

# Artificial Intelligence and Bank Profitability: What Really Matters?

## PRELIMINARY VERSION\*

Paolo Nicola Barbieri<sup>1</sup>, Alessandra Bettocchi<sup>1</sup>, Andrea Fabrizi<sup>1</sup>, and Rita Romeo<sup>1</sup>

<sup>1</sup>Prometeia Spa

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### Abstract

This paper examines the relationship between digitalization and bank performance by constructing a novel text-based index of digital engagement from the annual reports of more than 50 major banks worldwide over 2009–2023. Using natural language processing, we quantify banks’ attention to digital themes and trace their evolution over time. We document a steady increase in digital engagement and find a positive association with profitability indexes. To refine the analysis, we employ large language models to classify AI-related paragraphs by use case and implementation stage. The results show that aggregate AI adoption is linked to profitability and cost reduction; the relation is stronger if AI is fully operational—particularly in customer support, client profiling, and internal process optimization—contributing to efficiency gains. By contrast, early-stage initiatives and applications in regulatory reporting or credit scoring still have to generate measurable returns and represent a tangible cost for the banking system. Overall, our findings highlight that the impact of digitalization depends not only on its intensity but also on the maturity and functional orientation of AI adoption.

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# 1 Introduction

The widespread diffusion of new technologies in the financial industry is transforming the banking sector, which must complete its digitalization process to remain competitive, improve profitability, and comply with supervisory requirements. Digital adoption and resilience to cyber-risks have become supervisory priorities in the euro area, as technological change is viewed as essential to reduce costs, enhance efficiency, and strengthen resilience against cyber-attacks (Buch, 2024). The ECB’s first cyber stress test in 2024<sup>1</sup> underscored these concerns, highlighting the systemic risks arising from digital vulnerabilities. At the same time, post-pandemic years and higher interest rates have temporarily boosted banks’ profitability, offering an opportunity to increase investment in digital technologies. Yet, compared with non-bank financial intermediaries, the banking sector has been slower to innovate, and European banks in particular still lag behind US peers in IT investments (Liu, 2021, Chen et al., 2024).

Among the emerging technologies, artificial intelligence (AI), and generative AI in particular, stands out as the most disruptive, with the capacity to reshape business models and redefine competition. In 2024, the EU adopted the AI Act (Act, 2024), the world’s first comprehensive regulatory framework for artificial intelligence, which classifies AI systems by risk and imposes strict requirements for high-risk applications in finance. This highlights the dual nature of AI, which is both a driver of efficiency and a potential source of systemic risk.

Against this background, an important question is how investments in IT and the adoption of AI technologies relate to banks’ financial performance.

The main contribution of this paper is to investigate the relationship between bank profitability, operational efficiency, and the degree of digitalization, with particular attention to the role of artificial intelligence. To this end, we develop a novel text-based measure of digital engagement derived from annual reports and complement it with GPT-based paragraph-level classification of AI-related content by use case and implementation stage. This approach provides a granular representation of banks’ digital strategies, allowing us to distinguish between broad digital engagement, AI experimentation, and effective operational deployment.

Our findings show that digital engagement is positively associated with profitability on average. AI adoption, measured through AI-related disclosures, is associated with both higher profitability and lower operating costs. However, the effects vary substantially depending on the maturity and functional orientation of AI implementation. In particular, fully operational AI deployments, especially in client profiling and internal process optimization, are associated with cost reductions, while customer-support applications are more directly linked to profitability gains. By contrast,

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<sup>1</sup><https://www.bankingsupervision.europa.eu/press/pr/date/2024/html/ssm.pr240726~06d5776a02.en.html>

initiatives that remain at the planning stage, or those focused on regulatory reporting and credit scoring, do not generate measurable economic returns yet and appear to represent investments whose benefits may materialize only over a longer horizon. Overall, our results suggest that the economic impact of digitalization depends not only on the intensity of technological investment but also on how AI is integrated into banks' business models and operational processes. These findings carry important implications for both bank strategy and financial supervision, particularly in light of the increasing role of AI in shaping operational resilience and competitive dynamics in the banking sector.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and recent evidence on AI adoption in banking. Section 3 presents the methodology and data. Section 4 discusses the empirical results, and Section 5 concludes.

## 2 Literature Review

The literature on digital transformation and artificial intelligence in banking has expanded rapidly in recent years, reflecting the growing strategic importance of technological innovation for financial institutions. A first strand of research investigates the relationship between digitalization and bank profitability, while a more recent literature focuses on the role of artificial intelligence and the use of textual analysis to measure technological adoption.

Among the first contributions, [Chhaidar et al. \(2023\)](#) construct a text-based digitalization index using annual reports of 23 European banks over the period 2010–2019. Their index is based on the frequency of digital-related terms and is used within a panel regression framework to study its relationship with banks' profitability. The authors find a positive association between financial technology investments and return on assets (ROA), particularly for larger banks and in the post-2015 period. Similarly, [Arnaudo et al. \(2022\)](#) analyze 280 Italian banks between 2007 and 2018, constructing a measure of digital financial services from the Regional Bank Lending Survey (RBLS). Their findings suggest that the supply of digital services positively affects profitability, mainly through higher fee income, although they do not find significant effects on operating costs. They also document a negative relationship between digitalization and the number of bank branches, consistent with the increasing substitution of physical banking services with digital channels.

Other studies focus on the qualitative dimension of digital transformation. [Kriebel and Debener \(2020\)](#) perform sentiment analysis on US banks' annual reports, showing that institutions exhibiting a more positive attitude toward digital transformation tend to experience better economic performance. More recently, [Ca'Zorzi et al. \(2025\)](#) develop a textual measure of firms' exposure to Generative AI (GenAI) using earnings call transcripts of S&P 500 firms. They document a sharp increase in AI-related discussions after the release of ChatGPT in late 2022 and show that firms

with higher AI exposure experience stronger stock market performance. Finally, [Fascione et al. \(2025\)](#) construct a proxy for digitalization using web-scraped data from mobile banking applications for 110 significant European banks, showing that more digital banks tend to experience stronger deposit outflows during periods of financial stress.

Building on this literature, we develop a novel text-based measure of banks' digital engagement using annual reports of more than 50 major banks over the period 2009–2023. Compared to previous studies, our analysis covers a longer time horizon, including both the Covid-19 period and the emergence of Generative AI. Furthermore, we complement the baseline digitalization index with GPT-based paragraph-level classification of AI-related disclosures. This allows us to distinguish between different AI use cases and implementation stages, moving beyond simple frequency counts toward a more granular representation of banks' digital strategies.

Our contribution to the literature is threefold. First, we provide one of the most updated longitudinal analyses of digital transformation in banking. Second, we show how large language models can be integrated into an econometric framework to extract structured information from unstructured financial disclosures. Third, we document that the economic effects of AI adoption depend critically on implementation maturity and functional deployment, with operational AI systems associated with stronger efficiency gains than planning-stage initiatives.

## **2.1 AI Adoption in Banking - Benefits and Risks**

According to the European Banking Authority ([European Banking Authority, 2024](#)), European banks have significantly increased their adoption of digital technologies over the past five years, particularly artificial intelligence (AI), cloud computing, big data analytics, and biometrics. Among these technologies, AI has become increasingly embedded in banking operations, moving progressively from experimentation toward broader implementation. The most common applications include customer support, client and transaction profiling, fraud detection, AML/CFT activities, internal process optimization, and credit risk assessment.

The literature highlights several potential benefits associated with AI adoption in banking. AI and automation improve operational efficiency by streamlining back-office processes and reducing labor-intensive tasks ([Manyika et al., 2017](#)). AI-powered systems also enhance fraud detection and risk management by processing large transaction datasets in real time and improving anomaly detection capabilities ([Han et al., 2020](#), [Force, 2021](#)). On the customer side, AI-driven personalization and chatbots can improve service quality while reducing operational costs ([Gomber et al., 2017](#)). Furthermore, AI contributes to compliance and regulatory monitoring by automating AML/CFT checks and reporting processes ([Arner et al., 2017](#)). Overall, these studies suggest that AI adoption can generate measurable efficiency gains and improve banks' competitive positioning.

At the same time, recent evidence indicates that many banks are still in relatively early stages of implementation. According to [McKinsey \(2025\)](#), most financial institutions continue to rely on pilot projects or limited AI applications that have not yet scaled across core business functions. Similarly, [Saurabh et al. \(2025\)](#) report that only a minority of financial institutions currently use AI as a substantial source of competitive advantage. These findings suggest that the economic impact of AI depends not only on adoption itself, but also on the maturity and operational integration of AI systems.

The growing importance of AI has also attracted increasing attention from regulators and supervisory authorities. In 2024, the European Union adopted the AI Act, the first comprehensive regulatory framework for artificial intelligence worldwide. The Act introduces a risk-based approach and imposes stricter requirements on high-risk applications, including those used in financial services. This highlights that AI adoption is not only a technological issue, but also a regulatory and supervisory challenge.

From a policy perspective, AI also introduces new vulnerabilities, particularly in the area of cybersecurity and operational resilience. [European Union Agency for Cybersecurity \(2024\)](#) document that banks account for a large share of reported cyber incidents in Europe, while the [Infosecurity Europe \(2025\)](#) survey shows that banking executives increasingly perceive AI as a major cybersecurity concern. These developments reinforce the dual nature of AI in banking: while AI can improve efficiency and profitability, it may also generate new operational and systemic risks.

Our classification framework is designed to capture these dimensions by distinguishing between different AI use cases and implementation stages. This allows us to move beyond aggregate AI measures and analyze how the maturity and functional orientation of AI adoption relate to bank profitability and operational efficiency.

## 3 Methodology

### 3.1 The Digital Engagement Index

To track the evolution of the digitalization process in the banking sector, we construct a text-based measure from the annual reports of major World banks, referred to as the *Digital Engagement Index* (DEI). Following [Kriebel and Debener \(2020\)](#), [Chhaidar et al. \(2023\)](#), we apply natural language processing (NLP) techniques to the reports of more than 50 World significant institutions (SIs) from 2009 to 2023 (see [Table 2](#)), measuring the frequency of terms associated with digital transformation (see [Table 1](#)).

[Table 1 about here.]

[Table 2 about here.]

Compared to previous studies, we expand the keyword set to include more diverse and advanced expressions. These include: (1) broader and risk-related terms such as *ict*, *digitalisation*, and *digital risk*; (2) advanced technologies like *ML*, *LLM*, and *deep learning*; and (3) workforce-related terms reflecting the need for skill development, such as *reskilling initiatives* and *skill development*.

Each bank-year index is computed as the relative frequency of all digital keywords to the total number of words in the report, following the formula:

$$\text{DigitalEngagement}_{i,t} = \log \left( \sum_{m=1}^M \frac{\text{tf}_{m,i,t}}{\text{nw}_{i,t}} \right) \quad (3.1)$$

where  $\text{tf}_{m,i,t}$  is the frequency of the  $m$ -th keyword in the report of bank  $i$  at time  $t$ ,  $\text{nw}_{i,t}$  is the total number of words in that report, and  $M$  is the total number of keywords (in our case,  $M = 28$ ).

The index captures a steady upward trend in digital engagement over the period, with a notable increase in 2016 and a temporary decline in 2018. Digital engagement surged again during the early years of the COVID-19 pandemic (Figure 1), driven by the urgent need to enhance digital service offerings in response to social distancing restrictions. In recent years, the index has plateaued, with only a modest increase in 2023.

[Figure 1 about here.]

Figure 1 shows the average evolution of the index across banks, while Figure 2 presents country-specific trends. Italian banks, for instance, exhibit lower levels of digital engagement compared to the average European values and peers in United States and United Kingdom, although the gap has narrowed in recent years due to a catch-up in IT investments. These trends align with other digitalization indicators previously used in the literature (Arnaudo et al., 2022, Chhaidar et al., 2023).

[Figure 2 about here.]

Additionally, Figure 3 illustrates the indexed evolution of selected digital keywords, revealing a remarkable surge in the frequency of *artificial intelligence* over the last decade. While other terms such as *digital-skill* and *robotic* also increased in relevance, the exponential growth of AI-related mentions, particularly after 2018, positions *artificial intelligence* as the most prominent theme in banks' digital discourse. This reflects growing attention to cyber-risk and AI applications in banking, culminating in the 2024 ECB cybersecurity stress test aimed at assessing banks' resilience to

technology-driven risks. This trend justifies its central role in our econometric analysis and motivates the use of GPT-based classification techniques focused specifically on AI-related paragraphs to further explore use cases and implementation maturity.

[Figure 3 about here.]

## 3.2 GPT-Based Text Classification

Our work builds on a large body of research applying textual analysis in economics and finance. Early contributions relied on dictionary-based approaches to capture sentiment, risk, and uncertainty in financial disclosures, such as Tetlock (2007) and Loughran and McDonald (2011), as well as in earnings calls and annual reports. While these methods established the value of text as data, they often suffered from limitations in context sensitivity and domain adaptation.

More recently, advances in natural language processing have enabled the application of machine learning and transformer-based models, such as BERT or GPT, to economic and financial text (see, for example, Ca’Zorzi et al. (2025) for a recent application). In this paper, we contribute to this emerging strand by using GPT-based zero-shot classification of annual reports to track banks’ digital engagement and its impact on performance.

Our approach also contributes to the growing *sentometrics* literature (Algaba et al., 2020), which integrates textual analysis with econometric methods to extract quantifiable insights from qualitative data. In line with this strand, we leverage large language models to transform unstructured annual report narratives into structured measures of digital engagement, which we then embed in a panel econometric framework to study their relationship with bank performance.

Thus, in addition to the baseline digital engagement index, and to refine the textual content used in our analysis, we first apply GPT-based classification<sup>2</sup> to determine whether a given paragraph meaningfully discusses digitalization. This is done using a structured boolean prompt - referred to as `IS_DIGITAL` - which filters out paragraphs that mention digital terms superficially or out of context. Only paragraphs labeled as *True* are retained for downstream classification and analysis.

We then implement a more granular analysis of these filtered digital paragraphs. Specifically, we apply GPT-based zero-shot classification to each paragraph mentioning digital-related keywords in the annual reports. This allows us to go beyond frequency counts and identify the nature, sentiment, and maturity level of AI-related initiatives disclosed by banks. Our approach follows recent advances in applying large language models (LLMs) to financial and economic text. For example, Ca’Zorzi et al. (2025) employ paragraph-level zero-shot classification to earnings call transcripts to extract firm-level exposure to artificial intelligence, highlighting the advantages of paragraph granularity over sentence- or document-level analysis.

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<sup>2</sup> For our analysis we use OpenAI’s GPT-4o model (Hurst et al., 2024).

We focus on two dimensions:

- **AI Use Case:** according to the findings of the survey conducted by EBA [European Banking Authority \(2024\)](#), which identifies eight main areas where AI is commonly used among banks, each digital paragraph is classified into one of several categories - such as *Customer Support*, *Internal Process Optimization*, *Fraud Detection*, *AML/CFT*, *Credit Scoring*, *Regulatory and Supervisory Reporting*, *Profiling and Clustering of Clients* and *Transaction and Regulatory Credit Risk Modelling*. This classification captures the functional area of application for AI technologies within the bank.
- **Implementation Stage:** using structured prompts, we classify the stage of each AI-related initiative as either *Announced/Planned*, or *Operational*. This provides a proxy for the maturity of technological deployment.

These classifications are then aggregated at the bank-year level and used to construct both dummy variables (indicating whether a certain category is mentioned at all) and count variables (indicating how frequently each use case or stage is referenced). Figures 4 and 5 present the yearly evolution of GPT-classified mentions across banks.

[Figure 4 about here.]

[Figure 5 about here.]

Figures 4 and 5 highlight several interesting dynamics. In terms of use cases, the majority of mentions relate to internal process optimization and customer-facing applications, while regulatory-related use cases remain relatively limited until recent years. This suggests that banks primarily frame AI as a tool for efficiency gains and service innovation rather than for compliance purposes. Looking at implementation stages, most mentions are concentrated in the categories *Announced/Planned*, with a much smaller share classified as *Fully Operational*. This pattern indicates that, despite the growing strategic emphasis on AI, the actual deployment of mature AI systems in banking remains at an early stage. Taken together, the figures illustrate both the rising salience of AI in banks' discourse and the gap between strategic ambition and implementation maturity.

To enhance transparency and reproducibility, we include in the [Appendix A](#) the full prompt structures used in the GPT classification tasks. The prompts were designed to follow a structured zero-shot format, with fixed answer templates in JSON to allow for efficient parsing and systematic integration into the empirical dataset.

### 3.3 Model and Data

The primary objective of our analysis is to investigate the relationship between the level of digitalization within banks, their adoption of artificial intelligence (AI) technologies, and the overall profitability of the banking sector. To this end, and as a measure of sectoral profitability, we consider the Return on Assets (ROA) — a widely used financial performance indicator calculated as the ratio of net income to total assets. This metric provides a clear assessment of how effectively a bank utilizes its asset base to generate earnings. In view of the fact that, particularly in the context of more recent technological innovations, the most significant of which is artificial intelligence, the primary impact of IT technology adoption may be characterized by cost savings, this study also focuses on the relationship between digitalization, AI adoption and operational efficiency. Specifically, we consider operating costs, which represent the expenditure associated with the core operational activities of banks. The empirical sample includes more than 50 significant European banks; dependent variables as well as control variables, sourced from Capital IQ and annual report covering the period from 2009 to 2023. Variables related to digital engagement index (DEI), as well as those measuring AI adoption, including detailed information on use cases and implementation stages, are obtained using the methodologies and sources described in the previous sections.

To analyze the relationship between digitalization, AI adoption, profitability, and costs, we estimate the following baseline specification:

$$Y_{i,t} = \alpha + \beta_1 D_{i,t} + \beta_2 NPL_{i,t} + \beta_3 SOLV_{i,t} + \beta_4 \log TA_{i,t} + \beta_5 LIQ_{i,t} + \beta_6 CAR_{i,t} + \gamma X_{j,t} + \mu_i + \lambda_{j,t} + \varepsilon_{i,t} \quad (3.2)$$

where  $Y_{i,t}$  denotes either ROA or operating costs for bank  $i$  at time  $t$ , while  $D_{i,t}$  alternatively represents the Digital Engagement Index or AI adoption measures,  $\mu_i$  denotes bank fixed effects, while  $\lambda_{j,t}$  captures country-year fixed effects absorbing macroeconomic shocks and country-specific time variation.

Following [Chhaidar et al. \(2023\)](#), the control variables include: the logarithm of total assets as a proxy for bank size ( $TA$ ), the liquidity asset ratio ( $LIQ$ ), the solvency ratio ( $SOLV$ ), measured as total equity over total assets, the non-performing loan ratio ( $NPL$ ), and the total capital ratio ( $CAR$ ). In the pooled OLS specification, we additionally control for macroeconomic conditions through inflation ( $INF$ ) and real GDP growth ( $GDP$ ) for country  $j$ .

To account for unobserved heterogeneity, we estimate two main specifications:

- (i) a *pooled OLS model* including macroeconomic controls;
- (ii) (ii) a *saturated fixed effects specification* including bank and country-year fixed effects.

The inclusion of country-year fixed effects absorbs macroeconomic fluctuations and country-specific shocks, making the explicit inclusion of GDP growth and inflation unnecessary in the fixed-effects specification.

A descriptive statistic of the variables used and described above, is presented in the Appendix (Table 3). To deal with the presence of outliers in our data, we perform a winsorization at 96 per cent level on all the variables except for digital engagement and AI adoption. In the model we consider the first lag of both digital engagement AI adoption indexes, due to their nature, which tend to be a proxy of future investments rather than present ones. Indeed, since the use of new technologies may require experience before the investment can unfold its benefits, the inclusion of lagged variables may be necessary (Brynjolfsson, 1993).

[Table 3 about here.]

## 4 Results

This section investigates the relationship between digital engagement, AI adoption, profitability, and operational efficiency in the banking sector. We first estimate the average relationship between digitalization, AI adoption, and bank performance. We then explore whether the effects differ across AI use cases and implementation stages, distinguishing between operational deployments and planning-stage initiatives.

### 4.1 Digital engagement and AI adoption on profitability

In this section, we estimate Equation 3.2 to investigate the relationship between digital engagement, AI adoption, profitability, and operational efficiency. In particular, we focus on the impact of the Digital Engagement Index (DEI) and AI adoption measures on banks' return on assets (ROA) and operating costs.

To determine the most appropriate econometric specification, we perform Hausman tests (Hausman, 1978) to compare the fixed effects and random effects estimators in order to evaluate whether the unique errors are correlated with the regressors; under the null hypothesis, the random effects model is consistent and efficient, while the fixed effects model is only consistent under the alternative. The test statistics reject the null hypothesis of no correlation between regressors and individual effects, supporting the use of fixed effects estimators. Accordingly, our preferred specification includes bank fixed effects and country-year fixed effects, allowing us to control for both time-invariant bank heterogeneity and country-specific macroeconomic shocks, including heterogeneous effects associated with the Covid-19 period and different national responses. Estimation is conducted using the high-dimensional fixed effects approach proposed by Correia and Zylkin

(2015), which efficiently absorbs multiple layers of fixed effects without explicitly introducing a large number of dummy variables. For comparison purposes, we first estimate a pooled Ordinary Least Squares (OLS) specification including macroeconomic controls. We then progressively extend the model by introducing bank fixed effects and country-year fixed effects. For the sake of brevity, the paper reports only the estimates from the most saturated specifications, while additional estimation results are available upon request.

Tables 4-5 report the main estimation results for profitability and operating costs. Overall, both digital engagement and AI adoption are positively associated with banks' return on assets. The evidence suggests that banks exhibiting higher levels of digital engagement and AI adoption tend to report stronger profitability, even after controlling for bank-specific characteristics and macroeconomic conditions. These findings are consistent with previous evidence linking digitalization to improved bank performance and operational efficiency (Casolaro and Gobbi, 2007). At the same time, AI adoption remains a relatively recent phenomenon in banking. Figures 3 and 4 show that discussions around AI were already emerging before the release of ChatGPT in late 2022, with a first acceleration occurring around 2015. The publication of "Attention Is All You Need" (Vaswani et al., 2017) and subsequent developments in Generative AI further intensified the strategic relevance of AI technologies in banking (Ca'Zorzi et al., 2025). In line with recent literature (Zhang and Zhang, 2025), our results suggest that AI-related technologies may improve banks' performance by reducing informational frictions and enhancing operational efficiency. When operating costs are used as the dependent variable, AI adoption exhibits a negative and statistically significant relationship with costs, indicating that AI contributes directly to operational efficiency. By contrast, the coefficient associated with the broader Digital Engagement Index is not statistically significant in the most saturated specifications. This result suggests that broad digitalization strategies may involve substantial implementation and maintenance costs that offset short-run efficiency gains, whereas AI adoption appears to generate more immediate operational benefits.

Overall, the findings indicate that digital engagement and AI adoption act as complementary drivers of bank performance, although their economic effects differ substantially. While digital engagement captures broader technological transformation, AI adoption appears more directly related to operational efficiency improvements.

Regarding the control variables, the estimated coefficients are broadly consistent with the banking literature. Higher capital adequacy and solvency ratios are positively associated with profitability, while higher non-performing loan ratios negatively affect bank performance. Bank size mainly affects operational costs, reflecting scale economies in banking operations.

[Table 4 about here.]

[Table 5 about here.]

## 4.2 AI adoption: staging and use cases

To provide a more granular interpretation of the relationship between AI adoption and bank performance, Tables 6–7 report the estimation results obtained by decomposing AI adoption into implementation stages and functional use cases. In particular, we distinguish between operational and non-operational AI initiatives by collapsing the original implementation categories into two broader groups: (i) *Operational*, which includes both fully operational systems and initiatives in testing or pilot phase, and (ii) *Planned*, which includes announced or planned projects. In addition, we distinguish between different applications of AI, including customer support, internal process optimization, fraud detection, AML/CFT, credit scoring, regulatory reporting, and client profiling. Both staging and use-case dimensions are included in the regression models in the form of dummy variables.

The results highlight that the economic impact of AI adoption depends critically on the maturity of implementation. In particular, the only coefficients that consistently attain statistical significance are those associated with operational AI deployments, both in the profitability and cost specifications. This suggests that the benefits of AI materialize primarily once technologies are effectively integrated into banks' day-to-day operations, rather than during the planning or experimentation phase. By contrast, initiatives that remain at the planning stage do not appear to generate immediate profitability gains or operational improvements. The findings also reveal substantial heterogeneity across AI use cases. In the operating cost regressions, AI adoption related to internal process optimization and client profiling is associated with significant cost reductions. These results are consistent with the idea that AI technologies improve operational efficiency by automating repetitive and labor-intensive tasks, including transaction monitoring, compliance checks, and customer segmentation activities. AI-powered profiling and clustering systems may also enhance marketing efficiency and customer retention by improving the targeting and personalization of banking services (Chaturvedi, 2025, Chatterjee and Chaudhuri, 2022).

The relationship between AI adoption and profitability appears more nuanced. The strongest positive association with ROA emerges for customer-support applications, suggesting that AI may contribute to profitability not only through cost reductions, but also through improvements in customer experience, engagement, and cross-selling opportunities. By contrast, AI applications related to regulatory reporting and credit scoring are associated with higher operating costs and weaker profitability effects. These findings suggest that such initiatives may still represent investments in progress, requiring substantial implementation costs before generating measurable economic returns. More generally, the evidence indicates that not all AI applications contribute equally to bank performance, and that the economic effects of AI depend both on the functional area of deployment and on the maturity of implementation.

Overall, these patterns are consistent with recent evidence suggesting that the benefits of AI adoption emerge primarily when technologies move beyond pilot projects and become fully embedded within core business operations.

[Table 6 about here.]

[Table 7 about here.]

## 5 Conclusion

This paper develops a novel measure of banks' digital engagement by combining a text-based index with GPT-based paragraph-level classification of annual reports. By distinguishing between broad digitalization strategies, AI use cases, and implementation stages, our framework provides a more granular representation of technological transformation in the banking sector.

Our empirical results indicate that digital engagement is positively associated with bank profitability on average, while AI adoption is linked both to profitability and operational efficiency. However, the economic effects of AI vary substantially across implementation stages and functional applications. In particular, operational AI deployments are associated with stronger efficiency gains than planning-stage initiatives, suggesting that the benefits of AI materialize primarily once technologies are fully integrated into banks' core operations. The analysis also reveals substantial heterogeneity across AI use cases. AI applications related to internal process optimization and client profiling are associated with cost reductions, while customer-support applications appear more closely linked to profitability improvements. By contrast, AI initiatives focused on regulatory reporting and credit scoring do not yet generate measurable economic returns and may instead reflect investments whose benefits are expected to materialize only over a longer horizon.

More broadly, our findings suggest that understanding the economic impact of AI requires moving beyond aggregate adoption indicators toward more detailed measures of implementation maturity and functional deployment. In this respect, our paper contributes to the growing literature using large language models and textual analysis to extract structured information from unstructured corporate disclosures.

From a policy perspective, our results resonate with the supervisory concerns recently emphasized by [European Union Agency for Cybersecurity \(2024\)](#), [Infosecurity Europe \(2025\)](#), and [Damyanova \(2025\)](#). AI is both an opportunity for efficiency and customer innovation, and a source of systemic risk, particularly in cybersecurity. Recent developments in advanced AI systems have further heightened attention on potential vulnerabilities, as increasingly sophisticated tools could be exploited to conduct large-scale and highly targeted cyber-attacks, with implications that may extend beyond individual institutions to the broader stability of the financial system.

An important extension of this research concerns the incorporation of more recent data covering the rapid expansion of Generative AI adoption during most recent years (e.g., 2024-2025), as well as the inclusion of cybersecurity- and operational resilience-related terminology within the digital engagement framework. The growing relevance of cyber risk, cloud infrastructure, digital resilience, and AI-enabled security systems suggests that future measures of technological transformation in banking should move beyond traditional digitalization indicators and increasingly account for the interaction between AI adoption, operational efficiency, and cyber resilience. This evolution appears particularly relevant in light of recent supervisory initiatives such as the ECB cyber stress test, DORA implementation, and the broader regulatory focus on digital operational resilience.

Future research could therefore extend this framework by incorporating additional sources of technological information, such as IT investment data, fintech partnerships, or cybersecurity-related disclosures, as well as by expanding the analysis to broader sets of financial institutions and countries. More broadly, our results suggest that understanding the economic impact of AI requires moving beyond aggregate adoption metrics toward more detailed measures of implementation maturity, functional deployment, and technological resilience, an issue that is becoming increasingly central in both academic and policy debates.

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## A GPT Prompt Templates

To classify digital-related paragraphs, we used structured zero-shot prompts submitted to OpenAI's gpt-4o-mini model, deployed via a private API instance. Prompts were designed to elicit short and structured JSON responses for consistent parsing.

### A.1 IS\_DIGITAL: Boolean Classification

As preliminary step all paragraphs were filtered based on the presence of digital keywords and a prior GPT-based boolean classification indicating their relevance. Based on the following prompt code.

```
### QUESTION ###:
```

```
In the text reported between triple quotes, does it talk about or mention {keyword},
```

```
a digital term used to define the bank strategy to digitalize its internal processes?
```

```
Or upgrade its customers' services offered? Or more generally for commercial/cost-saving purposes?
```

```
Reason step-by-step to make sure you provide a correct answer.
```

```
### RESPONSE INSTRUCTIONS ###:
```

```
1) Respond with a JSON object using this structure: {"bool": True or False}
```

```
2) Respond {"bool": True} if you find mentions of digital strategies, investments or
```

```
specific actions related to the keyword provided.
```

```
3) If none of these are mentioned, respond: {"bool": False}.
```

```
Text:
```

```
""" [insert paragraph text here] """
```

### A.2 AI\_USECASE: Functional Classification

```
### QUESTION ###:
```

```
Read the following paragraph and classify the described AI-related activity into one of the following use cases:
```

1. Customer support
2. Optimisation of internal processes
3. Fraud detection
4. AML/CFT
5. Profiling / clustering of clients / transactions
6. Regulatory credit risk modelling
7. Regulatory or supervisory reporting
8. CWA / Credit scoring
9. General AI strategy / investment
10. None of the above / unclear

Respond with a JSON object using this format:

```
{"gpai_usecase": "YOUR_ANSWER"}
```

Paragraph:

```
""" [insert paragraph text here] """
```

### **A.3 STAGE: Implementation Maturity**

### QUESTION ###:

Based on the following paragraph, what is the stage of implementation of the described digital initiative?

Choose from:

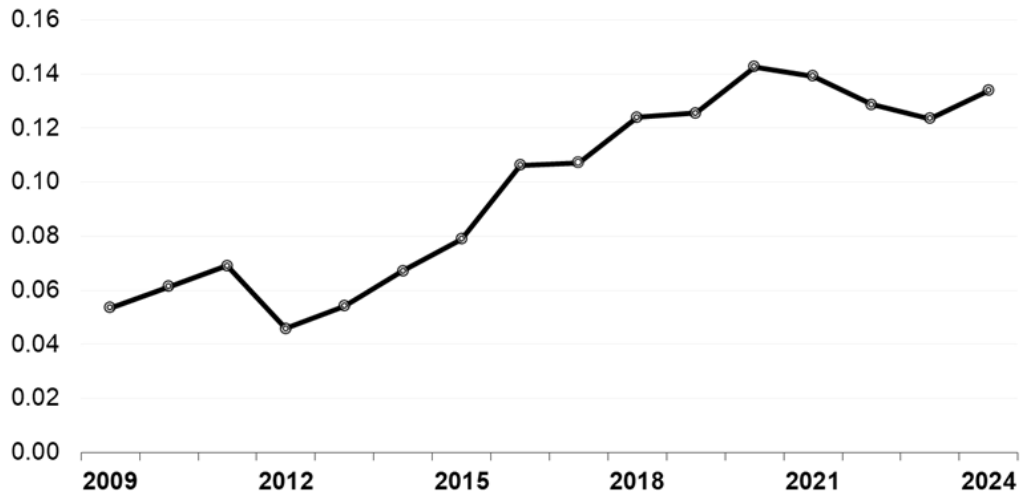
1. Announced / Planned
2. In Testing / Pilot Phase
3. Fully Operational

Respond with a JSON object using this format:

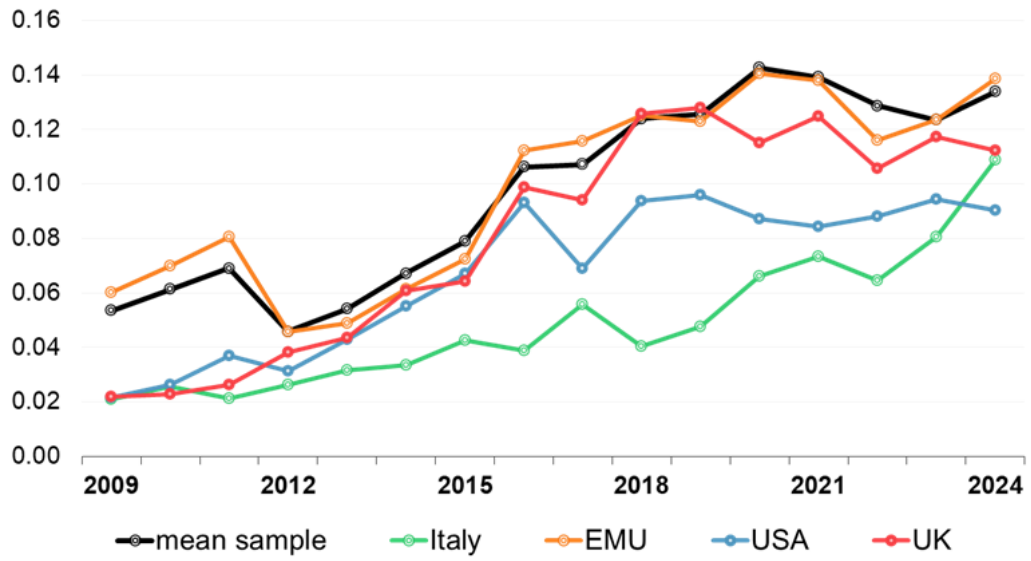
```
{"stage": "YOUR_ANSWER"}
```

Paragraph:

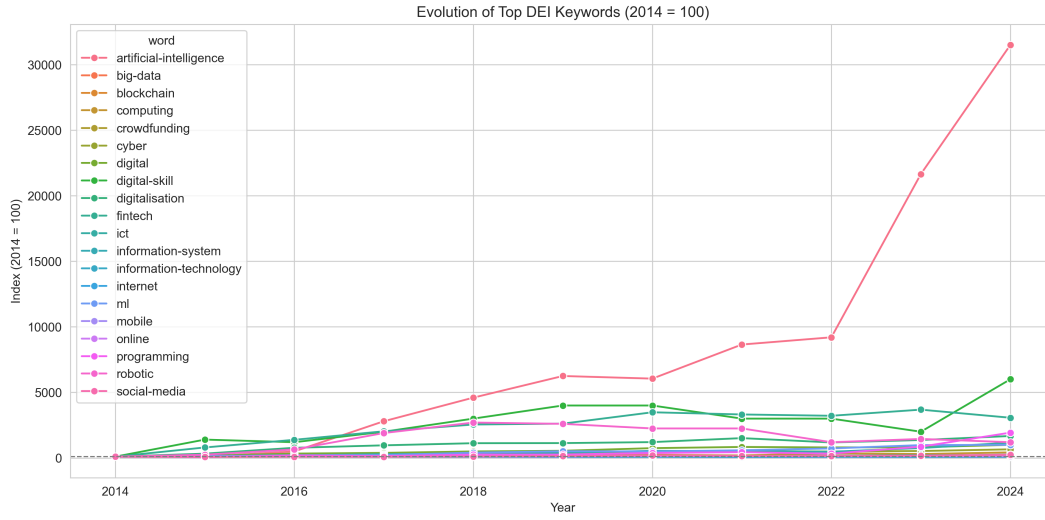
```
""" [insert paragraph text here] """
```



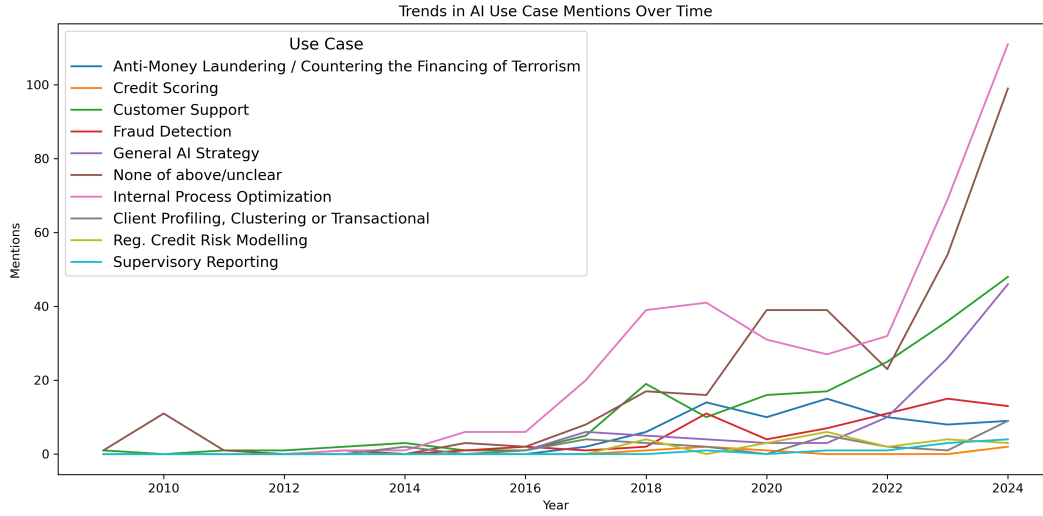
**Figure 1:** The Digital Engagement Index (Average Across Banks)



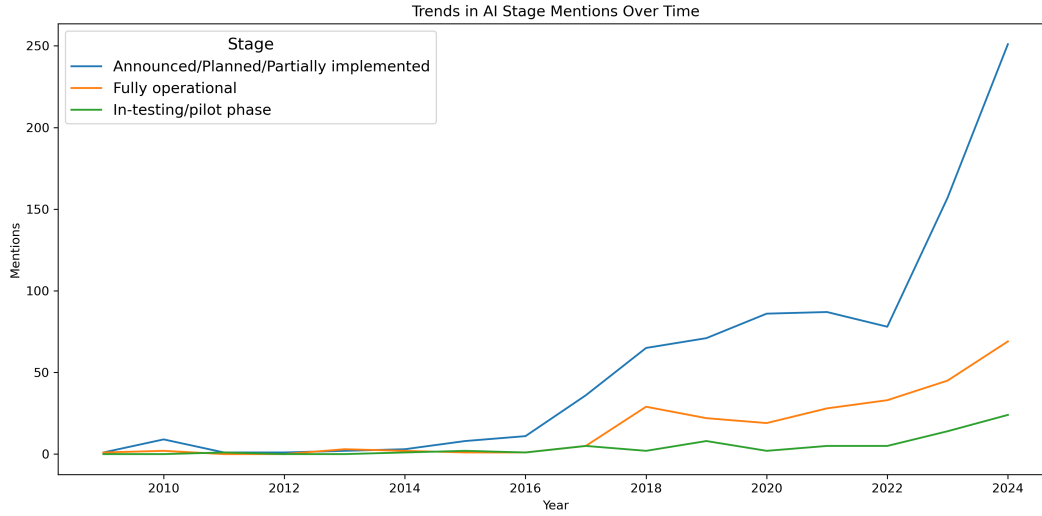
**Figure 2:** Country-Specific Digital Engagement Index



**Figure 3: Frequency of Selected Digital Keywords Over Time**



**Figure 4: Frequency of AI use case mentions over time.** The figure shows the annual frequency of paragraphs classified into distinct AI use cases using GPT-based zero-shot classification. Categories include customer-facing, regulatory, and internal functions. Based on GPT-based interpretation of each paragraph’s content.



**Figure 5: Frequency of AI implementation stage mentions over time.** Mentions are classified into three stages: *Announced/Planned*, *In Testing*, and *Fully Operational*. Based on GPT-based interpretation of each paragraph’s content.

**Table 1:** List of words used in the digital index

<b>Chhaidar et al. (2022)</b>		<b>Additions</b>
digital	social media	digital skill
mobile	artificial intelligence	digital risk
Internet	robotic	ict
cyber	online	ML
fintech	information technology	LLM
crowdfunding	information system	deep learning
blockchain	computing	machine learning
big data	programming	skill development
hack	computer science	reskilling initiatives
		digitalisation

**Table 2:** List of Banks in the Sample

<b>Bank</b>	<b>Country</b>	<b>Bank</b>	<b>Country</b>
ABN AMRO Bank N.V.	Netherlands	AIB Group plc	Ireland
Agricultural Bank China	China	Alpha Services & Holdings S.A.	Greece
BNP Paribas	France	BPER Banca SpA	Italy
Banca Monte dei Paschi di Siena	Italy	Banco BPM S.p.A.	Italy
Banco Bilbao Vizcaya Argentaria	Spain	Banco Comercial Português S.A.	Portugal
Banco Santander S.A.	Spain	Banco de Sabadell S.A.	Spain
Bank China	China	Bank of America Corporation	USA
Bank of Ireland Group Plc	Ireland	Bankinter S.A.	Spain
Barclays PLC	UK	Bayerische Landesbank	Germany
Belfius Bank SA	Belgium	Caixa Geral de Depósitos S.A.	Portugal
CaixaBank S.A.	Spain	China Construction Bank Corp.	China
Citigroup Inc.	USA	Commerzbank	Germany
Credit Suisse AG	Switzerland	Crédit Agricole Group	France
Crédit Mutuel Group	France	DZ Bk AG Deutsche Zentral-Geno	Germany
DekaBank Deutsche Girozentrale	Germany	Deutsche Bk Aktiengesellschaft	Germany
Erste Group Bank	Austria	Eurobank Ergasias Svcs & Hldgs	Greece
Groupe BPCE	France	HSBC Holdings plc	UK
ING Bank N.V.	Netherlands	Intesa Sanpaolo S.p.A.	Italy
JPMorgan Chase & Co.	USA	KBC Group	Belgium
La Banque Postale S.A.	France	Landesbank Baden-Württemberg	Germany
Landesbank Hessen-Thüringen	Germany	Lloyds Banking Group plc	UK
NORD/LB	Germany	NatWest Group plc	UK
National Bank Greece S.A.	Greece	Nordea Bank Abp	Finland
OP Financial Group	Finland	Piraeus Finl Hldgs S.A.	Greece
RBI AG	Austria	Rabobank	Netherlands
Société Générale Société anony	France	Standard Chartered PLC	UK
The Goldman Sachs Group	USA	UBS Group AG	Switzerland
UniCredit S.p.A.	Italy	Wells Fargo & Co.	USA
de Volksbank N.V.	Netherlands		

**Table 3: Summary statistics**

	Mean	Standard-dev	Min	Max
DIG	0.09	0.10	0.00	0.82
DIG (AI only)	0.00	0.00	0.00	0.07
ROA	0.29	0.95	-11.81	4.07
ROA (Winsorized)	0.33	0.61	-1.93	1.45
NPL Ratio	5.71	7.80	0.22	45.18
NPL Ratio (Winsorized)	5.64	7.46	0.52	36.80
Op. Costs / TA	1.46	0.59	0.38	4.04
Op. Costs / TA (Winsorized)	1.45	0.56	0.59	2.97
Tot. Capital Ratio	16.80	3.96	-6.10	37.77
Tot. Capital Ratio (Winsorized)	16.78	3.48	9.84	24.71
Equity/TA	6.15	2.36	-4.20	15.78
Equity/TA (Winsorized)	6.15	2.18	2.02	11.86
Liq. Asset ratio	34.95	13.99	5.53	74.19
Liq. Asset ratio (Winsorized)	34.91	13.73	12.31	67.13
(log) Total Assets	12.98	1.19	10.81	15.44
(log) Total Assets (Winsorized)	12.98	1.18	10.97	15.04
GDP	1.33	3.88	-10.94	22.34
Inflation	1.98	2.31	-6.23	11.63
Observations	912			

**Table 4:** ROA, estimation results: (1) and (3) are pooled OLS estimations; (2) and (4) are specifications with fixed effects. The estimation sample ranges from 2010 to 2023.

	(1)	(2)	(3)	(4)
	ROA	ROA	ROA	ROA
Liq. Asset ratio	-0.00132 (0.00141)	0.000568 (0.00373)	-0.00267** (0.00120)	0.000621 (0.00375)
(log) Total Assets	0.0178 (0.0180)	0.216 (0.158)	0.0212 (0.0181)	0.200 (0.158)
Equity/TA	0.123*** (0.0109)	0.156*** (0.0340)	0.124*** (0.0109)	0.156*** (0.0338)
NPL Ratio	-0.0396*** (0.00468)	-0.0356** (0.0159)	-0.0412*** (0.00471)	-0.0364** (0.0160)
Tot. Capital Ratio	-0.00587 (0.00586)	0.0240* (0.0133)	-0.00547 (0.00602)	0.0255* (0.0133)
Digital Eng.	0.665*** (0.257)	0.479* (0.275)		
infl	0.0127** (0.00619)		0.0120* (0.00632)	
gdp	0.0243*** (0.00562)		0.0254*** (0.00543)	
AI Adoption			3.715 (4.245)	9.664* (4.951)
Constant	-0.430 (0.290)	-3.746* (2.052)	-0.383 (0.295)	-3.549* (2.034)
Macro controls	Yes	No	Yes	No
FE: bank + country*year	No	Yes	No	Yes
Observations	682	668	682	668
R-squared	0.451	0.811	0.444	0.811

Standard errors in parentheses

Robust standard errors in parentheses

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 5:** Operative Costs, estimation results:(1) and (3) are pooled OLS estimations; (2) and (4) are specifications with fixed effects. The estimation sample ranges from 2010 to 2023.The estimation sample ranges from 2010 to 2023.

	(1)	(2)	(3)	(4)
	Op. Costs	Op. Costs	Op. Costs	Op. Costs
Liq. Asset ratio	0.00124 (0.00153)	-0.00673*** (0.00212)	0.00400** (0.00156)	-0.00689*** (0.00210)
(log) Total Assets	0.0459*** (0.0177)	-0.174** (0.0845)	0.0394** (0.0185)	-0.169** (0.0839)
Equity/TA	0.131*** (0.0101)	0.0428*** (0.0161)	0.128*** (0.0105)	0.0442*** (0.0159)
NPL Ratio	-0.000841 (0.00299)	-0.00194 (0.00559)	0.00243 (0.00293)	-0.00203 (0.00553)
Tot. Capital Ratio	-0.0379*** (0.00538)	-0.0112* (0.00654)	-0.0381*** (0.00550)	-0.0124* (0.00660)
Digital Eng.	-1.448*** (0.220)	-0.0321 (0.113)		
infl	0.00475 (0.00693)		0.00702 (0.00743)	
gdp	-0.0163*** (0.00420)		-0.0190*** (0.00448)	
AI Adoption			-10.47** (4.168)	-3.666* (2.203)
Constant	0.811*** (0.257)	3.896*** (1.121)	0.694*** (0.256)	3.856*** (1.110)
Macro controls	Yes	No	Yes	No
FE: bank + country*year	No	Yes	No	Yes
Observations	683	668	683	668
R-squared	0.331	0.951	0.294	0.952

Standard errors in parentheses

Robust standard errors in parentheses

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 6:** ROA, use cases (Panel A) and staging (Panel B). The estimation models have both year, bank fixed effect and interactions country-year. The estimation sample ranges from 2010 to 2023

	<i>Panel A: Use-cases</i>								<i>Panel B: Stage of development</i>	
	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA	(7) ROA	(8) ROA	(9) ROA	(10) ROA
Liq. Asset ratio	0.00121 (0.00380)	0.000684 (0.00386)	0.00000136 (0.00376)	0.0000886 (0.00374)	0.000200 (0.00378)	0.000137 (0.00375)	0.000188 (0.00376)	0.000173 (0.00373)	0.000524 (0.00382)	0.00113 (0.00377)
(log) Total Assets	0.220 (0.158)	0.206 (0.159)	0.219 (0.159)	0.212 (0.159)	0.213 (0.159)	0.213 (0.159)	0.211 (0.159)	0.209 (0.158)	0.208 (0.159)	0.216 (0.157)
Equity/TA	0.162*** (0.0340)	0.158*** (0.0339)	0.160*** (0.0342)	0.160*** (0.0341)	0.161*** (0.0342)	0.161*** (0.0341)	0.161*** (0.0341)	0.161*** (0.0340)	0.159*** (0.0340)	0.161*** (0.0339)
NPL Ratio	-0.0366** (0.0158)	-0.0372** (0.0158)	-0.0369** (0.0159)	-0.0369** (0.0159)	-0.0369** (0.0159)	-0.0369** (0.0159)	-0.0368** (0.0159)	-0.0373** (0.0160)	-0.0372** (0.0159)	-0.0372** (0.0157)
Tot. Capital Ratio	0.0236* (0.0134)	0.0220* (0.0134)	0.0221 (0.0134)	0.0217 (0.0134)	0.0219 (0.0134)	0.0218 (0.0134)	0.0218 (0.0134)	0.0225* (0.0134)	0.0223* (0.0134)	0.0244* (0.0134)
Customer Sup.	0.107*** (0.0382)									
Opt. Int. Proc.		0.0479 (0.0374)								
Fraud Detection			-0.0548 (0.0653)							
AML/CFT				-0.0386 (0.0417)						
Prof. Clients and Trans.					0.0448 (0.0570)					
Reg. Credit risk						0.0274 (0.0988)				
CWA Cred. Scoring							-0.0572 (0.0708)			
Reg. Sup. Reporting								-0.217* (0.126)		
Planned									0.0337 (0.0335)	
Operative/Testing										0.113** (0.0451)
Constant	-3.816* (2.041)	-3.560* (2.045)	-3.710* (2.059)	-3.619* (2.050)	-3.639* (2.055)	-3.635* (2.055)	-3.617* (2.057)	-3.603* (2.043)	-3.596* (2.051)	-3.775* (2.025)
FE: bank + country*year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668	668	668	668	668
R-squared	0.811	0.810	0.810	0.810	0.810	0.810	0.810	0.810	0.810	0.812

Standard errors in parentheses  
Robust standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1  
\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

**Table 7: Operative Costs,(Panel A) and staging (Panel B). The estimation models have both year, bank fixed effect and interactions country-year. The estimation sample ranges from 2010 to 2023**

	Panel A: Use-cases							Panel B: Stage of development		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs	Op. Costs
Liq. Asset ratio	-0.00675*** (0.00212)	-0.00727*** (0.00211)	-0.00676*** (0.00210)	-0.00670*** (0.00208)	-0.00683*** (0.00211)	-0.00662*** (0.00209)	-0.00684*** (0.00211)	-0.00676*** (0.00209)	-0.00691*** (0.00209)	-0.00712*** (0.00210)
(log) Total Assets	-0.174** (0.0845)	-0.167** (0.0833)	-0.169** (0.0851)	-0.174** (0.0843)	-0.174** (0.0844)	-0.174** (0.0845)	-0.171** (0.0844)	-0.171** (0.0841)	-0.171** (0.0845)	-0.175** (0.0834)
Equity/TA	0.0424*** (0.0161)	0.0447*** (0.0160)	0.0422*** (0.0160)	0.0424*** (0.0160)	0.0421*** (0.0161)	0.0429*** (0.0160)	0.0422*** (0.0160)	0.0422*** (0.0159)	0.0431*** (0.0160)	0.0423*** (0.0161)
NPL Ratio	-0.00187 (0.00557)	-0.00153 (0.00547)	-0.00183 (0.00555)	-0.00182 (0.00556)	-0.00185 (0.00556)	-0.00187 (0.00555)	-0.00194 (0.00557)	-0.00156 (0.00555)	-0.00169 (0.00553)	-0.00172 (0.00553)
Tot. Capital Ratio	-0.0112* (0.00650)	-0.0112* (0.00641)	-0.0109* (0.00649)	-0.0113* (0.00649)	-0.0111* (0.00646)	-0.0113* (0.00648)	-0.0110* (0.00647)	-0.0116* (0.00648)	-0.0113* (0.00647)	-0.0121* (0.00652)
Customer Sup.	-0.00526 (0.0237)									
Opt. Int. Proc.		-0.0472** (0.0196)								
Fraud Detection			-0.0377 (0.0404)							
AML/CFT				-0.0384 (0.0306)						
Prof. Clients and Trans.					-0.0605** (0.0270)					
Reg. Credit risk						0.0520 (0.0541)				
CWA Cred. Scoring							0.0938*** (0.0317)			
Reg. Sup. Reporting								0.179*** (0.0683)		
Planned									-0.0167 (0.0180)	
Operative/Testing										-0.0463* (0.0243)
Constant	3.897*** (1.120)	3.815*** (1.102)	3.836*** (1.126)	3.903*** (1.117)	3.895*** (1.118)	3.887*** (1.120)	3.859*** (1.118)	3.862*** (1.114)	3.869*** (1.118)	3.946*** (1.108)
FE: bank + country*year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668	668	668	668	668
R-squared	0.951	0.952	0.951	0.951	0.951	0.951	0.951	0.952	0.951	0.952

Standard errors in parentheses  
Robust standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1  
\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01