Journal of Central Banking Law and Institutions, Vol. 5 No. 1, 2026, pp. 79 - 124
e-ISSN: 2809-9885 – p-ISSN: 2827-7775
https://doi.org/10.21098/jcli.v5i1.431

NAVIGATING THE FUTURE OF FINANCE: THE TRANSFORMATIVE ROLE OF GENERATIVE AI

Hassnian Ali and Ahmet Faruk Aysan

Hamad Bin Khalifa University, Doha, Qatar
e-mail: haal50943@hbku.edu.qa (corresponding author)

Submitted: 7 March 2025 - Last revised: 17 September 2025 - Accepted: 30 December 2025

Abstract

Generative Artificial Intelligence (GenAI) has the potential to transform the financial services sector by advancing financial modelling, risk assessment, fraud detection, and customer service. This study employs Structured Topic Modelling (STM), a machine learning-based method for analysing unstructured text, to uncover key themes from academic and grey literature. Academic discourse focuses on technical applications, including portfolio optimisation and financial forecasting, while grey literature emphasises ethical risks, regulatory challenges, and operational concerns. The findings reveal that GenAI enhances operational efficiency, optimises risk management, and personalises services. However, challenges related to data security, algorithmic bias, and robust ethical governance persist. Policymakers must develop regulatory frameworks that balance innovation and consumer protection, ensuring privacy, transparency, and accountability. The study identifies five key areas for future research: ethical governance, blockchain integration, employment impacts, AI-driven risk management, and personalised financial services. These insights offer a roadmap for financial institutions, policymakers, and technology providers, highlighting GenAI's transformative potential while addressing ethical considerations for its responsible deployment.

Keywords: *artificial intelligence (AI); generative AI; chatGPT; finance; structure topic modelling*

I. INTRODUCTION

Generative Artificial Intelligence (GenAI) is rapidly transforming the financial services sector by enabling new approaches to data generation, analysis, and decision-making. Unlike traditional AI models, which are designed for specific tasks using structured data, GenAI models exhibit high generalisability, producing content that closely mimics human-generated content across various formats and contexts.[1] This capability has profound implications for the financial sector, particularly in financial modelling, risk management, fraud

[1] Ethan Mollick and Jim Euchner, "The Transformative Potential of Generative AI," *Research-Technology Management* 66, no. 4 (2023): 11–16, https://doi.org/10.1080/08956308.2023.2213102.

detection, and customer service.[2] As financial institutions increasingly explore the potential of GenAI, its role as a disruptor of traditional financial practices has become more evident.

While the adoption of GenAI has been swift in industries such as healthcare and content creation, where it has improved operational efficiencies and reduced costs, its integration into finance has been comparatively slower. Despite its relatively slow adoption, GenAI's potential to reshape financial processes is significant. The global market for GenAI is projected to reach $110 billion by 2030, driven by advancements in machine learning and algorithmic innovation.[3] Financial institutions are beginning to leverage GenAI to analyse vast datasets in real time, generating insights that can enhance investment strategies, optimise portfolio management, and improve risk assessment.[4] The ability to process unstructured data, such as market sentiment and macroeconomic indicators, gives financial institutions a competitive edge by enabling more informed, agile decision-making.

However, alongside these opportunities, integrating GenAI into finance poses several critical challenges. The use of AI in financial decision-making brings risks related to data security, algorithmic biases, and regulatory compliance.[5] These challenges are compounded by the potential for AI-driven systems to exacerbate existing inequalities in access to financial services, with discriminatory lending practices and biased algorithms posing significant risks. As a result, the financial sector faces urgent calls for robust governance frameworks that ensure transparency, fairness, and accountability in the deployment of AI. This need was emphasised during the 2023 World Economic Forum, where global leaders acknowledged the transformative potential of AI but stressed the importance of regulatory oversight to prevent systemic risks, including cybersecurity vulnerabilities and opaque decision-making processes.

The objective of this study is to analyse the evolving role of GenAI in the financial sector through a machine learning-based topic modelling approach. By examining both academic and grey literature, this study seeks to identify

---

[2] Hassnian Ali and Ahmet Faruk Aysan, "What Will ChatGPT Revolutionize in the Financial Industry?," *Modern Finance* 1, no. 1 (2023): 116–29, https://doi.org/10.61351/mf.v1i1.67.

[3] "The State of AI in 2023: Generative AI's Breakout Year," McKinsey, last modified August 1, 2023, https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year.

[4] Yifei Chen et al., "Expected Returns and Large Language Models," *NLP SoDaS Conference*, November 22, 2023, https://ssrn.com/abstract=4629694; Michael Dowling and Brian Lucey, "ChatGPT for (Finance) Research: The Bananarama Conjecture," *Finance Research Letters* 53 (January 2023): 103662, https://doi.org/10.1016/j.frl.2023.103662.

[5] Hasan, Tariqul, and Nusrat Jahan. "Artificial Intelligence and Ethical Challenges in Financial Services: A Framework for Responsible Data Governance and Algorithmic Transparency." *International Journal of Data Science, Big Data Analytics, and Predictive Modeling* 14, no. 8 (2024): 16-36.

key themes, trends, and gaps in the discourse surrounding GenAI's impact on financial modelling, decision-making, and operational efficiency. The novelty of this research lies in its comprehensive approach, combining insights from academic research with industry perspectives to provide a holistic view of GenAI's influence on finance. By employing Structured Topic Modelling (STM), the study integrates unsupervised learning algorithms to extract patterns and themes from a diverse body of literature. This dual focus on academic and grey literature ensures that the analysis captures both theoretical advancements and practical applications, addressing gaps that may be overlooked by academic research alone.

This study contributes to the ongoing discourse by offering actionable insights for financial institutions, policymakers, and technology providers. It highlights how GenAI can be leveraged to navigate ethical challenges, regulatory pressures, and operational risks. By providing a comprehensive analysis that bridges academic research and industry practice, this paper lays the foundation for understanding the full scope of GenAI's impact on the financial sector, ensuring that its adoption is both innovative and responsible.

The remainder of this paper is structured as follows. The Theoretical Framework section explores how GenAI disrupts traditional financial theories, focusing on key concepts such as market efficiency, decision-making under uncertainty, and risk management. The Methodology section details the machine learning-based topic modelling approach used to analyse data from both academic and grey literature. The Results section presents the key themes and trends identified in the GenAI discourse within finance, followed by a Discussion section that examines the implications of these findings for ethical governance, regulatory challenges, and practical applications. Finally, the Conclusion synthesises the study's insights, highlights the broader impact of GenAI on finance, and outlines directions for future research.

II. THEORETICAL FRAMEWORK

GenAI introduces a new paradigm for financial decision-making by processing and generating insights from vast amounts of unstructured data. Traditional AI models in finance have been constrained by structured, quantitative data and task-specific applications. In contrast, GenAI's ability to incorporate dynamic, real-time information—ranging from market sentiment to geopolitical events—fundamentally alters financial decision-making processes. Historically, financial decisions have relied on structured models such as time-series analysis and econometrics, which operate within fixed data sets and predefined assumptions. GenAI transcends these limitations by processing and generating insights from diverse, unstructured data, offering financial institutions a more comprehensive informational base for decision-making. This expanded access to information poses profound implications for market functioning and risk assessment.[6] The Efficient Market Hypothesis (EMH) has long been a cornerstone of financial theory, positing that asset prices reflect all available information.[7] EMH assumes that markets are efficient because all participants have equal access to the same information, preventing any single investor from consistently achieving abnormal returns. However, GenAI disrupts this assumption by processing vast streams of unstructured, real-time data—including corporate disclosures, geopolitical developments, and social sentiment—that are not easily accessible or interpretable through traditional financial models.[8] Investors with access to GenAI systems may have an informational advantage, enabling them to identify and exploit market inefficiencies before the broader market reacts. This advantage challenges the foundational premise of EMH, suggesting that asset prices may no longer fully reflect all available information in real time, thereby creating new inefficiencies in financial markets.[9]

In financial economics, decision-making under uncertainty is a key theoretical concern, with classical models such as Expected Utility Theory,[10] which assume that rational decision-makers have access to all relevant information. However, in real-world markets, information is often incomplete or uncertain. GenAI enhances decision-making by providing more accurate, real-time synthesis of diverse data sources. By processing vast, continuously updated datasets, GenAI enables financial institutions to make more informed decisions, even under volatile or uncertain market conditions. This improvement in informational completeness shifts decision-making processes away from reliance on incomplete historical data towards dynamic, forward-looking strategies. The ability of GenAI to analyse non-traditional data, such as news sentiment or political developments, further supports real-time adjustments

---

6 Bag, Surajit, Susmi Routray, Tarik Saikouk, and David Roubaud. "Generative AI-Powered Innovation on Data-Driven Financial Decision-Making in Operations and Supply Chain Management: A Moderated Mediation Analysis." *Information Systems Frontiers* (2025): 1-30. https://doi.org/10.1007/s10796-025-10662-7

7 Burton G. Malkiel and Eugene F. Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance* 25, no. 2 (1970): 383–417.

8 Ardekani, Aref Mahdavi, Julie Bertz, Cormac Bryce, Michael Dowling, and Suwan Cheng Long. "FinSentGPT: A universal financial sentiment engine?." *International Review of Financial Analysis* 94 (2024): 103291.https://doi.org/10.1016/j.irfa.2024.103291.

9 Ball, Ray. "The global financial crisis and the efficient market hypothesis: what have we learned?." *Journal of Applied Corporate Finance* 21, no. 4 (2009): 8-16.

10 John von Neumann and Oskar Morgenstern, *Theory of Games and Economic Behavior* (Princeton University Press, 1944).

in investment strategies, providing a strategic edge in uncertain financial environments.[11] GenAI also has profound implications for risk management and portfolio optimisation, particularly in relation to traditional models like Modern Portfolio Theory (MPT)[12] and the Capital Asset Pricing Model (CAPM).[13] Historically, these models have operated under the assumption that future risks can be predicted from past performance. However, GenAI upends these assumptions by incorporating non-traditional data sources, such as social media sentiment, real-time macroeconomic indicators, and geopolitical risk assessments. This allows for a more nuanced and comprehensive understanding of risk, extending beyond what can be predicted from historical performance alone.[14]

Moreover, while traditional portfolio optimisation models typically operate periodically, recalibrating at fixed intervals, GenAI enables continuous real-time portfolio adjustments based on market data. This dynamic recalibration enables more agile, responsive investment strategies, providing an advantage over static models that cannot account for rapidly changing market conditions.[15] Behavioural finance theories, which emphasise the role of psychological factors and market sentiment in driving investor behaviour, also align with this dynamic approach. By integrating behavioural elements, such as sentiment analysis, GenAI offers a more holistic understanding of market movements, helping to mitigate irrational decision-making.[16] Integrating GenAI into financial systems raises significant ethical and governance concerns. Financial decisions powered by AI can have far-reaching consequences, affecting market stability and individual financial outcomes. Governance theories emphasise the need for transparency, accountability, and fairness in the design and deployment of AI systems.[17] Current regulatory frameworks, such as those set out in the Basel Accords on risk management, will likely need to evolve to include specific guidelines for the ethical use of AI in financial decision-

[11] Mo, Hongwei, and Shumiao Ouyang. "(Generative) AI in Financial Economics." *Journal of Chinese Economic and Business Studies* 23, no. 4 (2025): 509-587.

[12] Harry Markowitz, "Portfolio Selection," *The Journal of Finance* 7, no. 1 (1952): 77–91.

[13] William F. Sharpe, "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk," *The Journal of Finance* 19, no. 3 (1964): 425–42.

[14] Joshi, Satyadhar. "Gen AI for market risk and credit risk learn agentically powered gen AI; gen AI agentic framework for financial risk management." *Gen AI Agentic Framework for Financial Risk Management (January 15, 2025)* (2025).

[15] Chen, Xuhui, Guanghui Cheng, and Yong He. "Mathematical modeling and optimization of platform supply chain in the digital era: A systematic review." *Mathematics* 13, no. 17 (2025): 2863.

[16] Richard H. Thaler, "The End of Behavioral Finance," *Financial Analysts Journal* 55, no. 6 (1999): 12–17.

[17] Minz, Nitish Kumar. "Ethical Considerations in AI Applications in Finance: Frameworks, Transparency, Accountability, and Case Studies." In *Risks and Challenges of AI-Driven Finance: Bias, Ethics, and Security*, pp. 277-290. IGI Global, 2024.

making.[18] Emerging regulations, such as the European Union's AI Act, are beginning to address these concerns, emphasising the need for AI systems to be transparent, explainable, and free from discriminatory bias.[19] However, these frameworks remain nascent, and much work remains to ensure that AI-driven financial systems operate within a robust ethical and regulatory framework that maintains trust in financial markets.

This theoretical framework highlights the diverse impact of GenAI on financial theory and practice. GenAI is reshaping how financial institutions operate in an increasingly data-driven world by challenging long-held assumptions about market efficiency, decision-making under uncertainty, risk management, and ethical governance. As GenAI continues to evolve, its implications for financial markets will require ongoing theoretical developments that integrate AI capabilities with foundational financial principles. This study contributes to this discourse by offering a comprehensive analysis of how GenAI interacts with and transforms traditional financial frameworks, providing valuable insights for scholars and practitioners navigating the complexities of AI-driven finance.

III. METHODOLOGY

III.A. Data Collection and Corpus Construction

This study adopts a comprehensive dual approach to data collection by combining scientific/academic literature with grey or non-academic literature. This approach ensures that the survey covers the rigorous, peer-reviewed academic discourse on GenAI in finance and the practical, industry-focused perspectives from these sources. Figures 1 and 2 illustrate the data collection process, showcasing the distinct streams for academic and grey literature.

For scientific/academic literature, data were gathered from leading academic databases, including Scopus, Web of Science, SSRN, Google Scholar, and ScienceDirect. The search period ranged from December 2022 to March 2024, ensuring that the most recent and relevant studies were captured. Search queries were refined using ChatGPT to optimise results, including terms such as "Generative AI and Finance", "Generative AI and Banking", and "Generative AI and Accounting". This search identified 140 documents, which were subsequently refined using the Abstract Speed-Reading Technique

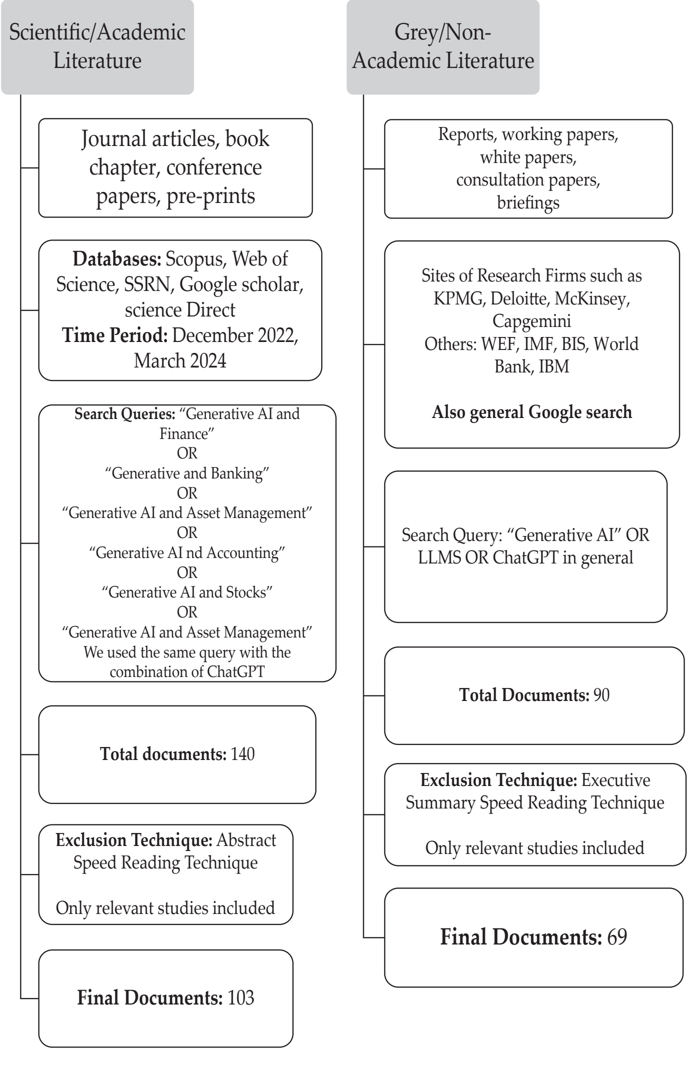
---

[18] Consultative Group on Risk Management (CGRM), "Governance of AI Adoption in Central Banks," *BIS Other* (29 January 2025): 1–49.

[19] European Parliament and the Council of the European Union, "Regulation (EU) 2024/1689 of 13 June 2024 Laying Down Harmonised Rules on Artificial Intelligence … (Artificial Intelligence Act)," (OJ L, 2024/1689, 12 July 2024): 1–144.

to assess their relevance. The final academic dataset comprised 103 papers after applying the exclusion criteria.

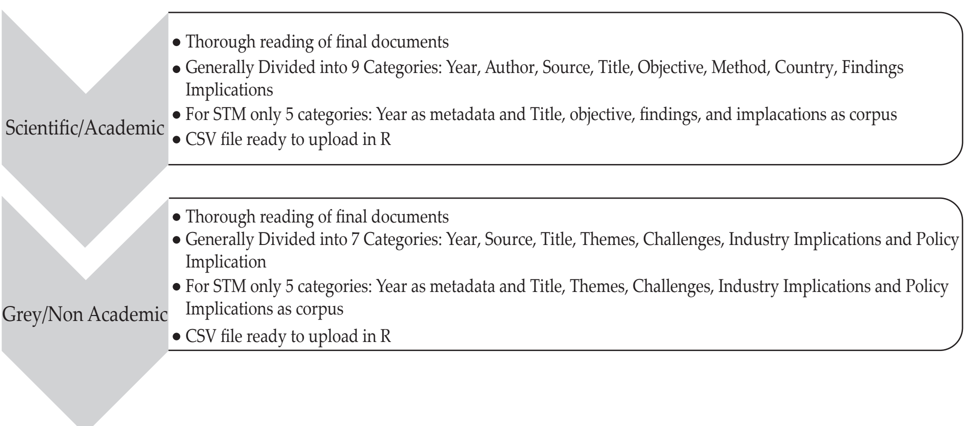
Fig 1. Data Extraction Process



Grey/non-academic literature, reports, white papers, working papers, consultation papers, and briefings were sourced from reputable organisations such as KPMG, Deloitte, McKinsey & Company, and IBM, as well as global institutions such as the World Economic Forum, IMF, Bank for International Settlements (BIS), and the World Bank. This data stream was crucial for capturing the latest industry perspectives on GenAI in finance. Search terms included "Generative AI", "Large Language Models (LLMs)", and "ChatGPT". A total of 90 documents were initially identified, filtered using the Executive Summary Speed Reading Technique[20], yielding a final set of 69 relevant grey literature documents.

This two-pronged data collection approach ensures the study draws on both theoretical and practical sources, offering a comprehensive view of how GenAI is applied, studied, and discussed across sectors.

Fig 2. Data Preparation Process for Analysis



III.B. Data Preparation for Analysis

Once the relevant documents were identified, data preparation involved systematically structuring the information for further analysis using STM. The academic and grey literature were prepared to ensure comparability across the two datasets.

For the scientific/academic literature, the final set of documents was classified into nine categories: Year, Author, Source, Title, Objective, Method, Country, Findings, and Implications. However, for STM analysis, only five categories were selected as pertinent variables: Year, Title, Objective, Findings, and Implications. These categories were chosen based on their relevance to the study's objectives and were used as metadata and corpus for the topic modelling. The data was organised in CSV format for upload into the R programming environment, where the STM analysis was conducted.

---

[20] Muhammad Yunus, "Developing the Students' Ability in Reading Through Speed Reading Technique at the First Year Students of SMKN 1 Watunohu," *Journal of Teaching and Education* 1, no. 2 (December 21, 2022), https://doi.org/10.31327/jte.v1i2.1895.

Similarly, the grey/non-academic literature was organised into seven categories: Year, Source, Title, Themes, Challenges, Industry Implications, and Policy Implications. As with the academic data, only five categories—Year, Title, Themes, Challenges, and Industry Implications—were used for STM analysis. This process ensured that the grey literature was treated consistently with the academic literature, allowing for a robust comparative analysis. The grey literature was also formatted as a CSV file for analysis in R.

To refine the document corpus and ensure that only meaningful terms were included in the topic model, we applied the Term Frequency-Inverse Document Frequency (TF-IDF) transformation. This method diminishes the weight of frequently occurring but non-informative terms (e.g., "study", "paper") while increasing the relevance of distinctive terms. Following the approach suggested by Jiang et al.,[21] we set the TF-IDF threshold at the 80th percentile (0.1736), ensuring that only the most distinctive terms were retained for topic modelling.

III.C. The STM Approach

The decision to employ STM over other topic modelling techniques, such as Latent Dirichlet Allocation (LDA), was driven by the complexity of the data and the need to account for document-level covariates. STM is particularly well-suited for studies that involve heterogeneous datasets with varying metadata, such as year of publication, source type, or document objectives. Unlike LDA, which assumes topic independence, STM allows incorporation of these covariates and models their relationships, providing a richer, more dynamic understanding of how themes evolve and correlate.[22]

STM was chosen because it allows us to analyse how different document attributes—such as publication year and source type—influence the prevalence of specific topics. This is particularly relevant for a study focused on the evolving discourse around GenAI in finance, where the themes of academic studies and industry reports have shifted significantly over time. STM's ability to capture these shifts and correlate topics across both academic and grey literature makes it the ideal tool for this analysis.[23]

The TF-IDF measure consists of two key components: term frequency (TF) and inverse document frequency (IDF). TF counts how many times a word appears, but it also takes the document length into account to prevent

[21] Hanchen Jiang et al., "A Topic Modeling Based Bibliometric Exploration of Hydropower Research," *Renewable and Sustainable Energy Reviews* 57 (2016): 226–37, https://doi.org/10.1016/j.rser.2015.12.194.

[22] Margaret E. Roberts et al., "Structural Topic Models for Open-Ended Survey Responses," *American Journal of Political Science* 58, no. 4 (2014): 1064–82, https://doi.org/10.1111/ajps.12103.

[23] Xiwen Bai et al., "Research Topics and Trends in the Maritime Transport: A Structural Topic Model," *Transport Policy* 102 (2021): 11–24, https://doi.org/10.1016/j.tranpol.2020.12.013.

longer texts from having undue weight. Here, we use D as the total number of documents and V be the total number of unique words in our data collection. In particular, the TF value (TF_{ij}) for the i-th word in the j-th document is defined as follows:

$$TF_{ij} = C_{ij}/N_j$$

C_{ij} represents how many times term i appears in document j, while N_j stands for the total number of words in that document.

On the flip side, the IDF part evaluates how unique or rare a term is across all documents. For example, words that show up very often—like "model" or "study" in academic articles—are considered less significant. The IDF formula, therefore, reduces the significance of these common words as follows:

$$IDF_i = \log_2(D/D_i)$$

In this context, IDF_i is the inverse document frequency for term i, and D_i is the number of documents in which term i appears. Then, by combining the TF and IDF values, we obtain the overall TF score for term i across the entire collection, effectively normalising its frequency.

$$TF_i = \sum_{j=1}^{D} TF_{ij} * IDF_i$$

In this study, we carefully set a TF-IDF threshold at 0.1736 (the 80th percentile). Any term scoring above this value is considered distinctive enough for our analysis. We then use the STM package for further examination. For a detailed technical explanation of how STM works, including its mathematical foundations and plate notation diagrams, please see Appendix A.

III.D. Empirical Validation and Topic Selection

To determine the optimal number of topics for STM analysis, we conducted a series of empirical tests, exploring models with 5-30 topics, following the approach established by Sharma et al.[24] The final number of topics was selected based on the average held-out likelihood, a standard measure of model fit in

[24] Anuj Sharma et al., "Fifty Years of Information Management Research: A Conceptual Structure Analysis Using Structural Topic Modeling," *International Journal of Information Management* 58 (2021): 102316, https://doi.org/10.1016/j.ijinfomgt.2021.102316.

topic modelling. After testing different numbers of topics, we determined that 10 topics provided the best balance between interpretability and model fit. This selection reflects the corpus's thematic complexity while ensuring the model remains parsimonious, and the results are easily interpretable for academic and industry audiences.

This study's methodological approach, combining rigorous academic research with practical grey literature, offers a comprehensive view of the evolving landscape of GenAI in finance. By employing STM, we ensure that the analysis captures the dynamic interplay between document attributes and thematic content, providing robust insights into the trends and challenges associated with AI applications in the financial sector. Using TF-IDF and STM ensures the analysis is technically rigorous and methodologically suited to addressing the study's core research questions.

IV. RESULTS

The results of the STM analysis reveal distinct thematic foci in both the academic and grey literature corpora regarding GenAI in finance. In the scholarly corpus, key topics emphasise Investing Strategies with GenAI, characterised by terms such as "ChatGPT", "invest", "portfolio", and "model", reflecting academia's focus on the application of AI in portfolio selection and financial decision-making (Table 1). Another prominent topic, generating economic value and managing risks, suggests that academic literature is concerned with AI's dual potential to generate value while addressing associated risks. Additionally, themes around GenAI and human intelligence highlight scholarly interest in understanding how AI complements human cognitive processes in decision-making.

In contrast, grey literature focuses more on practical concerns, such as the Potential Use of GenAI in the Financial Industry (e.g., "risk", "regulatory", "privacy"), which reflects industry-level discussions on risk management and the regulatory frameworks necessary for AI integration. Another notable topic in grey literature, ethical risks and regulatory considerations, centres on the ethical challenges faced by financial institutions, particularly in managing AI systems such as Large Language Models (LLMs). Grey literature also frequently addresses job transformation in the financial sector, reflecting industry concerns about job displacement driven by AI automation.

The divergence between academic and grey literature stems from their distinct objectives. Academic research tends to focus on theoretical advances, exploring AI's potential to enhance portfolio management, risk prediction, and financial forecasting.[25] In contrast, grey literature is more focused on the practical regulatory challenges, ethical risks, and operational issues presented by integrating AI technologies in the real world as institutions navigate compliance and privacy concerns.[26]

Table 1.
Top 10 topics and FREX words in the academic and grey corpus

Topic Labels (Academic)	FREX Words (Academic)	Topic Labels (Grey corpus)	FREX Words (Grey corpus)
Investing Strategies with GenAI: Portfolio Selection Models	chatgpt, invest, portfolio, model, select, stock, optimal, potential, financial, sentiment, decision-making, effect, market, enhance	Potential Use of GenAI in the Financial Industry	risk, generate, manage, data, regulatory, ethic, ensure, develop, framework, enhance, privacy, operation, finance, innovation, challenge
Generating Economic Value: Managing Potential Risks of GenAI	generate, risk, manage, potential, financial, data, model, challenge, finance, industry, ethic, impact, asset, economy, significant	Implementing GenAI in Central Bank Modeling Tasks	data, service, person, client, generate, privacy, ethic, risk, system, process, finance, enhance, train, accuracy, manage
GenAI and Human Intelligence: Gauging the Implications	intelligence, human, account, human, financial, artificial, similar, finance, process, address, enhance, potential, generative, communicate, intelligence	Ethical Risks and Regulatory Considerations in GenAI Data Handling	bank, central, logic, model, task, limit, LLMs, reason, generate, understand, language, data, highlight, large, comprehensive
Utilising ChatGPT in Academic Research: The Role of LLMS	chatgpt, account, llms, perform, education, question, gpt-, answer, model, bard, language, limit, use, potential, integrate	Integration of Blockchain Technology and GenAI	generate, technology, blockchain, intellectual, property, infrastructure, efficiency, concern, potential, innovate, safeguard, artificial, regard, intelligent, resource
Financial Forecasting: Using GenAI Models for Prediction	financial, generate, model, predict, price, stock, use, text, llms, data, gpt, task, domain, forecast	The Role of GenAI in Job Transformation within the Financial Sector	generate, job, ethic, finance, financial, data, potential, transform, skill, displace, innovate, impact, develop, industry, address
Enhancing Banking Services: Custom Solutions with ChatGPT	customer, chatgpt, bank, service, business, research, sector, improve, technology, potential, data, challenge, chatbot, need	Innovating Banking Services with Customer-Centric GenAI Technologies	govern, ensure, international, standard, develop, global, response, innovate, ethic, framework, regulatory, trust, need, risk, deploy

[25] Dowling, Michael, and Brian Lucey. "ChatGPT for (finance) research: The Bananarama conjecture." *Finance Research Letters* 53 (2023): 103662.

[26] Peterson K. Ozili,"Artificial Intelligence in Central Banking," in *Industrial Applications of Big Data, Ai, and Blockchain,* eds. Mahmoud El Samad et al. (IGI Global Scientific Publishing, 2024), https://doi.org/10.4018/979-8-3693-1046-5.ch004.

Table 1.
Top 10 topics and FREX words in the academic and grey corpus (Continued)

Topic Labels (Academic)	FREX Words (Academic)	Topic Labels (Grey corpus)	FREX Words (Grey corpus)
ChatGPT in Financial Advisory: Market Insights and Utilisation	financial, advice, chatgpt, market, provide, invest, test, model, gpt, potential, require, time, policy, rate, data	Developing Ethical Use Frameworks for GenAI Security	generate, ethic, business, innovate, enterprise, framework, legal, operation, enhance, need, product, potential, use, security, industry
Content Creation in Marketing: The Potential of GenAI	generate, market, content, technology, potential, challenge, digital, engage, significant, effect, explore, benefit, ethic, human, need	Establishing International Governance Standards for GenAI	bank, customer, innovate, service, regulatory, technology, operation, digital, integrate, transform, generate, challenge, navigate, GenAI, product
The Role and Potential of ChatGPT in Financial Research Analysis	chatgpt, finance, information, research, potential, model, search, significant, financial, use, relate, market, explain, human, highlight, chatgpt	Regulatory Challenges and Opportunities in GenAI for Financial Services	financial, generate, service, data, technology, regulate, challenge, risk, regulatory, industry, concern, manage, ethic, highlight, encompass
Potentials of GenAI Across Industries	potential, economy, chatgpt, impact, industry, account, collaborate, technology, labour, job, finance, disrupt, advance, ethic, significant	Investment Strategies for Investing in GenAI for the Financial Sector	generate, data, develop, regulatory, technology, invest, talent, model, skill, need, financial, response, product, innovate, customer

Figures 3 and 4 illustrate the distribution of top topics within the academic and grey literature corpora, underscoring the distinct thematic emphases in each. In the academic corpus (Figure 3), the most prominent topic labels Investing Strategies with GenAI: Portfolio Selection Models (18%), followed by Generating Economic Value: Managing Potential Risks of GenAI (13%) and Financial Forecasting Using GenAI Models (10%), reflecting a clear focus on applying GenAI to optimise financial decision-making and investment strategies. By contrast, the grey literature corpus (Figure 4) exhibits a broader focus, with the Potential Use of GenAI in the Financial Industry accounting for 19% of the total, alongside significant attention to Ethical Risks and Regulatory Considerations (15%) and Integration of Blockchain Technology and GenAI (10%). These distinctions suggest that while academic discourse is predominantly centered on the technical and financial implications of AI, grey literature is more concerned with regulatory, ethical, and technological integration issues, highlighting the practical challenges of AI adoption in the financial sector.

Fig 3. Extracted Topics and Their Proportions in the Academic Literature Corpus

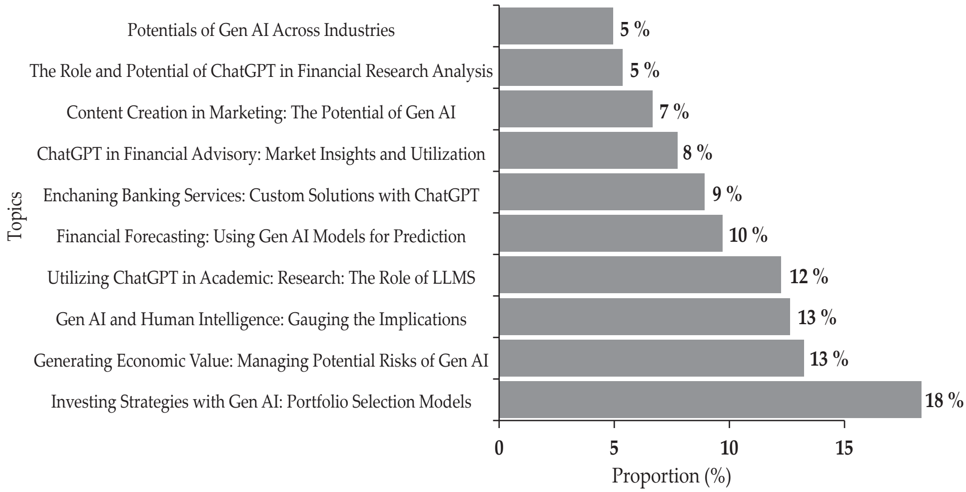
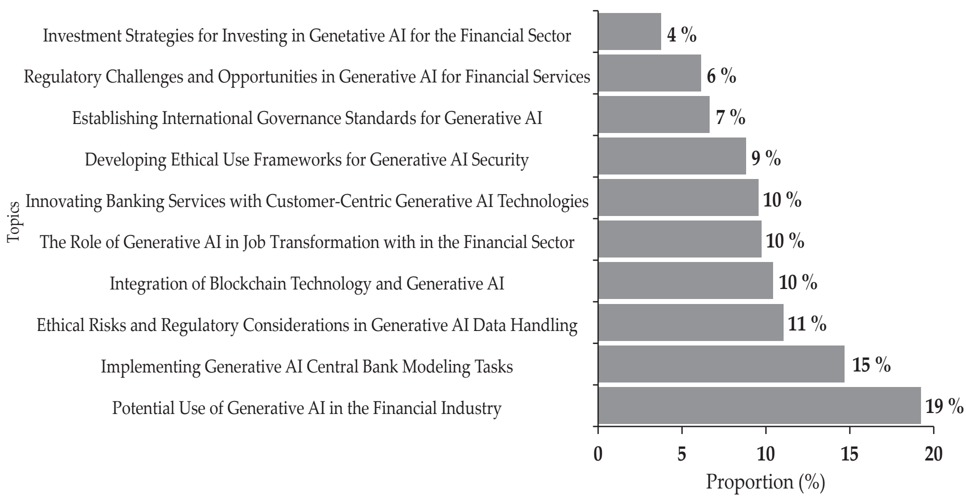


Fig 4. Extracted Topics and Their Proportions in the Grey Literature Corpus



In Figures 5 and 6 (Topic Coherence vs. Exclusivity), the academic literature corpus (Figure 5) reveals a high level of exclusivity for specialised topic labels, such as Investing Strategies with GenAI, whereas broader topic labels, like Content Creation in Marketing, exhibit stronger semantic coherence. This indicates that academic literature delves into niche financial applications and explores broader, cross-industry implications of GenAI. By contrast, the grey literature corpus (Figure 6) emphasises topics combining high coherence and exclusivity, such as regulatory frameworks, highlighting its focus on addressing industry-specific challenges requiring well-defined, practical, and actionable insights. This difference underscores the academic corpus's theoretical exploration versus the grey literature's practical orientation.

Fig 5. Topics Coherence vs. Exclusivity in the Academic Literature Corpus

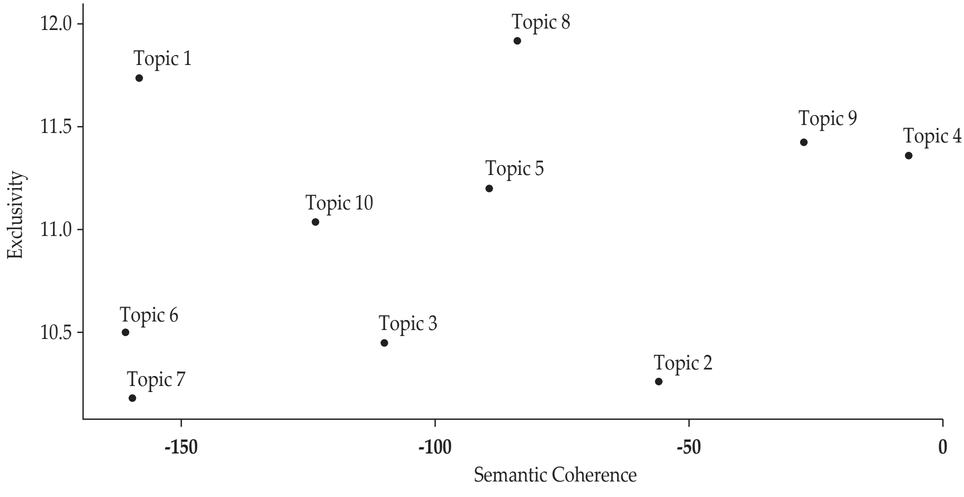
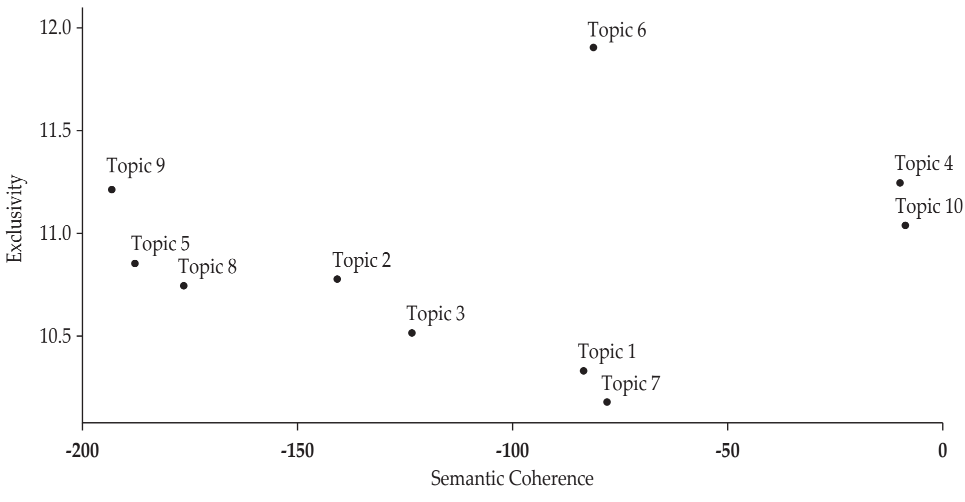


Fig 6. Topics Coherence and Exclusivity in the Grey Literature Corpus



The topic correlation networks in Figures 7 and 8 demonstrate the interrelationships between topics in the academic and grey literature corpus. In the academic corpus (Figure 7), issues such as ChatGPT in Financial Advisory and GenAI Across Industries exhibit a strong correlation, indicating that academic discourse frequently explores the intersection of AI applications in finance with broader, cross-industry impacts. In contrast, the grey literature corpus (Figure 8) highlights a close connection between Regulatory Challenges and Job Transformation, underscoring the sector's practical focus on regulatory frameworks needed to manage the workforce shifts brought about by integrating GenAI technologies. These insights suggest a divergence in the focus of academic and grey literature, with the former emphasising cross-disciplinary exploration and the latter prioritising regulatory and practical concerns.

Fig 7. Topics Correlation Network in Academic Corpus

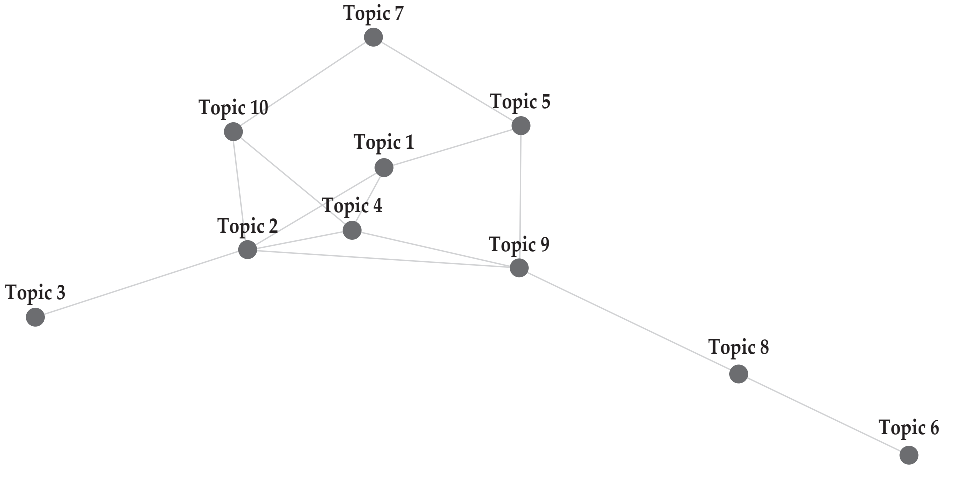
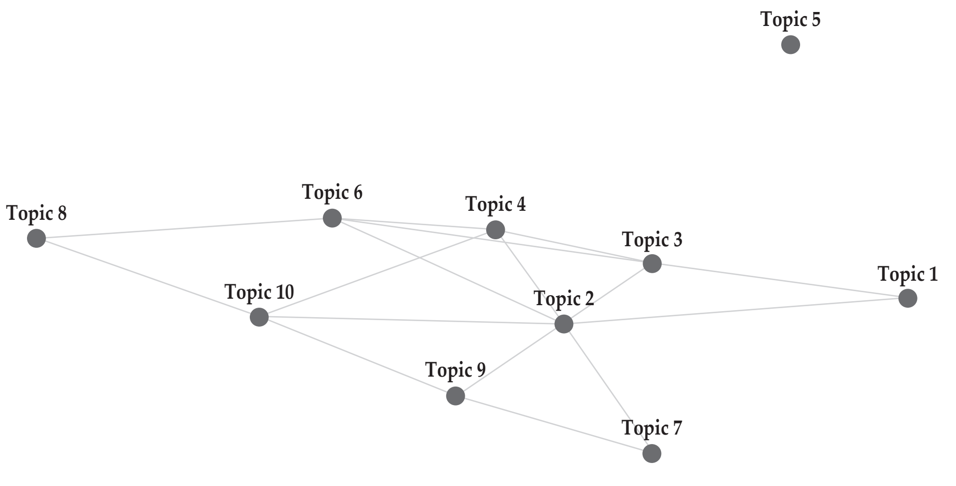


Fig 8. Topics Correlation Network in Grey corpus



Figures 9 and 10 present the topic correlation matrices for the academic and grey literature corpora, providing insights into the relationships between and among various topics. In the academic corpus (Figure 9), the correlations between topics are generally weak, with most coefficients clustering around zero, indicating limited overlap between distinct topics such as Investing Strategies with GenAI and ChatGPT in Financial Advisory. This suggests academic discussions treat issues in isolation, reflecting a more specialised approach. In contrast, the grey corpus (Figure 10) shows similarly weak correlations across topics, though slightly more pronounced connections between areas such as Regulatory Challenges and Job Transformation, indicating that grey literature, while still diverse in scope, places a somewhat stronger emphasis on interconnected challenges related to AI adoption, particularly in regulatory and workforce-related contexts. Both corpora reveal a broad thematic diversity with relatively weak inter-topic dependencies.

Fig 9: Correlation Matrix of Topics in the Academic Literature Corpus

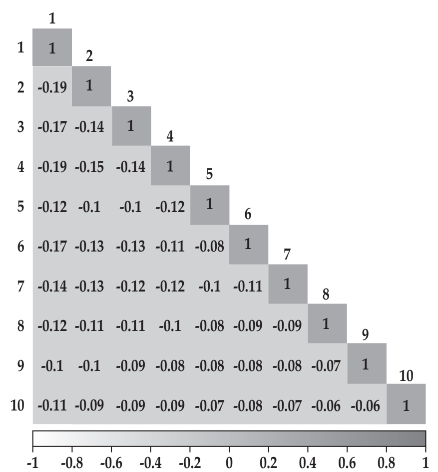
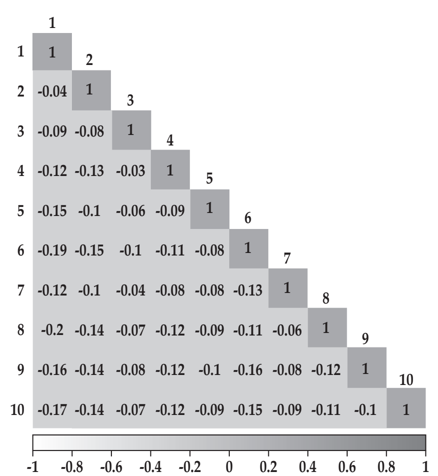


Fig 10: Correlation Matrix of Topics in the Grey Literature Corpus



Temporal analysis in Figures 11 and 12 demonstrates the evolution of topic prevalence over time. In the academic corpus (Figure 11), Investing Strategies with GenAI shows a steady increase in prevalence from 2021 to 2024, reflecting the rising scholarly interest in AI-driven portfolio optimisation. However, topics such as GenAI and Human Intelligence show a decline, suggesting a shift toward more practical AI applications. In the grey literature corpus (Figure 12), the Potential Use of GenAI in Finance has grown significantly since 2023, as institutions increasingly adopt AI for customer service, risk management, and regulatory compliance. Meanwhile, Ethical Risks and Regulatory Considerations continue to gain attention, reflecting ongoing concerns about AI governance and data privacy in the financial sector.

Fig 11. Topic Prevalence Over Time with 95% Confidence Level in the Academic Literature Corpus

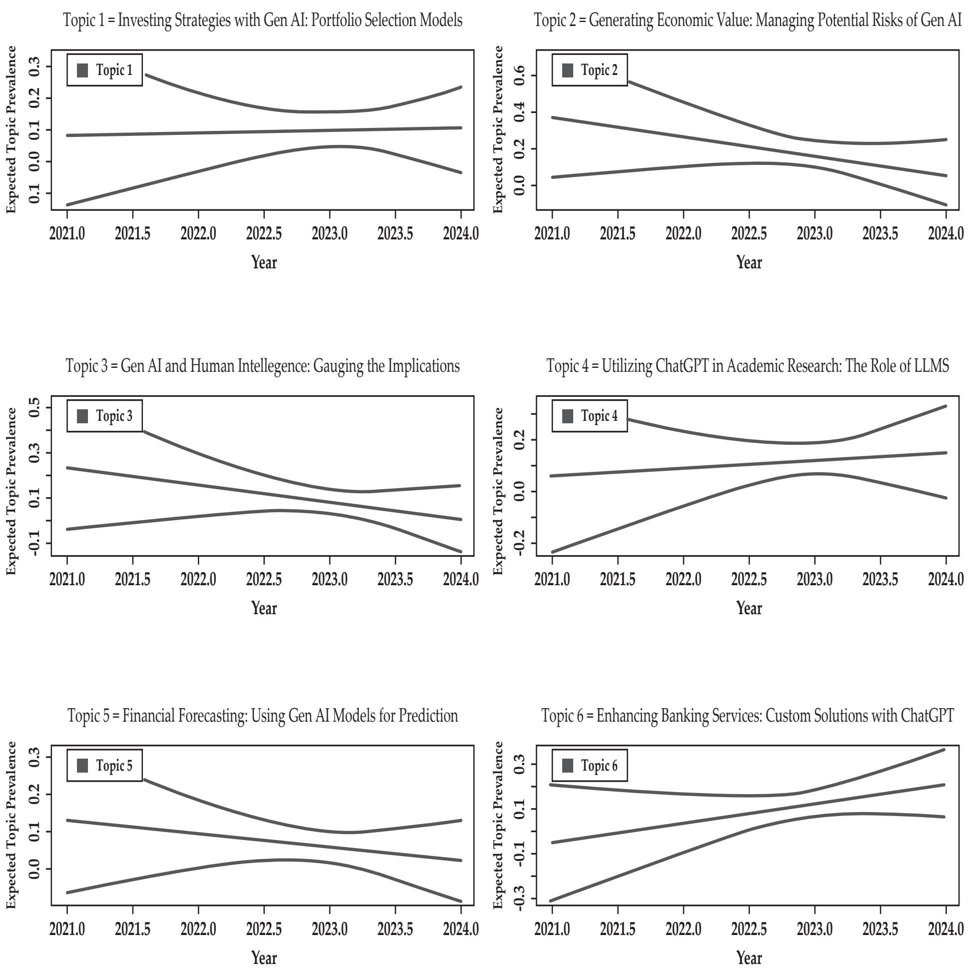


Fig 11. Topic Prevalence Over Time with 95% Confidence Level in the Academic Literature Corpus (Continued)

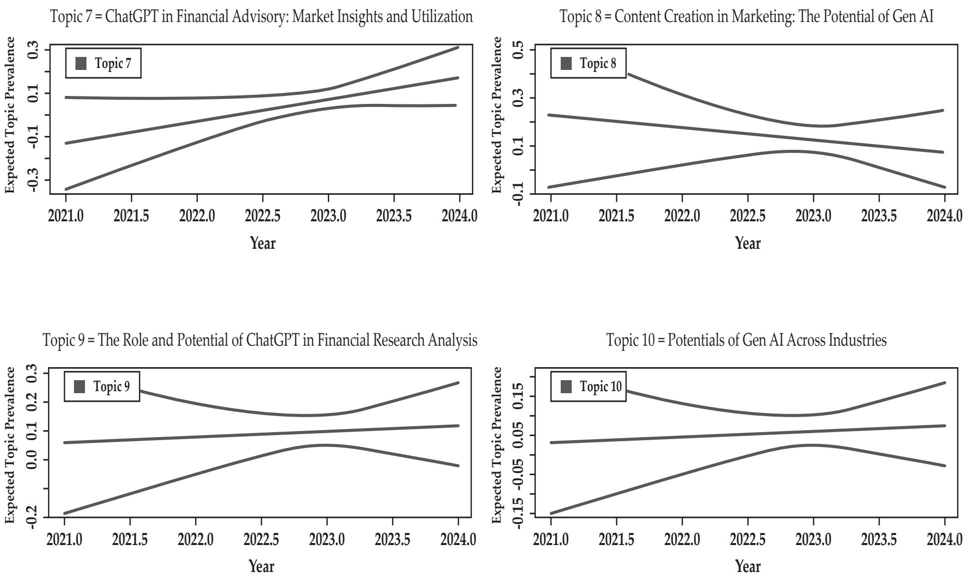


Fig 12. Topic Prevalence Over Time with 95% Confidence Level in Grey Corpus

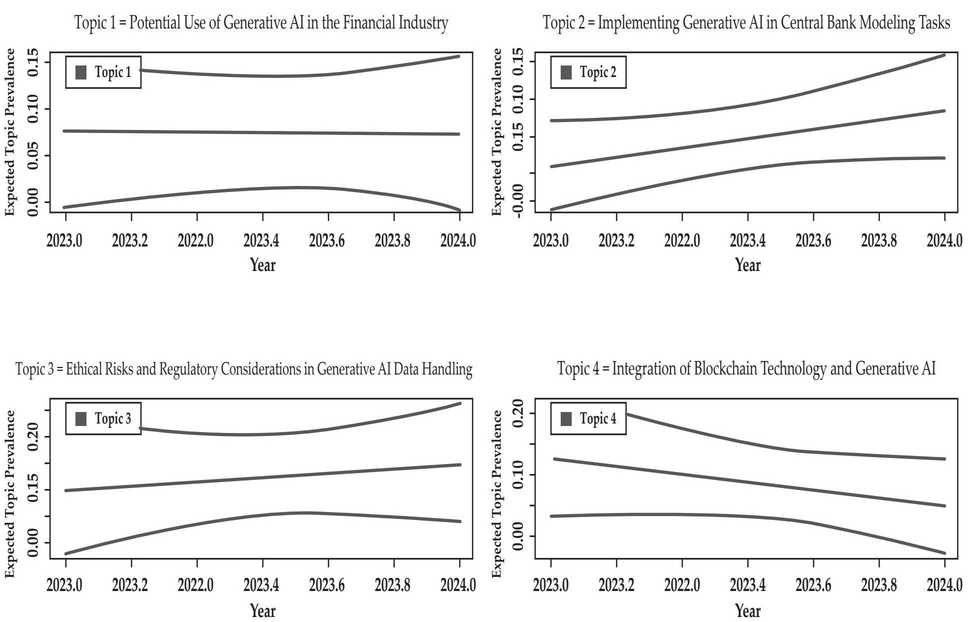


Fig 12. Topic Prevalence Over Time with 95% Confidence Level in Grey Corpus (Continued)

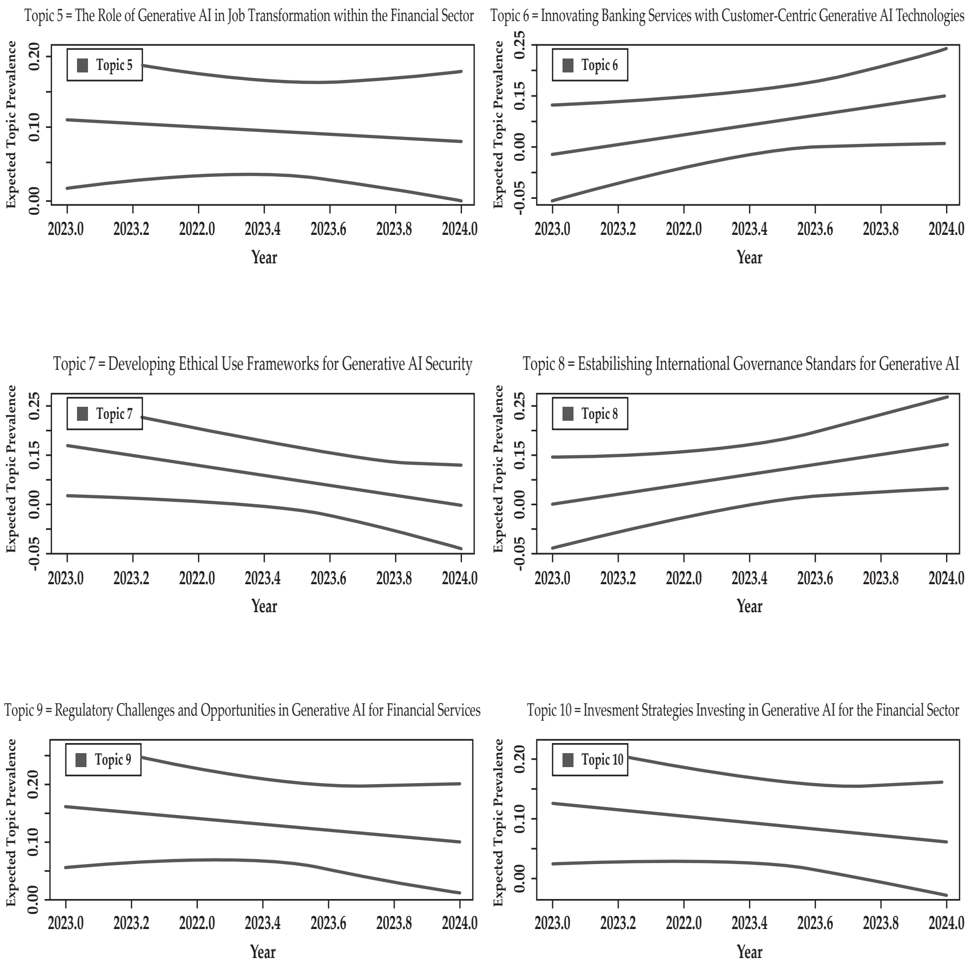


Fig 13. Word Cloud by Combining Academic and Grey Literature

Figure 13 presents a word cloud from the combined academic and grey literature on GenAI in finance, revealing key thematic areas and concerns. The most prominent terms, such as "financial", "genai", and "regulatory", reflect the dual focus of both theoretical and practical literature on the transformative potential of AI in finance and the associated regulatory and ethical implications. Terms like "challenges", "data", "management", and "risk" highlight the critical concerns related to governance, transparency, and the operational risks posed by AI-driven financial systems. The prominence of words like "frameworks", "integration", and "efficiency" underscores the industry's efforts to create structured approaches for integrating AI technologies into financial services while addressing ethical, operational, and compliance challenges. The word cloud encapsulates the broad scope of discourse surrounding GenAI, spanning technical applications, regulatory issues, and future implications for financial institutions, policymakers, and industry leaders.

The STM results of the combined dataset, presented in Appendix B, reveal a rich and multifaceted understanding of how GenAI is being discussed and applied across various domains in the financial sector. Figure B1, which illustrates the extracted topics and their proportions, indicates that "Generative AI Governance and Regulations for the Financial Industry" (17%) is the dominant theme, underscoring the growing importance of ethical governance and regulatory frameworks in mitigating risks associated with AI-driven decision-making. Other prominent topics, such as "Potential of LLMs in Accounting Education and Practice" and "Research on Price Prediction and

Market Dynamics Using Generative AI" (both at 12%), emphasise the dual focus on both educational advancements and predictive capabilities enabled by AI. The relatively high proportions of "Utilising ChatGPT for Financial Research and Modeling" and "Investment Strategies Using ChatGPT in Finance and Stocks" (11%) highlight the practical applications of GenAI tools in real-time financial modelling and investment optimisation, signalling a shift toward more data-driven, agile decision-making processes in finance.

Moreover, Figures B2 through B4 in Appendix B explore the relationships among these topics. The Topic Coherence vs. Exclusivity analysis (Figure B2) shows that issues related to "Ethical Considerations" and "AI Governance" are highly exclusive but demonstrate lower semantic coherence, suggesting that while these topics are distinct, they may still require further refinement in the academic discourse. Conversely, topics like "Price Prediction" and "LLM Applications in Education" exhibit higher coherence, indicating well-developed research areas. The Topics Correlation Network and Correlation Matrix (Figures B3 and B4, respectively) further reveal intricate interconnections between themes such as "Generative AI Models in Research" and "Ethical AI Governance," illustrating the intertwined nature of technical applications and ethical concerns. Finally, Figure B5 tracks topic prevalence over time, demonstrating a growing focus on "Business Innovation in Finance" and "Customer Service Optimisation" using GenAI, particularly post-2023, reflecting the increasing adoption and operational integration of AI technologies within the financial sector.

The results highlight key differences between academic and grey literature approaches to GenAI in finance. Academic research emphasises theoretical exploration and the technical applications of AI in areas like portfolio management and forecasting. At the same time, grey literature is more focused on immediate regulatory challenges and the ethical risks associated with AI deployment. These findings provide a comprehensive view of how GenAI shapes both theoretical advancements and practical implementations in the financial industry, with significant implications for researchers and practitioners.

V. DISCUSSION ON MAJOR TRENDS

V.A. Potential Use Cases of GenAI in Financial Services

The financial services industry, characterised by its data-rich environment, stands to benefit significantly from the integration of GenAI. Various studies and industry reports highlight how GenAI is set to transform financial processes, leading to more personalised services, enhanced efficiency, and innovative solutions. One such area is wealth management, where GenAI can play a pivotal role. By analysing large datasets, GenAI can offer customised investment advice, tailored to individual financial goals and risk tolerances, thereby demonstrating its practical applications in the financial industry.[27] The technology also supports client retention through enhanced lead generation and personalised communication.[28] Moreover, GenAI can significantly optimise customer engagement by transforming raw data into actionable insights, enabling highly personalised advice and services that boost customer satisfaction and loyalty.[29] Through natural language processing (NLP), GenAI powers real-time, context-aware customer interactions, revolutionising customer service and delivering seamless experiences.[30] These cases highlight the potential of GenAI to reshape financial institutions, leading to enhanced operational resilience, streamlined services, and improved client relationships. For risk management and compliance, GenAI provides valuable applications by automating risk assessment and monitoring compliance with regulatory standards.[31] Its ability to analyse financial datasets to ensure adherence to regulatory frameworks not only enhances resilience but also reduces the operational burden of manual compliance checks.[32] ChatGPT-4's capabilities in investment advice further illustrate GenAI's potential. Studies show that GenAI ratings correlate with future earnings and stock returns, suggesting that investment strategies informed by AI can yield positive financial outcomes.[33]

Table 2 provides an overview of critical use cases across various categories in the financial sector, summarising the most prominent applications of GenAI. The insights confirm that GenAI's impact spans diverse areas, including customer service, compliance, and forecasting, positioning technology as a transformative force in financial services. The incorporation of local large

---

[27] Qian Bi, "Analysis of the Application of Generative AI in Business Management," *Advances in Economics and Management Research* 6, no. 1 (2023): 36, https://doi.org/10.56028/aemr.6.1.36.2023.

[28] Osama Ahmed Abdelkader, "ChatGPT's Influence on Customer Experience in Digital Marketing: Investigating the Moderating Roles," *Heliyon* 9, no. 8 (2023): e18770, https://doi.org/10.1016/j.heliyon.2023.e18770.

[29] Pablo Rivas and Liang Zhao, "Marketing with ChatGPT: Navigating the Ethical Terrain of GPT-Based Chatbot Technology," *AI (Switzerland)* 4, no. 2 (2023): 375–84, https://doi.org/10.3390/ai4020019.

[30] Jeanne Bickford et al., "GenAI Is about to Transform Banks Front to Back," (Boston Consulting Group, 2024).

[31] Rahul Agarwal et al., "How Generative AI Can Help Banks Manage Risk and Compliance," McKinsey & Company, updated March 1, 2024; "The Generative AI Advantage in Financial Services: How Financial Services Executives Can Seize its Potential," *KPMG*, 2023, https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2023/the-gen-ai-advantages-in-financial-services.pdf.

[32] Haijun Wang et al., "Fintech Inputs, Non-Performing Loans Risk Reduction and Bank Performance Improvement," *International Review of Financial Analysis* 90 (2023), https://doi.org/10.1016/j.irfa.2023.102849.

[33] Matthias Pelster and Joel Val, "Can ChatGPT Assist in Picking Stocks?," *Finance Research Letters* 59 (2024): 104786, https://doi.org/10.1016/j.frl.2023.104786.

language models (LLMs) further expands GenAI's applicability to specific financial texts and scenarios, underscoring the importance of domain-specific models.[34]

Table 2.
Use Cases of GenAI in the Financial Industry

Category	Potential Use Cases
Customer Experience Enhancement[35]	Personalising customer interactions through chatbots and virtual assistants, creating more engaging and informative digital content.
Risk Management and Compliance[36]	Automating compliance processes, enhancing regulatory reporting through AI-driven data analysis, and predicting regulatory risks.
Operational Efficiency and Automation[37]	Streamlining back-office operations, reducing manual tasks through intelligent automation, and improving process efficiency.
Financial Advisory and Wealth Management[38]	Providing tailored financial advice using AI-driven analysis of financial data; automating portfolio management and optimisation.
Fraud Detection and Cybersecurity[39]	Enhancing fraud detection mechanisms with pattern recognition; improving cybersecurity defences through predictive threat analysis.

[34] Thomas Cook et al., "Evaluating Local Language Models: An Application to Bank Earnings Calls," *The Federal Reserve Bank of Kansas City Research Working Papers*, accessed November 6, 2023, https://doi.org/10.18651/rwp2023-12.

[35] Abdelkader, "ChatGPT's Influence;" Tiffany Fishman et al., "Realizing the Potential of Generative AI in Human Services: Use Cases to Transform Program Delivery A Report from the Deloitte Center for Government Insights," Deloitte, 2023; KPMG, "The Generative AI Advantage;" Dimitra Skandali et al., "Artificial Intelligent Applications in Enabled Banking Services: The Next Frontier of Customer Engagement in the Era of ChatGPT," *Theoretical Economics Letters* 13, no. 05 (2023): 1203–23, https://doi.org/10.4236/tel.2023.135066; Tulus Suryanto et al., "The Potential of Halal Tourism System on Growth for the Province Lampung's Tourism Industry," *Journal of Environmental Management and Tourism* 13, no. 6 (2022): 1616–28, https://journals.aserspublishing.eu/jemt/article/view/7274.

[36] Agarwal et al., "How Generative AI Can Help;" David Krause, "Mitigating Risks for Financial Firms Using Generative AI Tools," *SSRN Electronic Journal*, 2023, 1–22, https://doi.org/10.2139/ssrn.4452600.

[37] Antonio J. G. Busson et al., "Saturn Platform: Foundation Model Operations and Generative AI for Financial Services," *Companion Proceedings of the 29th Brazilian Symposium on Multimedia and Web*, 2023, 85–88, https://doi.org/10.5753/webmedia_estendido.2023.234354; Ron Shevlin, "Finding the Next Wave to Ride," Cornerstone Advisors, updated 2024, https://www.crnrstone.com/hubfs/WGOIB%202024/2024-Whats-Going-On-In-Banking_Cornerstone-Advisors.pdf; Oleksandr Romanko et al., "ChatGPT-Based Investment Portfolio Selection," *Operations Research Forum* 4, no. 91 (2023): 0–26, https://doi.org/10.1007/s43069-023-00277-6.

[38] Sathesh Sriskandarajah, "Generative AI Banking and Financial Services," Accubits Technologies, updated August 2023, https://accubits.com/white-papers/Generative-AI-in-Banking-and-Financial-Services-by-Accubits.pdf; Oliver Wyman., "How Generative AI Is Transforming Business and Society," (2024), https://www.oliverwymanforum.com/content/dam/oliver-wyman/ow-forum/gcs/2023/AI-Report-2024-Davos.pdf; Aleksandr Ahramovich, "AI In Wealth Management: Use Cases, Solutions & Adoption Guidelines," Itransition, 2023, https://www.itransition.com/ai/wealth-management.

[39] Dirk Beerbaum, "Generative Artificial Intelligence (GAI) with Chat GPT for Accounting – a Business Case," *SSRN Electronic Journal*, 2023, 1–14, https://doi.org/10.2139/ssrn.4385651; Infocomm Media Development Authority, "Model AI Governance Framework for Generative AI: Fostering a Trusted Ecosystem," 2024; Suman Kalia, "Potential Impact of Generative Artificial Intelligence(AI) on the Financial Industry," *International Journal on Cybernetics & Informatics* 12, no. 6 (2023): 37–51, https://doi.org/10.5121/ijci.2023.120604.

Table 2.
Use Cases of GenAI in the Financial Industry (Continued)

Category	Potential Use Cases
Product Development and Innovation[40]	Developing new financial products based on AI-generated market insights; utilising AI to simulate market conditions for product testing.
Regulatory and Policy Adherence[41]	Ensuring adherence to changing regulations through automated updates and simplifying policy interpretation with natural language processing.
Marketing and Customer Engagement[42]	Creating targeted marketing campaigns using AI-driven customer insights; enhancing customer relationship management through personalisation.
Human Resources and Talent Management[43]	Optimising recruitment processes with AI-driven candidate screening; supporting employee development through personalised learning platforms.
Data Management and Analytics[44]	Enhancing data quality and integrity for better decision-making; facilitating advanced analytics for strategic insights.
Stock prices, earnings and returns prediction[45]	Utilising as a tool for prediction and future forecasting of stock prices, earnings, and returns.

V.B. Ethical Framework and Governance of GenAI in the Financial Sector

While GenAI promises significant benefits, its deployment in the financial industry raises profound ethical concerns. One of the most pressing issues is the risk of bias in predictive models. AI models trained on biased historical data can reinforce and perpetuate inequalities, particularly in areas such as loan

40 Md Arman and Umama Rashid Lamiya, "Exploring the Implication of ChatGPT AI for Business: Efficiency and Challenges," *Journal of Innovation Information Technology and Application (JINITA)* 5, no. 1 (2023): 52–64, https://doi.org/10.35970/jinita.v5i1.1828; Nir Kshetri, "The Economics of Generative Artificial Intelligence in the Academic Industry," *Computer* 56, no. 8 (2023): 77–83, https://doi.org/10.1109/MC.2023.3278089; Muhamad Malik Mutoffar et al., "Exploring the Potential of ChatGPT in Improving Online Marketing and Promotion of MSMEs," *Jurnal Minfo Polgan* 12, no. 1 (2023): 480–89, https://doi.org/10.33395/jmp.v12i1.12440.

41 Douglas Kiarelly Godoy de Araujo et al., "Artificial Intelligence in Central Banking," *BIS Bulletin* no. 84 (2024), https://www.bis.org/publ/bisbull84.htm; Itamar Caspi et al., "Generative AI and the Future of Financial Advice Regulation," *GenLaw Center*, 2023, https://genlaw.org/CameraReady/19.pdf; Ben Neilson, "Artificial Intelligence Authoring Financial Recommendations: Comparative Australian Evidence," *Journal of Financial Regulation* 9, no. 2 (2023): 249–57, https://doi.org/10.1093/jfr/fjad004.

42 Chris Bushell, "Impacts of ChatGPT on Marketers: A Comprehensive Analysis" SSRN Electronic Journal, 2023, https://doi.org/10.2139/ssrn.4556646; Marko Vidrih and Shiva Mayahi, "Generative AI-Driven Storytelling: A New Era for Marketing," *arXiv,* 2023, http://arxiv.org/abs/2309.09048; Jochen Hartmann et al., "The Power of Generative Marketing: Can Generative AI Reach Human-Level Visual Marketing Content?," *SSRN Electronic Journal*, 2023, https://doi.org/10.2139/ssrn.4597899.

43 McKinsey & Company, "Beyond the Hype: Capturing the Potential of AI and Gen AI in Tech, Media, and Telecom,"McKinsey & Company, updated February 22, 2024, https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/beyond-the-hype-capturing-the-potential-of-ai-and-gen-ai-in-tmt; Karsten Wenzlaff and Sebastian Spaeth, "Smarter than Humans? Validating How OpenAI's ChatGPT Model Explains Crowdfunding, Alternative Finance and Community Finance," *SSRN Electronic Journal*, December 29, 2022, https://doi.org/10.2139/ssrn.4302443.

44 Australian Government Productivity Commission, "Making the Most of the AI Opportunity: AI Raises the Stakes for Data Policy," Australian Government Productivity Commission, 2024, https://assets.pc.gov.au/2025-10/ai-paper3-data.docx?VersionId=2GW50ODo932jjso8TzhMkEC0CsacJPGL.

45 Pelster and Val, "Can ChatGPT Assist;" Cook et al., "Evaluating Local."

eligibility and investment decisions.[46] This has far-reaching consequences, as these AI-generated outcomes can exacerbate existing inequalities and restrict access to financial services for vulnerable populations.

Moreover, the opacity of AI algorithms presents challenges regarding transparency and accountability. Financial decisions made by AI systems can significantly impact individuals and markets, yet the complexity of these algorithms makes it difficult for individuals to understand or challenge decisions.[47] This lack of transparency risks undermining trust in financial institutions and can erode confidence in the regulatory systems intended to safeguard against malfeasance. The challenge lies in ensuring algorithmic fairness, especially as AI systems become increasingly integral to high-stakes decisions such as lending and investment management.

The displacement of jobs in the financial sector due to AI automation also raises ethical questions about the future of labour.[48] While GenAI can drive recruitment efficiently, it can lead to significant workforce disruption. Addressing these changes requires thoughtful strategies, including retraining and redeployment of affected employees to ensure that techno logical progress does not result in social inequities.

Ethical issues extend to market manipulation risks, where GenAI could be exploited to gain unfair advantages by predicting or influencing market conditions.[49] Maintaining fair and equitable financial markets requires robust safeguards to prevent unethical behaviour.

To address these concerns, regulatory and governance frameworks must evolve. Regulatory bodies, such as the BIS[50] and the Center for American Progress,[51] emphasise the importance of transparency and accountability in AI systems. Regulations that enforce transparency, such as mandatory disclosures of AI algorithms, can mitigate biases and protect user privacy. Collaborative

[46] Muhammad Salar Khan and Hamza Umer, "ChatGPT in Finance: Applications, Challenges, and Solutions," *Heliyon* 10, no. 2 (2024), https://doi.org/10.1016/j.heliyon.2024.e24890.

[47] Alotaibi, Emran, and Nadia Nassif. "Artificial intelligence in environmental monitoring: in-depth analysis." *Discover Artificial Intelligence* 4, no. 1 (2024): 84.

[48] Alfonso Renato Vargas-Murillo et al., "Challenges and Opportunities of AI-Assisted Learning: A Systematic Literature Review on the Impact of ChatGPT Usage in Higher Education," *International Journal of Learning, Teaching and Educational Research* 22, no. 7 (2023): 122–35, https://doi.org/10.26803/ijlter.22.7.7.

[49] Michael Klenk, "Ethics of Generative AI and Manipulation: A Design-Oriented Research Agenda," *Ethics and Information Technology* 26, no. 9 (2024), https://doi.org/10.1007/s10676-024-09745-x.

[50] de Araujo et al., "Artificial Intelligence in Central Banking."

[51] Megan Shahi et al., "Generative AI Should Be Developed and Deployed Responsibly at Every Level for Everyone," Center for American Progress, updated, February 1, 2024, https://www.americanprogress.org/article/generative-ai-should-be-developed-and-deployed-responsibly-at-every-level-for-everyone/.

initiatives, such as the Singapore Authority's AI Governance Framework, further recognise the importance of open-source contributions and best practices for AI governance.[52] Thus, ethical and governance frameworks are essential for mitigating risks associated with GenAI, ensuring its application in finance is equitable, transparent, and accountable.

V.C. GenAI and Blockchain Integration in the Financial Sector

Integrating GenAI with blockchain technology opens new avenues for financial innovation. The synergy between AI's predictive capabilities and blockchain's immutability allows for improved solutions in areas such as risk management, fraud detection, and personalised banking services.[53] For example, AI-enhanced blockchain operations can lead to faster transaction processing and more accurate execution of smart contracts, reducing operational costs and improving efficiency.[54]

GenAI's ability to analyse vast datasets in real time enables continuous adjustments to smart contracts, ensuring they remain compliant with regulatory standards and adapt to changing market conditions. This dynamic approach not only streamlines regulatory compliance but also enhances the accuracy of fraud detection systems, making financial transactions more secure and efficient.[55]

Furthermore, by combining AI's advanced analytics with the transparency of blockchain networks, financial institutions can offer more personalised financial products and services. This includes tailored investment strategies, customised banking services, and enhanced fraud prevention mechanisms. Combining these technologies empowers financial institutions to offer more secure, customised, and innovative services, providing a competitive edge in the market.

Table 3 outlines specific use cases for integrating a combination of GenAI and blockchain in the financial sector, highlighting decentralised finance, smart contracts, and asset tokenisation. These use cases showcase the potential for disruption and innovation, as GenAI enables more efficient and secure financial operations, while blockchain ensures data integrity and transparency.

---

52 Infocomm Media Development Authority, "Model AI Governance Framework."

53 KPMG, "The Generative AI Advantage."

54 Yen Telles, "Generative AI and Blockchain," Vention, 2023, https://ventionteams.com/blog/generative-ai-blockchain.

55 Kamales Lardi, "Converging Generative AI With Blockchain Technology," Forbes, 2023, https://www.forbes.com/sites/forbesbusinesscouncil/2023/06/12/converging-generative-ai-with-blockchain-technology/?sh=570550f06112.

Table 3.
GenAI and Blockchain Integration and Use Cases in the Financial Industry

Applications of GenAI and Blockchain Integration	Description
Fraud Detection and AML	Enhance precision and speed in detecting and preventing fraudulent activities and money laundering through continuous learning from blockchain-recorded transactions.
Personalised Banking Services	Offer customised financial advice, investment strategies, and product recommendations by analysing individual transaction histories and preferences stored on the blockchain.
Regulatory Compliance and Audit	Streamline compliance reporting and audit processes using GenAI to analyse blockchain-recorded transaction data against regulatory requirements automatically.
Decentralised Finance (DeFi)	Revolutionise financial services without traditional intermediaries by enabling sophisticated financial instruments and predictive models for investment on DeFi platforms.
Smart Contracts Optimisation	Improve transaction processing speeds and accuracy of smart contracts by enabling GenAI to analyse datasets for optimal execution pathways and real-time adjustment.
Risk Management	Develop nuanced risk assessment models for more tailored financial products by leveraging GenAI's analytics and blockchain's secure data recording capabilities.
Asset Tokenisation	Facilitate the division of physical assets into digital tokens that can be easily traded on blockchain platforms, with GenAI optimising valuation and trading strategies.

V.D. Use of GenAI in Finance Education and Research

GenAI is poised to transform finance education and research, providing innovative tools for learning, analysis, and strategic decision-making in financial markets. The ability of GenAI to simulate real-world scenarios, coupled with its capacity to personalise educational experiences, has already reshaped how financial professionals and students engage with complex financial concepts.[56] Tools like ChatGPT are being used to offer customised learning experiences, allowing learners to interact with complex datasets and understand market dynamics through hands-on simulations.[57]

GenAI's role in finance research is also gaining prominence, particularly in its ability to process and analyse vast volumes of financial data more efficiently

[56] Ling Feng et al., "Inclusion of the RMB in SDRs and the Impossible Trinity in China," *Economic Systems* 47, no. 2 (2023), https://doi.org/10.1016/j.ecosys.2022.100941.

[57] Eva Blondeel et al., "Why Do Accounting Students Procrastinate? A Qualitative Analysis Using ChatGPT," *SSRN Electronic Journal*, (January 2023): 1–53, https://doi.org/10.2139/ssrn.4632334; Nitin Rane and Saurabh Choudhary, "Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Arts and Humanities," *Studies in Humanities and Education* 5, no. 1 (2024): 1–11, https://doi.org/10.48185/she.v5i1.999.

than traditional methods. For instance, it has been used to forecast market trends, predict corporate performance, and model various financial scenarios.[58] These predictive capabilities allow researchers to uncover insights from large datasets and improve the accuracy of their analysis.[59]

Moreover, finance professionals can now harness GenAI to model various financial outcomes, significantly enhancing strategic planning and decision-making processes. This shift towards AI-augmented research promises to make financial analysis more data-driven and forward-looking, enabling more informed investment and risk management decisions.

While the advent of GenAI in finance education and research offers significant benefits, it also presents challenges, such as ensuring the accuracy of AI-generated analyses and managing the transition towards AI-augmented practices.[60] As the field continues to evolve, striking a balance between human oversight and AI-driven automation will be crucial to ensuring that finance professionals remain at the forefront of making ethical and informed decisions.

Overall, the integration of GenAI into finance education and research marks a paradigm shift towards more personalised and innovative practices, with both academia and industry playing pivotal roles in realising their full potential.

V.E. Future of GenAI in the Financial Industry

The future of GenAI in the financial industry represents a pivotal juncture, with both immense potential and considerable challenges ahead. The growing body of academic and industry research from 2023 and 2024 indicates that GenAI has and will continue to reshape core aspects of the financial industry, ranging from data-driven decision-making to customer service enhancement.[61]

One of the most transformative capabilities of GenAI lies in its ability to analyse massive quantities of customer-centric data, unlocking new insights that can improve operational efficiency and foster deeper customer relationships. As financial institutions embrace GenAI, they are increasingly positioned to offer personalised services, risk management, and investment

[58] Ali and Aysan, "What Will ChatGPT Revolutionize;" Pelster and Val, "Can ChatGPT Assist."

[59] Dowling, Michael, and Brian Lucey. "ChatGPT for (finance) research: The Bananarama conjecture."

[60] IBM Institute for Business Value, "The CEO's Guide to Generative AI," IBM, updated October 7, 2024 https://www.ibm.com/thought-leadership/institute-business-value/en-us/report/ceo-generative-ai.

[61] Accenture, "Banking on AI: Banking Top 10 Trends for 2024," Accenture, updated 2024 https://www.accenture.com/content/dam/accenture/final/industry/banking/document/Accenture-Banking-Top-10-Trends-2024.pdf; de Araujo et al., "Artificial Intelligence in Central Banking."

strategies based on AI-driven insights.[62] This positions GenAI as a crucial component in financial innovation, where AI's capacity for predictive analytics and natural language processing can revolutionise customer interactions and decision-making.

However, the journey toward fully realising the potential of GenAI in finance is fraught with challenges. Among these challenges are the ethical implications of AI-driven decisions, particularly the risk of algorithmic bias and potential data breaches. As financial institutions grow increasingly reliant on AI systems, ensuring data security and algorithmic transparency will be essential to building trust with consumers and regulators alike.[63]

The regulatory landscape will also play a crucial role in shaping the future of GenAI in finance. The financial industry operates within a dynamic regulatory environment, where new standards are constantly being developed to address the ethical use of AI and data privacy concerns. As AI technologies evolve, financial institutions will need to adopt proactive governance strategies to remain compliant with emerging regulations and to ensure that they can navigate the legal and ethical challenges associated with AI adoption.[64]

Moreover, the impact on the workforce remains a key consideration. While GenAI is expected to enhance efficiency and drive innovation, it may also lead to job displacement in certain financial industry sectors. Addressing this challenge will require careful workforce planning, including retraining programs and strategies for integrating AI alongside human professionals to ensure a smooth transition.

As we look at the future, integrating GenAI within financial institutions will likely require a holistic strategy that balances technological innovation, ethical standards, and regulatory compliance. This approach will help institutions capitalise on GenAI's transformative potential while navigating its associated challenges, ultimately leading to more efficient, transparent, and inclusive financial services.

---

[62] Soups Ranjan, "GenAI in Financial Services," (2023), *Sardine* (blog), https://www.sardine.ai/jp/blog/genai-in-financial-services

[63] Infocomm Media Development Authority, "Model AI Governance Framework."

[64] Association of Southeast Asian Nations, "ASEAN Guide on AI Governance and Ethics," ASEAN, updated 2024, https://asean.org/wp-content/uploads/2024/02/ASEAN-Guide-on-AI-Governance-and-Ethics_beautified_201223_v2.pdf; Secretary of State for Science, Innovation and Technology. "A Pro-Innovation Approach to AI Regulation – Government Response to Consultation," Department for Science, Innovation & Technology, updated February 6, 2024, https://www.gov.uk/government/consultations/ai-regulation-a-pro-innovation-approach-policy-proposals/outcome/a-pro-innovation-approach-to-ai-regulation-government-response.

VI. CONCLUDING REMARKS

The study examined the intersection of GenAI and the financial sector through a machine learning–based topic modelling approach applied to both academic and grey literature. The analysis identified thematic divergences between academic works, which predominantly focus on targeted financial applications such as portfolio optimisation and forecasting, and grey literature, which emphasises ethical risks, regulatory requirements, and operational integration challenges. Collectively, these insights point toward five priority domains for future financial transformation: ethical governance, blockchain integration, employment impacts, AI-driven risk management, and personalised financial services.

A key outcome of this research is the recognition that these transformation areas are not confined to any single jurisdiction. The issues of data privacy, algorithmic bias, explainability, and interoperability of AI systems arise universally, irrespective of domestic legal traditions—whether common law, civil law, Islamic finance regulatory frameworks, or hybrid systems. This universality suggests that while national regulators must adapt GenAI oversight to local contexts, there is merit in developing baseline, globally recognised principles. International coordination could take the form of a multilateral convention, a model law, or binding/non-binding guidelines under the auspices of established bodies such as the BIS, IOSCO, or even the G20. Such instruments could set minimum standards for transparency, accountability, ethical use, and cross-border data governance, thereby reducing regulatory fragmentation, fostering interoperability, and enhancing trust in AI-enabled finance.

The findings have significant implications for various stakeholders across the financial ecosystem. For financial institutions, the adoption of GenAI offers transformative opportunities, especially in operational efficiency, customer personalisation, and risk management. By leveraging GenAI, institutions can generate actionable insights from large datasets, improving decision-making and fostering innovation in product and service offerings. For instance, GenAI can enhance financial advisory services by automating portfolio management and predictive analytics. While also supporting fraud detection through pattern recognition. However, the study also underscores the challenges these institutions face, particularly in terms of data security, algorithmic transparency, and the potential for biased decision-making. Financial institutions must develop robust governance frameworks to ensure AI technologies are deployed ethically and meet regulatory standards and consumer expectations.

For policymakers and regulators, the study emphasises the need for a dynamic regulatory approach that can keep pace with the rapid advancements in

GenAI. As financial institutions increasingly integrate AI into core operations, policymakers must focus on creating comprehensive frameworks that address issues such as privacy, algorithmic fairness, and accountability. The findings highlight the importance of algorithmic transparency and the mitigation of biases in AI-driven decision-making processes. Developing these frameworks will require ongoing collaboration between regulators, financial institutions, and technology providers to ensure that the adoption of GenAI aligns with principles of fairness, equity, and consumer protection.

Telecommunication stakeholders also play a crucial role in supporting the infrastructure necessary for the widespread adoption of GenAI in finance. As AI applications require secure, high-speed data transmission, telecommunications companies need to offer tailored solutions that enable financial services to leverage GenAI while fully maintaining data integrity and operational resilience.[65] The collaboration among financial institutions, telecommunications providers, and technology developers will be vital to scaling AI-driven solutions.

This study reveals several key areas for future research that are essential for advancing the field and addressing the complex implications of GenAI in finance:

1. Ethical and Governance Frameworks: There is a pressing need for more research on developing ethical standards to ensure that GenAI applications in finance are fair, transparent, and accountable. Given the potential for algorithmic biases and data security risks, future research should explore strategies to ensure that GenAI systems are used in ways that promote equitable access to financial services.
2. Integration of GenAI with Emerging Technologies: The potential for GenAI to integrate with technologies such as blockchain opens up new opportunities for innovation and security in financial services. Research on how these technologies can be combined to enhance risk management, fraud detection, and operational efficiency will be crucial as financial institutions explore more advanced AI-driven solutions.
3. Impact on Employment and Workforce Adaptation: As GenAI becomes more embedded in financial operations, its impact on the workforce will become increasingly significant. Future research should focus on strategies for workforce adaptation, including reskilling and upskilling initiatives, to address the job displacement challenges posed by AI-driven automation.[66]

[65] Rui Wang, "Research on the Impact of ChatGPT on the Chinas Economy," *Advances in Economics, Management and Political Sciences* 58 (2023): 274–82, https://doi.org/10.54254/2754-1169/58/20230931.

[66] Vargas-Murillo et al., "Challenges and Opportunities."

4. AI-Driven Risk Management and Compliance: With the rise of AI in financial risk management, research should delve deeper into how AI tools can be used to enhance real-time risk monitoring and automated compliance processes. This will be essential for both financial stability and regulatory alignment.
5. Enhancing Personalisation and Customer Experience: GenAI holds immense potential to transform the customer experience by offering highly personalised services. Future research should explore how AI can further optimise customer interaction, ensuring that the customer-centric services delivered are innovative and aligned with the ethical standards of the financial industry.

This study paves the way for ongoing research and exploration into how GenAI will continue to shape the future of finance, offering a roadmap for the responsible and impactful deployment of AI in one of the world's most critical industries.

REFERENCES

Abdelkader, Osama Ahmed. "ChatGPT's Influence on Customer Experience in Digital Marketing: Investigating the Moderating Roles." *Heliyon* 9, no. 8 (2023): e18770. https://doi.org/10.1016/j.heliyon.2023.e18770.

Accenture. "Banking on AI: Banking Top 10 Trends for 2024." Accenture. Updated 2024. https://www.accenture.com/content/dam/accenture/final/industry/banking/document/Accenture-Banking-Top-10-Trends-2024.pdf

Agarwal, Rahul, Andreas Kremer, Ida Kristensen, and Angela Luget. "How Generative AI Can Help Banks Manage Risk and Compliance." McKinsey & Company. Updated March 1, 2024. https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/how-generative-ai-can-help-banks-manage-risk-and-compliance.

Ahramovich, Aleksandr. "AI in Wealth Management: Use Cases, Solutions & Adoption Guidelines." Itransition, 2023. https://www.itransition.com/ai/wealth-management.

Ali, Hassnian, and Ahmet Faruk Aysan. "What Will ChatGPT Revolutionize in the Financial Industry?" *Modern Finance* 1, no. 1 (2023): 116–29. https://doi.org/10.61351/mf.v1i1.67.

Alotaibi, Emran, and Nadia Nassif. "Artificial Intelligence in Environmental Monitoring: In-Depth Analysis." *Discover Artificial Intelligence* 4, no. 1 (2024): 84.

Ardekani, Aref Mahdavi, Julie Bertz, Cormac Bryce, Michael Dowling, and Suwan Cheng Long. "FinSentGPT: A Universal Financial Sentiment Engine?" *International Review of Financial Analysis* 94 (2024): 103291.

Association of Southeast Asian Nations. "ASEAN Guide on AI Governance and Ethics." ASEAN. Updated 2024. https://asean.org/wp-content/uploads/2024/02/ASEAN-Guide-on-AI-Governance-and-Ethics_beautified_201223_v2.pdf.

Australian Government Productivity Commission. "Making the Most of the AI Opportunity: AI Raises the Stakes for Data Policy." Australian Government Productivity Commission, 2024. https://assets.pc.gov.au/2025-10/ai-paper3-data.docx?VersionId=2GW50ODo932jjso8TzhMkEC0CsacJPGL.

Bag, Surajit, Susmi Routray, Tarik Saikouk, and David Roubaud. "Generative AI-Powered Innovation on Data-Driven Financial Decision-Making in Operations and Supply Chain Management: A Moderated Mediation Analysis." *Information Systems Frontiers* (2025): 1–30.

Bai, Xiwen, Xiunian Zhang, Kevin X. Li, Yaoming Zhou, and Kum Fai Yuen. "Research Topics and Trends in the Maritime Transport: A Structural Topic Model." *Transport Policy* 102 (March 2021): 11–24. https://doi.org/10.1016/j.tranpol.2020.12.013.

Ball, Ray. "The Global Financial Crisis and the Efficient Market Hypothesis: What Have We Learned?" *Journal of Applied Corporate Finance* 21, no. 4 (2009): 8–16.

Beerbaum, Dirk. "Generative Artificial Intelligence (GAI) with ChatGPT for Accounting – a Business Case." *SSRN Electronic Journal* (2023): 1–14. https://doi.org/10.2139/ssrn.4385651.

Bi, Qian. "Analysis of the Application of Generative AI in Business Management." *Advances in Economics and Management Research* 6, no. 1 (2023): 36. https://doi.org/10.56028/aemr.6.1.36.2023.

Bickford, Jeanne, Rafal Cegiela, Julian King, et al. "GenAI Is about to Transform Banks Front to Back." Boston Consulting Group, 2024.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent Dirichlet Allocation." *Journal of Machine Learning Research* 2 (2003): 993–1022. https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf.

Blondeel, Eva, Patricia C. Everaert, and Evelien Opdecam. "Why Do Accounting Students Procrastinate? A Qualitative Analysis Using ChatGPT." *SSRN Electronic Journal*, no. November (2023): 1–53. https://doi.org/10.2139/ssrn.4632334.

Bushell, Chris. "Impacts of ChatGPT on Marketers: A Comprehensive Analysis." *SSRN Electronic Journal* (2023). https://doi.org/10.2139/ssrn.4556646.

Busson, Antonio J. G., Rennan Gaio, Rafael H. Rocha, Francisco Evangelista, Bruno Rizzi, Luan Carvalho, Rafael Miceli, Marcos Rabaioli, and David Favaro. "Saturn Platform: Foundation Model Operations and Generative AI for Financial Services." *Companion Proceedings of the 29th Brazilian Symposium on Multimedia and Web* (2023): 85–88. https://doi.org/10.5753/webmedia_estendido.2023.234354.

Caspi, Itamar, Sarith S. Felber, and Talia B. Gillis. "Generative AI and the Future of Financial Advice Regulation." GenLaw Center, 2023. https://genlaw.org/CameraReady/19.pdf.

Chen, Xuhui, Guanghui Cheng, and Yong He. "Mathematical Modeling and Optimization of Platform Supply Chain in the Digital Era: A Systematic Review." *Mathematics* 13, no. 17 (2025): 2863.

Chen, Yifei, Bryan Kelly, and Dacheng Xiu. "Expected Returns and Large Language Models." NLP SoDaS Conference, November 22, 2023. https://ssrn.com/abstract=4629694.

Consultative Group on Risk Management (CGRM). "Governance of AI Adoption in Central Banks." *BIS Other* (29 January 2025): 1–49.

Cook, Thomas, Sophia Kazinnik, Anne Hansen, and Peter McAdam. "Evaluating Local Language Models: An Application to Bank Earnings Calls." *The Federal Reserve Bank of Kansas City Research Working Papers*. Accessed November 6, 2023. https://doi.org/10.18651/rwp2023-12.

Cook, Thomas R., Sophia Kazinnik, Anne Lundgaard Hansen, and Peter McAdam. "Evaluating Local Language Models: An Application to Financial Earnings Calls." Available at SSRN 4627143, 2023.

Dowling, Michael, and Brian Lucey. "ChatGPT for (Finance) Research: The Bananarama Conjecture." *Finance Research Letters* 53 (January 2023): 103662. https://doi.org/10.1016/j.frl.2023.103662.

de Araujo, Douglas Kiarelly Godoy, Sebastian Doerr, Leonardo Gambacorta, and Bruno Tissot. "Artificial Intelligence in Central Banking." *BIS Bulletin* no. 84 (2024). https://www.bis.org/publ/bisbull84.htm.

European Parliament and the Council of the European Union. "Regulation (EU) 2024/1689 of 13 June 2024 Laying Down Harmonised Rules on Artificial Intelligence … (Artificial Intelligence Act)." (OJ L, 2024/1689, 12 July 2024): 1–144.

Feng, Ling, Duong Thuy Le, and Fan Yuan. "Inclusion of the RMB in SDRs and the Impossible Trinity in China." *Economic Systems* 47, no. 2 (2023). https://doi.org/10.1016/j.ecosys.2022.100941.

Fishman, Tiffany, Jamia McDonald, Hariharan Murthy, Naman Chaurasia, Joe Mariani, and Pankaj Kishnani. "Realizing the Potential of Generative AI in Human Services: Use Cases to Transform Program Delivery: A Report from the Deloitte Center for Government Insights." Deloitte, 2023.

Hartmann, Jochen, Yannick Exner, and Samuel Domdey. "The Power of Generative Marketing: Can Generative AI Reach Human-Level Visual Marketing Content?" *SSRN Electronic Journal* (2023). https://doi.org/10.2139/ssrn.4597899.

Hasan, Tariqul, and Nusrat Jahan. "Artificial Intelligence and Ethical Challenges in Financial Services: A Framework for Responsible Data Governance and Algorithmic Transparency." *International Journal of Data Science, Big Data Analytics, and Predictive Modeling* 14, no. 8 (2024): 16–36.

IBM Institute for Business Value. "The CEO's Guide to Generative AI." IBM. Updated October 7, 2024. https://www.ibm.com/thought-leadership/institute-business-value/en-us/report/ceo-generative-ai.

Infocomm Media Development Authority. "Model AI Governance Framework for Generative AI: Fostering a Trusted Ecosystem." 2024.

Jiang, Hanchen, Maoshan Qiang, and Peng Lin. "A Topic Modeling Based Bibliometric Exploration of Hydropower Research." *Renewable and Sustainable Energy Reviews* 57 (May 2016): 226–37. https://doi.org/10.1016/j.rser.2015.12.194.

Joshi, Satyadhar. "Gen AI for Market Risk and Credit Risk: Agentically Powered Gen AI; Gen AI Agentic Framework for Financial Risk Management." (January 15, 2025) (2025).

Kalia, Suman. "Potential Impact of Generative Artificial Intelligence (AI) on the Financial Industry." *International Journal on Cybernetics & Informatics* 12, no. 6 (2023): 37–51. https://doi.org/10.5121/ijci.2023.120604.

Khan, Muhammad Salar, and Hamza Umer. "ChatGPT in Finance: Applications, Challenges, and Solutions." *Heliyon* 10, no. 2 (2024). https://doi.org/10.1016/j.heliyon.2024.e24890.

Klenk, Michael. "Ethics of Generative AI and Manipulation: A Design-Oriented Research Agenda." *Ethics and Information Technology* 26, no. 9 (2024). https://doi.org/10.1007/s10676-024-09745-x.

KPMG. "The Generative AI Advantage in Financial Services: How Financial Services Executives Can Seize its Potential." KPMG, 2023. https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2023/the-gen-ai-advantages-in-financial-services.pdf.

Krause, David. "Mitigating Risks for Financial Firms Using Generative AI Tools." *SSRN Electronic Journal* (2023): 1–22. https://doi.org/10.2139/ssrn.4452600.

Kshetri, Nir. "The Economics of Generative Artificial Intelligence in the Academic Industry." *Computer* 56, no. 8 (2023): 77–83. https://doi.org/10.1109/MC.2023.3278089.

Kuhn, Kenneth D. "Using Structural Topic Modeling to Identify Latent Topics and Trends in Aviation Incident Reports." *Transportation Research Part C: Emerging Technologies* 87 (2018): 105–22. https://doi.org/10.1016/j.trc.2017.12.018.

Lardi, Kamales. "Converging Generative AI With Blockchain Technology." *Forbes* (2023). https://www.forbes.com/sites/forbesbusinesscouncil/2023/06/12/converging-generative-ai-with-blockchain-technology/?sh=570550f06112.

Lopez-Lira, Alejandro, and Yuehua Tang. "Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models." *SSRN Electronic Journal* (2023). https://doi.org/10.2139/ssrn.4412788.

Malkiel, Burton G., and Eugene F. Fama. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, no. 2 (1970): 383–417.

Markowitz, Harry. "Portfolio Selection." *The Journal of Finance* 7, no. 1 (1952): 77–91.

McKinsey. "The State of AI in 2023: Generative AI's Breakout Year." Last modified August 1, 2023. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year.

McKinsey & Company. "Beyond the Hype: Capturing the Potential of AI and Gen AI in Tech, Media, and Telecom." McKinsey & Company. Updated February 22, 2024. https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/beyond-the-hype-capturing-the-potential-of-ai-and-gen-ai-in-tmt.

Minz, Nitish Kumar. "Ethical Considerations in AI Applications in Finance: Frameworks, Transparency, Accountability, and Case Studies." In *Risks and Challenges of AI-Driven Finance: Bias, Ethics, and Security*, 277–290. IGI Global, 2024.

Mo, Hongwei, and Shumiao Ouyang. "(Generative) AI in Financial Economics." *Journal of Chinese Economic and Business Studies* 23, no. 4 (2025): 509–587.

Md Arman, and Umama Rashid Lamiya. "Exploring the Implication of ChatGPT AI for Business: Efficiency and Challenges." *Journal of Innovation Information Technology and Application (JINITA)* 5, no. 1 (2023): 52–64. https://doi.org/10.35970/jinita.v5i1.1828.

Mollick, Ethan, and Jim Euchner. "The Transformative Potential of Generative AI." *Research-Technology Management* 66, no. 4 (2023): 11–16. https://doi.org/10.1080/08956308.2023.2213102.

Mutoffar, Muhamad Malik, Sri Kuswayati, Fetty Tri Anggraeny, and Tarsinah Sumarni. "Exploring the Potential of ChatGPT in Improving Online

Marketing and Promotion of MSMEs." *Jurnal Minfo Polgan* 12, no. 1 (2023): 480–89. https://doi.org/10.33395/jmp.v12i1.12440.

Neilson, Ben. "Artificial Intelligence Authoring Financial Recommendations: Comparative Australian Evidence." *Journal of Financial Regulation* 9, no. 2 (2023): 249–57. https://doi.org/10.1093/jfr/fjad004.

von Neumann, John, and Oskar Morgenstern. *Theory of Games and Economic Behavior*. Princeton University Press, 1944.

Ozili, Peterson. "Artificial Intelligence in Central Banking." In *Industrial Applications of Big Data, AI, and Blockchain*, edited by Mahmoud El Samad, Ghalia Nassreddine, Hani El-chaarani, and Sam El Nemar. IGI Global Scientific Publishing, 2024. https://doi.org/10.4018/979-8-3693-10465.ch004.

Pelster, Matthias, and Joel Val. "Can ChatGPT Assist in Picking Stocks?" *Finance Research Letters* 59, no. October (2024). https://doi.org/10.1016/j.frl.2023.104786.

Rane, Nitin, and Saurabh Choudhary. "Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Arts and Humanities." *Studies in Humanities and Education* 5, no. 1 (2024): 1–11. https://doi.org/10.48185/she.v5i1.999.

Ranjan, Soups. "GenAI in Financial Services." Sardine (blog), 2023. https://www.sardine.ai/jp/blog/genai-in-financial-services.

Rivas, Pablo, and Liang Zhao. "Marketing with ChatGPT: Navigating the Ethical Terrain of GPT-Based Chatbot Technology." *AI (Switzerland)* 4, no. 2 (2023): 375–84. https://doi.org/10.3390/ai4020019.

Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, and David G. Rand. "Structural Topic Models for Open-Ended Survey Responses." *American Journal of Political Science* 58, no. 4 (October 6, 2014): 1064–82. https://doi.org/10.1111/ajps.12103.

Romanko, Oleksandr, Akhilesh Narayan, and Roy H. Kwon. "ChatGPT-Based Investment Portfolio Selection." *Operations Research Forum* 4, no. 91 (2023): 0–26. https://doi.org/10.1007/s43069-023-00277-6.

Rufaida, Dien, and Kemil Wachidah. "Literature Study of the Application of Skimming Techniques to Improve Speed Reading Ability in Indonesian Language Lessons for Class V Elementary School Students." *Indonesian Journal of Education Methods Development* 3 (August 20, 2018). https://doi.org/10.21070/ijemd.v3i0.586.

Secretary of State for Science, Innovation and Technology. "A Pro-Innovation Approach to AI Regulation – Government Response to Consultation." Department for Science, Innovation & Technology. Updated February

6, 2024. https://www.gov.uk/government/consultations/ai-regulation-a-pro-innovation-approach-policy-proposals/outcome/a-pro-innovation-approach-to-ai-regulation-government-response.

Shahi, Megan, Adam Conner, and Nicole Alvarez. "Generative AI Should Be Developed and Deployed Responsibly at Every Level for Everyone." Center for American Progress. Updated February 1, 2024. https://www.americanprogress.org/article/generative-ai-should-be-developed-and-deployed-responsibly-at-every-level-for-everyone/.

Sharma, Anuj, Nripendra P. Rana, and Robin Nunkoo. "Fifty Years of Information Management Research: A Conceptual Structure Analysis Using Structural Topic Modeling." *International Journal of Information Management* 58 (June 2021): 102316. https://doi.org/10.1016/j.ijinfomgt.2021.102316.

Sharpe, William F. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *The Journal of Finance* 19, no. 3 (1964): 425–42.

Shevlin, Ron. "Finding the Next Wave to Ride." Cornerstone Advisors. Updated 2024. https://www.crnrstone.com/hubfs/WGOIB%20 2024/2024-Whats-Going-On-In-Banking_Cornerstone-Advisors.pdf.

Skandali, Dimitra, Anastasios Magoutas, and Georgios Tsourvakas. "Artificial Intelligent Applications in Enabled Banking Services: The Next Frontier of Customer Engagement in the Era of ChatGPT." *Theoretical Economics Letters* 13, no. 05 (2023): 1203–23. https://doi.org/10.4236/tel.2023.135066.

Sriskandarajah Sathesh. "Generative AI Banking and Financial Services." Accubits Technologies. Updated August 2023. https://accubits.com/white-papers/Generative-AI-in-Banking-and-Financial-Services-by-Accubits.pdf.

Suryanto, Tulus, Mardhiyah Hayati, and Yeni Susanti. "The Potential of Halal Tourism System on Growth for the Province Lampung's Tourism Industry." *Journal of Environmental Management and Tourism* 13, no. 6 (2022): 1616–28. https://journals.aserspublishing.eu/jemt/article/view/7274.

Telles, Yen. "Generative AI and Blockchain." Vention, 2023. https://ventionteams.com/blog/generative-ai-blockchain.

Thaler, Richard H. "The End of Behavioral Finance." *Financial Analysts Journal* 55, no. 6 (1999): 12–17.

Vargas-Murillo, Alfonso Renato, Ilda Nadia Monica de la Asuncion Pari-Bedoya, and Francisco de Jesús Guevara-Soto. "Challenges and Opportunities of AI-Assisted Learning: A Systematic Literature Review on the Impact of ChatGPT Usage in Higher Education." *International Journal of Learning, Teaching and Educational Research* 22, no. 7 (2023): 122–35. https://doi.org/10.26803/ijlter.22.7.7.

Vidrih, Marko, and Shiva Mayahi. "Generative AI-Driven Storytelling: A New Era for Marketing." arXiv, 2023. http://arxiv.org/abs/2309.09048.

Wang, Haijun, Kunyuan Mao, Wanting Wu, and Haohan Luo. "Fintech Inputs, Non-Performing Loans Risk Reduction and Bank Performance Improvement." *International Review of Financial Analysis* 90 (2023). https://doi.org/10.1016/j.irfa.2023.102849.

Wang, Rui. "Research on the Impact of ChatGPT on the Chinas Economy." *Advances in Economics, Management and Political Sciences* 58 (2023): 274–82. https://doi.org/10.54254/2754-1169/58/20230931.

Wenzlaff, Karsten, and Sebastian Spaeth. "Smarter than Humans? Validating How OpenAI's ChatGPT Model Explains Crowdfunding, Alternative Finance and Community Finance." *SSRN Electronic Journal*, December 29, 2022. https://doi.org/10.2139/ssrn.4302443.

Yunus, Muhammad. "Developing the Students' Ability in Reading Through Speed Reading Technique at the First Year Students of SMKN 1 Watunohu." *Journal of Teaching and Education* 1, no. 2 (December 21, 2022). https://doi.org/10.31327/jte.v1i2.1895

APPENDIX A

Topic Modelling

Topic modelling is a collection of text-mining techniques for uncovering hidden themes in a body of text. It's increasingly popular in academic research because scholarly articles, with their naturally unstructured language, are ideal candidates for this type of analysis.[67] These models are excellent at quickly and efficiently identifying the main ideas present in large amounts of text, making them a top choice for researchers examining current trends across various academic disciplines. In this field, methods like Latent Dirichlet Allocation and the Structural Topic Model are commonly used.[68]

Latent Dirichlet Allocation Model (LDA)

LDA is the most widely used technique for topic modelling in document analysis. It is based on a generative probabilistic process, suggesting that this underlying mechanism produces documents and the words they contain. In this framework, each document is indexed by $d \in \{1, 2, \ldots, D\}$, topics by $k \in \{1, 2, \ldots, K\}$(with K set by the user), and individual word positions by $n \in \{1, 2, \ldots, N\}$. Blei et al.[69] explain the process as follows:

[67] Roberts et al., "Structural Topic Models."

[68] Bai et al., "Research Topics and Trends."

[69] David M. Blei et al., "Latent Dirichlet Allocation," *Journal of Machine Learning Research* 2 (2003): 993-1022, https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf.

- **Document Length:** The number of words in a document, Nd, follows a Poisson distribution.
- **Topic Distribution:** The topic distribution for each document, represented by θd, is modelled as a probability distribution over topics. This distribution is drawn from a Dirichlet distribution with parameter α.
- **Word Distribution:** Each topic has its own distribution over words, denoted as βk, which is assumed to be drawn from a Dirichlet distribution with parameter η.
- **Topic Assignment:** Each word's topic in a document, indicated by $Z_{d,n}$, is chosen according to the document's topic distribution θ_d, and the actual word $W_{d,n}$ is then sampled from the corresponding word distribution β_k.

Here, the matrices θ_d and β_k are key: θ_d helps determine the likelihood of a topic appearing in a document, while β_k highlights the most representative words for each subject.

LDA, however, has its drawbacks. It struggles to account for changes in topic and word representations influenced by external factors,[70] and it assumes topics are independent, ignoring potential correlations between them. To address these limitations, various modifications have been proposed, one being the Structural Topic Model (STM), which is used in our study.

Structural Topic Modelling

STM builds on the LDA framework by allowing topics to be correlated—something LDA's rigid Dirichlet distribution does not permit. Unlike LDA, STM incorporates document-specific covariates into both the topic prevalence (θ_d) and the topic content (β_k). This integration is achieved using a generalised linear model, which enables a more nuanced relationship between document characteristics and topic distribution.

Roberts et al.[71] explain that in STM, the topic prevalence θ_d is treated as a random variable drawn from a log-normal distribution, with covariate values influencing its parameters. On the other hand, the topic content β_k is modelled via a multinomial logit (MNL) approach. MNL elegantly captures the complex interplay among topics, document-specific attributes, and their effects on word distribution across issues.

Roberts et al.[72] introduce a mathematical framework to capture this relationship. In their formulation, each word in the vocabulary, represented

[70] Kenneth D. Kuhn, "Using Structural Topic modeling to Identify Latent Topics and Trends in Aviation Incident Reports," *Transportation Research Part C: Emerging Technologies* 87 (2018): 105-22, https://doi.org/10.1016/j.trc.2017.12.018.

[71] Roberts et al., "Structural Topic Models."

[72] Roberts et al., "Structural Topic Models."

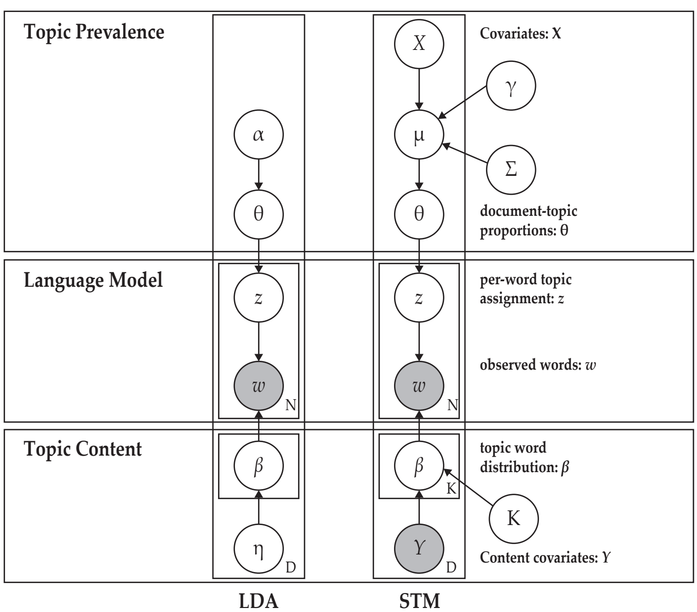
by v, has a baseline log frequency denoted as *mv*. Adjustments for both topic influences and external covariate effects are incorporated using $\kappa \varkappa$. As a result, the topic-word distribution for each document and topic, $\beta_{d,k,v}$, is defined as proportional to:

$$\beta_{d,k,v} \propto \exp\left(m_v, \kappa_v^{,,k} + \kappa_v^{y,\cdot} + \kappa_v^{y,k}\right)$$

This approach marks a significant departure from the traditional LDA model, offering a richer, more nuanced understanding of how external factors shape topics.

The differences between LDA and STM are made even more evident by comparing their plate notation diagrams, as shown in Figure A1.[73] This visual comparison highlights the underlying and methodological differences between the two models, emphasising how STM is better equipped to capture the complex interactions between topics and covariates.

Figure A1. Plate notation of LDA and STM



Source: Bai et al. (modified for clarity)

[73] Roberts et al., "Structural Topic Models."

APPENDIX B
STM Results of Combined Academic and Grey Corpora

Fig B1: Extracted Topics and their Proportions of Combined Data

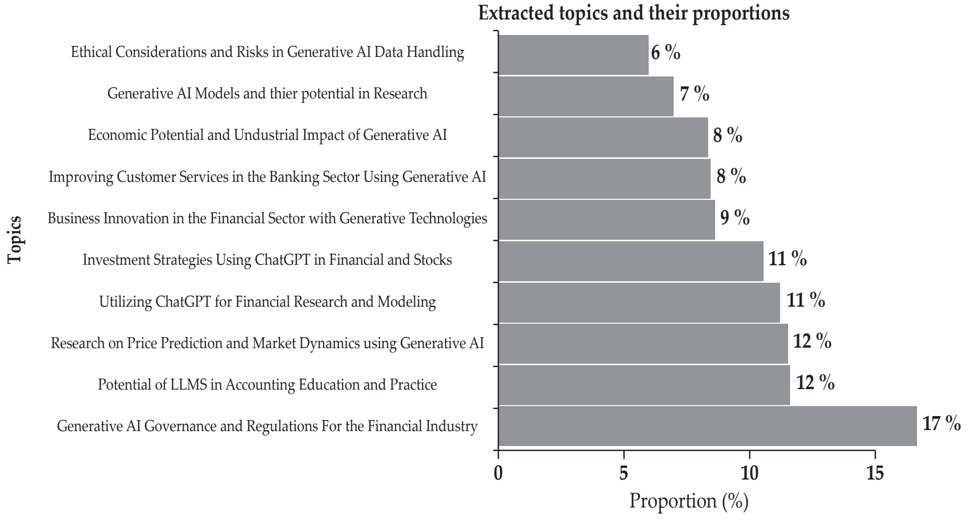


Fig B2: Topic Coherence vs Exclusivity of Combined Data

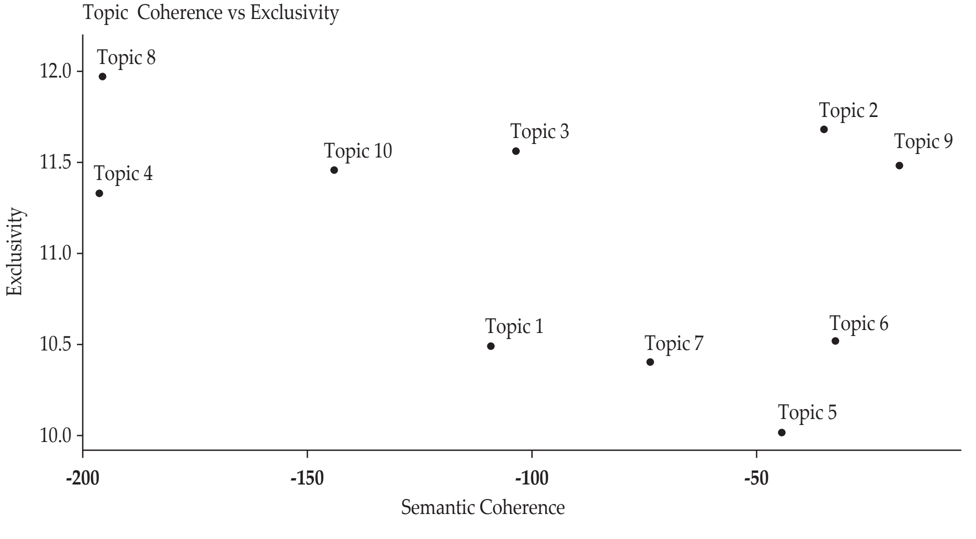


Fig B3: Topics Correlation Network of Combined Data

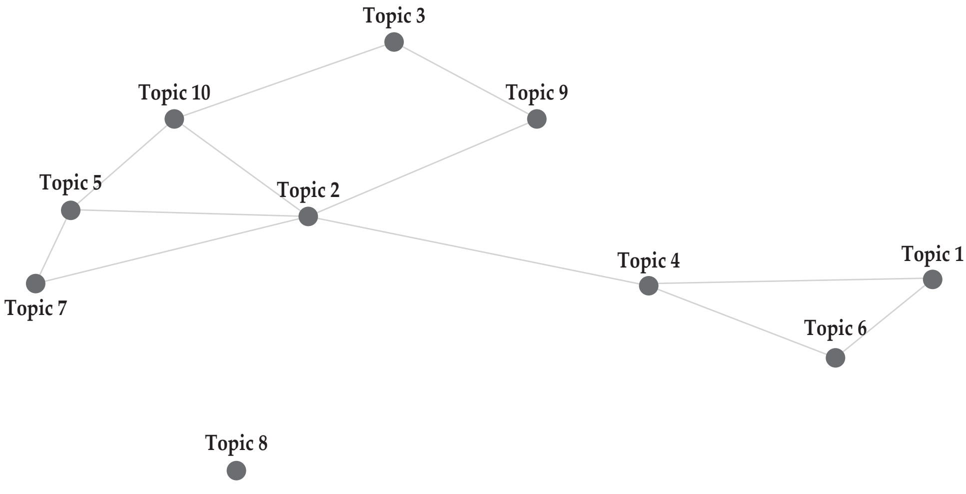


Fig B4: Topics Correlation Matrix of Combined Data

	1	2	3	4	5	6	7	8	9	10
1	1									
2	-0.03	1								
3	-0.09	-0.12	1							
4	-0.1	-0.12	-0.02	1						
5	-0.09	-0.09	-0.1	-0.11	1					
6	-0.06	-0.12	-0.1	-0.1	-0.08	1				
7	-0.14	-0.07	-0.14	-0.13	-0.13	-0.13	1			
8	-0.13	-0.21	-0.14	-0.18	-0.19	-0.01	-0.01	1		
9	-0.12	-0.18	-0.13	-0.12	-0.1	-0.12	-0.12	-0.1	1	
10	-0.03	-0.17	-0.14	-0.13	-0.14	-0.12	-0.14	-0.08	-0.07	1

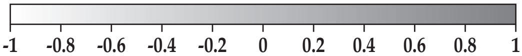
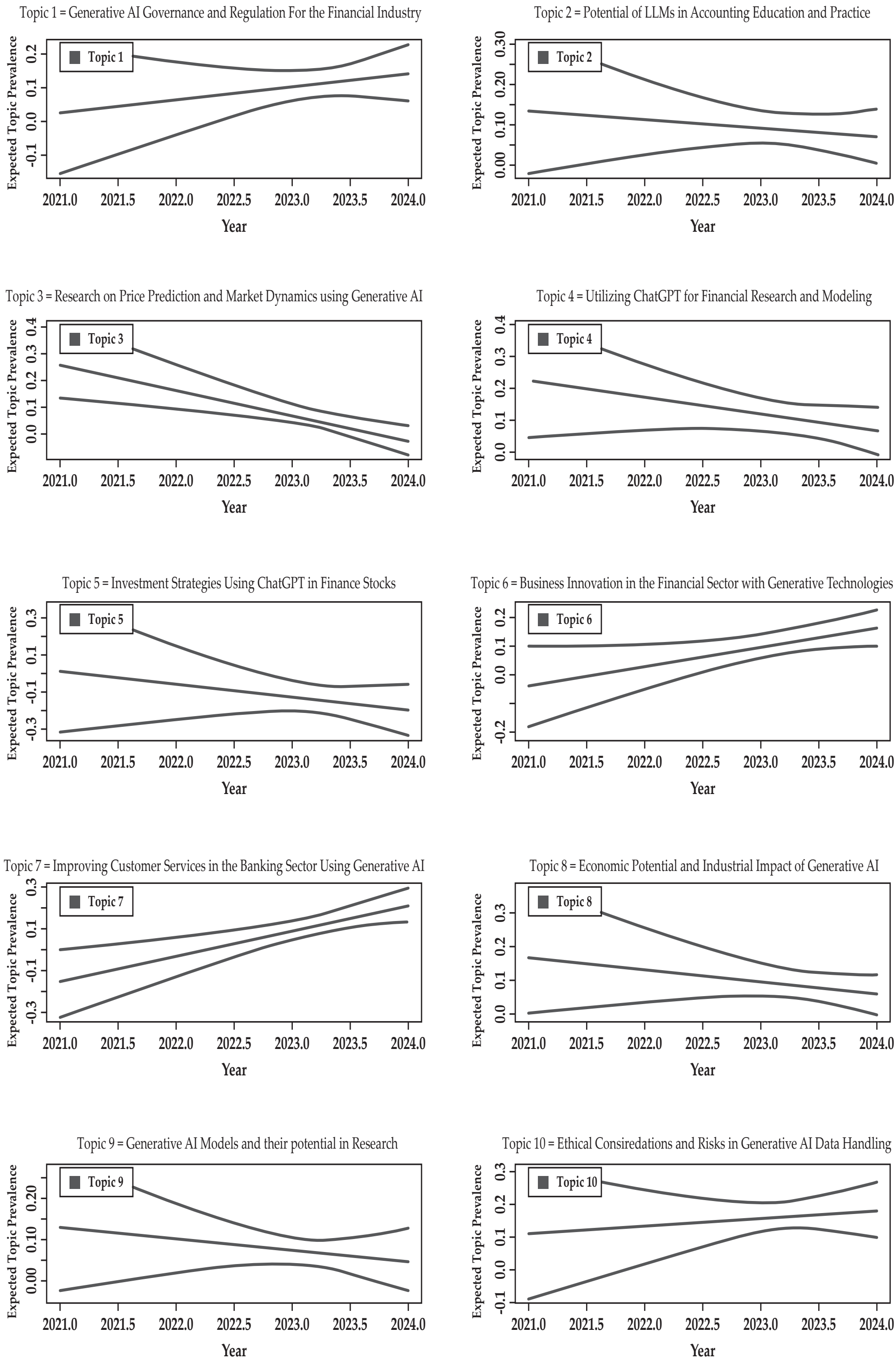


Fig B5: Topics Prevalence over Time of Combined Data



This page is intentionally left blank