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Artificial Intelligence in Banking:

Who Wins, Who Waits, and Why It Matters

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Abstract

This paper examines the impact of artificial intelligence (AI) adoption on bank performance, stability, and risk in the Middle East and North Africa (MENA) region. We develop a disclosure-based AI-readiness index that encompasses five dimensions: vision and strategy, data and technology infrastructure, people and expertise, implementation and impact, and governance and risk management, and then match it to panel data from 68 banks from 2016 to 2023. Dynamic panel estimations reveal that AI use is associated with higher profitability, wider margins, stronger risk control, and greater balance-sheet stability, while its impact on equity performance remains limited. The impact is heterogeneous: banks that connect strategic direction with execution benefit the most, whereas institutions that invest only in infrastructure or staff capacity gain less. Profitability, scale, and risk exposure also influence how far each bank advances in AI adoption, suggesting a feedback loop between financial strength and technological depth. The results provide guidance for investors evaluating AI disclosures, for regulators designing targeted incentives, and for researchers examining how digital technologies are transforming financial intermediation.

Keywords: artificial intelligence; banking competition; financial stability; regulation; MENA region

Jel Classification: G21, G28, E44, O33, C55

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1. Introduction

Artificial intelligence (AI) technologies are progressively incorporated into core decision-making and operational mechanisms, altering the landscape of the banking sector in a structural manner. AI systems underpin a diverse array of financial operations, including but not limited to real-time fraud detection, algorithmic credit assessment, and real-time dynamic portfolio optimization. The speed of adoption increased with the advent of fintech firms, which compete with traditional banks by providing state-of-the-art digital solutions for banking operations (Choudhury et al., 2025). Consequently, banking stakeholders face increasing pressure to integrate artificial intelligence into their operations to reduce costs and enhance operational efficiency (Fuster et al., 2022). These tools are particularly powerful in high-frequency financial environments, where speed and accuracy in credit risk scoring, trading, and liquidity provision can significantly affect outcomes (Choudhury et al., 2025). Similarly, more sophisticated AI models are being used to enhance the customer life cycle by automatically detecting vulnerable customers and conducting targeted marketing (Berg et al., 2020).

Theoretically, we can argue that AI helps to reduce the information asymmetries in financial intermediation and boosts allocative efficiency, which is endorsed by agency theory and the economics of information (Molavi et al., 2025). However, the full realization of AI's potential is often obstructed by legacy IT infrastructure and misaligned internal incentives, which inhibit agile innovation (Loughran & McDonald, 2011). These frictions are compounded by compliance pressures, particularly in jurisdictions where black-box algorithms conflict with mandates for transparency and auditability (Fuster et al., 2022). Regulators also face the challenge of interpreting machine-based decisions, which pose fundamental challenges to the explainability of AI-based risk models (Bölükbaşi, 2025). The challenge is not only technical but also institutional and requires comprehensive management strategies and inter-departmental digital literacy (Danielsson et al., 2021). Organizational inertia remains a serious constraint on performance improvements, even where AI tools are available (Khang, 2025).

On the demand side, consumer expectations are changing to accommodate with AI-competitive level of personalization where banks can customize services based on behavioral and contextual data (Mer & Virdi, 2025). A new class of technologies, including recommendation engines, AI-invehicle systems, and predictive analytics, is not only transforming the customer experience but also increasing engagement, especially among digital-native customers (Fuster et al., 2022). However, these systems also pose risks of algorithmic bias and raise legal and ethical concerns regarding fairness in credit allocation and service provision (Loughran & McDonald, 2011). These issues underscore the growing importance of fairness-by-design principles and responsible AI governance in the financial services sector (Ikhsan et al., 2025). Empirical research reveals positive correlations between AI adoption and performance indicators, including return on assets (ROA) (Gulshad et al., 2024). Measurable efficiency increases and widening margins can be found by banks at higher levels of digital maturity, although it can be argued that these same capabilities will create new operational vulnerabilities (Danielsson et al., 2021). AI systems, when deployed at scale, become potential points of systemic failure, especially in the absence of robust scenario planning and internal stress testing (Fuster et al., 2022).

Another concern associated with AI integration is homogenization. As banks increasingly rely on similar third-party vendors, data pipelines, and model architectures, the diversity of decision systems narrows. Such a model monoculture weakens the benefits of portfolio diversification and heightens vulnerability to tail events (Boztepe et al., 2025) The risk is particularly acute for large and systemically important banks, where a single model's failure can magnify market disruptions during periods of stress (Daníelsson et al., 2022). To address these emerging threats, regulators are experimenting with regulatory sandboxes that test algorithmic behaviors under simulated real-time conditions (Fuster et al., 2022). At the same time, machine-learning models have expanded access to credit by improving the assessment of small- and medium-sized enterprises (Berg et al., 2020). Taken together, these developments support broader financial-stability and inclusion goals by promoting more efficient capital allocation and economic resilience (Danielsson et al., 2021). Central banks have recognized these risks and are experimenting with ways to integrate AI into systemic-risk frameworks. (Papathomas et al., 2025).

While there are numerous studies documenting various aspects of AI in business transformation, there is very limited empirical evidence quantifying the effects of AI adoption on the banking sector. Prior efforts have largely relied on proxy outcomes or aggregate industry trends, which compromise causal inference (Baffour Gyau et al., 2024). To bridge this gap, our study presents a new disclosure-based AI index derived from the textual analysis of annual reports and public communications from 68 banks in the MENA region. Unlike prior work, this index captures the depth and specificity of AI implementation at the firm level, enabling more comprehensive and time-varying measurement. This is combined with dynamic panel data estimation and a two-step system generalized method of moments (GMM) to address endogeneity alongside persistence in performance indicators (Majewska & Majewski, 2025). Our dependent variable includes ROA, Net Interest Margin (NIM), Risk (RSK), Z-scores (ZSC), and Return on Equity (ROE). The analysis reveals that AI adoption has a statistically and economically significant impact on various financial performance dimensions; however, these impacts are heterogeneous across institutions and depend on the operational context. Our findings underscore the importance of strategically aligning digital capability and business model design to maximize the potential of AI, with implications for the regulation of banks, competitive dynamics, and financial stability.

A natural question arises: why focus on the MENA region? The MENA region offers a particularly valuable context because its financial systems are largely bank-based, making banks the dominant source of credit and liquidity. Empirical evidence using non-structural measures such as the H-statistic and the Lerner index shows that banking competition in the region is generally weaker than in peer economies. This limited competition creates a distinctive environment for examining the balance between financial stability and efficiency. Moreover, the region's diverse institutional setting, ranging from state-dominated systems to rapidly liberalizing and Islamic finance-oriented markets, provides a unique opportunity to explore how varying regulatory and market structures influence competition and intermediation dynamics.

In bank-dependent systems, even modest shifts in banks' behavior or regulatory constraints can strongly affect credit supply, loan pricing, and portfolio risk. Cross-country evidence shows that the mix between bank- and market-based finance shapes both real-sector outcomes and the intermediation risk–return trade-off (Demirgüç-Kunt et al., 2013; Demirgüç-Kunt & Maksimovic, 1998). Within the MENA region, multi-country studies document monopolistic competition and comparatively weak competitive intensity, leaving banks more exposed to shocks that alter cost structures or screening technologies (Anzoategui et al., 2010; El Moussawi & Mansour, 2022; González et al., 2017). These structural characteristics are precisely where modern AI tools can reshape competition and stability.

AI and machine learning techniques expand the information set available for screening and monitoring, providing a critical advantage in cases where hard data is scarce. Their deployment in these sectors could enhance the quality of loan approval, loan pricing, and credit on a larger scale. The canonical theory and ground evidence highlight that the presence of a strong information environment decreases the strains on the credit system and creates avenues for disciplined risk-taking (Brown et al., 2009; Jappelli & Pagano, 2000). Empirical results from leading finance journals confirm that ML models using digital footprints and behavioral data outperform traditional bureau scores in predicting defaults and allocating credit (Berg et al., 2020; Fuster et al., 2022). In a bank-centric and concentrated landscape such as the MENA region, these information gains are more likely to alter equilibrium behavior by lowering screening costs, tightening margins, and intensifying rivalry effects, which have measurable implications for stability metrics.

The competitive consequences of technology adoption also depend on market structure and regulatory design, both of which differ systematically across MENA economies. Foundational work links competition intensity to banks' pricing power and risk-taking (Claessens & Laeven, 2004) while quasi-experimental studies show that greater contestability enhances asset quality and reduces failure risk through profitability and screening channels (Goetz, 2018; Petersen & Rajan, 1995). Taken together, these mechanisms and the region's documented market power make MENA an ideal laboratory for examining how AI adoption modifies effective competition and, through that channel, financial stability.

Because banking remains central to financial intermediation in the MENA region, exhibits measurable market power, and is at a stage where AI can meaningfully alter information flows and pricing, evidence from the region directly informs the regulatory balance between competition and stability in bank-dominated economies. The regional focus is thus not merely a contextual background, but an integral part of the identification strategy that links regulation, competition, AI adoption, and financial stability.

This paper makes several key contributions to the emerging literature on artificial intelligence (AI) in banking. It develops a novel disclosure-based AI Readiness Index that measures banks' strategic commitment, technological infrastructure, human capital, implementation practices, and governance frameworks related to AI. By applying textual analysis to 544 annual reports from 68

MENA banks (2016–2023), the study provides the first comprehensive, multi-dimensional, and time-varying measure of AI adoption in a predominantly bank-based financial system. Using a dynamic panel system for GMM estimations, this study empirically demonstrates that AI adoption enhances profitability, margins, risk control, and stability, although its impact on equity performance remains limited. The findings highlight heterogeneous effects, with an AI strategy that aligns with implementation gains yielding the most benefits, while those focusing only on infrastructure or staff capacity benefit less. By integrating disclosure analytics with econometric modeling, this study advances both methodological and policy debates on how AI reshapes financial intermediation, competition, and stability in emerging markets, particularly within the unique institutional and regulatory context of the MENA region.

The findings reveal that AI adoption significantly improves banks' financial performance and stability across the MENA region, though its effects are nuanced and heterogeneous. The paper finds that higher AI readiness is positively associated with return on assets (ROA), net interest margins (NIM), risk management efficiency, and Z-scores, indicating stronger profitability, balance-sheet resilience, and sounder risk control. However, AI's impact on return on equity (ROE) is weaker or even negative in some models, suggesting that the benefits of AI are more operational and long-term rather than immediately reflected in equity returns. Among the AI sub-dimensions, strategic vision and effective implementation contribute most strongly to performance gains, while investments in infrastructure, governance, and human capital yield more gradual payoffs due to high initial costs and compliance burdens. Overall, the results underscore that the depth and alignment of AI integration, rather than its mere presence, drives sustainable value creation in banking. Banks with stronger capitalization, efficiency, and favorable macroeconomic environments tend to leverage AI more effectively.

The paper is structured to provide a comprehensive examination of how the adoption of artificial intelligence (AI) affects bank performance, stability, and risk in the MENA region. It begins with an introduction that outlines the growing role of AI in banking, the theoretical foundations linking AI to financial intermediation, and the motivation for focusing on the bank-based economies of the MENA region. The literature review then synthesizes existing research on AI and banking, highlighting methodological gaps and the lack of empirical studies using disclosure-based measures. The methodology section introduces the construction of a novel AI Readiness Index, developed through textual analysis of 544 annual reports from 68 banks across five key dimensions: strategy, infrastructure, expertise, implementation, and governance. It also details the dynamic panel GMM framework used for estimation. The empirical results section presents both aggregate and disaggregated findings, demonstrating the heterogeneous effects of AI on profitability, stability, and risk under different macroeconomic conditions. Finally, the conclusion discusses the policy implications for regulators and investors, emphasizing that AI's strategic alignment, rather than its mere adoption, determines its transformative impact on financial performance and resilience in bank-centered economies.

2. Literature review and the justification for a new approach

AI has emerged as a defining feature of digital transformation in the banking sector, prompting a growing volume of academic research into its implications for financial performance, institutional competitiveness, and systemic stability. While early contributions primarily focused on the benefits of automation and labor substitution, the more recent literature emphasizes the strategic dimensions of AI and its role in enabling dynamic risk assessment, personalized client services, and data-driven resource allocation. Several studies suggest that AI adoption is associated with improved profitability indicators such as ROA and NIM, particularly when deployed in areas like credit risk modeling, fraud detection, and customer retention strategies (Lian & Li, 2025). Yet, despite these promising findings, consensus remains elusive. Differences in methodology, sample construction, and definitions of AI adoption contribute to considerable variation in reported outcomes, limiting the generalizability of results (Chelliah et al., 2025; Rawal et al., 2025).

In recognition of these inconsistencies, recent research has transformed its focus from a binary notion to a comprehensive understanding of digital infrastructure and its capabilities. The researchers believe that the impact of AI is not merely about its presence in the system, but rather about how deeply rooted AI is within institutional processes. Evidence shows that banks with a strong built-in AI infrastructure, a proper governance system, and AI-literate leadership are more likely to realize the performance gains (Manglani & Bokhare, 2021). These institutions are best equipped with the resources to integrate AI into their daily operations, aligning them with business objectives and responding to queries in real-time. In addition, institutions that focus more on pilot projects and disconnected initiatives often struggle to reap the benefits of AI. Agrawal (2024) shows that without proper organizational alignment, even the most sophisticated AI would fail to deliver meaningful results. However, measuring the actual outcome is still a major challenge, as most studies either use interviews or internal assessments. Which provides valuable insights but lacks in terms of generalizability.

The other strands of literature focus on exploring broader ecosystem shifts fueled by AI adoption. Banks are continuously embedded in a comprehensive web of systems, including fintech startups, cloud providers, and algorithm specialists and providers. On one hand, it generates numerous opportunities, but on the other hand, it also creates numerous vulnerabilities. As banks continue to utilize available AI platforms and algorithms without developing their own internal, sophisticated systems, they expose themselves and their institutions to data governance, cyber risks, and vendor lock-ins (Luu & Hung, 2021). As AI is concentrated among a few prominent suppliers, it increases the risk of system-wide disruptions from shared technologies. Several researchers have drawn attention to the model monotonousness, where the same algorithm used by different organizations leads them to perform similarly under market stress, further intensifying volatility while undermining diversity (Nama et al., 2020).

Legal issues concerning fairness, transparency, and responsibility often hinder the adoption of comprehensive AI models, particularly in domains like fraud detection, money laundering, credit assessments, and compliance checks (Bölükbaşi, 2025). An unambiguous regulatory environment, combined with the technical challenges of implementing AI, discourages its application in high-risk areas. The old regulatory rules regarding transparency and reviews are ill-suited to the new age of AI. Hence, we need a more diversified and dynamic oversight; black box experimental frameworks and algorithm audits may provide the necessary solution. However, how fast these new regulations will be developed and applied remains inconclusive. Much analysis still considers regulation as fixed rather than as the dynamic interplay between institutions and policymakers (Asante et al., 2024).

Many studies use simplistic variables for AI adoption, often binary variables, neglecting the depth and the strategies of banking in AI implementation (Konstantinova et al., 2024). Those variables demonstrate the integration of AI in the banking system, but fail to interpret the current level of adoption, how banks are utilizing these AI systems, and what actually improves as a result of AI integration. This severely restricts the potential for rigorous comparison or longitudinal study. Lacking standardized, scalable metrics also hampers the development of robust econometric models able to capture AI's true causal impact on performance (Asante et al., 2024).

A growing number of studies now employ natural language processing techniques and text mining to extract AI-related signals from public disclosures such as annual reports, quarterly conference calls, and regulatory filings (Nica & Domenteanu, 2024). These novel approaches generate continuous, time-varying indices of AI involvement, providing a more comprehensive view of how financial institutions perceive and prioritize AI over time. In addition to improving measurement validity, this strategy facilitates cross-firm comparability and presents a way to connect strategic discourse to quantifiable outcomes. Still, utilization of such indices remains scarce in the financial literature, and very few studies have leveraged them jointly with sophisticated panel data estimation methods to assess long-term impacts on financial performance. What remains absent from the literature is a unified framework that combines disclosure-based measures of AI engagement with rigorous, multi-dimensional analysis of outcomes across a broad set of institutions. Most studies continue to focus on narrow performance metrics, usually return on assets or cost proportions, without accounting for more encompassing measures such as risk sensitivity, asset quality, or financial stability. Furthermore, issues of endogeneity and serial correlation are often addressed superficially, weakening the reliability of causal claims. Despite the increasing recognition of the importance of heterogeneity across institutions in terms of size, digital maturity, regulatory exposure, and market positioning, few studies systematically control for these factors in their empirical designs.

This study addresses these critical gaps by constructing a novel AI index based on the textual content of annual reports from commercial banks, capturing the depth and evolution of AI discourse through time. This index is then paired with corresponding financial data to evaluate correlations between AI involvement and key metrics, including ROA, NIM, risk, and Z-scores. To strengthen conclusions, a dynamic panel data approach is adopted, a GMM that accounts for unobserved heterogeneity, autocorrelation, and potential reverse causality between AI usage and financial outcomes. In doing so, it aims to contribute to a more rigorous and comprehensive understanding of how AI integration influences bank performance, not merely as a technological artifact but as a dynamic, strategic, and institutionally contingent process that varies over time.

3. Methodology

The purpose of this study is to empirically assess whether the integration of AI, as reflected in banks' public disclosures, translates into measurable improvements in financial performance across 68 MENA banks observed from 2016 to 2023. To achieve this, we construct a novel, disclosure-based AI Readiness Index that captures the depth and breadth of AI integration at the firm-year level. Prior literature has largely relied on binary proxies or self-reported adoption metrics Konstantinova et al., 2024), limiting the ability to capture heterogeneity and evolution in AI strategies. By contrast, we employ a hybrid textual analysis framework that combines rule-based linguistic extraction and semantic similarity analysis to derive a continuous, multidimensional index from annual reports, aligning with recent advances in disclosure-based measurement (Chelliah et al., 2025; Nica & Domenteanu, 2024).

The dataset comprises 544 annual reports retrieved from publicly available sources, which have been systematically processed into machine-readable text. Each report was parsed by bank and fiscal year, yielding a balanced panel suitable for longitudinal analysis. To isolate AI-relevant content, the text was screened using a curated set of filter keywords drawn from prior research and industry practice (Asante et al., 2024). Relevant paragraphs were then evaluated across five theoretical dimensions: Vision & Strategy, Data & Technology Infrastructure, People & Expertise, AI Implementation & Impact, and Governance & Risk Management (see Table 1). These dimensions reflect the organizational and institutional facets of AI integration identified in the literature (Boztepe et al., 2025; Ikhsan et al., 2025; Mer & Virdi, 2025)

Table 1: Scoring Criteria

Dimension	**Definition**	**Score Range**	**Scoring Criteria**
Vision & Strategy	How clearly and prominently does the bank articulate AI as part of its strategic priorities?	0-5	0: No mention of AI 1: AI vaguely acknowledged 2: Part of digital transformation, but lacks specifics 3: AI highlighted with some objectives 4: AI integrated into strategy with budget/governance 5: AI is a top priority with detailed programs
Data & Technology Infrastructure	Assess the bank's readiness in terms of data architecture, IT	0-5	0: No mention of AI-related tech infrastructure 1: Basic tech upgrades, no AI linkage 2: Some big data tools but not AI-focused 3: Clear AI-supporting infrastructure

	systems, and platforms for AI deployment.		4: AI initiatives with vendor partnerships 5: Enterprise-wide AI infrastructure
People & Expertise	Evaluates the banks' disclosures around AI skill sets, specialized hires, training, and AI talent structures.	0-5	0: No discussion of AI-related talent 1: Vague mention of 'digital talent' 2: Some AI team mentions, a little detail 3: Formal AI unit and leadership 4: Large-scale AI workforce strategy 5: Comprehensive AI hiring/training strategy
AI Implementation & Impact	Looks at actual AI use cases in production, their scope, and quantifiable impact.	0-5	0: No AI applications mentioned 1: Small AI pilots, no outcomes 2: Some AI deployments, minimal details 3: Multiple AI projects with modest impact 4: AI used widely with a clear impact 5: AI is integral with quantifiable benefits
Governance & Risk Management	Assesses whether the bank has established AI-related governance structures, risk controls, and compliance measures.	0-5	0: No AI governance or risk discussion 1: AI within general risk policies 2: Some AI risk acknowledgment 3: AI governance framework mentioned 4: Dedicated AI committees/processes 5: Board-level AI governance strategy

For each dimension, we developed a lexicon of tiered key phrases representing increasing depth of AI engagement, ranging from basic mentions to institutionalized practices (see Table 2). Each report was scored using two complementary algorithms. The first, a rule-based scoring system, assigned a score of one to five based on the highest-level key phrase detected in the text. The second employed a transformer-based semantic model (all-MiniLM-L6-v2 from sentence-transformers) to identify semantically equivalent statements with cosine similarity thresholds calibrated at 0.70, consistent with prior applications of embedding models in financial text analysis (Nica & Domenteanu, 2024). The final score for each dimension was determined by taking the maximum of the rule-based and semantic scores, thereby combining explicit and implicit disclosure signals. The five-dimensional scores were summed to yield a composite index ranging from 0 to 25, which was subsequently normalized to a 0–100 scale to facilitate interpretation.

Table 2: Details of sub-dimensions

Dimension	Score	Associated Keywords
Vision & Strategy	1	AI is an area of interest, vaguely interested in AI, mentions of AI, and briefly discusses AI
	2	Digital transformation, part of our digital agenda, sees AI as part, AI exploration, limited AI involvement, brief mention of AI, AI referenced in passing
	3	Key strategic pillar, pilot program, improving customer experience, AI integration in customer service, exploratory AI projects, initial AI projects, digital initiative, AI mentioned as part of broader digital transformation
	4	Invest in AI, plan to invest, reports quarterly, AI-driven transformation, significant AI investment, accelerated digital transformation, AI roadmap, targeted AI strategy, clear strategic focus on AI
	5	Board AI Committee, 5-year plan, explicit ROI, dedicated AI unit, cornerstone of our strategy, AI as a strategic priority, comprehensive AI vision, major AI investment, strategic AI initiative, detailed AI roadmap with timelines
Data & Technology Infrastructure	1	Upgraded our core banking system, minimal tech investment, basic IT system updates, traditional technology
	2	Data warehouse, basic analytics, big data tools, traditional IT systems, legacy systems, significant investments in information technology systems
	3	Cloud-based data lake, machine learning use cases, real-time data processing, integrated analytics, data modernization initiatives, improved IT systems
	4	Enterprise AI platform, partnered with robust data pipelines, advanced cloud computing, scalable data solutions, modern IT infrastructure, significant tech investment, comprehensive digital architecture
	5	Unified AI platform, automated data governance, GPU-based computing clusters, enterprise-wide AI infrastructure, state-of-the-art analytics infrastructure, cutting-edge data architecture, fully integrated data lake, advanced real-time analytics
People & Expertise	1	Expanding our IT workforce, digital talent, generic tech hiring, minimal mention of AI expertise
	2	Small data science team, exploring AI, limited AI hires, occasional training in AI, sporadic AI training
	3	Advanced Analytics Center of Excellence, Head of AI, dedicated AI unit, specialized data team, selected AI hires, formed a data science team
	4	AI talent pipeline, upskilling programs, structured training, university partnerships, focused recruitment in AI, targeted training programs, advanced training in AI
	5	Chief AI Officer, multiple data science teams, mandatory AI training, formal AI training curriculum, board-level oversight, comprehensive AI talent strategy, extensive AI expertise, dedicated AI center, strategic hiring for AI, established AI research group
	1	Small chatbot experiment, testing AI in a pilot, pilot experiment, trial AI, experimental AI

AI Implementation & Impact	2	Pilot-to-production, credit scoring model, limited deployment, initial AI pilot, proof of concept, trial AI deployment, basic AI test
	3	Multiple AI projects, AI-driven fraud detection, AI-based chatbot, machine learning model deployed, pilot program transitioned to production, AI pilot results, initial implementation of AI, tested AI solution, partial deployment, proof of concept in AI
	4	Enterprise-wide AI usage, clear outcome metrics, cost savings, revenue growth, risk reduction, significant AI deployment, successful AI implementation, robust AI solution, AI-driven process improvement, enhanced efficiency, substantial AI impact
	5	Integrated into our operations, operational cost reduction, cross-sell revenue, real-time trading, quantifiable impact, fully deployed AI solution, production-ready AI, full-scale AI deployment, significant cost savings, measurable ROI from AI, optimized operations, enterprise-wide AI impact
Governance & Risk Management	1	General risk controls, follow applicable regulations, minimal oversight, limited mention of AI governance
	2	Monitor AI for bias, risk framework, basic AI risk controls, initial risk management, minimal risk procedures
	3	Model Risk Committee, guidelines for fairness, transparency, regular oversight of AI, basic governance measures, periodic risk assessments
	4	AI Ethics Board, dedicated AI committee, tracking model performance for bias, formal AI governance framework, structured risk management, developed AI risk guidelines, established AI compliance
	5	Board AI Oversight Committee, continuous monitoring, bias auditing, board-level AI governance, explainability, comprehensive AI risk management, advanced governance framework, strict AI compliance policies, robust AI ethics program

This approach provides a comprehensive and continuous measure of AI readiness that improves upon binary or qualitative proxies commonly employed in empirical banking research. By capturing both linguistic specificity and semantic proximity, the index aligns with emerging best practices in natural language processing for finance (Chelliah et al., 2025; Choudhury et al., 2025) and responds to calls for more nuanced, disclosure-based measures of technological integration (Baffour Gyau et al., 2024). The index was merged with annual financial data to explore its association with key performance indicators, including return on assets, return on equity, net interest margin, Z-score, and risk exposure.

Following Blundell and Bond (1998), we estimate the model using the GMM, a widely accepted estimator for dynamic panels with potential endogeneity and autocorrelation. Estimation was implemented in a two-step robust specification with robust standard errors to improve finite-sample inference (Roodman, 2009).

We measure profitability using return on assets defined as net income divided by average total assets and return on equity defined as net income divided by average total equity (Demirgüç-Kunt and Huizinga 1999). Earnings capacity is captured by net interest margin defined as net interest income divided by average interest earning assets (Saunders and Schumacher 2000; Demirgüç-

Kunt and Huizinga 1999). Risk is proxied by earnings volatility computed as the three year rolling standard deviation of return on assets (Lepetit, Nys, Rous, and Tarazi 2008). Insolvency risk is summarized by the bank z score calculated as the sum of return on assets and the equity to assets ratio divided by the standard deviation of return on assets (Laeven and Levine 2009). Capital adequacy ratio is defined as total regulatory capital to risk weighted assets (Laeven and Levine 2009). Asset quality is measured as nonperforming loans to total gross loans and managerial efficiency is measured by the cost to income ratio defined as operating expenses divided by the sum of net interest revenue and other operating income both standard indicators in cross country bank studies (Beck, Demirgüç-Kunt, and Merrouche 2013). Funding resilience is captured by a liquidity ratio defined as liquid assets to deposits and short term funding (Beck, Demirgüç-Kunt, and Merrouche 2013) (see Table 3).

Table 3: Variable Category

Variable Category	**Variables**	**Abbreviations**
Dependent Variable	Return on Asset	ROA
	Return on Equity	ROE
	ZScore	ZSC
	Earnings	NIM
	Risk	RSK
Independent Variable	AI Readiness Index	AI
	VS	AI Vision & Strategy
	DTI	AI Data & Technology Infrastructure
	PE	AI People & Expertise
	AIII	AI Implementation & Impact
	GRM	AI Governance & Risk Management
	Capital Adequacy Ratio	CAP
	Asset Quality Ratio	ASQ
	Efficiency Ratio	MEF
	Liquidity Ratio	LIQ
	Total Asset	SIZ
	Inflation	INF
	Economic Growth	ECG
	Financial Freedom	FINF

The distribution of ROA, ROE, ZSC, NIM, RSK, and AI (Table 4) indicates significant variation in profitability, stability, and technological adoption across banks. The dispersion in ZSC and LIQ reflects wide differences in solvency and liquidity positions, while variability in AI suggests uneven progress in digital transformation across the sample. Heterogeneity in RSK and NIM points to differing approaches to risk exposure and income structure. These patterns, along with variation in CAP, ASQ, MEF, INF, ECG, and FINF, underline the institutional and macroeconomic diversity of the sample. Taken together, the descriptive statistics confirm the presence of non-trivial cross-sectional variation and justify the use of dynamic panel estimation to address unobserved heterogeneity and endogeneity

Table 4: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	544	1.684	1.90	-9.87	14.97
ROE	544	12.57	10.48	-75.74	56.77
ZSC	544	102.15	133.40	-0.22	874.68
NIM	544	3.34	1.64	-2.49	14.96
RSK	544	0.54	1.32	0	11.63
AI	544	25.86	14.83	0	76
CAP	544	13.6	8.41	4	78.89
ASQ	544	4.45	3.82	0	28.31
MEF	544	44.69	18.48	0	159.95
LIQ	544	32.71	88.48	0	867.38
SIZ	544	10.08	0.62	7.90	11.02
INF	544	5.41	13.07	-17.46	67.47
ECG	544	0.30	3.28	-17.14	6.98
FINF	544	58.21	10.98	0	80

Note: The table presents summary statistics for all variables used in the regression analysis across the full sample.

Table 5 shows low to moderate correlations among AI, CAP, ASQ, MEF, LIQ, SIZ, INF, ECG, and FINF, with no indication of multicollinearity concerns. AI is weakly correlated with all other variables, suggesting its variation is largely independent from CAP, ASQ, MEF, LIQ, SIZ, INF, ECG, and FINF, consistent with heterogeneous adoption patterns across banks. The positive correlation between CAP and LIQ reflects a link between capitalization and liquidity. In contrast, the negative correlations between SIZ and CAP, ASQ, and MEF indicate size-related differences in capital structure, asset quality, and efficiency. Correlations between INF, ECG, FINF, and other variables remain small, indicating that macro factors operate independently from most bank-level controls.

Table 5: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) AI	1.000								
(2) CAP	-0.021	1.000							
(3) ASQ	-0.104	-0.158	1.000						
(4) MEF	-0.193	-0.105	0.273	1.000					
(5) LIQ	-0.082	0.544	-0.082	0.044	1.000				
(6) SIZ	0.228	-0.390	-0.116	-0.366	-0.214	1.000			
(7) INF	0.036	0.200	0.022	-0.051	-0.008	-0.207	1.000		
(8) ECG	0.078	-0.110	0.042	-0.040	-0.038	0.096	0.026	1.000	
(9) FINF	-0.067	-0.135	0.180	0.163	0.023	-0.016	-0.348	0.091	1.000

Note: The table gives the correlations among key variables to assess multicollinearity and preliminary relationships.

Table 6 presents system GMM estimates for the dependent variables of ROA, ROE, NIM, ZSC, and RSK. AI shows positive associations with ROA, NIM, ZSC, and RSK, and a negative association with ROE. This suggests that AI improves profitability on assets, margins, stability, and risk control, while reducing returns to equity holders, which aligns with evidence that AI enhances operational outcomes rather than immediate equity returns (Demirguc-Kunt & Huizinga, 1998). CAP is positively related to ROA, NIM, ZSC, and RSK, showing that stronger capital positions support profitability and stability, as seen in studies of emerging and developed markets (Demirguc-Kunt & Huizinga, 1998). ASQ is negatively associated with ROA, ROE, and RSK, but positively with ZSC, reflecting that lower asset quality increases risk and reduces profitability, while affecting reported solvency (Bouwman, 2013).

MEF is negatively related to ROA and ROE, indicating that higher costs reduce profitability, while its positive association with ZSC suggests cost control affects perceptions of stability (Delis, 2008). LIQ is negatively associated with all dependent variables, supporting findings that excess liquidity may lower returns and stability in banking (Zu et al., 2019). SIZ shows negative effects on ROA, ROE, and RSK, reflecting possible diseconomies of scale or regulatory costs associated with size (Litimi et al., 2023). INF is positively associated with ROA and ZSC, while ECG has positive links with ROA, ROE, and ZSC, suggesting that macroeconomic growth supports bank performance (Demirguc-Kunt & Huizinga, 1998). FINF is positively related to ROA and ZSC, but negatively to ROE and NIM, pointing to complex effects of financial freedom on banking outcomes (Agnese et al., 2024). The lagged dependent variables are significant, confirming persistence in profitability, margins, stability, and risk. Diagnostic tests show no second-order autocorrelation and valid instruments, supporting the robustness of the estimates.

Table 6: Main regression with macroeconomic variables

	ROA	ROE	NIM	ZSC	RSK
L.ROA	-0.201**				
	(0.005)				
AI	0.013**	-0.074**	0.019*	0.577**	0.012**
	(0.003)	(0.034)	(0.010)	(0.168)	(0.001)
CAP	0.288**	-0.111	0.085**	0.271	0.043**

	(0.004)	(0.099)	(0.031)	(0.353)	(0.001)
ASQ	-0.057**	-0.930**	0.011	5.385**	-0.006*
	(0.015)	(0.189)	(0.053)	(0.801)	(0.003)
MEF	-0.089**	-0.347**	-0.009	1.167**	0.002**
	(0.002)	(0.045)	(0.011)	(0.300)	(0.001)
LIQ	-0.001**	-0.001**	-0.000	-0.008**	-0.00**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
SIZ	-0.954**	-4.951*	-0.477	18.818	-0.73**
	(0.138)	(2.677)	(0.376)	(11.939)	(0.044)
INF	0.017**	-0.085**	-0.003	0.229**	0.002**
	(0.001)	(0.012)	(0.006)	(0.069)	(0.000)
ECG	0.031**	0.670**	0.036	2.814**	-0.03**
	(0.004)	(0.073)	(0.029)	(0.282)	(0.002)
FINF	0.013*	-0.299**	-0.032*	1.673**	-0.03**
	(0.008)	(0.112)	(0.017)	(0.539)	(0.002)
L.ROE		0.093*			
		(0.056)			
L.NIM			0.428**		
			(0.071)		
L.ZSC				0.174**	
				(0.017)	
L.RSK					0.529**
					(0.005)
Constant	10.943**	103.242**	7.455*	-307.69**	8.953**
	(1.346)	(23.760)	(4.369)	(113.375)	(0.395)
AR(1)	0.051	0.084	0.089	0.003	0.048
AR(2)	0.243	0.573	0.419	0.424	0.404
Hansen test	0.129	0.235	0.132	0.196	0.300
Sargan test	0.000	0.001	0.000	0.001	0.000
Number of	60	31	21	61	61

instruments					
Number of groups	68	68	68	68	68

Note: The table presents the baseline regression results, assessing the impact of the overall AI index on financial outcomes. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$.

Table 7 presents the system GMM estimates excluding macroeconomic controls, providing a robustness check for the main model in Table 6. The positive associations of AI with ROA, NIM, ZSC, and RSK remain significant and similar in magnitude, reinforcing the finding that AI contributes to profitability, margins, stability, and risk control independently of macro conditions (Berg et al., 2020). AI's association with ROE, previously negative and significant, becomes positive but insignificant, suggesting that AI's impact on equity returns is sensitive to the inclusion of macro controls. CAP, ASQ, MEF, LIQ, and SIZ maintain similar patterns across both tables, indicating stable effects of capital, asset quality, efficiency, liquidity, and size, irrespective of macro factors (Bouwman, 2013).

Notably, the magnitude of SIZ's effect on ZSC increases substantially, suggesting that controlling for macroeconomic variables partly attenuates the relationship between size and stability. The significance and direction of lagged dependent variables remain consistent, confirming the persistence of performance across specifications. Model diagnostics remain satisfactory, with no evidence of second-order autocorrelation and valid instruments.

Table 7: Main regression without macroeconomic variable

	ROA	ROE	NIM	ZSC	RSK
L.ROA	-0.269**				
	(0.008)				
AI	0.025**	0.043	0.041**	0.394*	0.027**
	(0.004)	(0.027)	(0.011)	(0.234)	(0.003)
CAP	0.289**	0.108**	-0.071	2.517**	0.015**
	(0.009)	(0.038)	(0.053)	(0.289)	(0.003)
ASQ	-0.102**	-0.543**	0.045	-4.624**	0.044**
	(0.031)	(0.146)	(0.035)	(0.655)	(0.022)
MEF	-0.103**	-0.605**	-0.056**	2.310**	-0.002
	(0.007)	(0.026)	(0.019)	(0.209)	(0.002)

LIQ	-0.001**	-0.001**	0.001**	-0.005**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
SIZ	-1.421**	-1.948	-2.853**	50.942**	-2.696**
	(0.304)	(1.398)	(0.819)	(9.303)	(0.176)
L.ROE		-0.048**			
		(0.020)			
L.NIM			0.816**		
			(0.118)		
L.ZSC				0.260**	
				(0.013)	
L.RSK					0.292**
					(0.015)
Constant	17.231**	59.486**	31.649**	-573.71**	26.700**
	(3.369)	(14.342)	(9.134)	(101.402)	(1.717)
AR(1)	0.035	0.083	0.014	0.001	0.019
AR(2)	0.253	0.040	0.203	0.411	0.802
Hansen test	0.259	0.121	0.068	0.110	0.245
Number of instruments	42	42	15	56	42
Number of groups	68	68	68	68	68

Note: The table presents the regression results without macroeconomic variables, assessing the impact of the overall AI index on financial outcomes. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$.

Table 8 estimates the effects of AI sub-indices and control variables on ROA, ROE, NIM, ZSC, and RSK using system GMM, controlling for macroeconomic conditions. Among the AI-related dimensions, VS and AIII show consistent positive associations with ROA, NIM, and RSK. This suggests that banks with clear AI strategic direction and effective implementation tend to perform better and manage risk more effectively, in line with research showing that institutional clarity and integration are central to extracting value from AI investments (Bouwman, 2013). DTI and PE show negative relationships with ROA and ROE, but improve NIM and RSK. These patterns suggest that while technological infrastructure and skilled personnel are essential for AI adoption, they may involve upfront costs that depress near-term profitability and equity returns (Demirguc-Kunt & Huizinga, 1998). GRM negatively affects ROA and ZSC, indicating that enhanced AI-related governance may introduce compliance burdens that reduce short-term returns and perceived stability (Bouwman, 2013).

The control variables show largely consistent results. CAP is positively linked to ROA, NIM, ZSC, and RSK, underscoring the importance of capital buffers for bank performance and solvency (Demirguc-Kunt & Huizinga, 1998). ASQ weakens ROA and ROE but improves NIM, reflecting a trade-off between credit quality and earnings. MEF reduces ROA and ROE but improves ZSC, consistent with the idea that cost inefficiency hurts profitability but may be perceived as less risky (Delis, 2008). LIQ negatively affects most outcomes, suggesting that holding excess liquidity may lower both earnings and stability (Zu et al., 2019). SIZ is associated with lower ROA, ROE, and RSK, but higher NIM and ZSC, indicating mixed scale effects.

Macroeconomic factors indicate that ECG enhances ROA, ROE, NIM, and ZSC, confirming the positive impact of favorable growth conditions on bank performance. FINF has negative effects on ROE, NIM, and RSK, suggesting that greater financial liberalization may increase competitive pressures and risk-taking (Agnese et al., 2024). INF effects are limited and inconsistent across outcomes.

Table 8: Sub-index regression with macroeconomic variables

	ROA	ROE	NIM	ZSC	RSK
L.ROA	-0.140**				
	(0.018)				
VS	0.160**	-0.217	0.092**	-1.547	0.133**
	(0.048)	(0.384)	(0.044)	(9.424)	(0.014)
DTI	-0.465**	-1.516**	-0.410**	1.523	0.191**
	(0.069)	(0.544)	(0.063)	(20.913)	(0.021)
PE	0.079	-1.830*	0.313**	3.459	0.245**
	(0.195)	(1.031)	(0.106)	(21.369)	(0.104)
AIII	0.219**	0.115	0.135**	2.730	0.063**
	(0.056)	(0.412)	(0.043)	(14.611)	(0.019)
GRM	-0.188*	-0.072	0.097	-13.706	-0.166**

	(0.112)	(0.508)	(0.060)	(16.761)	(0.039)
CAP	0.244**	-0.076	0.145**	2.673	0.041**
	(0.011)	(0.071)	(0.005)	(1.967)	(0.005)
ASQ	-0.139**	-0.845**	0.107**	-5.659	0.017
	(0.024)	(0.212)	(0.020)	(4.089)	(0.011)
MEF	-0.062**	-0.369**	0.021**	2.559**	-0.006**
	(0.011)	(0.048)	(0.003)	(0.940)	(0.002)
LIQ	-0.001**	-0.001**	-0.001**	-0.006	-0.000**
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)
SIZ	-0.677**	-5.876**	0.330**	41.935	-0.854**
	(0.331)	(1.892)	(0.122)	(29.042)	(0.093)
INF	-0.000	-0.093**	0.009**	0.763	0.000
	(0.001)	(0.014)	(0.002)	(0.587)	(0.001)
ECG	0.062**	0.744**	0.033**	12.437**	-0.033**
	(0.012)	(0.083)	(0.009)	(3.656)	(0.005)
FINF	-0.029	-0.352**	-0.016*	0.853	-0.029**
	(0.019)	(0.105)	(0.009)	(2.402)	(0.005)
L.ROE		0.088			
		(0.067)			
L.NIM			0.293**		
			(0.020)		
L.ZSC				0.277**	
				(0.109)	
L.RSK					0.514**
					(0.015)
Constant	11.136**	115.417**	-3.734**	-497.993*	10.376**
	(2.699)	(16.978)	(1.186)	(287.878)	(0.883)
AR(1)	0.041	0.060	0.083	0.001	0.013
AR(2)	0.408	0.374	0.763	0.271	0.780
Hansen test	0.810	0.557	0.480	0.819	0.646
Sargan test	0.000	0.026	0.000	0.634	0.000

Number of instruments	57	43	57	29	57
Number of groups	68	68	68	68	68

Note: The table presents the regression results, dividing the AI index into sub-components to assess the impact of the overall AI index on financial outcomes. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$.

Table 9 presents system GMM estimates analyzing the determinants of the AI sub-indices (VS, DTI, PE, AIII, GRM), using financial performance (ROA, ROE, NIM), stability (ZSC), and risk (RSK) as explanatory variables. The ROA has a positive association with AIII and GRM, implying that banks with strong performance in profitability are more likely to invest in the AI implementation and governance framework, reflecting their capacity to commit resources towards AI adoption (Papathomas et al., 2025). However, ROE has a negative association with DTI, AIII, and GRM, indicating that banks focusing on equity returns prioritize short-term profits over the long term. Furthermore, it highlights the pressure from shareholders that can limit AI adoption (Berg et al., 2020).

ZSC negatively affects VS and DTI but positively affects PE, implying that more stable banks may delay digital transformation efforts while channeling resources toward human capital development. This pattern aligns with studies highlighting that organizational stability may reduce urgency for technological disruption, but encourages training and capacity-building (Danielsson et al., 2021). RSK increases DTI but lowers AIII and GRM, suggesting that riskier banks prioritize technological infrastructure but may hesitate to proceed with full AI implementation or formal governance structures, likely reflecting cautious adoption strategies under risk exposure (Ali et al., 2025). NIM positively influences VS, DTI, and PE but negatively influences AIII and GRM, indicating that banks with stronger earnings channels emphasize strategic vision, infrastructure, and expertise investment while delaying implementation and governance, a pattern consistent with gradualist adoption models (Öztürk & Kula, 2021).

Table 9: Sub-index as dependent variables

	VS	DTI	PE	AIII	GRM
L.VS	0.683^{**}				
	(0.038)				
ROA	-0.030	-0.008	-0.028^{**}	0.348^{**}	0.070^{**}
	(0.025)	(0.029)	(0.010)	(0.021)	(0.029)
ROE	0.000	-0.030^{**}	0.000	-0.039^{**}	-0.021^{**}
	(0.005)	(0.015)	(0.002)	(0.005)	(0.005)
ZSC	-0.002^{**}	-0.003^{*}	0.000^{**}	-0.001	-0.000
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)
RSK	0.029	0.080^{**}	0.012	-0.303^{**}	-0.075^{**}
	(0.033)	(0.038)	(0.010)	(0.056)	(0.030)
NIM	0.031^{*}	0.065^{*}	0.025^{**}	-0.223^{**}	-0.022^{*}
L.DTI		0.334^{**}			
		(0.103)			
L.PE			-0.335^{**}		
			(0.011)		
L.AIII				0.404^{**}	
				(0.081)	
L.GRM					0.426^{**}
					(0.039)
	(0.018)	(0.036)	(0.007)	(0.037)	(0.012)
Constant	0.836^{**}	0.786^{**}	0.006	1.197^{**}	2.211^{**}
	(0.101)	(0.291)	(0.030)	(0.113)	(0.162)
AR(1)	0.000	0.000	0.030	0.000	0.000
AR(2)	0.770	0.589	0.473	0.118	0.126
Hansen test	0.308	0.465	0.877	0.223	0.502
Sargan test	0.545	0.733	0.001	0.029	0.752
Number of instruments	42	25	36	36	42

Number of groups	68	68	68	68	68

Note: The table presents the regression results with AI sub-components as Dependent Variables, assessing the impact of the overall AI index on financial outcomes. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$.

4. Conclusion

This study provides a comprehensive empirical assessment of how artificial intelligence (AI) adoption affects bank performance, stability, and risk in the MENA region, a financial environment that remains largely bank-centered and thus highly sensitive to technological transformation. By constructing a novel disclosure-based AI Readiness Index that spans vision and strategy, data infrastructure, human expertise, implementation, and governance, the paper offers an innovative and methodologically rigorous approach to capturing the depth and quality of AI integration through textual analysis of 544 annual reports from 68 banks between 2016 and 2023. This approach represents a methodological advancement over prior research, which relied mainly on binary or survey-based proxies of AI use, thereby enabling a dynamic, multidimensional, and time-varying measurement of technological maturity at the institutional level.

The empirical findings demonstrate that AI adoption significantly enhances bank profitability (ROA), net interest margins (NIM), risk management, and balance-sheet stability (Z-scores), confirming that AI contributes to both operational efficiency and financial resilience. However, the impact on return on equity (ROE) is limited, suggesting that the immediate financial gains of AI are often absorbed by long-term investments in technology, governance, and compliance. Among the AI sub-dimensions, strategic vision and implementation capacity emerge as the most influential drivers of performance, whereas investments in infrastructure, governance, and personnel, though essential, deliver benefits more gradually due to their upfront costs. The results thus reveal a non-linear and heterogeneous relationship between AI readiness and financial outcomes, highlighting that performance improvements depend not on the mere presence of AI but on its strategic alignment with institutional goals and internal systems.

The implications of these findings are threefold. For policymakers, the study provides evidence that AI can strengthen the stability and efficiency of bank-based economies if supported by targeted and adaptive regulatory frameworks. Rather than enforcing uniform AI mandates, regulators should recognize the varying levels of readiness across institutions and incentivize responsible AI adoption through tiered supervision, sandboxes, and capacity-building initiatives. For investors, the results suggest that AI engagement should be read as a signal of long-term resilience, operational discipline, and superior risk management, rather than as a short-term profitability driver. For banks, the paper offers actionable insights: aligning AI strategy with business execution, investing in organizational learning, and embedding governance mechanisms are essential to transform AI investment into measurable financial and stability gains.

Overall, this paper makes both empirical and methodological contributions by introducing a disclosure-based, multidimensional AI index that bridges textual analytics and econometric modeling, and by providing robust evidence from a region where banking systems are undergoing an accelerated digital transition. Looking forward, future research could expand this framework cross-regionally to compare AI's impact in bank versus market-based systems, integrate alternative data such as AI-driven lending or payment transaction records, and examine how AI readiness interacts with ESG objectives and macroprudential stability. By combining methodological innovation with policy relevance, this study contributes to a deeper understanding of how AI is reshaping the economic architecture of financial intermediation in emerging markets.

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