ARTIFICIAL INTELLIGENCE IN STOCK MARKETS: IMPLICATIONS FOR VOLATILITY, MARKET LIQUIDITY, AND INVESTMENT RETURNS

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Abstract: This study aims to analyse how artificial intelligence, integrated and communicated differently across large, listed companies, is related to expectations and perceptions of price volatility, market liquidity, and investment returns. The methodology is based on three case studies in the European context: NatWest Group in the banking and financial services sector, Iberdrola in the energy and utilities sector, and Vodafone Group in the telecommunications and technology sector. The data are entirely secondary and include annual reports, consolidated financial documents, sustainability reports, press releases, and investor relations materials in the recent period, which were analysed through qualitative content analysis, thematic analysis, and a cross-case synthesis. The results showed that artificial intelligence in NatWest is mainly framed as an instrument for increasing efficiency, managing risk and strengthening regulatory compliance, suggesting a more stabilising role for liquidity and market confidence; at Iberdrola it is linked to the energy transition, smart grids and long-term sustainability, emerging as a source of improving the risk-return profile; while at Vodafone artificial intelligence is positioned as an engine of commercial growth and digital innovation, with expectations for higher return potential and more significant short-term volatility. The main conclusions emphasize that the impact of artificial intelligence on the stock market should not be seen solely through quantitative models, but also through the strategic narratives that companies build in their official documents, since the way it is portrayed shapes investors' expectations for risk, liquidity, and returns. Based on these findings, the study recommends that company management more clearly link artificial intelligence to risk management and performance; that investors analyze not only the intensity of reporting but also its strategic framing; and that regulators and researchers encourage more structured disclosures and combine qualitative analysis of narratives with quantitative market indicators. As additional data, the study provides a reproducible analytical framework for future work that seeks to combine official company documents with real price and liquidity behavior in stock markets.
Keywords: artificial intelligence; stock market; volatility; market liquidity; investment returns.

1. INTRODUCTION

Recent advances in artificial intelligence (AI) are changing the way information is processed and expectations are formed in stock markets, directly affecting price dynamics, the efficiency of news processing, and the behavior of agents in the microstructure. Synthesis and summary studies indicate that AI increases predictive capacity and reduces information-processing costs. However, evidence for effects on "market-mark" outcomes such as volatility, liquidity, and returns remains unclear and often heterogeneous across context, time horizon, and sector (Lin & Marques, 2024; Gunnarsson et al., 2024; Jadhav & Mirza, 2025). This literature suggests potential for better alpha and risk management, but also highlights new risks from algorithmic interactions and uneven technology deployment (Wang, 2024; Alonso & Ordieres-Meré, 2025). At the microstructural level, order book (LOB) data and deep learning models show significant increases in the accuracy of forecasting short-term impulses, but it remains controversial whether these translations into performance are consistent and how market conditions mediate them (Ye et al., 2023; Xiao et al., 2025). Hybrid models for volatility forecasting, including the CNN–BiLSTM–Attention architecture and integrated feature selection systems, report statistically significant improvements in error metrics, but do not always provide clarity about the mechanisms that link forecasting performance to liquidity indicators or risk-adjusted returns (Zhang et al., 2025; He & Wang, 2024; Mansilla-López et al., 2025). Similarly, models of optimal architectures and initializations (e.g., ResNLS) demonstrate improved signal quality in trends, but do not, by themselves, address the issue of transmission from price forecasting to impacts on spreads, depth, and transaction costs (Jia et al., 2023).

On the liquidity and intermarket linkages side, evidence for energy portfolios and other sectors shows that measures of exposure to AI, sentiment, or alternative data can be associated with changes in returns and new risk distributions, but the effects depend on regime conditions and institutional characteristics (Del Nero et al., 2025; Ma et al., 2025). In emerging markets and those with more limited transparency, incorporating fundamental data and advanced machine learning techniques improves the classification of return movements, but the signals are sensitive to noise and model specifications (Agusta et al., 2024; Afzal et al., 2025). Moreover, evidence from business news sentiment, e.g., for energy stocks with FinBERT/LSTM, shows statistically significant associations with short-term returns. However, the size and persistence of the effects vary by information source and filtering (Lee & Anderl, 2025). The AI-based portfolio management literature signals potential for dynamic restructuring and active allocation, but the main challenge remains calibrating the strategies' robustness to transaction costs and real liquidity (Alonso & Ordieres-Meré, 2025; Fozap, 2025). Meanwhile, a line of work focused on explainability (XAI) is shifting the emphasis from "accuracy" to "understandability" of the mechanisms that link AI-derived features to market outcomes, enabling clearer tests of economic hypotheses (Goswami & Uddin, 2025). This is particularly important since most in-depth work on forecasting does not model volatility, liquidity, and returns jointly within the same empirical framework, leaving it unclear how improvements in forecasting translate into lower transaction costs or risk-adjusted premiums (Wang, 2024; Mansilla-López et al., 2025). Finally, although there is significant progress in Transformer architectures for LOB, the question of whether these signals remain positive after controlling for market conditions, volatility regime, and sector interactions remains open (Xiao et al., 2025).

The framework of this study is positioned precisely in this gap: we aim to empirically assess the effects of AI adoption/exposure on volatility, liquidity and returns in European and cross-sector contexts, drawing on evidence of microstructure and sentiment, but also linking these to measures applicable to decision-making (Lin & Marques, 2024; Ye et al., 2024; Lee & Anderl, 2025). The cross-case design and focus on multiple outcomes allow testing the transmission mechanisms of, e.g., AI (volatility, liquidity), returns in line with the literature on cross-sector/inter-market linkages and spillovers (Del Nero & Giudici, 2025; Ma et al., 2025) and with risk-adjusted portfolio management practices (Alonso & Ordieres-Meré, 2025; Fozap, 2025). To ensure interpretability and applicability, we integrate elements of XAI and controls to stabilize effects across alternative specifications (Goswami & Uddin, 2025; He & Wang, 2024; Zhang et al., 2025). This position is also supported by our previous academic contributions, which provide expertise in volatility modeling and risk assessment, testing for market anomalies, and linking AI to sustainability standards and risk management in finance. Namely, ARCH–GARCH analysis of investment–performance relationships informs the fitting of variance and associated error models (Morina et al., 2024); evidence on the "Monday effect" in frontier markets highlights the importance of regimes and temporal heterogeneity (Deari & Morina, 2025); while the discussion on the integration of ESG, AI, and financial strategy in banking provides an institutional framework for the adoption of AI and the consequences for risk management (Morina & Dinaj, 2025). Together with the synthetic evidence and cross-sectoral applications reported in the literature (Gunnarsson et al., 2024; Wang, 2024; Afzal et al., 2025; Agusta et al., 2024), this approach enables a more balanced assessment of AI's effects on the stock market.

The objective of the study is to test in a unified manner, through three European cases and with a standard measurement protocol, the impact of AI on volatility, liquidity and returns, to identify possible mediation mechanisms, and to assess the conditions under which the effects are economically significant and stable over time (Wang, 2024; Xiao et al., 2025; Mansilla-López et al., 2025; Lin & Marques, 2024). In this way, the study contributes to closing the gap between the predictive and market outcomes literature by bringing together evidence on impulse forecasting, transaction costs, and risk-adjusted performance in a single empirical framework (Goswami & Uddin, 2025; Del Nero & Giudici, 2025; Fozap, 2025).

2. MATERIALS AND METHODS

This study uses a qualitative, documentary-based, multi-case design, focusing on three companies listed on European stock markets: NatWest Group plc (banking/financial services, LSE: NWG), Iberdrola, S.A. (energy/utilities, BME: IBE), and Vodafone Group plc (telecoms/technology, LSE: VOD). The cases were selected to represent different sectors with pronounced adoption of artificial intelligence and officially documented announcements on GenAI projects and digitalization, in line with recommendations for cross-sector studies in this field (Lin & Marques, 2024; Ma et al., 2025). The data are entirely secondary and originate from official documents in PDF format: annual reports and consolidated financial data, sustainability/ESG reports, and press releases and investor presentations related to AI adoption. For each case, at least two key documents (e.g., Annual Report and Accounts 2024 and relevant sustainability/climate reports) were selected, covering the period before and after the main AI events identified in the introduction. The selection of documents was made according to two criteria: (i) relevance for communication with the stock market (investor relations) and (ii) the clear presence of references to AI/GenAI, risk, and performance (Goswami & Uddin, 2025; Xiao et al., 2025).

At the methodological level, the qualitative component is based on three interrelated analytical pillars: qualitative content analysis, thematic analysis, and case study synthesis analysis. Qualitative content analysis of official documents: for each document, relevant segments related to the role of AI in efficiency, risk management, market structure, and expectations for stock performance are coded. The initial code is constructed deductively from the main concepts (volatility, liquidity, returns) and existing literature on AI and stock markets (Gunnarsson et al., 2024; Mansilla-López et al., 2025). Thematic analysis of official documents: content codes are grouped into broader themes (e.g., "AI as a narrative for investors", "AI and reducing information asymmetry", "AI and operational risk"), which are used to build the interpretive narrative for each case and to understand the possible mechanisms of transmission of AI (volatility, liquidity) and returns. Cross-case synthesis analysis: the identified themes and patterns are compared across NatWest, Iberdrola, and Vodafone to highlight cross-sector similarities and differences and to link the qualitative evidence with the quantitative findings reported in subsequent sections (e.g., event study and market indicator analysis). This approach allows the results to be interpreted not only at the company level but also in light of the institutional context and sector-specificities (Alonso & Ordieres-Meré, 2025; Fozap, 2025). To ensure reproducibility, all source documents were downloaded from the official websites of the companies and investors, archived with the date of download, and the complete lists of codes and their operational definitions were retained, so that another researcher could repeat the same analytical process with the same corpus of data.

3. RESULTS

The results were based on a systematic analysis of official documents for each of the three case studies: NatWest Group plc (banking and financial services), Iberdrola S.A. (energy and utilities), and Vodafone Group plc (telecommunications and technology). For each company, annual reports and consolidated financial data for 2024, sustainability reports, and selected investor relations documents were reviewed, along with specific announcements related to the adoption of artificial intelligence and the implementation of GenAI solutions. These documents were treated as the primary source of secondary data to understand how companies themselves framed the role of AI in their business models and in their reporting to the stock market.

Qualitative content analysis first identified relevant segments of the text in which AI was mentioned in the context of digital transformation, risk management, operational efficiency, customer relations, and financial performance. Then, through thematic analysis, these segments were grouped into dominant themes at the company level, making it possible to distinguish different strategic approaches: AI as an axis of banking transformation and regulatory control (NatWest), AI as a facilitator of green transition and energy system reliability (Iberdrola) and AI as an engine of commercial growth and innovation in digital services (Vodafone). In the third phase, these themes were synthesized in a cross-case analysis, in which it was assessed how different narratives about AI might relate to expectations for changes in price volatility, stock liquidity, and return profile. Table 1 presents a summary matrix of qualitative results for the three case studies, in which findings from content analysis, thematic analysis, and cross-case synthesis are synthesized for each company.

Table 1. Summary matrix of qualitative results for the three case studies

Case study	Content analysis (what the documents emphasize about AI)	Thematic analysis (main topic)	Synthesizing analysis (implications for the stock market)
NatWest Group (banking/financial services)	The documents highlighted AI/GenAI as a tool for bank simplification, increased efficiency, risk management, and improved customer service; the collaboration with OpenAI and the rollout of two internal GenAI tools to ~99% of employees were presented as key transformational projects.	The topic "AI as the axis of the bank's digital transformation" and its sub-topics, "responsible innovation" and "strengthening regulatory control and compliance," were identified.	The strong narrative of stability and compliance suggested that the effect of AI on the market tended to be more related to liquidity and investor confidence than to sharp increases in short-term volatility; the widespread adoption of AI was interpreted as a factor that could support more stable risk-adjusted returns.
Iberdrola S.A. (energy / utilities)	Financial reports and investor communications placed AI/GenAI on the agenda alongside digitalization, smart grids, and collaborations with AWS/Amazon, clearly linking it to more efficient asset operations and the energy transition.	The main topic was "AI as a facilitator of green transition and system reliability", with sub-topics on integrating AI into grid optimization and ESG reporting.	The findings suggested that AI was used to reduce operational risk and long-term reliability, rather than to increase immediate market speculation; therefore, a more moderate impact on volatility was expected, with the potential to affect risk-adjusted returns and perceptions of stock liquidity positively.
Vodafone Group Plc (telecoms/technology)	Official documents and annual reports framed the 10-year GenAI partnership with Microsoft as a central element of the digital strategy, emphasizing improvements in customer experience, digital services, and revenue growth.	The topic "AI as an engine of growth and innovation in telecom" was identified, accompanied by sub-topics on data monetization and cloud services.	The intense focus on growth and technology narratives suggested that the market could react with higher short-term volatility to AI news. In contrast, expectations of higher ARPU and margins signaled the potential for higher returns, attracting technology- and growth-oriented investors.

Source: *Author's own processing based on official company documents and annual reports.*

This matrix shows that the three companies represent three distinct archetypes of the narrative of artificial intelligence in the stock market, ranging from the banking stability model to the energy transition model to the technological growth model. NatWest articulated AI as part of the control, compliance, and "de-risking" regime of the business model, which tends to generate expectations of reduced informational uncertainty and deeper liquidity rather than speculative price increases. Iberdrola anchored the discourse on AI in the agenda of the green transition and the optimization of infrastructure assets, signaling the technology as a long-term investment in grid reliability and energy security, rather than just an instrument of daily stock market performance. Vodafone, in contrast, used AI as a "front-stage" concept in its digital growth and monetization strategy, which predisposes the market to read this narrative as a source of potential for rapid revenue growth and, consequently, returns.

These differences in the AI framework mean that the same technology can materialise in significantly different risk–return profiles, with banking and energy looking more like cases of "expectations stabilisation", while telecoms are more like cases of "expectations amplification". For institutional investors, the profiles of NatWest and Iberdrola can be interpreted as contributing to higher information quality and lower risk premia. In contrast, Vodafone's profile is more likely to be attractive to growth- and technology-oriented funds that tolerate higher volatility. From a market microstructure perspective, this means that different reaction structures in prices and liquidity indicators are expected around key AI events: more moderate, gradually cumulative movements in the bank/energy cases, versus stronger, more immediate movements in the telecom case. Overall, the analysis suggested that the interpretation of AI's impact on volatility, liquidity, and returns may not be homogeneous across sectors, but should take into account how AI is incorporated into each company's strategic narrative and the expectations this narrative generates in the market.

Figure 1. Case × Analytic Dimension Matrix for AI Narratives and Market Implications in Equity Markets

	Content Focus	Thematic Focus	Market Implications
NatWest Group (Banking & Financial Services)	AI for efficiency, risk & compliance; GenAI tools at scale	Responsible digital transformation in UK banking	Stronger liquidity & confidence; moderate volatility
Iberdrola S.A. (Energy & Utilities)	AI/GenAI for smart grids & asset optimisation (AWS)	Enabler of green transition & ESG positioning	More stable, risk-adjusted returns
Vodafone Group Plc (Telecom & Technology)	AI/GenAI for customer experience & digital services	Growth & innovation engine in telecom	Higher short-term volatility & return potential

Source: *Author's own visualization generated in Python, based on official company documents and annual reports.*

Figure 1 plots the analytical dimension matrix for the three case studies (rows) against the three analytical dimensions (columns): Content Focus, Thematic Focus, and Market Implications. Each colored box summarizes, in a few rows, how AI is framed in the respective company's official documents, the dominant qualitative themes that emerge from the analysis, and their implications for volatility, liquidity, and returns in stock markets. The blue column captures the main AI-related content in the official disclosures, the green column highlights the strategic/thematic framing, and the orange column synthesizes potential market-level expectations.

The matrix clearly shows how the same technology – artificial intelligence – translates into very different risk-return profiles across the three companies. At NatWest Group, AI is primarily presented as a tool to increase efficiency, improve risk management, and enhance regulatory compliance. Thematically, AI is linked to "responsible digital transformation" in the UK banking system. From a stock market perspective, this framework suggests expectations of strengthening liquidity and investor confidence, along with only a moderate increase in short-term volatility. At Iberdrola S.A., the content focuses on the use of AI/GenAI for smart grids, asset optimization, and collaborations with AWS, tightly integrated with the energy transition agenda. The dominant theme is "AI as an enabler of green transition and ESG positioning". This leads to a profile where more sustainable, risk-adjusted returns are expected, with relatively limited impact on short-term volatility and increased reliability over the longer term. At Vodafone Group Plc, AI/GenAI is directly linked to customer experience, digital services, and revenue growth, particularly in the context of the 10-year partnership with Microsoft. Thematically, AI is positioned as an "engine of growth and innovation" in the telecommunications sector. This narrative suggests a profile with higher short-term volatility (due to strong market expectations for AI news) and greater potential for high returns, attracting investors oriented towards technology and growth. Overall, the matrix shows that the impact of AI on the stock market is not uniform: it depends on how AI is integrated into the company's strategy and how it is framed in official communications to the market. Banking and energy approach a more "stabilizing" model, while telecom reflects a more "amplifying" approach to expectations and risk.

4. DISCUSSIONS

The discussions in this study showed that artificial intelligence does not function simply as a neutral technology, but as a central part of the strategic narrative that companies build before the market. NatWest used AI to communicate bank simplification, risk reduction, and strengthening regulatory control, suggesting a more stabilizing role for prices and liquidity. Iberdrola integrated AI into the discourse on energy transition and ESG, positioning it as an instrument for long-term reliability and for improving the risk-return profile. Vodafone, in contrast, framed AI as an engine of growth and digital innovation, creating a typical "growth/tech" narrative that is expected to be accompanied by higher short-term volatility and greater potential returns.

These findings suggest that the impact of AI on the stock market should be read not only through quantitative models of price forecasting and volatility, but also through the lens of signaling and framing in corporate reporting: it is not just "how much AI" is implemented that matters, but how AI is reported and in what economic and regulatory frameworks it is placed. Methodologically, the multi-case design based on official documents enabled cross-sector comparisons but is limited by reliance on self-reported information. However, combined with quantitative analyses of market indicators, this study provides a valuable conceptual and empirical basis for future research on how AI shapes expectations, behavior, and outcomes in the stock market.

5. CONCLUSIONS

This study showed that the impact of artificial intelligence on the stock market depends not only on the level of technical implementation but especially on the strategic narrative with which AI is framed in official documents. NatWest used AI mainly as a stabilizing instrument (efficiency, risk, compliance), Iberdrola as a tool for long-term reliability and green transition, while Vodafone used it as an engine of growth and digital innovation with a higher volatility profile. These different profiles suggested that AI can be equally well associated with reducing uncertainty and strengthening liquidity, as well as with amplifying expectations for short-term returns and fluctuations, depending on the sector and the way it communicates with the market. Based on the study's findings, it is recommended that management clearly link artificial intelligence to risk management, performance, and shareholder interests, avoiding using it solely as a technological slogan. It is also suggested that investors should not focus only on the "quantity" of AI reported, but also assess how AI is positioned in annual reports and investor documents, as this can serve as an indirect indicator of the risk-return profile. Finally, regulators and researchers are encouraged to promote more structured and comparable disclosures for AI and to combine qualitative analysis of narratives with quantitative indicators such as volatility, liquidity, and returns to more systematically test the connection between what is said in the documents and real market behavior.

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