocks and volatility persistence in determining the NGN/INR exchange rate's conditional variance, with significant implications for risk management and forecasting in the foreign exchange market for both Nigeria and India. Also, the model fit statistics indicate a solid explanatory power for the NGN/INR exchange rate. An Adjusted R-squared value of 0.509970 suggests that approximately 51% of the variation in the NGN/INR exchange rate is captured by the variation in the independent variables. This is a confirmation of the model's reliability and robustness in capturing key drivers of NGN/INR exchange rate.

The estimates for the NGN/CNY exchange rate's conditional volatility as reported in Table 19 indicated a considerable persistence in volatility of 0.531137 < 1. There is a significant leverage effect as denoted by 0.15294. All conditions for non-negativity of variance equation coefficients are met, that is, 0.23597 > 0; 0.14623 > 0, 0.76315 >= 0. The coefficient for the ARCH(-1)^2 term is 0.14623, with a highly significant probability value of 0.0000, indicating that past shocks to the exchange rate (residuals) have a strong and persistent impact on current volatility. This suggests that volatility exhibits autocorrelation, meaning that past volatility influences future volatility. The GARCH(-1) coefficient is -0.76315, with a probability value of 0.0006, indicating that past volatility positively and significantly affects current volatility. These findings jointly highlight the persistent volatility in the CNY/NGN exchange rate, which is crucial for understanding the dynamics of exchange rate risk and volatility forecasting. Also, having adjusted for number of degrees of freedom, the adjusted R-squared value of 51% suggests that the model offers a moderate fit to the data, explaining a reasonable proportion of the NGN/CNY exchange rate's variation. This indicates that while the model captures some key factors driving the CNY/NGN exchange rate, there may be other unaccounted influences.

The volatility of the ZAR/NGN exchange rate as reported in Table 20. The constant of the variance equation is 0.177017, with a z-statistic of 2.878664 and a p-value of 0.0040, indicates a significant baseline level of volatility. The ARCH(-1)^2 term, with a coefficient of 0.14519 and a p-value of 0.0141, demonstrates significant short-term volatility crowding, where past shocks strongly influence current volatility. The GARCH(-1) component, with a coefficient of -0.69573, suggests that past volatility has a dampening effect on future volatility, confirming a mean-reverting pattern in ZAR/NGN exchange rate volatility. The statistical significance of these components underscores the model's robustness in capturing the dynamic nature of volatility in the exchange rate.

Overall, the ARCH (-1)^2 and GARCH(-1) terms in the variance equations across all currencies demonstrate statistically significant influences of past shocks and mean-reverting tendencies, enhancing the reliability of VaR-GARCH methodology. According to the current results, exchange rate of the Naira in relation to each of the BRICS currencies (NGN/BRL, NGN/RUB, NGN/INR, NGN/CNY, NGN/ZAR) reacted positively and significantly to changes in one-period lagged value. Consequently, **the** GARCH model reveals critical insights into exchange rate volatility. The ARCH term as given by the coefficient of RESID(-1)^2 given as α is negative and significant at 5% level except for China and South Africa. The leverage effect as measured by the coefficient of RESID$(-1)^2$*(RESID(-1)<0) given as γ was positive and significant all through the model indicating presence of leverage effect. With the exception of the NGN/ZAR exchange rate, the GARCH(-1) term was positive care able to deduce that the volatility is very persistent and aggregating because the GARCH coefficients are larger than the ARCH coefficient. When times of high volatility persist, the significant coefficients for lagged squared residuals effectively climaxes volatility crowding. The strength of the feedback effect of the Naira's volatility relative to the BRICS currencies is indicated by the volatility perseverance. By implication, even if to a lesser degree, future volatility shocks to the Naira exchange rate relative to the Real, Ruble, Rupee, Yuan, and Rand will be felt.

As a result, risk management may be impacted by the volatility in the dynamics of the exchange rate between the Naira and the BRICS currencies. Therefore, the persistence of this volatility in the dynamics of the exchange rate between the Naira and the BRICS currencies can affect risk management by causing financial market instability, mispricing assets, influencing how Nigerian businesses allocate their portfolios, and having a detrimental effect on economic activity and productivity. These findings agree with those of Chen et al. (2019) who deployed the GARCH models are useful tools for managing currency risk because they can adjust to deviations during times of crisis, even though they are compatible with the EMH in calm market conditions.

Based on the Efficient Market Hypothesis (EMH), the authors assessed how well the GARCH family models estimated the VaR of the EUR/USD exchange rate under various volatility regimes. Although there may be variations during times of market volatility, the EMH contends that asset prices accurately reflect all available information. The study concentrated on how well the EGARCH model captured two important aspects of exchange rate movements: asymmetric volatility and clustering effects. The findings of the present study showed a high prevalence of the leverage effect; for all models, the leverage parameter is positive and significant even at the 1% level. This suggests that when it comes to the Naira exchange rate in relation to the BRICS currencies, bad news has a greater effect than good news. Furthermore, negative shocks to the NGN/BRL, NGN/RUB, and NGN/INR have a greater effect on the conditional volatility projections than positive shocks, according to the negative ARCH(-1) coefficients of lag one. Nigeria's vulnerability to macroeconomic and financial market shocks, such as trade, monetary policy, output, external debt, and oil price shocks, is reflected in these dynamics.

Since the market value of the Naira/Real rate has large reactions to negative changes in oil prices, foreign debt, and positive changes in money supply; the study affirmed findings of Obuareghe et al. (2025) that changes in crude oil prices together with past values of broad money supply significantly and positively impact the exchange rate of the Naira in relation to foreign currencies. The results show that the Naira exchange rate against the Russian Rubble has significant and negative responsiveness to changes in output growth rate, BRENT crude oil prices and external debt levels. This aligns with the findings of Gainetdinova et al. (2024) where it was established that the Rubble has significant vulnerability to oil prices. The findings also agree with the findings of Oyadeyi (2024) who reported monetary policy rate of the CBN, oil prices and financial development are all significant determinants of exchange rate volatility in Nigeria. The authors derived their results and findings from the ARCH, nonlinear GARCH and the ARDL model estimations.

The pricing of the Naira/Yuan has major sensitivities to negative fluctuations in BRENT crude oil prices, external debt, CBN policy rate and a positive output growth. The results of our research lend credence to the results obtained by Suhendra et al. (2022), Williams & Prasad (2019), Khan et al. (2019). Suhendra et al. (2022) reported that the discount rate of the central bank of Indonesia caused significant adverse variations in Indonesian exchange rate. Williams & Prasad (2019) discovered that net trade significantly caused the exchange rates of Japan and India to fluctuate, but only had marginal impact on the Yuan. The results of Khan et al. (2019) indicate that output growth and trade openness impacted positively and significantly the USD/CNY exchange rate while interest and inflation rates negative and significantly impacted the exchange rate. The valuation of the Naira/Rupee exchange rate is significantly responsive to the vulnerability of trade balance (deficit or surplus), external reserves, foreign debt, monetary policy rate, and BRENT crude oil prices. Hasan & Islam (2023) found that foreign exchange reserve; amongst other variables are the most influential determinants of exchange rate movements in Bangladesh. The results of the present research align with the with the findings of Ghauri et al. (2024) who based their findings on ARDL model estimation to conclude that interest rates, is amongst the significant determinants of the fluctuations in the exchange rate, noting that exchange rate positively reacted to interest rate changes.

The value of the Naira/Rand is highly susceptible to shifts in external reserves, debt levels, and the money supply, which are indicators of financial soundness. The results of our research lend credence to the results obtained by Ohaegbulem & Iheaka (2024) that the NGN exchange rate fluctuations respond significantly and positively to changes in external reserve, and the level of external debt. The findings align with those of Eduardo et al. (2024) who found that countries with enormous government debt suffered undervalued currencies. In terms of comparative analysis, in order to predict and quantify exchange rate volatility and

VaR, this study mainly estimated the VaR with the goal of increasing the precision of risk forecasting, and volatility modeling. With a macro-financial viewpoint, the study findings compare with those of Efuntade & Efuntade (2023) who analyzed long-term effects of oil price volatility on Nigeria's foreign exchange rate as well as those reported by Hashmi et al. (2022), and Ateba et al. (2024). These authors emphasize lopsidedness and country-specific dynamics in the analysis of heterogeneity of oil price shock impacts on currency rates in oil-exporting nations using the ARDL Bound test/error correction technique, using quantile ARDL and quantile-on-quantile regression (QQR) technique. Hashmi et al. (2022) highlights how oil prices and currency rates impact stock prices differently in bullish and bearish markets. The evidence of asymmetric oil shock impacts provided by Ateba et al. supports the need for nation-specific policy formulation in reaction to changes in the world oil price. Our results are similar to those obtained by Bouslama (2023) for dynamic BRICS stock-oil dependence based on VaR analysis.

5.1. Policy implications and recommendations

The necessity of developing country-specific policies in response to shifts in the global oil price is supported by the evidence of possible losses prediction during unfavorable currency fluctuations. Similarly, by contextualizing VaR within crisis moments and Nigeria/BRICS's currency rate-money supply and oil price variation connections, the study offers more direct insights into dynamic dependencies under financial stress. The oil-selling BRICS' predictive capabilities are ideal for risk management and market monitoring, while the macro-structural analysis and policy implications of the oil-dependent emerging nations offer the depth and context required for economic planning.

By implementing dynamic and data-driven VaR-based models for tracking the Naira's exposure to BRICS currencies, the Central Bank of Nigeria (CBN) and pertinent financial authorities can fortify their foreign exchange risk management frameworks, thereby reducing exchange rate risk and improving financial stability. In light of the substantial volatility concerns found in the research, particularly in bilateral exchange rate interactions with currencies like the Russian ruble and the Chinese Yuan, the following steps are advised:

1. Predict possible losses during unfavorable currency fluctuations which reflect a longer-term view of structural linkages, particularly among Nigeria's main trading and investment partners among the BRICS, use VaR-based stress testing to national foreign exchange reserves and financial institutions.
2. The Naira exchange rate vis-à-vis currencies of the BRICS share a vulnerability to oil shock and debt levels, emphasizing the need for robust economic management and dynamic forecasting models. The implications of the findings underscore the need for strategic interventions to enhance macroeconomic stability, mitigate external vulnerabilities, and foster sustainable exchange rate management in Nigeria.
3. Additionally, strengthening the regulatory framework to manage speculative activities is a key to reducing excessive volatility in the foreign exchange market. Traded currency markets, such as those involving the NGN/JPY and NGN/BRL pairs, are highly susceptible to volatility. Enhancing market depth and providing liquidity support through central bank interventions can stabilize these markets.
4. Addressing macroeconomic vulnerabilities, fostering economic diversification, and enhancing forecasting capabilities are essential steps to achieve exchange rate stability and economic growth in Nigeria. By adopting these policy measures, Nigeria can better navigate the complexities of global financial markets while safeguarding the value of the Naira.
5. Strengthening fiscal policies, enhancing trade balances, and mitigating external vulnerabilities can foster exchange rate stability and support informed decision-making for policymakers and stakeholders. To assist Nigerian importers, exporters, and investors in mitigating currency risk, promote the creation and accessibility of financial products such currency futures, forwards, and swaps.
6. Establish early causation system that initiate policy actions when currency risk thresholds are crossed, and build institutional capacity in financial institutions for real-time VaR monitoring. By providing significant causal findings and policy effects, this study highlights the necessity of enhanced foreign exchange management in developing nation like Nigeria.

6. Conclusion

This study evaluates exchange rate dynamics and VaR for BRICS currencies (BRL/NGN, RUB/NGN, INR/NGN, CNY/NGN, and ZAR/NGN) against the Nigerian Naira. The study reveals a mix of stability and volatility behavior for Naira against BRICS currencies influenced by domestic policies and external conditions. Accordingly, the CBN must consciously rebalance its exposure to BRICS currencies by employing risk-weighted analysis rather than merely trading volumes in view of the asymmetric risk. Also, the CBN should, for instance, seek more local currency settlement arrangements with the BRICS nations. This could lessen reliance on the US dollar and exposure to its volatility. These were made evident in the empirical influences exerted by macroeconomic factors such as financial healthiness measured as changes in broad money supply as a percentage of output (m2/gdp), trade balance-deficit or surplus, external reserves, monetary policy rate, changes in BRENT crude oil prices, and output growth rate in determining exchange rate movements. The MCS confirms the robustness of the risk metrics executed under the VaR analysis for the Naira exchange rate in relation to BRICS currencies. The analysis of the exchange rates of the Naira in relation to currencies of the BRICS reveals significant trends, volatility patterns, and predictive accuracy challenges. Periods of heightened global or domestic instability amplify uncertainty and forecasting challenges, as seen in post-2020 trends across all currencies. This study has made significant contributions to the understanding of foreign exchange forecasting and VaR estimation for the Nigerian Naira, particularly in relation to BRICS currencies. The research findings confirm that macroeconomic factors influencing exchange rate movements, including interest rate differentials, market volatility, and inflation rate differentials play a critical role in determining the exchange rate of the Naira against both major currencies and BRICS currencies, with varying degrees of impact based on currency pairs and market conditions. Interest rate differentials were found to have a positive and significant influence on exchange rates for some pairs. The generalizability of the findings may be restricted to the currencies of BRICS covered by the study. The results may not directly apply to other currencies due to differences in economic structures, policy environments, and global market dynamics. VaR estimations are effective. The estimations derived from the V-C, MCS, and H-S approaches, however, depend on the data as well as the pattern of distribution applied during the V-C and MCS processes. Since non-normalities are frequently seen in financial data, including exchange rates that reveal a variety of mean, standard deviation, skewness, and tail features; V-C, MCS, and H-S approaches may produce entirely different VaR estimations. Future research could explore the application of machine learning algorithms, such as neural networks and deep learning models, to forecast exchange rates and assess risks, particularly in highly volatile markets. These methods could capture non-linear interactions and adapt to new data patterns, offering a more dynamic and adaptable approach to forecasting. Having performed the MCS and H-S as a check of robustness on the V-C technique in the computation of VaR, this study contributes valuable insights into exchange rate forecasting and exchange risk valuation, providing a foundation for further research and practical applications in emerging markets. Thus, further research is necessary to refine and expand upon the findings of this study. This provides deeper intuition into the complexities of foreign exchange forecasting and risk management in emerging markets like Nigeria, contributing to more robust economic policy formulation and improved financial decision-making.

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Appendix 1. Unit root results for Naira/Real exchange rate

Variables	Critical Values 5%	ADF T-Statistic	Order Of Stationary	Remark
EXCR	-2.909206	-8.165319	I(1)	Stationary
m2/gdp	-2.909206	-7.759645	I(1)	Stationary
Tbal	-2.909206	-6.585367	I(1)	Stationary
ERev	-2.909206	-7.836475	I(1)	Stationary
Opr	-2.909206	-13.25672	I(1)	Stationary
OgR	-2.909206	-9.289482	I(1)	Stationary
Mpor	-2.909206	-8.051474	I(1)	Stationary

Source: authors' estimation results (2025).

Appendix 2. Unit Root Results for Naira/Rubbles exchange rate

Variables	Critical Values 5%	ADF T-Statistic	Order Of Stationary	Remark
EXCR	-2.909206	-8.194029	I(1)	Stationary
m2/gdp	-2.909206	-7.818122	I(1)	Stationary
Tbal	-2.909206	-6.585367	I(1)	Stationary
ERev	-2.909206	-7.851219	I(1)	Stationary
Opr	-2.909206	-6.234728	I(1)	Stationary
OgR	-2.909206	-8.129365	I(1)	Stationary
Mpor	-2.909206	-10.546879	I(1)	Stationary

Source: authors' estimation results (2025).

Appendix 3. Unit root results for Naira/Rupee exchange rate

Variables	Critical Values 5%	Adf T-Statistic	Order Of Stationary	Remark
EXCR	-2.909206	-3.572430	I(1)	Stationary
m2/gdp	-2.909206	-5.902116	I(1)	Stationary
Tbal	-2.909206	-6.585367	I(1)	Stationary
ERev	-2.909206	-7.916867	I(1)	Stationary
Opr	-2.909206	-10.36192	I(1)	Stationary
OgR	-2.909206	-9.267913	I(1)	Stationary
Mpor	-2.909206	-8.156739	I(1)	Stationary

Source: authors' estimation results (2025).

Appendix 4. Unit root results for Naira/Yuan exchange rate

Variables	Critical Values 5%	ADF T-Statistic	Order Of Stationary	Remark
EXCR	-2.909206	-7.748633	I(1)	Stationary
m2/gdp	-2.909206	-7.759613	I(1)	Stationary
Tbal	-2.909206	-6.585367	I(1)	Stationary
ERev	-2.909206	-7.906332	I(1)	Stationary
Opr	-2.909206	-10.32874	I(1)	Stationary
OgR	-2.909206	-8.193675	I(1)	Stationary
Mpor	-2.909206	-9.872196	I(1)	Stationary

Source: authors' estimation results (2025).

Appendix 5. Unit root results for Naira/Rand exchange rate

Variables	Critical Value 5%	ADF T-Statistic	Order Of Stationary	Remark
EXCR	-2.909206	-8.211739	I(1)	Stationary
m2/gdp	-2.909206	-7.747689	I(1)	Stationary
Tbal	-2.909206	-6.585367	I(1)	Stationary
ERev	-2.909206	-7.970241	I(1)	Stationary
Opr	-2.909206	-6.309256	I(1)	Stationary
OgR	-2.909206	-9.672058	I(1)	Stationary
Mpor	-2.909206	-7.292540	I(1)	Stationary

Source: authors' estimation results (2025).

Appendix 6. Co-integration test results for NGN/BRL exchange rate

Co-integrating Equations	Eigenvalue	Trace Statistic	Critical value (5%)	P-Value
None	0.280192	68.87248	47.85613	0.0014
At most 1	0.176491	18.81742	29.79707	0.5061
At most 2	0.090892	6.972401	15.49471	0.5809
At most 3	0.018831	1.159623	3.841466	0.2815

Source: authors' estimation results (2025).

Appendix 7. Co-integration test results for NGN/RUB exchange rate

Co-integrating Equations	Eigenvalue	Trace Statistic	Critical value (5%)	P-Value
None	0.334146	49.41380	47.85613	0.0016
At most 1	0.154628	19.60604	29.79707	0.4500
At most 2	0.130483	9.359375	15.49471	0.3332
At most 3	0.013523	0.830502	3.841466	0.3621

Source: authors' estimation results (2025).

Appendix 8. Co-integration test results for NGN/INR exchange rate

Co-integrating Equations	Eigenvalue	Trace Statistic	Critical value (5%)	P-Value
None	0.315846	67.56857	47.85613	0.0007
At most 1	0.227067	22.41469	29.79707	0.2760
At most 2	0.100212	6.703371	15.49471	0.6124
At most 3	0.004286	0.261996	3.841466	0.6087

Source: authors' estimation results (2025).

Appendix 9. Co-integration test results for NGN/CNY exchange rate

Co-integrating Equations	Eigenvalue	Trace Statistic	Critical value (5%)	P-Value
None	0.287983	50.87775	47.85613	0.0026
At most 1	0.215995	23.15889	29.79707	0.2383
At most 2	0.122248	8.315121	15.49471	0.4323
At most 3	0.005905	0.361263	3.841466	0.5478

Source: authors' estimation results (2025).

Appendix 10. Co-integration rest results for NGN/ZAR exchange rate

Co-integrating Equations	Eigenvalue	Trace Statistic	Critical value (5%)	P-Value
None	0.314706	50.00466	47.85613	0.0010
At most 1	0.284865	26.95234	29.79707	0.1028
At most 2	0.092178	6.500016	15.49471	0.6364
At most 3	0.009803	0.600915	3.841466	0.4382

Source: authors' estimation results (2025).

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Navigating Risks in Multi-Stage Translations for Sustainability Communication in the Age of Artificial Intelligence

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Purpose
In teaching and science, texts are translated from different languages. In this context, the present study investigates the potential distortions and systemic risks that arise when a source text on energy transition and sustainability is translated multiple times across different languages and by different agents, including professional translators and AI-based translation models. The research aims to analyze how these translations impact meaning, tone, and factual integrity, particularly in the context of complex topics like energy transition and related systemic risks. By comparing multiple versions of a text across English, Polish, and German, the study assesses the implications of translation-mediated communication in sustainability discourse.

Design / Methodology
First, an English source text was created, summarizing two scientific articles on the urgent need for energy transition and related system risk of such a transition. This text was translated into Polish by AI (text A) and by two professional translators (text B and C). The analysis of complexity (using Jasnopis) showed that the Polish texts were more complex (7/7, 7/7 and 6/7) for respectively texts A, B and C, than the English original text (O, 5/7). Text C was selected

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for translation into German by AI and by two professional translators. For comparison, the English source text was translated into German. The complexity of these translations was compared to the source text and the Polish versions. Afterwards, linguistic and semantic comparisons were carried out, evaluating shifts in meaning using cosine similarity (TF-IDF) and Levenshtein distance (edit distance). Furthermore, changes in emphasis, severity, and emotional tone across translations were analyzed.

Findings: This study shows that multi-stage translations in sustainability communication introduce significant distortions, affecting meaning, tone, and emphasis. AI translations tend to neutralize urgency and emotional intensity, while human translations introduce biases, either amplifying or softening risk perceptions. Additionally, differences in sentence complexity and terminology shift the focus of sustainability discourse. These findings highlight the risks of translation-mediated miscommunication in critical topics like energy transition and systemic risks.

Research limitations
The article presents a case study based on a small sample of translations. The results should be the basis for a more detailed research, comparing a larger group of AI translation and professional translations due to translator's bias, language-specific issues and the complexity of sustainability related notions.

Originality / Value
This research contributes to the sustainability communication discourse by focusing on the risks of multi-stage translations, where small wording changes can lead to significant distortions in meaning of notions and key-concepts, where miscommunication can impede decision-making and stakeholder involvement.

Keywords: translation accuracy, sustainability communication, multi-stage translation, systemic risks in translation, AI vs. human translation, computational linguistics, language education.
JEL: Q54, Z13, O33, C63.

1. Introduction

All over the world, research institutes, universities and policy makers deal with challenges of sustainable development (Leal Filho et al. 2023; Lozano et al. 2013). The notion of sustainability is grounded in theories of complex systems (Meadows 1998, 1999), which as such is difficult to understand for individuals (Kahneman 2011). The concepts of sustainability and sustainable development itself have multiple definitions, based on, for example, focus on environmental, social or economic aspects (Rao 2000), reflecting the contested nature of these concepts (Stough 2023). Furthermore, worldviews (Platje et al. 2022) as well as view on the limitations of resources and resilience of ecosystems (Gladwin et al., 1995) lead to great controversies in scientific and policy discussions. An additional challenge is that although much of the research is published in English, the authors have different linguistic backgrounds, and therefore educational materials and policy documents are written in multiple languages.

This study investigates the potential distortions and systemic risks that arise when a source text on energy transition and sustainability is translated multiple times across different languages and by different agents, including professional translators and AI-based translation models. The research aims to analyze how these translations impact meaning, tone, and factual integrity, particularly in the context of complex topics like energy transition and related systemic risks. By comparing multiple versions of a text across English, Polish, and German, the study assesses the implications of translation-mediated communication in sustainability discourse.

For the aim of this study, an English source text summarizing two scientific articles on the urgent need for an energy transition and its associated system risks was translated into Polish using Artificial Intelligence (AI) (text A) and by two professional translators (texts B and C). These translations were analyzed for complexity (using Jasnopis), semantic shifts (cosine similarity, TF-IDF, Levenshtein distance), and sentence-level differences, before being translated into German for further comparison.

The analysis shows that translation introduces meaning shifts, particularly in emphasis and severity, with AI and professional translations differing in phrasing choices, and stylistic preferences influencing accuracy—ultimately increasing systemic risks in sustainability communication across multiple translation layers.

2. Translation accuracy in sustainability communication

AI driven translation of texts has rapidly increased in importance during the last few years. Similar to human translations, mistranslations can lead to misinterpretations of sustainability regulations, and standard translation of key notions becomes elementary (Spahiu et al., 2024). For example, the notion "sustainable development" has many translations in Polish, depending on the focus of the author. Legally, it has been translated as "zrównoważony rozwój," as expressed in the country's constitution (Dz.U. 1997, No. 78, item 483). "Zrównoważony rozwój" literally means "balanced growth," which, while being the most cited definition of the notion, for example, does not reflect the meaning of sustainability itself. Sustainability can, for example, be perceived from the point of view of resilience, and following ecological economics focuses rather on preventing the collapse of ecosystems, social systems, political systems and economic systems. The translation "ekorozwój" (eco-development) tends to focus on the ecosystem as the basis for a society's sustainability (see Gladwin et al., 1995), strongly related to ecological economic theory and so-called strong sustainability. Natural resources cannot be replaced by physical and human capital, and thus limited environmental resources lead to the assumption that economic growth reduces the available natural resource base by reducing non-renewable resources and overusing renewable resources (see Georgescu-Roegen 1971; Daly 1996). On the contrary, balanced growth seems to assume continuous economic growth, implicitly assuming weak sustainability, adhering to the idea that technology and innovation can lead to the replacement of (scarce) natural resources (see Rao 2000; Gladwin et al. 1995).

When comparing machine translation (MT) and human experts, MT may not capture nuances and specific theoretical issues (Klosi et al. 2024a;b). Furthermore, AI tools might be able to translate but are not designed for the specific purpose of translations, therefore could provide differences in nuance and interpretation. For example, when asking AI tools questions on sustainability issues, it does not clearly relate to system risk. This risk that an economic system, a market, a logistic chain or another system loses its resilience and collapses (Platje et al. 2022) needs to be specifically addressed in prompts. MT may focus on mainstream knowledge used as an input, and as a result is biased towards mainstream interpretation of key notions (Yao 2024). While distorted translations may lead to wrong risk assessment (Ramadilla, Surbakti 2025), they also may lead to system risks. For example, in a serious situation of conflict a wrong word or translation may have serious irreversible consequences. It has been argued that the nuclear bombing of Hiroshima and Nagasaki on 6 and 9 August was triggered by a mistranslation of the Japanese word "*mokusatsu.*" In 1945 the Japanese Prime Minister Kantarō Suzuki responded to the Potsdam Declaration using the word *mokusatsu*. This word can mean either "to ignore with contempt" or "to withhold comment." Supposedly, Western translators interpreted it as a complete rejection. This would have led the Allies to believe Japan refused to surrender, triggering the decision to drop the atomic bombs on Hiroshima and Nagasaki. However, Naimushin (2024) argues that it is rather politics than linguistics that is relevant for the decision-making. He argues that when looking at the whole text, the message was clear, and that the bombs were dropped for other reasons.

These are examples of miscommunication regarding single notions and words. It shows that sustainability related terms, like the ones used in this study ("renewable energy transition," "system risk") are sensitive to linguistic adaptation and misinterpretation. This can lead to ambiguities in different languages. Multi-stage translations tend to increase such problems, an issue widely discussed (e.g., Biel 2017; Matulewska, Wagner 2021; Chidlov et al. 2014). However, the impact of multi-language translation distortions on energy transition and related system risk concerning decision-making for sustainable development, remains relatively underexplored.

Some studies have reported on the importance of considering linguistic and cultural contexts when discussing (and implementing) sustainability. Using South Korea as a case study, Baek and Ko (2015) address the difficulties in translating "sustainable development" into non-Western languages. The authors argue that direct translations often fail to capture the term's comprehensive meaning, leading to misunderstandings and misapplications in policy and practice. They suggest that without culturally and linguistically appropriate translations, the implementation of sustainability initiatives may be compromised. Also, within the African context, Ulmer et al. (2023) point towards the lack of equivalent terms for "sustainability" in local languages. This causes lack of effective communication and understanding, and a gap in awareness among the general population.

Furthermore, within a business context, discourse studies have shown that sustainability as a term has been translated and adapted in order to "fit" the narrative of the sector. For example, focusing on the Norwegian salmon farming industry, Aarset et al. (2020) explore how the ambiguous concept of sustainability is interpreted and legitimized by industry stakeholders. In other words, firms employ various discursive strategies to justify their (un)sustainable practices (e.g. Zappettini, Unerman 2016). While the literature refers to these business practices as discursive strategies, the underlying effects related to misinterpretations arising from direct translations can lead to ineffective policies and practices as well, highlighting the need for culturally sensitive approaches to sustainability discourse.

However, whereas mistranslation seems to be unavoidable in the context of AI translation, it may also occur in human translation. As Tabakowska observes, one of the relevant aspects of translation consists in "the translator's decision making process" (2014: 132). Therefore, mistranslation may occur simply due to the inaccurate decisions made by translators. Significant differences may appear between translations of the same Source Text conducted by different translators, insofar as the process of rendering a text into another language is also a subjective process, relying on the individual knowledge and experiences of the translator, who filters the translated text through his or her own perception (Tabakowska 2014: 132). Additionally, whereas the risk of mistranslation increases in the case of multi-staged translations, it may also occur in the context of direct translation, which was discussed for example by Catford (1965). The author observes that certain departures from the original text are unavoidable due to differences between languages, which results in the so called "translation shifts" (1965: 73).

Furthermore, direct translation may not always be possible due to structural or metalinguistic differences between languages or in the situation when there is no corresponding concept in the target language. In this case, oblique translation involving methods such as transposition or modulation is applied. Whereas transposition generally does not change the meaning of the message, modulation, for example, may distort the receiver's understanding of the given concept, insofar as it involves the change of point of view with respect to a given concept in the Source Language (Vinay, Darbelnet 1995: 84-89). Therefore, while "every translation is an interpretation" (Skwara 2019: 30), with respect to texts referring to issues such as sustainability or system risk, the subjectivity of translators shall be reduced to minimum, insofar as it may have serious consequences, as illustrated by the aforementioned example concerning Hiroshima and Nagasaki.

3. Method

The issue of system risk was chosen for analysis, as it concerns the base line of sustainable development—system resilience and survival. This is an issue that is mentally difficult to grasp in a society focused on growth and innovation, as it requires the precautionary principle, withhold from action when the consequences can lead to irreversible collapse of a system or organization. Excerpts from two articles on this issue by one of the authors of this article (Platje et al. 2022, 2024) were selected (see Appendix 1). With help of AI (Gemini), these texts were integrated and summarized, expressing the main message of system risks in energy transition. Afterwards, two professional translators and AI translated the English text into Polish. These texts were compared with regard to their complexity using the program "Jasnopis." The second professional translation was selected as the basis for the translation into German, as it had the lowest level of complexity (6 out of 7, compared with 7 out of 7 for the other translations). The original text and the translations into Polish and German can be found in the Appendix (Tables A and B).

In order to analyze the differences between the English translation into Polish, and one of the Polish translations into German, three methods were used: complexity analysis, semantic similarity analysis (cosinus similarity), translation accuracy Levenshtein similarity.

First, an analysis of the text difficulty (readability) was carried out, using the Polish programme Jasnopis (www.jasnopis.pl). While Jasnopis analyzes word complexity (rare and difficult words), syntax complexity and specialized vocabulary, it does not account for the average length of sentences.

The cosine similarity (TF-IDF) (Manning 2008) measures semantic similarity between texts based on word distribution. However, it does not detect word order changes and can be affected by the use of synonyms. The Levenshtein similarity method (Levenshtein 1966) measures character-level differences, reflecting structural similarity. It does not consider meaning, and is sensitive to word order changes. The cosine similarity method measures on a scale from 0 to 1 the word frequencies and similarities, where closer to 1 means greater semantic similarity. This is done in order to assess whether the meaning remains in the translation process and to measure the translation accuracy. Levenshtein similarity (edit distance) measures structural and formatting differences through the number of insertions, deletions, or substitutions needed to translate a text.

Furthermore, changes in emphasis, severity, and emotional tone across translations were analyzed.

4. Results and discussion

German and Polish languages tend to be more complex than English language (Morciniec 2016). The analysis of complexity (using Jasnopis) showed that the Polish texts were more complex (7/7, 7/7 and 6/7 for respectively texts A, B and C), than the English original text (5/7). This means that the Polish text is understandable for people with specialist knowledge. This creates a significant challenge in communicating system risk and related issues of resilience and the precautionary principle. The Polish translations had longer average sentence length (17.5 (text A), 17.88 (text B), 17.22 (text C) than the original text (16.75). German texts (D, E, F) have the highest sentence length (20.75 for D, the AI generated translation, 19.5 for E and 18.8 for F). The longer sentences created by AI for the German translation, 20.75 words per sentence, stand against the length of the direct English-German translation with average 18.1 words per sentence.

The results of the cosine similarity test and the Levenshtein similarity test are presented in Table 1. A value of cosine similarity closer to 1 indicates a stronger similarity in the meaning. The results range between 0.5 and 0.58 for the respective three Polish versions and the four German versions. This can be interpreted as moderate similarity. A similarity of 0.5 means that about 50% of the key terms in the compared texts overlap. The difference of maximum 0.07 between the texts as such is not very significant. The meaning is similar, but the style, wording, sentence structure, phrasing and word order differ. The result for D-G, a cosine similarity of 0.572, is an indication that direct translation leads to less significant loss of meaning. While this probably does not change the core message, it shows potential differences in emphasis, severity, and emotional tone. The change in meaning between different languages cannot be analyzed sensibly with the cosine similarity test.

For the Levenshtein Similarity, a higher value (closer to 1) means that the structure of the text is more similar. While the translation by AI of the original text into Polish (O-A) has a value of 0.85, the values for the translation from Polish (text C) into German range between 0.7 and 0.8. This is not such a surprising result of indirect translation, where similarity is lost. The German texts are more similar than the Polish texts.

Table 1. Cosine similarity score and Levenshtein similarity

	Cosine similarity score	Levenshtein similarity (Edit Distance)
O-A	--	0.851
O-B	--	0.827
O-C	--	0.794
O-D	--	0.695
O-E	--	0.757
O-F	--	0.760
O-G	--	0.775
A-B	0.511	0.972
A-C	0.575	0.933
B-C	0.508	0.960
C-D	--	0.876
C-E	--	0.954
C-F	--	0.957
C-G	--	0.977
D (German AI) - E (German prof. 1)	0.515	0.918
D (German AI) - F (German prof. 2)	0.555	0.915
D (German AI) - G (German translated from original English by AI)	0.572	0.897
E-F	0.566	0.997
E-G	0.554	0.977
F-G	0.547	0.980

Source: analysis with use of Scholar GPT.

There are important limitations in the use of AI in text analyses. In the analysis using Chat GPT 4o, differences were observed in the analysis process. Although this may be because of ambiguous prompts, with same prompts minor differences were observed. Reasons provided by Chat GPT 4o for differences in the calculation of cosine similarity were – the standardization process (lowercasing, removing excess spaces) may differ, the TF-IDF vectorization process (Term Frequency-Inverse Document Frequency, a statistical measure used to evaluate how important a word is within a document relative to a collection of documents) may differ across runs and stop word effects and tokenization artifacts may appear.

Changes in emphasis, severity, and emotional tone across translations

Translations are likely to alter the original meaning (Morciniec 2016). In the context of system risks in energy transition, which can lead to irreversible collapse scenario's, severity, urgency and consequences embraced in the text are relevant. For example, the analysis shows that the original English text has a slightly negative tone (-0.05 polarity).[1] This disappears in the translations to Polish and also German. In other words, the emotional intensity is removed. This can, on the one hand, mean that the translations tend to make the argument more objective and neutral. However, the original source was a scientific test on the need of an energy transition, as there are pressing problems such as expected increased energy scarcity and climate change, both likely to destabilize society as we know it. A neutral tone may not communicate the existing dangers properly.

Interestingly, the emphasis change is visible in the translation of the title. As presented in Table 3, the severity and urgency depend on the translator. AI translations tend to stay close to the original. The translator may have cognitive biases influencing the urgency, like with the German translation E, strengthening the fear factor.

[1] Polarity measures whether the overall emotional tone is negative, neutral of positive, while subjectivity measures the level of factuality (Morciniec 2016).

Table 3. Changes in severity and urgency in the translated title

Title	Changes in severity and urgency
English (O): “Looming Catastrophes: the Urgent Need for Renewable Energy”.	Alarmist tone: “looming catastrophes” suggests imminent danger.
Polish A (AI): „Nadchodzące katastrofy: pilna potrzeba odnawialnych źródeł energii” (close translation).	Close translation of the original.
Polish B: „Widmo nadciągających katastrof: energia odnawialna jest nam coraz pilniej potrzebna” (stronger emphasis on impending disaster).	Amplifies the fear factor by using “widmo” (specter, looming threat)—a metaphor that enhances the sense of doom.
Polish C: „Katastrofy na horyzoncie: nagląca potrzeba przejścia na energię odnawialną” (slightly softer wording, more distant „on the horizon”).	Softens the tone slightly, with “katastrofy na horyzoncie” (disasters on the horizon) suggesting something expected but not yet urgent.
German D (AI translation via Polish C): “Katastrophen am Horizont: die dringende Notwendigkeit des Übergangs zu erneuerbaren Energien”.	Weaker alarmism, similar to Polish C.
German E (translation via Polish C): “Ein Schreckgespenst drohender Katastrophen – erneuerbare Energien werden immer dringender benötigt” (most dramatic, “Schreckgespenst” means “scary specter”).	The most fear-inducing—it adds “Schreckgespenst” (ghostly terror), making the disaster feel almost haunting.
German F (translation via Polish C): “Drohende Katastrophengefahr: erneuerbare Energie immer dringender benötigt” (implies dangerous situation, but removes metaphorical aspect).	More neutral, removing the metaphoric specter and making the tone more factual.
German G (direct AI translation from English): “Drohende Katastrophen: Die dringende Notwendigkeit erneuerbarer Energien” (most faithful to English).	Stays closest in urgency and alarm.

Table 4. Change in focus of the translation

	Changes in focus: causes and consequences	**Example shift in causal emphasis:**	**The Fukushima disaster example: interpretation differences**
English (O):	Focuses equally on causes (fossil fuels) and consequences (catastrophes).	“Fossil fuels have fueled economic growth, but their limited resources and depletion pose a dire threat of future economic collapse and environmental catastrophe.”	“The Fukushima disaster tragically exemplifies how neglecting these factors can culminate in man-made catastrophes.”
Polish A (AI):	Tend to highlight economic consequences more than environmental ones.	„Paliwa kopalne napędzały wzrost gospodarczy, jednak ich ograniczone zasoby i wyczerpywanie się stanowią poważne zagrożenie przyszłym załamaniem gospodarczym i katastrofą środowiskową” (economic collapse is emphasized before environmental disaster).	
Polish B:	Tend to highlight economic consequences more than environmental ones.	Similar to Polish A.	
Polish C:	Tend to highlight economic consequences more than environmental ones.	Similar to Polish A.	„Katastrofa w Fukushimie jest tragicznym przykładem tego, jak zaniedbanie tych czynników może doprowadzić do katastrofy zawinionej przez człowieka”.“Katastrofa zawiniona przez człowieka” (human-caused disaster) explicitly blames human error, making the argument more accusatory than the English version.

Table 4. Cont.

German D (AI translation via Polish C):			"Die Katastrophe von Fukushima ist ein tragisches Beispiel dafür, wie die Vernachlässigung dieser Faktoren zu einer von Menschen verursachten Katastrophe führen kann." Similar to Polish C but slightly softer: "von Menschen verursacht" (caused by humans) sounds less directly accusatory than "zawiniona".
German E (translation via Polish C):	Emphasize the catastrophic dangers more (leaning into risk perception).	"Fossile Brennstoffe sind zwar der Wachstumsmotor unserer Volkswirtschaften, doch ihre endlichen und schwindenden Ressourcen stellen eine ernste Gefahr künftiger wirtschaftlicher Zusammenbrüche und Umweltkatastrophen dar". (Economic threats are more central, while environmental risks are secondary.)	
German F (translation via Polish C):	Emphasize the catastrophic dangers more (leaning into risk perception).		
German G (direct AI translation from English):	Follows the original most closely in balance.		

It can be argued that while the Polish translations seem to focus more on neglect of environmental threats, the base line of sustainability, the German translations seem to soften the accusation of human cause of system risk. While the English original contains a balanced mix of urgency, risk and factual discussion, the Polish translations tend to focus on economic risk and human error. The German translation E has a tendency to amplify the fear aspect, which seems to be more neutral in the two other German translations (D, F). The direct English (O) German translation (G) is closest in tone and meaning. Translations into Polish show some shifts in emphasis, influencing severity perception. If the goal is maximum urgency, English O, Polish B, and German E are the most alarmist. If the goal is factual neutrality, Polish C and German F are the most objective translations.

5. Discussion and conclusion

This study focused on the challenges posed by multi-stage translations in the context of sustainability communication, particularly regarding the energy transition. The findings demonstrate that both human and AI-based translations introduce distortions that can change the meaning, severity, and focus of critical sustainability concepts. The cosine similarity and Levenshtein similarity showed differences in meaning and structural accuracy between languages. Not surprisingly, in multiple stage translations something is "lost in translation."

AI translations are more neutral regarding emotional intensity and urgency. This is also not surprising, as AI in translation processes itself does not show cognitive biases related to the mindset. However, the input for the learning processes of AI is biased, as it was created by human beings. As each individual differs in mindsets, worldviews, values, and perceptions regarding sustainability (e.g. Caniëls et al. 2021), differences can be expected. This can either amplify or soften risk-related narratives.

Furthermore, there exists the risks of relying solely on AI-based translation models, which, while efficient, may prioritize linguistic coherence over contextual precision, reinforcing mainstream narratives at the expense of nuanced, system-level discussions. Translation goes beyond linguistic transfer. The transformation of meaning is influenced by cultural, cognitive, and technical factors. This influences the emotional load, changing the urgency. This, in turn, can impact decision-making processes, which is a topic of further research. This distortion in risk perception poses a serious challenge in crisis situations, where accurate communication of system risks is essential for timely intervention. If a translation minimizes the urgency of a potential collapse scenario, decision-makers may underestimate the need for precautionary measures, leading to inadequate policy responses. Conversely, an exaggerated emphasis on risk could result in alarmist reactions, diverting resources inefficiently or fostering public distrust in sustainability initiatives.

The emergence of advanced AI translation systems will profoundly influence the translation profession, which triggers calls for reflection of translation automation in light of sustainability (cf. Moorkens et al. 2024; Xiaoying 2024). Translators are increasingly faced with machine translations that they have to edit, which requires new skills and competences (Çetiner 2021; Liu et al., 2022). Furthermore, in the context of sustainability, specific competencies (e.g. Birdman et al. 2022; Brundiers et al., 2021; Cebrian et al. 2019; Lambrechts 2019; Lambrechts, Van Petegem 2018) and knowledge (e.g. Stough et al. 2023) is needed to grasp the complexity, uncertainty and urgency of sustainability issues. Identifying and further conceptualising competencies in the context of translation education, as well as how such competencies could be integrated in translation curricula and study programs, is a recommendation for future research. Furthermore, integrating sustainability knowledge into translation education is essential to deepen understanding of students (future translators) of sustainability and societal challenges (Kim 2005), as well as raising awareness about potential risks in translation approaches when dealing with complex challenges.

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Appendix 1. The original text before AI summarizing (from Platje et al. 2022, 2023)

From Platje et al. (2024):
The world economy has been heavily dependent on fossil fuels for the last decades (United Nations 1992). Economic growth has been based on technological development, increasing the dependency on non-renewable fossil fuels (United Nations 1997; Smil 2022). There are physical limitations to the global fossil fuel energy reserves. The expected shortages of fossil fuels in the future are expected to lead to a rise and increase in the volatility of fossil fuel prices (Servigne, Stevens 2020). This creates a threat to global economic growth. Furthermore, the use of fossil fuels is strongly connected to the threat of global climate change. Global climate change is a long-term process, characterized by increasing average temperatures as well as a statistically significant increased number and intensity of extreme events such as heat waves, droughts, floods, and hurricanes (United Nations 1997; Smil 2022). In order to prevent a climate catastrophe and economic crises, an energy transition towards renewables is required (United Nations 1997; Smil 2022). In order for the energy transition to be sustainable, it should be directed toward locally-governed, resilient systems based on renewable energy supply (Ecker et al. 2017).
Energy transitions involve a high level of uncertainty. In general, transitions are extremely slow processes that may take decades (Sovacool 2018). This inertia is due to technological and economic lock-ins in the highly complex energy supply chains (Andersen 2013; Servigne, Stevens 2020). These complex integrated global supply chains also entail vulnerabilities (Taleb et al. 2014). Therefore, autarkic (e.g. decentralized and independent) solutions become attractive (Culley et al. 2013). These solutions also make the consumer less dependent on oligopolistic producers (Gattie 2020; Berg et al. 2021).

From Platje et al. (2022):

There are many reasons for ignorance of different types of risk. Ignorance can be rational (Downs 1957), or be a result of a focus on short-term myopic goals (Alvesson, Spicer 2012), or due to the structure of the human brain (focus on cause-consequence explanations, quick decision-making based on emotions, etc.) (Swaab 2015; Beck 2017), difficulties in understanding probabilities, statistical data and uncertainties (Kahneman 2011). People tend to have difficulties in grasping the non-linear aspects of the existing threats (Sterman 2000), such as runaway processes in climate change (Allen, Frame 2007) or chain reactions in, e.g., large scale systems of nuclear plants having the potential to create a large-scale catastrophe (Taleb et al. 2014). In risk assessment models, the importance of unexpected events as a threat to systems sustainability is often neglected, denied, or poorly understood. Random events and processes play an important role, not only as a probabilistic driver of change (Lem 1968; Mandelbrot 2008). They also reveal the vulnerabilities and fragilities in a system (Taleb 2012). It can be argued that it was only a matter of time that the Fukushima Daiichi Nuclear Power Station accident in March 2011 would happen. Like most disasters (Casti 2013), this disaster was man-made as "international best practices and standards" were not followed, and information "of large tsunamis inundating the region surrounding the plant about once every thousand years" was ignored (Acton, Hibbs 2012: 1).

Appendix 2. Texts developed and selected in our study

Table A. The texts for research and analysis of the level of difficulty - Polish translation

Original text (O)	**Gemini translation (Text A)**	**Professional translation 1 (Text B)**	**Professional translation 2 (Text C)**
Looming Catastrophes: the Urgent Need for Renewable Energy Fossil fuels have fueled economic growth, but their limited resources and depletion pose a dire threat of future economic collapse and environmental catastrophe. A rapid transition to renewable energy is essential to avert these disasters. This shift is complex due to entrenched energy systems and human decision-making biases. Decentralized renewable sources offer greater control and security compared to traditional, centralized systems, which are vulnerable to single points of failure. Ignoring these risks, including potential shortages and system risks, can be due to short-sightedness, cognitive limitations, or a failure to consider	**Nadchodzące katastrofy: pilna potrzeba odnawialnych źródeł energii** Paliwa kopalne napędzały wzrost gospodarczy, jednak ich ograniczone zasoby i wyczerpywanie się stanowią poważne zagrożenie przyszłym załamaniem gospodarczym i katastrofą środowiskową. Szybka zmiana na odnawialne źródła energii jest niezbędna, aby uniknąć tych katastrof. Przejście na energię odnawialną jest złożone ze względu na utrwalone systemy energetyczne i ludzkie błędy poznawcze w podejmowaniu decyzji. Zdecentralizowane źródła odnawialne oferują większą kontrolę i bezpieczeństwo w porównaniu z tradycyjnymi, scentralizowanymi systemami,	**Widmo nadciągających katastrof: energia odnawialna jest nam coraz pilniej potrzebna** Co prawda paliwa kopalne napędzają wzrost naszych gospodarek, ale ich ograniczone i wyczerpujące się zasoby stanowią poważne zagrożenie w postaci przyszłego załamania gospodarczego i katastrofy ekologicznej. Aby zapobiec tym katastrofom, konieczne jest szybkie przejście na energię odnawialną. Jest to złożona kwestia z powodu skostniałych systemów energetycznych i ludzkich uprzedzeń decyzyjnych. Zdecentralizowane źródła odnawialne oferują większą kontrolę i bezpieczeństwo w porównaniu do tradycyjnych, scentralizowanych systemów,	**Katastrofy na horyzoncie: nagląca potrzeba przejścia na energię odnawialną** Paliwa kopalne od dawna są siłą napędową wzrostu gospodarczego, jednak ich ograniczone i coraz bardziej kurczące się zasoby stanowią poważne zagrożenie i mogą w przyszłości doprowadzić do załamania gospodarki oraz katastrofy ekologicznej. Aby zapobiec tym czarnym scenariuszom, niezbędne jest szybkie przejście na energię odnawialną. Wprowadzenie tej zmiany będzie niezwykle skomplikowane ze względu na utrwalone wzorce energetyczne oraz liczne uprzedzenia w procesach podejmowania decyzji. Zdecentralizowane źródła odnawialne zapewniają większą kontrolę i

unpredictable events, potentially leading to catastrophic consequences. The Fukushima disaster tragically exemplifies how neglecting these factors can culminate in man-made catastrophes. This disaster, entirely preventable, underscores the urgency of a global shift to renewable energy sources.	które są podatne na awarie pojedynczego punktu. Ignorowanie tych ryzyk, w tym potencjalnych niedoborów i ryzyka systemowego, może wynikać z krótkowzroczności, ograniczeń poznawczych lub zaniedbania uwzględnienia nieprzewidywalnych zdarzeń, co może prowadzić do katastrofalnych skutków. Katastrofa w Fukushimie jest tragicznym przykładem tego, jak zaniedbanie tych czynników może doprowadzić do katastrofy spowodowanej przez człowieka. Ta całkowicie możliwa do uniknięcia katastrofa podkreśla pilną potrzebę globalnego przejścia na odnawialne źródła energii.	które są podatne na punktowe awarie. Ignorowanie tych zagrożeń, w tym potencjalnych niedoborów i zagrożeń systemowych, może wynikać z krótkowzroczności, ograniczeń poznawczych lub nieuwzględnienia nieprzewidywalnych zdarzeń, potencjalnie prowadząc do katastrofalnych w swojej skali konsekwencji. Katastrofa elektrowni w Fukushimie jest przykładem tego, jak zaniedbanie tych czynników może doprowadzić do tragicznych skutków spowodowanych czynnikiem ludzkim. Katastrofa ta, której można było całkowicie zapobiec, podkreśla pilną potrzebę globalnego przejścia na odnawialne źródła energii.	bezpieczeństwo w porównaniu z tradycyjnymi, scentralizowanymi systemami, które są podatne na punktowe awarie. Ignorowanie tych zagrożeń, w tym potencjalnych niedoborów i ryzyka systemowego, może wynikać z krótkowzroczności, ograniczeń poznawczych lub nieuwzględnienia niedających się przewidzieć zdarzeń, które mogą prowadzić do zgubnych konsekwencji. Katastrofa w Fukushimie jest tragicznym przykładem tego, jak zaniedbanie tych czynników może doprowadzić do katastrofy zawinionej przez człowieka. Tragedia ta, której można było w pełni zapobiec, uwypukla pilną potrzebę globalnego przejścia na odnawialne źródła energii.

Source: developed based on excerpts from Platje et al. (2022, 2023).

Table B. The texts for research and analysis of the level of difficulty - German translation

Professional translation 2 (Text C)	Scholar GPT translation (Text D)	Professional Translation 1 (Text E)	Professional translation 2 (Text F)	Scholar GPT translation English-German (Text G)
Katastrofy na horyzoncie: nagląca potrzeba przejścia na energię odnawialną. Paliwa kopalne od dawna są siłą napędową wzrostu gospodarczego, jednak ich ograniczone i coraz bardziej kurczące się zasoby stanowią poważne zagrożenie i mogą w przyszłości doprowadzić do załamania gospodarki oraz katastrofy ekologicznej. Aby zapobiec tym czarnym scenariuszom, niezbędne jest szybkie przejście na energię odnawialną. Wprowadzenie tej zmiany będzie niezwykle skomplikowane ze względu na utrwalone wzorce energetyczne oraz liczne uprzedzenia w procesach podejmowania decyzji. Zdecentralizowane źródła odnawialne zapewniają większą kontrolę i	**Katastrophen am Horizont: Die dringende Notwendigkeit des Übergangs zu erneuerbaren Energien** Fossile Brennstoffe waren lange Zeit die treibende Kraft des wirtschaftlichen Wachstums, doch ihre begrenzten und zunehmend schrumpfenden Ressourcen stellen eine ernsthafte Bedrohung dar und könnten in Zukunft zu einem wirtschaftlichen Zusammenbruch sowie zu einer ökologischen Katastrophe führen. Um diese düsteren Szenarien zu verhindern, ist ein rascher Übergang zu	**Ein Schreckgespenst drohender Katastrophen - erneuerbare Energien werden immer dringender benötigt** Fossile Brennstoffe sind zwar der Wachstumsmotor unserer Volkswirtschaften, doch ihre endlichen und schwindenden Ressourcen stellen eine ernste Gefahr künftiger wirtschaftlicher Zusammenbrüche und Umweltkatastrophen dar. Um diese Katastrophen zu verhindern, ist ein schneller Übergang zu erneuerbaren Energien notwendig.	**Drohende Katastrophengefahr: erneuerbare Energie immer dringender benötigt** Zwar treiben fossile Brennstoffe das Wachstum unserer Wirtschaftszweigen an, aber ihre begrenzten und ausgelaugten Ressourcen stellen eine ernsthafte Bedrohung in Form eines zukünftigen wirtschaftlichen Zusammenbruchs und einer ökologischen Katastrophe dar. Um diese Katastrophen zu vermeiden, ist ein unverzüglicher Übergang zu erneuerbaren Energien unerlässlich. Aufgrund starrer Energiesysteme und	**Drohende Katastrophen: Die dringende Notwendigkeit erneuerbarer Energien** Fossile Brennstoffe haben das Wirtschaftswachstum angetrieben, doch ihre begrenzten Ressourcen und Erschöpfung stellen eine ernste Bedrohung für einen zukünftigen wirtschaftlichen Kollaps und eine Umweltkatastrophe dar. Ein rascher Übergang zu erneuerbaren Energien ist unerlässlich, um diese Gefahren abzuwenden. Dieser Wandel ist jedoch komplex, da bestehende Energiesysteme tief verwurzelt sind und menschliche Entscheidungsprozesse oft von Verzerrungen beeinflusst werden. Dezentrale erneuerbare

bezpieczeństwo w porównaniu z tradycyjnymi, scentralizowanymi systemami, które są podatne na punktowe awarie. Ignorowanie tych zagrożeń, w tym potencjalnych niedoborów i ryzyka systemowego, może wynikać z krótkowzroczności, ograniczeń poznawczych lub nieuwzględnienia niedających się przewidzieć zdarzeń, które mogą prowadzić do zgubnych konsekwencji. Katastrofa w Fukushimie jest tragicznym przykładem tego, jak zaniedbanie tych czynników może doprowadzić do katastrofy zawinionej przez człowieka. Tragedia ta, której można było w pełni zapobiec, uwypukla pilną potrzebę globalnego przejścia na odnawialne źródła energii.	erneuerbaren Energien unerlässlich. Die Umsetzung dieses Wandels wird äußerst komplex sein, da etablierte Energiemuster sowie zahlreiche Vorurteile in Entscheidungsprozessen bestehen. Dezentralisierte erneuerbare Energiequellen bieten im Vergleich zu traditionellen, zentralisierten Systemen, die anfällig für punktuelle Ausfälle sind, eine größere Kontrolle und Sicherheit. Die Ignorierung dieser Bedrohungen, einschließlich potenzieller Engpässe und systemischer Risiken, kann auf Kurzsichtigkeit, kognitive Einschränkungen oder die	Aufgrund veralteter Energiesysteme und einer menschlichen Voreingenommenheit bei Entscheidungen handelt es sich hierbei um ein komplexes Problem. Dezentrale und erneuerbare Energien bieten im Vergleich zu herkömmlichen, zentralisierten Systemen, die anfällig für Ausfälle sind, mehr Kontrolle und Sicherheit. Das Ignorieren dieser Risiken, zu denen auch potenzielle Engpässe und systemische Bedrohungen zählen, kann auf eine Kurzsichtigkeit, kognitive Einschränkungen oder die Nichtberücksichtigung unvorhersehbarer	menschlicher Entscheidungsvorurteile ist das jedoch ein komplexes Problem. Dezentrale erneuerbare Energiequellen bieten mehr Kontrolle und Sicherheit im Vergleich zu traditionellen, zentralisierten Systemen, die anfällig für Stellenausfälle sind. Das Ignorieren dieser Bedrohungen, darunter potenzieller Engpässe und systemischer Gefährdung, kann aus Kurzsichtigkeit, kognitiver Einschränkungen oder Nichtberücksichtigung unvorhersehbarer Ereignisse resultieren und maßstäblich zu katastrophalen Nachfolgen führen. Die Katastrophe des Kernkraftwerks in Fukushima ist ein Beispiel dafür, wie die Vernachlässigung dieser	Energiequellen bieten mehr Kontrolle und Sicherheit im Vergleich zu traditionellen, zentralisierten Systemen, die anfällig für einzelne Ausfallpunkte sind. Die Ignorierung dieser Risiken, einschließlich möglicher Engpässe und Systemrisiken, kann auf Kurzsichtigkeit, kognitive Einschränkungen oder das Versäumnis zurückzuführen sein, unvorhersehbare Ereignisse zu berücksichtigen – was potenziell katastrophale Folgen haben kann. Die Fukushima-Katastrophe ist ein tragisches Beispiel dafür, wie die Vernachlässigung dieser Faktoren in menschengemachten Katastrophen gipfeln kann. Diese vollständig vermeidbare Katastrophe unterstreicht die Dringlichkeit eines

	Nichtberücksichtigung unvorhersehbarer Ereignisse zurückzuführen sein, die verheerende Konsequenzen haben könnten. Die Katastrophe von Fukushima ist ein tragisches Beispiel dafür, wie die Vernachlässigung dieser Faktoren zu einer von Menschen verursachten Katastrophe führen kann. Diese Tragödie, die vollständig vermeidbar gewesen wäre, unterstreicht die dringende Notwendigkeit eines globalen Übergangs zu erneuerbaren Energiequellen.	Ereignisse zurückzuführen sein und möglicherweise katastrophale Folgen haben. Die Nuklearkatastrophe von Fukushima ist ein Beispiel dafür, wie die Vernachlässigung dieser Faktoren zu tragischen, vom Menschen verursachten Folgen führen kann. Diese völlig vermeidbare Katastrophe unterstreicht die dringende Notwendigkeit einer weltweiten Umstellung auf erneuerbare Energiequellen.	Faktoren zu tragischen Folgen durch menschliches Versagen führen kann. Diese Katastrophe, die ganz und gar zu vermeiden war, betont die dringende Notwendigkeit eines globalen Übergangs zu erneuerbaren Energiequellen.	weltweiten Übergangs zu erneuerbaren Energiequellen.

Source: developed based on excerpts from Platje et al. (2022, 2023).