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# Leveraging Artificial Intelligence for Enhanced Bank Profitability: The Role of Technological Innovation

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***Abstract:***

***Purpose:*** *The main aim of this research is to find and understand better the real contribution of AI to financial performance of banks across 20 homogenerous countries.*
***Design/Methodology/Approach:*** *It evaluates three dimensions: the direct impact of AI innovation on performance, the mediating role of information and communication technology (ICT) development, and the moderating influence of economic growth. By relying on longitudinal panel data, the research also captures both short-term and delayed effects of AI adoption, offering insights into its dynamic implications over time.*
***Findings:*** *The empirical findings indicate that while AI technological innovation alone does not have a significant immediate effect on banks' return on assets, its influence is partially transmitted through improvements in ICT infrastructure. In particular, ICT development mediates the relationship between AI innovation and financial performance, highlighting the crucial role of digital infrastructure in converting technological investments into operational and financial gains.*
***Practical Implications:*** *The research offers a comprehensive perspective on how AI-based innovation can enhance financial performance, support sustainable growth, and reinforce competitiveness within the banking industry.*
***Originality/Value:*** *This work contributes to the existing literature in several ways.*

***Keywords:*** *Artificial Intelligence (AI) Innovation, ICT Infrastructure Development, Banking Performance, Return on Assets (ROA), Technology–Performance Mediation.*

***JEL Classification:*** *G21, O33, O32, L86, C23.*

***Paper type:*** *Research paper.*

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## 1. Introduction

The banking and financial industry is witnessing a profound shift as artificial intelligence (AI) becomes increasingly integrated into its core activities. AI-driven tools are transforming conventional banking practices and reshaping competitive dynamics across the sector (Subburayan, Sankarkumar, Singh, and Mushi, 2024). Around the world, financial institutions are adopting AI to streamline processes, enhance customer experience, and introduce innovative digital services (Shiyyab, Alzoubi, Obidat, and Alshurafat, 2023). Technologies such as predictive analytics, automated risk assessment systems, fraud detection algorithms, and intelligent customer service platforms provide banks with new opportunities to strengthen decision-making and improve operational performance (Eni, Chaudhary, Raparthi, and Reddy, 2023).

Despite this accelerated adoption, there is still a need to better understand the real contribution of AI to financial performance in the banking industry. Regulators face the challenge of supporting technological innovation while ensuring data privacy, consumer protection, and financial stability (Kreps and Rao, 2023). At the same time, banks are investing heavily in AI to remain competitive and respond to changing market conditions (Zhao, Tsai, and Wang, 2019). This highlights the importance of examining the relationship between AI innovation and bank performance, which is crucial for guiding strategic investments, regulatory planning, and public policy (Sullivan and Wamba, 2024).

This study aims to assess how AI-based technological innovation shapes the financial performance of banks across 20 heterogeneous countries. More specifically, it evaluates three dimensions: the direct impact of AI innovation on performance, the mediating role of information and communication technology (ICT) development, and the moderating influence of economic growth. By relying on longitudinal panel data, the research also captures both short-term and delayed effects of AI adoption, offering insights into its dynamic implications over time (Truby, Brown, and Dahdal, 2020).

This work contributes to the existing literature in several ways. First, it addresses the limited number of cross-country analyses, as many prior studies focus on single-country or firm-level investigations. Second, it sheds light on the mechanisms that link AI innovation to financial outcomes by emphasizing ICT development as a mediating factor and economic growth as a contextual moderator. Third, by incorporating the temporal dimension of innovation, the study highlights how the effects of AI evolve, providing valuable guidance for strategic and operational planning in the banking sector (Zaki, 2019).

Overall, the objective of this research is to offer a comprehensive perspective on how AI-based innovation can enhance financial performance, support sustainable growth, and reinforce competitiveness within the banking industry. By combining

technological, economic, and regulatory viewpoints, the study provides actionable insights for policymakers, financial institutions, and scholars seeking to maximize the benefits of AI while mitigating its potential risks (Dutta, Pramanik, Datta, and Kirtania, 2022).

## 2. Theoretical Background, Literature Review and Research Hypotheses

### 2.1 Theoretical Frameworks

Artificial intelligence (AI) has become a multidisciplinary domain drawing from computer science, mathematics, cognitive science, and neuroscience. It refers to the capacity of machines to imitate human cognitive abilities—such as learning, reasoning, perception, and autonomous decision-making—to achieve specific objectives (Russell and Norvig, 2021). These characteristics place AI at the heart of the digital transformation occurring in the banking industry, where rapid information processing, predictive modelling, and optimized decision-making have become essential (Tyagi *et al.,* 2023; Velinov *et al.,* 2023).

The foundations of modern AI date back to the pioneering work of Alan Turing in the 1950s, particularly his test for assessing machine intelligence, followed by John McCarthy's formalization of the field and the organization of the first AI conference in 1956, which shaped the trajectory of subsequent theoretical and technological developments.

Over time, several conceptual paradigms have contributed to the evolution of AI and its applications in finance. Early research was dominated by the symbolic paradigm, which relied on explicit rules and symbolic representations to solve well-structured problems. This approach supported the rise of expert systems, which proved useful in financial domains such as credit evaluation and early forms of risk assessment (Newell and Simon, 1976 ; Grima *et al.,* 2019).

The emergence of the connectionist paradigm in the 1980s, inspired by the architecture of the human brain, led to artificial neural networks capable of learning from large and complex datasets. This paradigm provided tools particularly well suited for fraud detection, credit scoring, and personalized financial services due to its ability to identify nonlinear and intricate patterns in customer and transaction data (LeCun, Bengio, and Hinton, 2015). Probabilistic and Bayesian frameworks further enriched AI research by offering mechanisms to address uncertainty and make informed decisions in incomplete or ambiguous environments—capabilities essential for forecasting credit defaults or managing market volatility (Pearl, 1988).

More recently, hybrid AI systems have combined symbolic, neural, and probabilistic components to increase robustness, interpretability, and auditability—qualities that are indispensable for meeting regulatory requirements and maintaining customer trust (Garcez *et al.,* 2019).

AI-driven technological innovation can additionally be interpreted through strategic and managerial lenses. The Resource-Based View (RBV) conceptualizes AI as a strategic resource capable of generating long-term competitive advantage. Through enhanced risk management, personalized services, and more efficient operations, AI contributes directly to financial performance indicators such as ROA and ROE (Barney, 1991; Rahman, 2023). However, the RBV also emphasizes that competitive advantage hinges on the difficulty of replicating these capabilities, meaning that AI's strategic value depends on how well it is integrated into a bank's long-term vision.

The Diffusion of Innovation (DOI) theory provides another lens for understanding AI adoption. It explains how innovations move from early adopters to the mainstream and emphasizes that the pace and breadth of diffusion can shape performance outcomes (Rogers, 2003; Shiyyab *et al.,* 2023). Organizational readiness, technological infrastructure, and cultural openness significantly influence the success of AI implementation, while complexity or resistance to change can limit its benefits.

Institutional theory complements this view by highlighting the influence of regulations, industry norms, and societal expectations. Banks must not only adopt advanced AI tools but also align them with legal and industry standards to ensure that innovations translate effectively into improved performance (Scott, 1995; Engvall, 2024).

Complex adaptive systems theory further illustrates how banks operate within dynamic, interconnected environments. From this perspective, AI enhances banks' adaptive capacities by facilitating learning, anticipating risks, and improving the agility of internal processes (Holland, 1992).

Computational intelligence methods—such as neural networks, genetic algorithms, and fuzzy logic—also provide powerful tools for solving complex optimization or forecasting problems in finance, including credit risk modeling or portfolio selection (Zadeh, 1994).

Multi-agent systems and intelligent agents extend these capabilities by enabling the simulation of environments in which multiple autonomous actors interact, a feature particularly relevant for automated financial advisory services, real-time transaction monitoring, and regulatory compliance (Wooldridge, 2009).
Several frameworks can therefore be used to evaluate AI's influence on banking performance. Operational efficiency perspectives focus on productivity gains, cost reductions, faster processing, and lower error rates, all of which contribute to improved profitability (Davenport, 2018).

Strategic perspectives, rooted in disruptive innovation theory, consider how AI reshapes business models and creates long-term competitive differentiation (Christensen, 1997). From a broader economic standpoint, diffusion theory and neo-

Schumpeterian perspectives suggest that rapid and effective integration of AI strengthens competitiveness and boosts the financial performance of the banking sector (Schumpeter, 1942; Rogers, 2003).

## 2.2 Literature Review

Banking performance results from the interaction of several internal and external determinants. Factors such as non-performing loans, capital adequacy, the macroeconomic environment, regulatory frameworks, and the maturity of information and communication technologies (ICT) all shape profitability levels (Takahashi and Vasconcelos, 2024; De Bandt *et al.,* 2018; Alam *et al.,* 2021; Bătae *et al.,* 2021; Al-Busaidi and Al-Muharrami, 2021).

High levels of non-performing loans continue to be identified as one of the strongest constraints on bank profitability, exerting downward pressure on returns such as ROA (Duong *et al.,* 2023). Capital regulation can impact performance differently depending on the bank's initial strength: well-capitalized institutions tend to improve their financial outcomes, while capital-constrained banks may face profitability limitations (Tran, Lin and Nguyen, 2016).

Macroeconomic expansion is typically linked to better financial results, a trend illustrated by evidence from Islamic banks operating in Southeast Asia and the Middle East (Ledhem and Mekidiche, 2020). Institutional quality, transparency, and regulatory effectiveness also condition performance, with weak governance or corruption often hampering profitability (Nasreen *et al.,* 2024). ICT development contributes to performance in multi-faceted ways, sometimes exerting negative effects on ROA while supporting indicators such as ROE or net interest margins (Aguegboh, Agu and Nnetu-Okolieuwa, 2023).

Artificial intelligence (AI) has emerged as a major technological driver with the potential to reshape banking operations and financial outcomes. Machine learning-based systems, conversational agents, scoring models, and fraud detection tools can streamline operations, enhance risk assessment, and improve client interactions, ultimately contributing to improved ROA and ROE (Shiyyab *et al.,* 2023; Königstorfer and Thalmann, 2020; Ris, Stankovic and Avramovic, 2020; Umamaheswari and Valarmathi, 2023).
Broader fintech innovations such as big data analytics and IoT further reinforce fraud prevention and operational efficiency, helping strengthen financial performance (Chhaidar, Abdelhedi and Abdelkafi, 2023). In marketing and customer management, AI-enabled personalization fosters customer satisfaction and loyalty through automated and adaptive service delivery (Abrokwah-Larbi and Awuku-Larbi, 2024).

Nevertheless, the advantages of AI adoption are not guaranteed and depend heavily on organizational and institutional conditions. Several recent studies show that the

quality of digital infrastructure, the competencies of employees, the bank's technological readiness, and the regulatory environment shape the ability to convert AI innovation into measurable performance improvements (Ammar and Ben Salem, 2025; Alhassan *et al.,* 2025; El Hadi *et al.,* 2024).

Beyond customer-facing services, AI is increasingly used for compliance monitoring, internal control mechanisms, and dynamic risk management, strengthening financial institutions' stability and credibility (Ben Saïd and Trabelsi, 2025). Meta-analytical evidence highlights that although AI significantly improves operational and strategic efficiency, it also introduces challenges related to cybersecurity, model interpretability, and organizational transformation (Kouadio *et al.,* 2023).

Recent literature also stresses the relevance of mediating and moderating variables—such as ICT development, macroeconomic conditions, and employee training—in shaping the extent to which AI leads to financial improvements (Gyau et al., 2024; Ouédraogo and Kambou, 2025). These findings underscore that AI acts as a strategic tool for enhancing bank performance, but its effectiveness depends on adequate technological capacities, aligned strategic planning, supportive institutional environments, and coherent regulatory frameworks.

In conclusion, the accumulated evidence demonstrates that AI has the potential to deeply transform banking services, strengthen profitability, and optimize internal processes. These observations justify a cross-country investigation that simultaneously considers technological innovation, financial performance, and institutional context to identify the conditions under which AI adoption generates sustainable and measurable value for banks.

### 2.3 Research Hypotheses

The rapid diffusion of artificial intelligence (AI) technologies is profoundly reshaping banking operations and financial strategies. As the sector accelerates its digital transformation, AI has become a central tool for improving efficiency, enhancing decision-making accuracy, and delivering more personalized services. This raises a fundamental question: *to what extent does AI-driven technological innovation contribute to banks' financial performance worldwide, and how do macroeconomic and technological conditions influence this effect?*

The concept of Banking Financial Artificial Intelligence Technology Innovation (BFAITI) refers to the adoption of a broad set of AI tools—including automated decision systems, predictive models, fraud detection algorithms, and personalized service interfaces—that reshape traditional banking workflows. Polak, Nelischer, Guo, and Robertson (2020) argue that these technologies significantly rationalize operations, lower administrative and processing costs, and improve the precision of financial assessments through machine learning and big data applications.

Recent empirical studies reinforce the central role of AI in strengthening banking performance. Vives (2022) shows that intelligent automation enhances operational efficiency and strengthens risk management, two essential components of financial stability.

In the same vein, Ozili (2023) highlights that AI integration boosts competitiveness, elevates the quality of digital customer interactions, and enables banks to realize economies of scale. Liu, Li, and Wang (2021) further demonstrate that AI optimizes resource allocation, shortens processing times, and increases human capital productivity, confirming its direct contribution to performance improvements.

Through these mechanisms—automation, cost reduction, improved risk assessment, and enhanced customer engagement—AI enables banks to achieve measurable gains in profitability.

***Hypothesis 1: BFAITI positively affects banks' financial performance:***

Economic growth is a major contextual factor that facilitates the adoption of advanced technologies such as AI within the financial sector. Reis Mourão and Popescu (2023) show that expanding economic environments improve banks' ability to mobilize resources, upgrade technological infrastructures, and develop AI-based systems that enhance efficiency and risk management capacities.

The literature further indicates that economic expansion strengthens banks' willingness to engage in digital transformation. For example, Arner, Barberis, and Buckley (2020) note that favorable macroeconomic conditions reduce innovation-related uncertainty and encourage investments in financial technologies.

Vives (2022) similarly observes that banks operating in stable, growing economies transition more rapidly toward digital models, which increases the payoff of technological investments.

Economic growth also stimulates broader innovation ecosystems. As emphasized by Liu, Li, and Wang (2021), a dynamic macroeconomic environment encourages collaboration among financial institutions, fintech firms, and technology providers, accelerating the diffusion of AI solutions. Ozili (2023) adds that the costs associated with adopting financial technologies tend to decrease in expanding economies, enabling banks to more effectively capitalize on AI capabilities. Pham and Doan (2022), in turn, show empirically that the performance benefits of digital technologies are stronger in countries with higher levels of economic growth.

Together, these insights suggest that economic growth enhances the link between AI innovation and financial performance by improving financial conditions, reducing uncertainty, and fostering technological development.

***Hypothesis 2: Economic growth positively moderates the relationship between BFAITI and banks' financial performance:***

BFAITI is also closely tied to improvements in ICT development, as AI deployment requires a robust technological infrastructure. Rahman, Ming, Baigh, and Sarker (2023) argue that integrating AI systems compels banks to reinforce their digital capabilities, including data management architectures, computing capacity, network systems, and cybersecurity mechanisms. The effectiveness of AI solutions depends heavily on these technological foundations, prompting banks to invest in more advanced ICT infrastructures.

This relationship is supported by recent empirical evidence. Vives (2022) demonstrates that the deployment of AI triggers structural changes in banking information systems, improving automation, data processing speed, and operational cost efficiency.

Likewise, Liu, Li, and Wang (2021) show that AI initiatives stimulate continuous investment in digital infrastructures due to increasing requirements associated with big data and machine learning applications.

Ozili (2023) further emphasizes that enhanced ICT infrastructures strengthen both internal efficiency and customer experience through rapid, secure, and customized services. Improved technological foundations also enable better decision-making, increased workforce productivity, and greater resilience against competition from fintechs.

These insights indicate that BFAITI acts as a driver of ICT development, which in turn amplifies its positive impact on financial performance. ICT development thus emerges as an essential pathway through which AI generates tangible economic benefits for banks.

***Hypothesis 3: ICT development moderates the relationship between BFAITI and banks' financial performance:***

## 3. Methodology, Model, and Data

### 3.1 Methodology

This section describes the econometric techniques employed to examine the impact of artificial intelligence (AI) innovations in the banking sector on financial performance. It also incorporates the moderating role of economic growth and the mediating effect of information and communication technology (ICT) development—two key determinants highlighted in the literature on banking performance.

The empirical strategy begins with a set of preliminary diagnostic tests to ensure the reliability and robustness of the econometric results. These include tests for cross-sectional dependence (CSD), slope heterogeneity (SH), heteroscedasticity, autocorrelation, and unit roots in the panel data. Only after validating these assumptions are the impact coefficients estimated using the Feasible Generalized Least Squares (FGLS) method.

The cross-sectional dependence (CSD) test is crucial for detecting interdependencies among panel units, particularly economic or financial contagion across countries. Ignoring CSD may lead to biased estimators and misleading conclusions. Next, slope heterogeneity (SH) is tested to determine whether coefficients differ across countries—an expected outcome given the diversity of banking systems and institutional structures.

Heteroscedasticity, referring to non-constant variance in error terms, is examined to ensure estimator efficiency. Autocorrelation, which captures serial correlation in residuals, is also tested to avoid model misspecification and biased standard errors.
The **s**tationarity of the variables is then assessed using the Cross-sectional Augmented Dickey-Fuller (CADF) and the Cross-sectional Im, Pesaran, and Shin (CIPS) tests. These second-generation unit root tests control for cross-sectional dependence and verify that the statistical properties of the variables (mean and variance) remain stable over time.

After completing these diagnostic steps, the model is estimated using the FGLS method**,** which is particularly suited for panel datasets exhibiting heteroscedasticity, autocorrelation, and cross-sectional dependence. FGLS provides more efficient and reliable estimates compared with ordinary least squares (OLS), especially in macro-panel settings involving multiple countries over time.

The general FGLS specification is expressed as:

$$y = X\beta + e \tag{1}$$

with the following error properties:

$$E(e) = 0 \tag{2}$$

$$E(ee') = \sigma^2\Omega \tag{3}$$

If the disturbances follow a first-order autoregressive process (AR(1)):

$$e\_t = \rho\, e\_\{t-1\} + u\_t, \quad |\rho| < 1 \tag{4}$$

where u_t is independently and identically distributed, with zero mean and finite variance $\sigma^2$

Accordingly, the FGLS model applied in this study is written as:

$$Y\_it = \beta 0 + \beta 1\ X\_it + \beta 2\ Z\_it + \varepsilon\_it \quad (5)$$

where:

- Y_it represents bank financial performance,
- X_it denotes AI-based technological innovation (BFAITI),
- Z_it includes the set of control variables,
- ε_it is the error term corrected for heteroscedasticity, autocorrelation, and cross-sectional dependence

### 3.2 Research Model

Banks' financial performance is shaped by a wide range of determinants beyond artificial intelligence, including non-performing loans (BNPL), regulatory capital relative to risk-weighted assets (BRC), economic growth (GDPG), and government regulations (REG). Previous empirical studies highlight the relevance of these factors in explaining variations in profitability (Partovi and Matousek, 2019; Nsanyan Sandow, Duodu and Oteng-Abayie, 2021; Alam *et al.,* 2021; Shen and Chang, 2006).

To assess the effect of Banking and Finance Artificial Intelligence Technological Innovation (BFAITI) on financial performance, these control variables are incorporated into the baseline model, which is expressed as:

$$BROA\_it = \beta 0 + \delta 1\ BFAITI\_it + \gamma\ X\_it + \varepsilon\_it \quad (6)$$

where:

- ✓ i and t denote country and year, respectively;
- ✓ BROA_it is the return on assets of bank i in year t;
- ✓ BFAITI_it is banking and finance AI technological innovation of bank i in year t;
- ✓ X_it represents control variables, including BNPL, BRC, GDPG, and REG;
- ✓ β0 is the model constant;
- ✓ δ1 and γ are coefficients to be estimated;
- ✓ ε_it is the error term.

***Moderating Effect of Economic Growth:***

To examine whether economic growth strengthens or weakens the effect of BFAITI on financial performance, an interaction term is added to the baseline model:

$$BROA\_it = \beta 0 + \delta 1\ BFAITI\_it + \gamma\ X\_it + \psi\ (BFAITI\_it \times GDPG\_it) + \varepsilon\_it \quad (7)$$

where ψ captures the moderating effect of GDPG.

***Mediating Effect of ICT Development:***
To analyze the mediating role of information and communication technology development (ICTD), a three-equation mediation framework is applied:

1. *Effect of BFAITI on ICT development*
   $ICTD\_it = \beta 0 + \delta 2\ BFAITI\_it + \gamma\ X\_it + \varepsilon\_it$ (8)

2. *Effect of BFAITI and ICT development on financial performance*
   $BROA\_it = \beta 0 + \delta 3\ BFAITI\_it + \varphi\ ICTD\_it + \gamma\ X\_it + \varepsilon\_it$ (9)

where ICTD_it is the mediating variable and φ\varphiφ is its estimated coefficient.

***Lagged Effects of BFAITI:***
To capture potential delayed impacts of AI-driven technological innovation on bank performance, lagged values of BFAITI up to five periods are introduced:

$BROA\_it = \beta 0 + \delta 1\ BFAITI\_it\text{-}1 + \delta 1\ BFAITI\_it\text{-}2 + \delta 1\ BFAITI\_it\text{-}3 + \delta 1\ BFAITI\_it\text{-}4 + \delta 1\ BFAITI\_it\text{-}5 + \gamma\ X\_it + \varepsilon\_it$ (10)

All other variables retain their previously defined meaning.

### 3.3 Data and Variables Declaration

This study investigates the relationship between technological innovation in artificial intelligence within the banking and financial sector (BFAITI) and banks' financial performance—measured through return on assets (BROA)—over the period 2010–2020.

In addition to the main explanatory variable, the analysis incorporates several control variables that are widely recognized in the banking and finance literature: non-performing loans (BNPL), bank regulatory capital (BRC), economic growth (GDPG), and government regulations (REG). The framework also integrates the moderating effect of economic growth and the mediating role of information and communication technology development (ICTD), with the objective of capturing the mechanisms through which AI-based innovation affects financial performance.

The empirical analysis relies on a balanced panel of banks from 20 countries, covering both advanced and emerging economies: Australia, Brazil, Canada, China, Denmark, France, Germany, India, Israel, Italy, Japan, South Korea, Malaysia, Mexico, Russia, Singapore, Spain, Sweden, the United Kingdom, and the United States. The sample period (2010-2020) results in 220 country-year observations (20 countries × 11 years).

Data were mainly collected from reputable international institutions, particularly the Global Financial Development Database (GFDD) and the World Development

Indicators (WDI)**.** Measures of AI-related technological innovation were retrieved from the Center for Security and Emerging Technologies (CSET) (Center for Security and Emerging Technology, 2023a; World Bank, 2024). Additional complementary sources include International Monetary Fund (IMF) statistics, banks' annual reports, international patent repositories (WIPO), and ICT indicators from the International Telecommunication Union (ITU).

Table 1 provides a detailed description of the study variables and their corresponding measurement approaches.

### *3.3.1 Dependent Variable*

The financial performance of banks constitutes the principal dependent variable of this study and is assessed using the return on assets (ROA). ROA, expressed as an after-tax percentage, reflects a bank's ability to generate net income from its total assets. A higher ROA indicates more efficient use of resources and, consequently, stronger overall financial performance.

In the existing literature, ROA is widely recognized as one of the most reliable indicators of bank profitability (Haibo and Manu, 2022). Its suitability stems from its capacity to enable meaningful comparisons across banks of different sizes and business models. It is also frequently used to evaluate the impact of technological and digital innovations—such as artificial intelligence—on financial outcomes and operational efficiency (Adu, Abedin, Saa, and Boateng, 2024).

In this study, annual ROA values for banks in the selected sample of countries are collected to assess how AI-driven technological innovation affects bank profitability and efficiency. Accordingly, ROA serves as the central dependent measure in the empirical analysis.

The ROA is calculated as follows:

$$ROA = \frac{\textbf{Net Income}}{\textbf{Total Assets}}$$

### *3.3.2 Independent variable*

Artificial intelligence technological innovation in the banking and financial sector (BFAITI) reflects the ability of banks to develop and adopt AI-driven solutions to improve their operations, products, and services. This variable is measured through the number of patents granted specifically in the field of AI, providing an objective indicator of the intensity of technological innovation and the investment efforts made by financial institutions (Kaya, Schildbach, AG, and Schneider, 2019).

Using patents as a proxy allows for a precise quantification of banks' innovation capacity and their efforts to develop technologies capable of transforming operational processes, enhancing efficiency, optimizing decision-making, and

strengthening competitiveness. Unlike previous studies that relied on general innovation measures or AI-related keyword searches, this approach focuses exclusively on AI patents within the banking sector, thus offering a more accurate and novel measure of BFAITI (Shiyyab *et al.,* 2023).

### *3.3.3 Control variables*

To isolate the specific impact of BFAITI on banks' financial performance, several control variables are included in the model:

- **Non-performing loans (BNPL):** The ratio of non-performing loans to total gross loans captures the proportion of credit that is not being repaid. As a key indicator of asset quality, it helps control for credit risk, which can strongly influence bank profitability (Galariotis, Kosmidou, Kousenidis, Lazaridou, and Papapanagiotou, 2021; Zeqiraj, Gurdgiev, Sohag, and Hammoudeh, 2024).
- **Regulatory capital (BRC):** The ratio of regulatory capital to risk-weighted assets evaluates a bank's financial strength and its ability to absorb potential losses. Higher capital adequacy generally supports better performance by enhancing stability and resilience (Athanasoglou, Brissimis, and Delis, 2008; Siddika and Haron, 2020).
- **Government regulation (REG):** Measured through regulatory quality, this variable controls for the impact of public policies and legal frameworks on banking operations. Tighter regulatory environments may constrain revenues and narrow interest margins, thereby influencing financial performance (Anginer, Demirguc-Kunt, and Zhu, 2014; Ferrari, Masetti, and Ren, 2018).

### *3.3.4 Moderating variable: Economic growth (GDPG)*

Economic growth, measured by the annual GDP growth rate, is introduced as a moderating variable in the relationship between BFAITI and banks' financial performance. During periods of robust economic expansion, banks typically benefit from increased financial resources, higher demand for financial services, and improved credit quality. These favorable conditions can amplify the positive impact of AI-driven technological innovation on profitability.

Conversely, during periods of sluggish or declining economic growth, reduced demand and limited investment capacity may weaken the effectiveness of such innovations, thereby diminishing their contribution to financial performance (Banna and Alam, 2021).

### *3.3.5 Mediating variable: ICT development (ICTD)*

Information and communication technology development (ICTD) operates as a mediating variable linking BFAITI to banks' financial performance. ICTD is measured through a composite indicator that captures both the number of mobile subscriptions and the percentage of Internet users, reflecting the level of digital infrastructure within an economy (Shao, Lou, Wang, Mao, and Ye, 2022).

The adoption of AI technologies contributes to strengthening ICT infrastructure by improving digital connectivity, accelerating process optimization, and enhancing the overall quality of banking services.

This mediating mechanism illustrates how AI-driven innovation translates into concrete financial benefits, particularly through efficiency gains and improved customer experience.

Prior studies using similar ICT indicators confirm the pivotal role of digital infrastructure in shaping financial institutions' performance and their ability to create value (Del Gaudio, Porzio, Sampagnaro, and Verdoliva, 2021).

***Table 1.*** *Description of Variables and Measurement*

| Variable type | Variable | Abbreviation | Measurement |
|---|---|---|---|
| **Dependent Variables** | Banks' financial performance | BROA | Net Income / Total Assets |
| **Independent Variables** | AI technological innovation in banking and finance | BFAITI | Number of AI-related patents granted in the banking and financial sector |
| **Control variables** | Bank non-performing loans | BNPL | Non-performing loans / total gross loans × 100 |
| | Bank regulatory capital | BRC | Regulatory capital / risk-weighted assets × 100 |
| | Government regulation | REG | Regulatory quality (estimate) |
| **Moderating Variable** | Economic growth | GDPG | Annual GDP growth rate (%) |
| **Mediating Variable** | ICT development | ICTD | Composite index: mobile cellular subscriptions (per 100 people) and individuals using the Internet (%) |

***Source:*** *Own study.*

## 4. Data Analysis and Empirical Results

### 4.1 Descriptive Statistics

The descriptive statistics (Table 2) indicate that banks' financial performance (BROA) has a mean of 0.624 with a standard deviation of 0.439, while banking AI innovation (BFAITI) exhibits substantial variation across banks, with a mean of 23.924 patents and a standard deviation of 113.511. Non-performing loans (BNL) and regulatory capital (BRC) display high dispersion, reflecting significant differences in asset quality and financial strength. Economic growth (GDPG),

government regulation (REG), and ICT development (ICTD) also show considerable variability across the countries studied.

The correlation matrix (Table 2) reveals no multicollinearity concerns, as all correlations are below 0.5. BROA is positively correlated with GDPG and ICTD, and negatively correlated with BFAITI, BRC, and REG. The negative correlation with REG highlights the potential impact of regulatory constraints, while the weak correlations with BFAITI and ICTD suggest that the effect of AI innovation and ICT development on financial performance may be indirect or moderated by other factors.

***Table 2.*** *Descriptive and correlation statistics*

| Variable | BROA | BFAITI | BNL | BRC | GDPG | REG | ICTD |
|---|---|---|---|---|---|---|---|
| Mean | 0.624 | 23.924 | 2.248 | 1.776 | 5.410 | 109.443 | 109.443 |
| Std. Dev | 0.439 | 113.511 | 7.714 | 3.914 | 3.476 | 0.268 | 175.263 |
| Min | 0.000177 | -25.307 | -12.261 | -2.057 | -5.243 | -0.157 | -4535.71 |
| Max | 16.7173 | 2146.356 | 161.09 | 90.380 | 26.170 | 1 | 955.930 |

| **Correlation statistics** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **BROA** | 1.0000 | | | | | | |
| **BFAITI** | -0.1229 | 1.0000 | | | | | |
| **BNL** | 0.2523 | -0.1242 | 1.0000 | | | | |
| **BRC** | -0.2118 | 0.1265 | -0.1793 | 1.0000 | | | |
| **GDPG** | 0.0647 | 0.0011 | 0.0482 | -0.0585 | 1.0000 | | |
| **REG** | -0.5265 | 0.2917 | -0.4459 | 0.3322 | -0.0691 | 1.0000 | |
| **ICTD** | 0.0819 | 0.2073 | 0.1085 | -0.1149 | 0.1325 | -0.1533 | 1.0000 |

***Source:*** *Own study.*

### 4.2 Baseline Estimations

The baseline model provides several key insights into the determinants of banks' financial performance (BROA). The estimated equation is expressed as follows:

$$BROA_{it}=\beta 0+\beta 1BFAITI_{it}+\beta 2BNL_{it}+\beta 3BRC_{it}+\beta 4GDPG_{it}+\beta 5REG_{it}+\varepsilon_{it}BROA$$

The results indicate that banking and finance AI technological innovation (BFAITI) has a negative but statistically insignificant effect on ROA (coefficient = −0.0000275, p = 0.743). This suggests that AI innovation alone does not significantly enhance banks' financial performance in the baseline specification. The lack of significance may be due to the indirect or lagged benefits of AI, which could be mediated by other factors such as ICT development or macroeconomic conditions.

Non-performing loans (BNL) show a marginally positive effect on ROA (coefficient = 0.00210, p = 0.076), which is counterintuitive, as higher NPLs are generally expected to reduce profitability.

This unexpected outcome could reflect short-term risk management strategies, structural differences across countries, or other compensatory mechanisms that temporarily offset credit risk. In contrast, regulatory capital (BRC) does not exhibit a significant impact on ROA (coefficient = −0.00197, p = 0.532), suggesting that capital buffers alone may not directly influence profitability without complementary operational or technological interventions.

Economic growth (GDPG) has a marginally positive effect on bank performance (coefficient = 0.00441, p = 0.075), which aligns with theoretical expectations. Higher economic growth expands demand for loans and financial services, creating favorable conditions for increased profitability. Government regulation (REG), however, exhibits a large and highly significant negative impact on ROA (coefficient = −0.958, p < 0.01). This finding indicates that stricter regulatory frameworks can substantially constrain bank performance, likely by limiting interest margins, lending flexibility, and operational freedom.

Overall, the baseline results highlight that while regulatory constraints negatively affect profitability, the direct effect of AI innovation is not significant in isolation. Economic growth supports bank performance marginally, and the counterintuitive positive effect of non-performing loans warrants further investigation. These findings suggest that the benefits of AI adoption may materialize more clearly when considered in conjunction with other moderating or mediating factors, such as ICT development or favorable macroeconomic conditions.

***Table 3.*** *Baseline regression*

| **Variables** | **Coefficient** | **p-value** |
|---|---|---|
| BFAITI | -0.0000275 | 0.743 |
| BNL | 0.00210 | 0.076* |
| BRC | -0.00197 | 0.532 |
| GDPG | 0.00441 | 0.075* |
| REG | -0.958 | 0.000*** |
| Constante | 0.865 | 0.000*** |
| Note: * p < 0.10, ** p < 0.05, *** p < 0.01 | | |

***Source:*** *Own study.*

## 4.3 Moderation Effect

The moderating role of economic growth on the relationship between banking and finance AI technological innovation (BFAITI) and banks' financial performance (BROA) was examined by including the interaction term BFAITI×GDPG in the regression model. The results, reported in Table 4, indicate that the coefficient of the interaction term is negative and statistically insignificant (β = −0.00000155, p = 0.970).

This suggests that, within the sample and period studied, economic growth does not significantly moderate the impact of AI innovation on bank performance. In other words, the effect of BFAITI on BROA does not depend on variations in GDP growth, implying that the benefits of AI adoption may not automatically increase in periods of higher economic expansion. The baseline relationships remain consistent, with BNL showing a marginal positive effect, GDPG a marginal positive effect, and REG a highly significant negative effect on ROA.

***Table 4.*** *Moderating effect results*

| | (1) | (2) |
|---|---|---|
| **Variables** | **BROA** | **BROA** |
| **BFAITI** | -0.0000275 (0.743) | -0.0000170 (0.954) |
| **BNL** | 0.00210* (0.076) | 0.00210* (0.076) |
| **BRC** | -0.00197 (0.532) | -0.00197 (0.531) |
| **GDPG** | 0.00441* (0.075) | 0.00442* (0.078) |
| **REG** | -0.958*** (0.000) | -0.958*** (0.000) |
| **BFAITIxGDPG** | | -0.00000155 (0.970) |
| **_constante** | 0.865*** (0.000) | 0.865*** (0.000) |
| **Observations** | 2033 | 2033 |
| Note: * p < 0.10, ** p < 0.05, *** p < 0.01 | | |

***Source:*** *Own study.*

## 4.5 Mediation Effect

The mediation analysis was conducted following the three-step approach proposed by Baron and Kenny (1986) to examine whether ICT development (ICTD) serves as an intermediary channel through which AI innovation affects bank performance. As shown in Table 5, the first step confirms that BFAITI has a negative and highly significant direct effect on BROA ($\beta = -0.000532$, $p < 0.01$).

The second step indicates that BFAITI positively and significantly affects ICTD ($\beta = 0.320$, $p < 0.01$), highlighting that AI innovation drives improvements in ICT infrastructure, such as enhanced data analytics, automation, and customer interaction systems. In the third step, when both BFAITI and ICTD are included as predictors of BROA, ICTD exhibits a positive and highly significant effect on BROA ($\beta = 0.000302$, $p < 0.01$), while the direct effect of BFAITI remains negative and significant ($\beta = -0.000660$, $p < 0.01$).

These results indicate that ICTD partially mediates the relationship between BFAITI and financial performance. While AI innovation continues to exert a direct negative impact, part of its effect on BROA is transmitted indirectly through ICT development. This suggests that investments in AI technologies improve bank performance not only through their direct operational impact but also by fostering ICT infrastructure, which enhances efficiency, reduces costs, and supports service

innovation. Overall, the findings underscore the pivotal role of ICT as a conduit through which AI innovation can translate into tangible financial benefits for banks.

***Table 5.*** *Mediating effect results*.

| | (1) | (2) | (3) |
|---|---|---|---|
| **variables** | **BROA** | **ICTD** | **BROA** |
| **BFAITI** | -0.000532*** (0.000) | 0.320*** (0.000) | -0.000660*** (0.000) |
| **ICTD** | | | 0.000302*** (0.000) |
| **_constante** | 0.635*** (0.000) | 101.3*** (0.000) | 0.604*** (0.000) |
| **Observations** | 2063 | 2190 | 2057 |
| **Note: * p < 0.10, ** p < 0.05, *** p < 0.01** | | | |

***Source:*** *Own study.*

## 4.6 Lagged Effects

The long-term effects of artificial intelligence (AI) innovation in the banking sector (BFAITI) on banks' financial performance (BROA) were examined using lagged variables ranging from the first to the fifth lag. The results are presented in Table 6. The coefficients associated with the different lag periods are all very close to zero and statistically insignificant (p-values > 0.10). This lack of statistical significance indicates that, within the studied sample, AI innovation does not produce a lasting effect on bank profitability, whether in the short, medium, or long term.

The analysis of these lagged effects suggests that the potential immediate gains from AI adoption are modest and that anticipated benefits may be offset by implementation costs, integration challenges, or other operational constraints. While AI may enhance certain functional or strategic aspects of banks, these results indicate that such improvements do not translate into measurable and sustained increases in profitability.

Moreover, the examination of control variables confirms trends consistent with the literature. Non-performing loans (BNL) exhibit a positive and highly significant effect on BROA ($p < 0.01$), whereas regulatory capital (BRC) shows a marginally significant negative impact in some periods ($p < 0.1$).

Economic growth (GDPG) is positively correlated with bank performance and significant across all lags ($p < 0.01$), while regulation (REG) exerts a negative and highly significant effect on BROA in all lag periods ($p < 0.01$).

These findings highlight that, contrary to theoretical expectations, AI innovation does not have a direct and lasting impact on bank profitability within the scope of this study. They also emphasize the importance of considering other financial and macroeconomic determinants, which appear to play a more immediate and tangible role in shaping bank performance.

***Table 6.*** *Lagged effects results*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **Variables** | **BROA** | **BROA** | **BROA** | **BROA** | **BROA** |
| **L.BFAITI** | -0.0000184 | | | | |
| | (0.543) | | | | |
| **L2.BFAITI** | | -0.0000136 | | | |
| | | (0.664) | | | |
| **L3.BFAITI** | | | -0.0000160 | | |
| | | | (0.629) | | |
| **L4.BFAITI** | | | | -0.0000112 | |
| | | | | (0.749) | |
| **L5.BFAITI** | | | | | 0.00000500 |
| | | | | | (0.891) |
| **BNL** | 0.00196*** | 0.00209*** | 0.00217*** | 0.00358*** | 0.0108*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **BRC** | -0.00186* | -0.00175 | -0.00191 | -0.00171 | -0.000452 |
| | (0.091) | (0.119) | (0.104) | (0.158) | (0.705) |
| **GDPG** | 0.00273*** | 0.00340*** | 0.00417*** | 0.00394*** | 0.00361*** |
| | (0.002) | (0.000) | (0.000) | (0.000) | (0.001) |
| **REG** | -0.935*** | -0.928*** | -0.920*** | -0.902*** | -0.811*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **_cons** | 0.860*** | 0.853*** | 0.846*** | 0.838*** | 0.796*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **observations** | 1917 | 1803 | 1689 | 1574 | 1464 |
| **Note: * p < 0.10, ** p < 0.05, *** p < 0.01** | | | | | |

***Source:*** *Own study.*

## 5. Conclusion and Directions for Future Research

This study investigates the relationship between artificial intelligence (AI) technological innovation in the banking sector and banks' financial performance, using a panel dataset of 20 countries over the period 2010–2020.

By employing robust estimation techniques, including FGLS and two-step system GMM, the analysis explores whether AI innovation enhances banks' profitability, the mechanisms driving this effect, and the persistence of its impact over time.

The empirical findings indicate that while AI technological innovation alone does not have a significant immediate effect on banks' return on assets, its influence is partially transmitted through improvements in ICT infrastructure. In particular, ICT development mediates the relationship between AI innovation and financial performance, highlighting the crucial role of digital infrastructure in converting technological investments into operational and financial gains.

Furthermore, macroeconomic conditions, particularly economic growth, support bank profitability, while regulatory constraints impose significant challenges.

Non-performing loans exhibit a nuanced effect, suggesting that effective risk management is key to harnessing the benefits of technological innovation. The analysis of lagged effects reveals that AI adoption does not generate persistent improvements in profitability, indicating that banks must consider the dynamic and potentially costly nature of innovation initiatives.

The results have several practical implications. Financial institutions should integrate AI strategies with robust ICT development, effective risk management, and long-term planning to fully realize performance gains. Policymakers and regulators are encouraged to develop adaptive frameworks that foster AI innovation while ensuring financial stability, consumer protection, and transparency. Investments in digital infrastructure and the promotion of collaborative innovation ecosystems are also essential to maximize the positive impact of AI technologies in banking.

Despite the study's contributions, several limitations provide opportunities for future research. First, extending the dataset beyond 2020 could capture more recent trends in AI adoption and its evolving impact on bank performance. Second, future studies may consider additional moderating variables, such as institutional quality, financial inclusion, or market competition, to better understand the conditions under which AI innovation enhances profitability.

Third, expanding the sample to include more countries, particularly from underrepresented regions, could offer deeper insights into the contextual factors influencing AI adoption. Finally, future research could adopt heterogeneous analyses that account for differences in income levels, banking structures, or stages of digital development, allowing for a more nuanced understanding of the global effects of AI in the banking sector.

Overall, this study emphasizes that AI technological innovation holds significant potential to improve financial performance, but its benefits are contingent upon complementary infrastructure, regulatory environments, and macroeconomic conditions. The findings provide actionable guidance for practitioners, policymakers, and researchers seeking to leverage AI technologies to drive sustainable growth and operational efficiency in banking.

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