Generative AI and Banking Information Systems: A Systematic Literature Review of Enablers and Emerging Opportunities.

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Abstract - *The rapid pace of Generative Artificial Intelligence (GenAI) integration is transforming the business environment in the world banking market. Although the scholarly attention is increasing, a dedicated comprehension of the specific way GenAI is implemented into the Banking Information Systems (BIS) is still scattered. This paper fills that gap by developing a systematic literature review (SLR) of 228 peer-reviewed articles published between 2018 and 2025, based on the PRISMA protocol. The study is based on Dynamic Capabilities Theory, Resource-Based View, and Organizational Learning Theory and recognizes nine major GenAI technology enablers, including Large Language Models (LLMs) up to Synthetic Data Generation, and aligns them with 80 Banking Information Systems (BIS) functions. These encompass some of the key areas like detection of fraud, credit risk evaluation, adherence to regulations, individual customer interactions, and next generation banking analytics. This review provides the strategic framework of risk-resilient, inclusive, and innovation-based BIS development by connecting the emergent GenAI technologies to the real-time banking workflow. Its results provide practical recommendations to banks, policymakers, and fintech creators who want to manage the AI-driven revolution in the financial service industry.*

Keywords: Artificial Intelligence in Banking, Banking Information Systems, Digital Innovation, Emerging Opportunities, FinTech, Generative AI, Generative AI Enablers, Large Language Models, Responsible AI, Systematic Literature Review,

I. INTRODUCTION

The move toward the convergence of Artificial Intelligence (AI) and digital banking is rapidly prompting a paradigm shift in the financial services industry worldwide. Unlike other types of AI, Generative AI (GenAI) is distinguished by generating new outputs, such as synthetic datasets or hyper-personalized customer interactions, marking a new era in the intelligence-based banking model. GenAI is no longer considered a futuristic concept; it has become a vital driver of change in the financial industry, enabling banks to move beyond passive forms of automation to active, self-educating ecosystems (McKinsey & Company, 2023; Dwivedi et al., 2021).

The academic discussion of the role of GenAI in Banking Information Systems (BIS) is, however, disjointed despite its disruptive potential. BIS also supports all layers of operations in contemporary financial institutions, including core banking systems, credit engines, compliance systems, and customer service ecosystems. The application of GenAI in BIS not only promises better fraud detection, real-time compliance, and smart onboarding, but it also poses an urgent threat to algorithmic bias, data privacy, model transparency, and ethical governance (Brueggen et al., 2025; McKnight et al., 2024).

There is a lot at stake in the economic regard. As per the recent estimates, GenAI would open up to USD 340 billion of banking value in a year by streamlining their operations, credit risk optimization, and personalized services (McKinsey & Company, 2023). At the same time, concrete value is being shown by GenAI technologies such as Large Language Models (LLMs) and Generative Adversarial networks (GANs) in applications, as in the case of fraud analytics, regulatory reporting, and ESG risk assessment (Dubey et al., 2024; Pimentel and Veliz, 2024; Şahin and Karayel, 2024).

However, a methodical synthesis of the ways in which GenAI technologies can be integrated with the functions of BIS, particularly in different geographies and regulatory settings, has been lacking. The lack is especially notable in new economies, where the variability of infrastructures presents both opportunities and limitations for AI implementation (Cano-Marin, 2024).

To address this gap, the present study is a Systematic Literature Review (SLR) of 228 peer-reviewed studies published between 2018 and 2025. The study has three goals, as it is anchored in organizational theories, namely, the Dynamic Capabilities Theory (DCT), the Resource-Based View (RBV), and the Organizational Learning Theory (OLT). The study aims to: (a) determine the emerging opportunities that GenAI has generated in BIS. (b) map systematically GenAI enablers into BIS functions. (c) provide scholarly resources through strategic advice to researchers, practitioners, and policymakers about responsible, high-impact GenAI implementation.

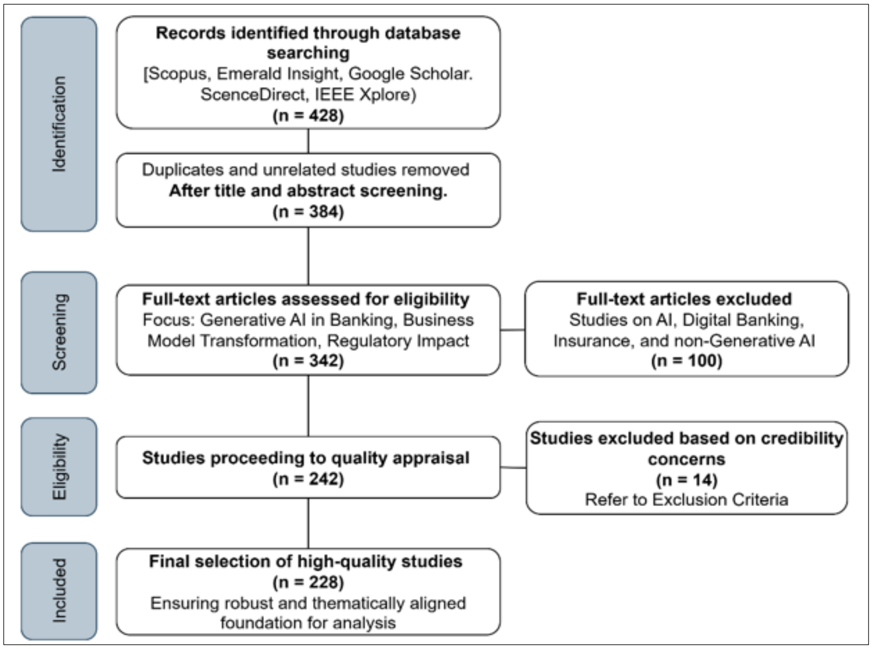
By doing so, this paper will provide a structured roadmap for aligning GenAI with banking infrastructure, regulatory foresight, and long-term innovation agendas.

II. LITERATURE REVIEW

A. Systematic Literature Review (SLR) Methodology Implementation

The Systematic Literature Review (SLR) methodology was employed to critically analyze the state of knowledge and identify gaps in the current literature. Such a method is commonly accepted as the best one and the most rigorous methodologically to synthesize both empirical and conceptual studies in new areas. The principles of transparency, reproducibility, and academic rigor informed the SLR process. The review process, based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, was carefully planned to provide methodological consistency, minimize potential bias, and increase the reliability and transparency of study selection and data synthesis. The PRISMA model played a key role in organizing the search, screening, and analysis of the review. The PRISMA 2020 guidelines were used to select the studies. A preliminary list of 428 records was obtained on Scopus, Emerald Insight, Google Scholar, ScienceDirect, and IEEE Xplore. Following a duplicate elimination and abstract filtering, 342 articles were reviewed in their entirety. Studies relating to non-generative AI contexts were excluded, as well as those involving insurance and digital banking (n = 100). An additional 14 articles were excluded due to the quality of their methods. The last dataset contained 228 peer-reviewed articles that offered a strong and thematically pertinent basis for this review (see Figure 1: PRISMA Flowchart)

Figure 1. PRISMA Flowchart



Source: Author's Creation.

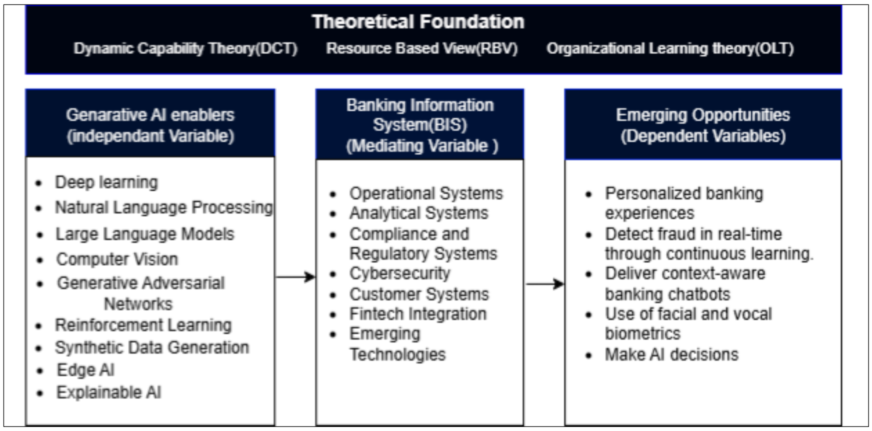
B. Inclusive and Exclusive Criteria

The study's inclusion and exclusion criteria were well-established to ensure that they are relevant to the study, of high quality, and within the scope. Only articles published after 2018-2025 were included, as they are the most up-to-date developments in Generative AI. However, occasionally, original works published before 2018 may be included if they are deemed critical to the field of study. Only English language publications were reviewed, and any non-English publications were not included unless there was a reliable translation. To ensure topical relevance, studies that directly addressed the applications of Generative AI in banking information systems were selected, while those that referred to other areas were excluded. Additionally, the methodology criterion stipulated that both empirical and theoretical research should be peer-reviewed, and sources that were not peer-reviewed, such as blogs or opinion articles, were not to be considered.

C. Conceptual Framework

The theoretical framework that supports this research task aims to capture the multidimensional position of Generative AI (GenAI) in transforming banking practices in emerging economies. It is based on the Dynamic Capability Theory (DCT), Resource Based View (RBV), and Organizational Learning Theory (OLT) and uses the support of GenAI as a strategic enabler to improve organizational adaptability, renewed capabilities, and innovation of the business model. The framework is empirically supported by an increasingly vast amount of Q1 and Q2 journal papers. Other studies, including those by Gupta and Agarwal (2024), focus on how explainable AI (XAI) and governance systems enhance trust and transparency in AI-driven decision systems, which overlap with the ethical and governance considerations within the framework. Likewise, Ding, Ning, Dhelim, and Lifelo (2024) recognize the transformative nature of the interaction between the capabilities of GenAI and operational and customer-level performance, resulting from the introduction of digital infrastructure through the influence of Banking Information Systems (BIS).

Figure 2. Genai-bis Conceptual Framework



Source: Author's Creation.

1) Framework Dynamics: It is based on the assumption that Generative AI Enablers (independent variables, Scholarly Evidence Supporting Generative AI Technology, nine key enablers in the Banking Sector). These enablers include Deep Learning credit scoring and fraud detection (Hassani et al., 2020), Natural Language Processing for customer service and document summarization (Gao et al., 2021), and Large Language Models for the production of compliance reports and personalized financial advice (Liu et al., 2023). Other examples of Computer Vision include KYC procedures (Kalmani, 2022), the use of Generative Adversarial Networks to generate synthetic data for secure model training (Kate et al., 2023), and Reinforcement Learning to make dynamic decisions in financial services (Singh et al., 2022). We also discuss Synthetic Data

Generation to develop privacy-preserving models (Potluru et al., 2023), Edge AI to process data in real-time (Eswaran et al., 2025), and Explainable AI to make decisions made by AI transparent (Hanif, 2021). Among the emerging technologies that overlap with the Generative AI paradigms but are not one of the nine main Generative AI Enablers (GAEs) that the banking and financial services industry (BFSI) was focused on is set in the broader context of the field of Artificial Intelligence. These are Transfer Learning (Singh et al., 2022), Multimodal AI (Gao et al., 2021), Federated Learning (Konecny et al., 2016), Automated Machine Learning (AutoML) (Feurer et al., 2019) and Diffusion Models (Ho et al., 2020). Although they both have high potential, their core functions are not directly compatible with the aspect of generative capabilities needed in Banking, Financial Services, and Insurance (BFSI) transformation. An example of this is that Transfer Learning is usually integrated into bigger model architectures and used to boost performance in low-data settings. Nevertheless, it does not produce new content and artifacts of data on its own. Similarly, an orchestration layer provides a more accurate characterization of Multimodal AI, which combines heterogeneous inputs, such as text, images, and speech, rather than relying on a generative engine (Gao et al., 2021). Federated Learning is primarily concerned with privacy-preserving collaborative training that enables institutions to create models without requiring the participation of sensitive data; however, it is not concerned with data or content creation, but rather with the distributed learning infrastructure (Konecny et al., 2016). AutoML simplifies the model development pipelines within the field of operations by automating hyperparameter tuning and feature selection. Although it makes the process more efficient, it is not inherently generative (Feurer et al., 2019). Finally, Diffusion Models are considered potentially effective in generating synthetic tabular data. However, they are still in the infancy stage of financial-related developments and have not been empirically validated or aligned with regulations in the BFSI setting (Ho et al., 2020). Therefore, these technologies do not fit the stated scope of the proposed framework, even though they are relevant in other related areas of AI, because they only have an indirect generative role or are not yet mature enough for adoption in the financial services field.

Table 1. Generative AI Enablers Mapped to Banking Information Systems

Banking Information System	Deep Learning-Based Algorithms	Natural Language Processing (NLP)	Large Language Models (LLMs)	Computer Vision	Generative Adversarial Networks (GANs)	Reinforcement Learning	Synthetic Data Generation	Edge AI	Explainable AI (XAI) Techniques	Supporting Literature
Core Banking System (CBS)	✓								✓	(Marshall et al., 2024)
Savings & Deposit Management System	✓									(Bhatnagar & Mahant, 2024)
Loan Management System	✓								✓	(Moharrak & Mogaji, 2024)
Fixed Deposit (FD)/Recurring Deposit (RD) Systems	✓									(Cao & Feinstein, 2024)
Mortgage Management System	✓						✓			(Dixit, 2024)
Teller Automation System				✓				✓		(Lin & Lee, 2024)
ATM Management System								✓		(Jin et al., 2024)

Branch Automation System				✓			✓		(Liao et al., 2024)
Cheque Truncation & Processing System				✓	✓				(Desai et al., 2024)
Payment Switching System (NEFT, RTGS, IMPS, SWIFT, UPI)	✓					✓			(Chege, 2024)
Internet Banking System	✓	✓							(Hari et al., 2022; Lin & Lee, 2024)
Mobile Banking Platform	✓						✓		(Dwivedi et al., n.d.)
Wallet & Digital Payments Systems	✓					✓			(Chege, 2024)
QR/Scan-to-Pay Solutions				✓			✓		(Liao et al., 2024)
Neobank/ Virtual Bank Backend Systems			✓					✓	(Marshall et al., 2024)
Digital Kiosk & Self-Service Terminals				✓			✓		(Lin & Lee, 2024)
SMS/USSD Banking		✓							(Hari et al., 2022)

Infrastructure							
Customer Relationship Management (CRM) System		✓	✓			✓	(Hari et al., 2022; Chege, 2024)
Digital Onboarding System	✓			✓			(Shin et al., 2023; Liu et al., 2024)
Biometric Identity Verification System	✓			✓			(Shin et al., 2023)
Voice/Chatbot AI Platforms		✓	✓			✓	(Hari et al., 2022; Lin & Lee, 2024; Dwivedi et al., n.d.)
Customer Feedback & Complaint Redressal System		✓	✓			✓	(Shin et al., 2023; Chege, 2024)
Customer Data Platform (CDP)	✓				✓		(Li et al., 2023; Desai et al., 2024)
Credit Scoring Engine	✓				✓	✓	(Xia et al., 2024; Nobanee et

					al., 2024)
Loan Origination System (LOS)	✓			✓	(Xia et al., 2024; Moharrak & Mogaji, 2024)
Risk Management Information System (RMIS)			✓	✓	(Marshall et al., 2024; Kanbach et al., 2023)
Market Risk Analysis System			✓	✓	(Kanbach et al., 2023; Bhatnagar and Mahant, 2024)
Operational Risk Control System	✓			✓	(Nobanee et al., 2024)
Capital Adequacy and Basel Reporting System				✓	(Cao & Feinstein, 2024)
Collateral & Appraisal Management System	✓	✓			(Liu et al., 2024)

Credit Underwriting Automation System	✓						✓	(Moharrak & Mogaji, 2024; Xia et al., 2024)
Know Your Customer (KYC) System		✓		✓				(Shin et al., 2023; Hari et al., 2022)
Anti-Money Laundering (AML) System	✓				✓			(Nobanee et al., 2024; Moharrak & Mogaji, 2024)
Transaction Monitoring System	✓						✓	(Jin et al., 2024)
Sanctions Screening (OFAC/UN/EU) System		✓	✓					(Li et al., 2023)
Fraud Detection & Prevention System	✓				✓	✓		(Moharrak & Mogaji, 2024; Liao et al., 2024)
Regulatory Reporting			✓				✓	(Cao & Feinst

System (FATCA, CRS, MiFID, Basel, RBI)							ein, 2024)
Internal Audit Management System			✓			✓	(Kanbach et al., 2023)
SAR/STR Case Management Systems		✓	✓				(Shin et al., 2023)
Business Intelligence (BI) System	✓				✓		(Desai et al., 2024; Nobanee et al., 2024)
AI/ML Fraud Analytics	✓				✓	✓	(Dixit, 2024; Nobanee et al., 2024)
Predictive Analytics Platform							
Customer Segmentation & Profiling Engine	✓				✓	✓	(Li et al., 2023; Desai et al., 2024)
Portfolio Optimization System	✓			✓			(Bhatnagar & Mahant, 2024)

Robo-Advisory Engine		✓	✓				✓	(Desai et al., 2024; Marshall et al., 2024)
Explainable AI (XAI) Dashboard							✓	(Korzynski et al., 2023)
Synthetic Data Generation Platform				✓		✓		(Desai et al., 2024)
Reinforcement Learning Engine (for trading or pricing)					✓			(Bhatnagar & Mahant, 2024)
Enterprise Resource Planning (ERP)	✓							(Kanbach et al., 2023)
Financial Accounting System							✓	(Cao & Feinstein, 2024)
Treasury & Investment Management System (TMS/IMS)					✓	✓		(Bhatnagar & Mahant, 2024)
Procurement & Vendor Managem		✓					✓	(Korzynski et al., 2023)

ent System								
Human Resource Management System (HRMS)			✓				✓	(Desai et al., 2024)
Document Management System (DMS)		✓		✓				(Dixit, 2024)
Inventory & Asset Management System	✓					✓		(Lin & Lee, 2024)
IT Helpdesk & Ticketing Systems		✓	✓					(Hari et al., 2022)
Identity & Access Management (IAM) System	✓						✓	(Shin et al., 2023)
Digital Signature & e-Stamp Systems		✓						(Chege, 2024)
Cyber Threat Detection & Response	✓					✓		(Jin et al., 2024)
GDPR/Data Privacy Consent Management			✓				✓	(Cao & Feinstein, 2024)
Security Information & Event	✓				✓			(Moharrak &

Management (SIEM)								Mogaji, 2024)
Multi-Factor Authentication & Biometric Security System	✓			✓				(Shin et al., 2023)
Open Banking API Gateway			✓				✓	(Li et al., 2023)
Bank-Fintech Integration Hub			✓			✓		(Dencik et al., 2023)
PSD2/Account Aggregator Infrastructure		✓					✓	(Liang, 2024)
Third-Party Risk Management Systems	✓						✓	(Kanbach et al., 2023)
Consent-Based Data Sharing Portals			✓			✓		(Tang et al., n.d.)
Trade Finance & LC Management System		✓	✓					(Li et al., 2023)
Wealth Management Platform		✓						(Desai et al., 2024)

Insurance & Bancassurance Distribution System		✓	✓						(Li et al., 2023)
Forex & Currency Management Platform					✓	✓			(Bhatnagar & Mahant, 2024)
SME/Corporate Loan Management System	✓							✓	(Xia et al., 2024)
Green Finance & ESG Monitoring Systems					✓			✓	(Kanbach et al., 2023)
P2P Lending System	✓		✓						(Khan et al., n.d.)
Edge AI for Real-Time Fraud Detection	✓						✓		(Jin et al., 2024)
Blockchain Ledger for Cross-Border Settlements								✓	(Marshall et al., 2024)
Tokenization & Digital Assets System				✓		✓			(Dencik et al., 2023)
IoT-Enabled Banking Devices							✓		(Lin & Lee, 2024)

Infrastructure							
Voice Biometrics & AI Voice Verification	✓	✓					(Shin et al., 2023)
AR/VR Applications in Banking Experiences				✓	✓		(Dixit, 2024)

Source: Author’s Creation.

Table 1 is the systematic mapping of Nine Generative AI technology enablers (rows) to essential categories of Banking Information Systems (columns). A mark that at least one of the reviewed literature satisfied the criteria of a peer-reviewed study that reported the use of the respective enabler in the respective system. The correspondence between Generative AI Technology Enablers (GAEs) and Banking Information Systems (BIS) highlights the strategic presence of AI throughout the financial sector. Deep Learning and Explainable AI (XAI) have a positive impact on the core banking systems, including the Core Banking System (CBS) and Loan Management Systems, to improve decision-making and risk assessment (Marshall et al., 2024; Bhatnagar & Mahant, 2024). In the context of customer engagement systems, including Customer Relationship Management (CRM) systems and AI-powered chatbots, Natural Language Processing (NLP) and Large Language Models (LLMs) play a crucial role in enhancing customer interactions and personalization (Hari et al., 2022; Lin & Lee, 2024). Systems such as Anti-Money Laundering (AML) and Fraud Detection utilize Synthetic Data Generation and Reinforcement Learning to enhance accuracy and efficiency in the fields of compliance and fraud prevention (Desai et al., 2024; Moharrak & Mogaji, 2024). Such mapping is effective in encompassing the specific AI enablers that are related to every banking system, supported by solid scholarly evidence. Qualitative result synthesizing and structuring are based on the Systematic Literature Review (SLR) process. The result of the SLR process influences different constructs of the conceptual framework, which are depicted in the following links: Categorical mapping of the insights obtained through SLR to every key constituent of the conceptual framework.

Table 2. SLR Contributions to Conceptual Framework

Framework Construct	SLR Contribution
Generative AI Enablers (Independent Variable)	Literature reveals the key technologies (e.g., LLMs, NLP, GANs, Edge AI). SLR identifies enabling tools adopted globally and their use cases in financial sectors.
Banking Information System (Mediating Variable)	Studies on digital banking platforms, core banking software, and AI-driven compliance tools explain how BIS becomes the delivery mechanism for GenAI.
Emerging Opportunities. Opportunities in BIS through GenAI (Dependent Variable)	Based on the comprehensive Systematic Literature Review, emerging opportunities in Banking Information Systems via Generative AI (GenAI) enablers have been identified

Source: Author's Creation.

The theoretical underpinnings of this study provide essential interpretive frameworks for understanding Gen AI-driven transformations in banking. The following linkages demonstrate how each theoretical model informs various components of the conceptual framework: the framework is rooted in three core theories.

Table 3. Theoretical Foundations of GenAI in BIS

Theory	Scope	Focus
Dynamic Capability Theory (DCT)	Strategic Management	DCT emphasizes organizational agility and the ability to reconfigure capabilities in response to dynamic environments. GenAI adoption requires banks to reengineer BIS to accommodate adaptive, intelligence-driven processes.
Resource-Based View (RBV)	Strategic Advantage	RBV conceptualizes GenAI as a rare and valuable strategic resource. When combined with proprietary customer data and skilled talent, it offers a source of sustainable competitive advantage for banks.
Organizational Learning Theory (OLT)	Organizational Behavior	OLT underscores continuous adaptation and learning. According to the lens of GenAI, effective BIS change relies on the internalization of AI-related knowledge by the institutions and change in governance, culture, and practices.

Source: Author's Creation.

Table 4. Mapping Theories to Framework Constructs

Construct / Pathway	Linked Theory	Explanation
Generative AI Enablers → BIS	RBV	GenAI is treated as a strategic resource. If well-leveraged (with rare skills or data), banks gain a competitive advantage.
BIS → Opportunity of Gen AI	DCT + OLT	Deployment success depends on how quickly banks learn and adapt to new Gen AI tools.

Source: Author's Creation.

Table 5. Anchoring Theories for BIS and GenAI

Framework Construct	Anchoring Theory	Why
Generative AI Enablers	RBV	AI is a valuable, rare, and hard to imitate resource
Banking Information System	DCT	Reconfiguration of tech/processes is key for transformation
Opportunities for Generative AI Adaptation	OLT + DCT	Banks must adapt and learn from the implementation

Source: Author's Creation.

The Banking industry in any country is subject to unique regulatory, technological, and infrastructural forces that influence the adoption of Generative AI. The following connections emphasize the relationship between contextual factors and the evolution of banking via Generative AI.

III. FINDINGS AND THEMATIC ANALYSIS

A. Thematic Synthesis of Existing Literature

The paper provides an overview of the results of the systematic literature review (SLR) wherein the thematic analysis critically assesses the effects of Generative Artificial Intelligence (AI) in the contemporary banking industry. The analysis of the theme is carried out using Elicit cloud-based software license. The systematic literature review (SLR) is a transparent and replicable method of applying academic literature on the subject of AI adoption in banking in accordance with the PRISMA principles (Moher et al., 2009). The transformative potential and risks of implementing AI in the financial services sphere can be discussed with the help of the thematic synthesis methodology that was constructed by Thomas and Harden (2008) and can help understand the repetition of the conceptual patterns and thematic frameworks that occur more than once in literature. Table 1 describes a systematic mapping of Generative AI technological enablers to some Banking Information Systems, which includes the scope and complexities of their uses. The analysis reveals specific trends in adoption. Deep Learning and NLP are the most widely used enablers that drive fraud detection, credit scoring, sentiment analysis, and customer engagement, both in transactional and digital banking platforms. Computer Vision and Edge AI can be instrumental in security-related scenarios, particularly in biometric authentication, ATM administration, and mobile banking authentication, where real-time processing is a crucial requirement. Large Language Models (LLMs) and Explainable AI (XAI) are assuming a more prominent role in customer-facing systems and regulatory compliance, offering transparency in decision-making and fostering trust in AI-driven services. Synthetic Data Generation and

Generative Adversarial Networks (GANs) play a critical role in addressing imbalanced data issues, enabling powerful fraud analytics, credit modeling, and regulatory simulation while preserving data privacy. Reinforcement Learning (RL), which is less common, has demonstrated high potential in areas such as portfolio optimization, dynamic pricing, and adaptive risk management. The mapping suggests that the GenAI facilitators are not isolated technologies, but an integrated system of efficiency, security, personalization and innovators within the financial ecosystem.

B. Generative AI Technologies Connect with Banking Systems to Unlock New Opportunities

Table 6 gives an overall picture of how the Generative AI enablers are applied to Banking Information Systems (BIS) to harness the increased opportunities in the financial market. The nine GenAI enablers discussed in the literature such as Large Language Models (LLMs), Generative Adversarial Networks (GANs), Deep Learning, Natural Language Processing (NLP), Reinforcement Learning (RL), Computer Vision, Synthetic Data Generation, Edge AI, and Explainable AI (XAI) are aligned with the respective BIS functions systematically, and the opportunities described in the scholarly literature are listed in the table. The use of BIS as the mediating construct enables the table to indicate the causal relationship through which the GenAI capabilities are converted into tangible banking outputs, such as fraud detection, credit scoring, personalized services, and regulatory automation. These mappings are put into context of the larger organizational paradigm by the introduction of theoretical frameworks, such as the Dynamic Capability Theory, the Resource-Based View, and the Organizational Learning Theory, into the study. It also depicts that banks can use GenAI as a strategic asset, redefine BIS, and institutionalize AI-powered learning. The overall mapping, based on 228 peer-reviewed articles, provides a visual map to practitioners, policymakers and researchers to gain a clear understanding of how technological enablers, banking infrastructure and opportunities interact with various sectors.

Table 6. GenAI-BIS-Opportunities Mapping

Generative AI Enablers	Banking Information Systems	Emerging Opportunities	Theoretical Foundation	Supporting Literature
Computer Vision	KYC System	Facial recognition for real-time onboarding	DCT	(Zhang, 2021)
	Mobile Banking Platform	Face authentication for mobile transaction approval	DCT	(Oliveira et al., 2018)
	Customer Onboarding System	Cross-domain face matching for remote account opening	DCT	(Oliveira et al., 2018)
	Fraud Detection & Prevention System	Visual identity verification to prevent impersonation fraud	DCT	(Tistarelli & Grosso, 2000)
	Document Management System	OCR-based document digitization and identity extraction	DCT	(Gombos et al., n.d.)
Deep Learning	Fraud Detection & Prevention System	Anomaly detection in real-time transactions	DCT	(Wang et al., 2024)
	Credit Scoring Engine	Improved accuracy in credit risk modelling	DCT	(Xia et al., 2024)
	Credit Scoring Engine	Improved default prediction accuracy using ANN models	DCT	(Wahab et al., 2024)
	Credit Risk Assessment System	Pattern recognition in large credit datasets for enhanced risk evaluation	DCT	(Wahab et al., 2024)
Edge AI	Mobile Banking Platform	On-device fraud detection	DCT	(Baffour et al., 2024)
	Document Management System	On-device intelligent character recognition for real-time document processing	DCT	(Baffour et al., 2024)
	Operational Workflow System	AI-driven automation of routine banking tasks at the edge	DCT	(Baffour et al., 2024)
	Customer Experience Management System	Personalized on-device analytics for enhanced customer engagement	DCT	(Baffour et al., 2024)

	AI Innovation Management System	Competitive advantage through proprietary edge-deployed AI models	RBV	(Baffour et al., 2024)
Explainable AI	Fraud Detection & Prevention System	Interpretable fraud risk indicators	OLT	(Bellagarda & Abu-Mahfouz, 2022)
	Credit Scoring Engine	Transparent and interpretable score generation	OLT	(Verhoeven et al., 2022)
	Credit Scoring Engine	Interpretable credit decisions using SHAP/LIME explanations	OLT	(Verhoeven et al., 2022)
	Fraud Detection & Prevention System	Transparent fraud analytics using model explanations	OLT	(Michalakelis et al., 2024)
	Robo-Advisory System	Explainable investment advice for building customer trust	OLT	(Zhu et al., 2024)
	Customer Profiling System	Transparent cash flow analysis and transaction categorization	OLT	(Kotios et al., 2022)
	Model Governance System	Improved model validation and compliance documentation	RBV	(Gramespacher et al., 2021)
	AI Virtual Assistant	Customer understanding of AI-driven responses	OLT	(Baffour et al., 2024)
	Investment Advisory Platform	Transparent reasoning behind portfolio allocations	OLT	(Tóth & Blut, 2024)
	Risk Management System	Explainability in market and operational risk assessment	DCT	(Kokina et al., 2025)
Generative Adversarial Networks	Fraud Detection & Prevention System	Synthetic data for rare fraud pattern simulation	RBV	(Teng et al., 2024)
	Fraud Detection & Prevention System	Synthetic fraud data generation to address class imbalance	RBV	(Teng et al., 2024)

	Credit Risk Assessment System	Hybrid GAN-LightGBM model for accurate credit risk prediction	DCT	(Zhuang et al., 2024)
	Credit Default Swap Prediction System	Forecasting CDS using FN-Regression-GAN with sentiment and leverage data	RBV	(Lin et al., 2022)
	Customer Behavior Modeling System	Generation of synthetic profiles for behavior prediction and segmentation	RBV	(Dakalbab et al., 2024)
	Anti-Money Laundering System	Synthetic laundering scenarios to train AML algorithms	DCT	(Aftabi et al., 2023)
	Document Management System	GAN-enhanced quality for scanned document analysis	DCT	(Caceres & Moews, 2024)
	Stress Testing System	Synthetic economic scenarios for portfolio stress testing	RBV	(Caceres & Moews, 2024)
Large Language Models	Mobile Banking Platform	Voice assistants for query support	RBV	(Khennouche et al., 2024)
	Credit Scoring Engine	Automated credit narrative generation	RBV	(Xia et al., 2024)
	Customer Support Chatbot System	24/7 personalized support and intent classification via fine-tuned LLMs	OLT	(Khennouche et al., 2024; Lajčinová et al., 2024)
	Credit Scoring Engine	Narrative-based loan scoring using LLM-FP-CatBoost	DCT	(Xia et al., 2024)
	Regulatory Reporting System	Automated Basel III capital requirement interpretation	RBV	(Cao & Feinstein, 2024)
	Market Forecasting System	Text-based stock prediction using LLM-Stock2Vec	DCT	(Gerling & Lessmann, 2023)
	ESG Compliance System	Detection of greenwashing in disclosures via BERT and LLMs	RBV	(Gerling & Lessmann, 2023)
	Cybersecurity Threat Modeling System	LLM-driven STRIDE threat modeling with mitigation code generation	DCT	(Yang et al., 2024)

	Document Management System	Multi-modal document parsing with LayoutXLM	DCT	(Gerling & Lessmann, 2023)
	Internal Communication System	Analysis of feedback and communication climate using LLMs	OLT	(Tkalac Vercic et al., 2021)
Natural Language Processing	KYC System	Document verification via semantic analysis	OLT	(Dong, 2025)
	Mobile Banking Platform	Intent detection for query resolution	OLT	(Lajčinová et al., 2024)
	Customer Support Chatbot System	Multilingual, 24/7 AI-assisted customer interaction	OLT	(Cherif et al., 2022; Bansal et al., 2024)
	Fraud Detection & Prevention System	Anomaly detection from transaction descriptions using NLP	DCT	(Wang et al., 2021a; Cerchiello et al., 2017)
	Credit Scoring Engine	SME credit risk prediction from narrative assessments	DCT	(Stevenson et al., 2020)
	Document Management System	Automated extraction from contracts, IDs, and legal docs	DCT	(Baviskar et al., 2023; Du et al., 2024)
	Regulatory Compliance System	Real-time document scanning for compliance risks	RBV	(Sema Admass et al., n.d.)
	Market Intelligence System	Sentiment analytics from social/news data to inform strategy	RBV	(Pantoja Rojas et al., 2023; Alamsyah & Girawan, 2023)
	ESG Risk Analysis System	ESG scoring from corporate disclosures and social media	RBV	(Dong, 2023)
	Investment Risk Management System	IPO prospectus text mining for underwriting risk	DCT	(Zhang et al., 2024)
Reinforcement Learning	Portfolio Management System	Adaptive asset allocation using PPO and DRL agents	DCT	(Vo et al., 2019; Belyakov & Sizykh, 2024)

	Algorithmic Trading System	RL agents for market-adaptive trading strategies	RBV	(Martínez et al., 2019; Gašperov & Kostanjčar, 2021)
	Fraud Detection & Prevention System	Adaptive fraud detection through RL-based pattern learning	DCT	(Koratamaddi et al., 2021; Teng & Lee, 2019)
	Credit Risk Assessment System	Deep RL for feature-optimized credit scoring	DCT	(Ha et al., 2016; Zhang et al., 2023)
	Personalized Financial Advisory System	RL-driven collaborative filtering for product recommendation	OLT	(Zhang, 2024)
	Liquidity Risk Monitoring System	Hybrid ANN-RL framework for balance sheet optimization	RBV	(Tavana et al., 2018)
	Systemic Risk Surveillance System	RL modeling of interbank contagion risks	DCT	(Yu et al., 2020)
	Regulatory Compliance System	RL-assisted optimization of regulatory adherence strategies	RBV	(Königstorfer & Thalmann, 2020)
Synthetic Data Generation	Credit Scoring Engine	Privacy-preserving credit scoring training	RBV	(Caceres & Moews, 2024)
	Fraud Detection & Prevention System	Balancing fraud datasets with synthetic outliers to improve detection	DCT	(Teng et al., 2024; Aftabi et al., 2023)
	Risk Modeling System	Synthetic augmentation of financial statements for risk analysis	RBV	(Aftabi et al., 2023)
	Privacy-Compliant Data Platform	Enable anonymized data sharing via synthetic datasets	RBV	(Caceres & Moews, 2024)
	Customer Profiling System	Model customer churn and preferences using synthetic personas	OLT	(Caceres & Moews, 2024)
	Credit Scoring Engine	Support low-data segments (e.g. SMEs)	DCT	(Implied use case)

		with generated loan records		
	AI Model Development Environment	Training and evaluation of ML models without using sensitive data	RBV	(Aftabi et al., 2023)
	Fraud Detection & Prevention System	Derived synthetic features for fraud detection (e.g., vertical/horizontal ratios)	DCT	(Aftabi et al., 2023)

Source: Author's Creation

IV. DISCUSSION

A. Strategic Integration of GenAI in Banking Systems

As the trend of innovation among financial institutions shifts towards the use of Generative AI (GenAI), it is crucial to implement it strategically. NLP, Generative Adversarial Networks (GANs), and Explainable AI (XAI) are GenAI technologies that are transforming customer service, compliance, credit scoring, and fraud detection. These capabilities are leaving the experimental stage and becoming ingrained in the operational foundation of modern Banking Information Systems (BIS).

Banks need to put first-line infrastructure in place, such as secure data lakes, scalable cloud platforms, and real-time analytics engines, to extract real value. GenAI will be able to provide highly personalized services, proactive risk notifications, and decision-making processes automation with the help of these digital underpinnings (Gerling and Lessmann, 2023; Khennouche et al., 2024). As an illustration, tier-1 support is now automated with AI-based virtual assistants and chatbots, which leave the human agent to deal with more complex interactions, and credit engines enhanced with GenAI present more inclusive and dynamic lending models (Aftabi et al., 2023).

One of the most promising applications is fraud detection. As GenAI can simulate and learn based on artificial transaction data, banks will be able to identify uncommon fraud patterns through their traditional models (Baffour et al., 2024). Furthermore, the explanation AI will help financial institutions to fulfill the changing regulatory needs and retain model transparency.

B. Responsible Adoption and Governance

Despite such developments, there are no significant challenges related to the adoption of GenAI. The issue of bias, accountability, and data misuse is an aspect of ethical issues that should not be ignored. Based on the study results, it is possible to conclude that there is an increasing necessity to develop open AI governance frameworks capable of ensuring innovation and adherence to compliance, as well as fairness. Specifically, cross-border regulatory coordination and domain-specific auditability structures will be necessitated by scaling GenAI in international banking business (McKnight et al., 2024; Cano-Marin, 2024).

As technology becomes more established, organizations should also invest in AI fluency in top management and make human control central to the GenAI-enabled decision-making process. It is through this moderate approach that GenAI will become a dependable tool in the financial field.

C. Addressing Gaps and Advancing AI-Related Financial Studies

The rapid evolution of AI in finance presents numerous opportunities for academic research. Researchers should focus on developing more sophisticated AI models tailored specifically for financial applications, such as improved natural language processing for sentiment analysis of financial news and social media (Xing, Cambria, & Welsch, 2023). There is also a need for interdisciplinary research combining finance, computer science, and ethics to address the complex challenges of AI adoption in banking (Tóth & Blut, 2024).

Future studies should explore the long-term economic impacts of AI adoption in the financial sector, including its effects on employment, market stability, and financial inclusion (Vučinić & Luburić, 2024). Researchers should also investigate the potential of emerging AI technologies, such as quantum machine learning and neuromorphic computing, in solving complex financial problems (Kanbach et al., 2023).

There is a significant gap in research on AI adoption in emerging markets and developing economies. Scholars should conduct more studies on the unique challenges and opportunities for AI implementation in these contexts, particularly focusing on regulatory frameworks and infrastructure limitations (Alamsyah, Raras, & Astuti, 2025). Additionally, research on the societal implications of AI-driven financial services, including issues of algorithmic bias and digital divide, is crucial for ensuring equitable AI adoption (Wach et al., 2023).

V. CONCLUSION

A. Summary of Key Insights

This review gathers evidence on 228 academic resources and is able to define GenAI as a game-changing facilitator of Banking Information systems (BIS). Large Language Models (LLMs), GANs, and NLP technologies are implemented in fraud detection, customer service, credit risk modeling and regulatory compliance. Such applications demonstrate an observable change in cost efficiency, customization of the service, and scalability of the operations (Gerling & Lessmann, 2023; Liao et al., 2024).

B. Contributions and Significance

In addition to academic mapping, this study has a practical value, being one of the first systematic frameworks between GenAI technologies and BIS functions. It provides banking professionals, policymakers, and AI developers with a decision-support mechanism on identifying high impact provisions of AI investment. It provides conceptual depth through the integration of organizational theories, such as RBV, DCT, and OLT, which enable the transformation of technical enablers into strategic capabilities.

C. Limitations of the Study

Despite its contributions, this study has several limitations. Firstly, the rapid pace of AI development means that some findings may become outdated quickly. Lastly, the study's reliance on published literature may have excluded valuable insights from unpublished or proprietary sources in the banking industry.

D. Recommendations for Future Research

More empirical studies are required to test the longitudinal effects of GenAI in a variety of financial settings. Cases, pilot projects, and industrial-academic partnerships will play a pivotal role in the optimization of adoption models and the establishment of their practical efficiency. The role of GenAI in the sphere of financial inclusion, particularly the underserved markets, should be given special consideration.

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