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Drivers and Barriers to Artificial Intelligence Adoption in the Banking Sector: Evidence from Cambodia

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ABSTRACT

Driven by the Fourth and Fifth Industrial Revolutions, global financial institutions are aggressively deploying artificial intelligence (AI) technologies to optimize operations, risk management, and customer engagement. However, empirical investigation into AI adoption dynamics within emerging economies remains critically sparse, as established technology acceptance frameworks predominantly reflect advanced or industrialized environments. This study investigates the primary determinants—encompassing both technological, organizational, and environmental drivers and barriers—influencing AI adoption across the banking sector in Cambodia, evaluating 25 hypotheses to establish an integrated conceptual model tailored to emerging financial settings. A mixed-methods design with concurrent triangulation was executed. Quantitative data were gathered via a survey of 83 banking institutions and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Qualitative insights were extracted via content analysis on 17 semi-structured interviews. As a result, PLS-SEM path modeling confirmed 17 of 25 hypotheses as statistically significant drivers. Primary drivers include top management's innovativeness, business scope, top management's support, familiarity with innovation, and relative advantage. Surprisingly, traditional economic and structural inhibitors—technical complexity, cost, centralization, formalization, organization size, slack, government policies, and geographical settings—were statistically unsupported as firm-level barriers in the quantitative model. Nonetheless, qualitative content analysis supported 24 of 25 factors, exposing a profound perception-reality gap where operational friction is overridden by top-down executive mandates and competitive survival pressures. AI adoption in emerging banking markets operates under a Strategic Survival Mandate, wherein banking institutions bypass cost and complexity constraints to maintain market relevance. Policy interventions are critical to promoting sound adoption.

KEYWORDS: Artificial Intelligence Adoption, Banking, Technology-Organization-Environment (TOE), PLS-SEM, Emerging Markets

I. INTRODUCTION

The global economy is currently navigating a profound structural paradigm shift driven by digital convergence and the Fourth Industrial Revolution (4IR), characterized by the seamless integration of artificial intelligence (AI), cloud computing, big data analytics, robotics, 3D printing, and blockchain architectures [1]. As industrial and service sectors transition into the Fifth Industrial Revolution (5IR)—which emphasizes human-centric innovation, ethical governance, environmental sustainability, and symbiotic collaboration between human intellect and intelligent machines [2]—the financial service sector has emerged as an aggressive early adopter of cutting-edge technologies. The intersection of finance and technology (FinTech) has fundamentally reshaped traditional banking business models, transitioning physical branch networks toward high-speed, data-driven digital channels [3, 4].

Over the past decade, artificial intelligence technologies—spanning machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, robotic process automation (RPA), and expert systems—have disrupted banking operations across front-office customer interactions, middle-office risk underwriting, and back-office regulatory compliance [5, 6]. By automating complex decision-making, optimizing credit scoring, detecting real-time fraudulent transactions, and tailoring personalized wealth advisory

services, AI offers unprecedented capabilities for operational efficiency, cost reduction, and strategic competitiveness [7–9].

While major financial institutions in advanced economies (e.g., North America, Europe, and developed Asia) have made substantial progress in deploying enterprise-wide AI solutions, technology adoption across emerging economies remains underdeveloped and empirically under-researched [10, 11]. Cambodia, a lower-middle-income economy in Southeast Asia, presents an exceptionally valuable empirical setting. Over the past two decades, Cambodia's banking sector has experienced extraordinary growth, with total industry assets reaching $100.2 billion USD (double the national GDP), customer loans totaling $63.7 billion USD, and customer deposits reaching $64.2 billion USD [12]. The banking industry experienced sustained double-digit annual growth exceeding 10% in assets, loans, and deposits for decades leading up to 2023. In the post-pandemic period, customer deposits maintained a robust growth rate of approximately 15% annually [13]. Digital payment transactions increased by 80.8% annually in 2025, totaling 2.2 billion transactions valued at $170 billion USD—equivalent to 3.4 times the national GDP [14]. Backed by high mobile penetration (117%) and a youthful, digitally native population, Cambodian banks have rapidly deployed mobile banking applications, self-service terminals, and blockchain-based interbank payment systems like Bakong [15, 16].

Digital financial inclusion in Cambodia has expanded rapidly. According to the UNCDF Mobile Tracker Survey, the percentage of formal financial service users in Cambodia increased from 59% in 2015 to 67% in 2021, moving steadily toward the 70% target established in the National Financial Inclusion Strategy 2019–2025 [17]. By 2025, physical and digital banking operations expanded across 2,722 branch locations, 36,860 banking agents, 6,004 ATMs/SSTs, and 43,081 POS terminals, serving 31.8 million deposit accounts (held by approximately 18.6 million customers), 17.9 million electronic wallet accounts, 7.41 million banking cards, and 4.5 million loan accounts (held by approximately 4.3 million borrowers) [12, 14].

Despite this superficial digital readiness, AI adoption within Cambodia remains in a nascent phase, constrained by acute technical talent shortages, unstandardized legacy data silos, fragmented digital infrastructure, and regulatory uncertainty [10]. Most published literature on banking AI [4, 7, 9, 18–22] focuses on advanced economies, relying on single theoretical perspectives or descriptive, secondary data. Empirical studies addressing emerging ASEAN economies fail to synthesize drivers, barriers, and multi-stakeholder perspectives (banks, FinTechs, regulators) into a unified explanatory model. Existing localized studies in Cambodia focus narrowly on general digital adoption [23, 24], single AI use cases such as securities index forecasting [25], broad industry overviews [26–28], or preliminary landscape descriptions [10].

This study fills these critical gaps by addressing two core research questions:

RQ1: What are the primary drivers influencing the adoption of artificial intelligence (AI) applications in Cambodia's banking sector?

RQ2: What are the primary barriers hindering the adoption of artificial intelligence (AI) applications in Cambodia's banking sector?

To comprehensively address these research questions, this study formulates three specific sub-objectives: (1) to systematically evaluate the technological, organizational, and environmental drivers promoting AI adoption in the banking sector; (2) to analyze the technological, organizational, and environmental barriers impeding AI adoption in the banking sector; and (3) to construct and empirically test an integrated conceptual framework combining the Technology-Organization-Environment (TOE) framework, Diffusion of Innovations (DOI) theory, and Digital Transformation theory within an emerging market in ASEAN.

II. LITERATURE REVIEW

A. Conceptualizing Artificial Intelligence

Artificial Intelligence (AI) is defined as an advanced domain of computer science dedicated to equipping machines with the ability to replicate and perform cognitive functions historically associated with human intellect, including logical reasoning, pattern recognition, continuous learning, and natural language understanding [29]. The historical evolution of artificial intelligence traces back to Alan Turing's seminal 1950 proposal on machine cognition and John McCarthy's coining of the term in 1956 [30, 31]. Following periods of capital shortage known as 'AI winters' during the late 20th century, the field experienced explosive growth post-2011 driven by cloud computing, exponential processing power, and big data availability [22, 32]. Contemporary AI operates predominantly in the Artificial Narrow Intelligence (ANI) stage, leveraging supervised, unsupervised, and reinforcement learning algorithms to process both structured database records and unstructured textual, vocal, and visual data [33–35].

Categorized by cognitive, emotional, and social intelligence capabilities, AI evolves across three generations: (1) Artificial Narrow Intelligence (ANI) Analytical AI, which exhibits purely cognitive intelligence traits for pattern recognition and forecasting; (2) Artificial General Intelligence (AGI) Human-Inspired AI, which integrates cognitive and emotional intelligence to recognize human emotional states via visual and vocal algorithms; and (3) Artificial Super Intelligence (ASI) Humanized AI, which integrates cognitive, emotional, and social intelligence to achieve self-conscious, self-aware interactions [34]. While contemporary commercial banking deploys Analytical AI at scale, experimental implementations are moving toward Human-Inspired conversational interfaces.

AI typologies encompass Machine Learning (ML) which independently learn from data patterns without explicit programming for each given task like predictive credit risk modeling and market trend forecasting [36]; Deep Learning (DL) multi-layered neural networks modelled after the architecture of the human brain for analyzing intricate unstructured data used for sentiment analysis and facial biometric authentication [37]; Natural Language Processing (NLP) capable for processing human language used for multi-lingual conversational agents, voicebots, and regulatory text extraction [38]; Computer Vision which comprehends visual information from the environment used for remote document authentication and self-service terminal interaction [39]; Expert Systems emulating human experts or a knowledge base used for automated rule-based compliance checking [40]; and Robotic Process Automation (RPA) combined with Optical Character Recognition (OCR) for automated Know-Your-Customer (KYC) document verification [41, 42]. These AI applications span the entire banking value chain across multiple functional operational domains:

1) *Front-Office Customer Services and Marketing:* 24/7 intelligent conversational chatbots, localized language voicebots, hyper-personalized product recommendation engines, drive-thru banking voice systems, self-service terminals or kiosks (SSTs), customer churn prediction, partner collaboration engines, and sentiment analysis across social media channels [43–47].
2) *Middle-Office Risk Management and Credit Underwriting*: Algorithmic credit scoring incorporating non-traditional alternative data (mobile money transactions, e-commerce history, utility bill payments), real-time anti-money laundering (AML) pattern recognition, topic modeling, cluster analysis, non-performing loan (NPL) prediction, blacklist detection, risk-based pricing, and portfolio risk management via robo-advisors [8, 48–52].
3) *Back-Office Operations, IT and Compliance:* Regulatory technology (RegTech) for automated prudential reporting, credit file processing, automated account opening, fraud reporting, AI coding review, IT documentation, cybersecurity monitoring, early warning systems, internal knowledge bases, and automated liquidity forecasting models developed in collaboration with banking authorities [20, 53–57].

B. Global Landscape of AI Adoption in Finance

Globally, financial sector spending on AI reached $35 billion in 2023 and is projected to surpass $97 billion by 2027 [58]. However, adoption trajectories vary substantially across global regions.

1) *North America:* Financial institutions deploy generative AI and deep learning at enterprise scale. Key implementations include Bank of America's Erica assistant (1.5B+ interactions) [59], JPMorgan Chase's COIN contract analysis [60], Discover Financial's Zest machine learning underwriting [61], Wells Fargo's Dialogflow integration [62], Vanguard's robo-advisory engines [43], and Citibank's Citi Smart Match remittance matching [63]. Major capital commitments, such as the $500 billion Stargate Project infrastructure initiative [64], alongside federal roadmaps like the Pan-Canadian AI Strategy in 2017 [65] and US National AI Research Strategy (2016/2023) [66], accelerate adoption.
2) *Europe*: Adoption focuses business process innovation and regulatory compliance. Prominent cases include Standard Chartered's IBM Trade AI engine [61], HSBC's Deepgram voice authentication [43], Barclays' Copilot/AWS's Bedrock security integration [67], Deutsche Bank's tax/corporate RPA [42], Banco Santander's Kairos event impact predictor [61], UBS's Red client assistant, AI Hub and Data Mesh [68, 69], and several Russian banks' applications in customer services, anomaly detection, and risk management [70]. Regulatory landmarks like the EU AI Act (2024) and national strategies across the UK, Finland, Denmark, Norway, and Iceland establish global regulatory and ethical benchmarks [71–74].
3) *Advanced Asian Economies:* Mobile-first banking and mega-platform ecosystems stimulate AI implementation. China Merchants Bank pioneers intelligent investing with Capricorn Investment, subsequently followed by many prominent banks [60]. DBS Singapore delivers hyper-personalized FX insights to 3.5M+ clients [75]. Mizuho, MUFG, and SMBC in Japan deploy Fujitsu Kozuchi generative AI [76, 77]. Korean banks (Hanna, KakaoBank, Kbank, Shinhan, and KB Kookmin) utilize LLMs and AI bank tellers [78–81]. National strategies in China Next Gen AI in 2017 [82], Singapore NAIS 2.0 in 2023 [83], Japan in 2017/2022 [84], and South Korea in 2019 [85] supply state-level momentum.
4) *Emerging Economies:* AI accelerates financial inclusion via alternative data lending and mobile money integrations. Notable global cases are highlighted. Nubank in Latin America (over 114M clients utilize Olivia AI and GPT-4 pilots) [86]. Kenya's M-Pesa advances microloans and investments [87]. Numerous Nigerian banks leverage AI in customer relationship management, fraud detection, and risk assessment [88]. Several Egyptian banks utilize AI in digital staff [89], back office automation [90], and IT infrastructure modernization [91]. In the UAE and Saudi Arabia (Middle East), major banks such as Emirates NBD [92] and Bank ABC [93], Saudi Awwal Bank [94] implemented AI in hyper-personalization, emotional intelligence, and risk management, respectively. Prominent banks in India present remarkable AI-driven chatbots and virtual assistant such as State Bank of India [95], Punjab National Bank [96], HDFC Bank [97], Bank of Baroda (Aditi/GyanSahay) [98], and ICICI (iPal) [99]. GenAI in customer services and recommendation is

implemented in Indonesia such as Bank Jago (Vertex AI) [100], Bank Negara Indonesia (ASLa), and Bank Mandiri (Livin and Kopra), and Bank Syariah Indonesia [101]. Malaysia presents innovative use cases such as customer relation of GXBank (VoC360) [102] and Ryt Bank [103], compliance and financial crime of Maybank [104]. AI is embraced by Vietnam's large banks such as VPBank, Techcombank, VIB, ACB, Vietcombank TPBank, VietABank, and VietinBank in customer support, asset management, security, and fraud prevention [77, 105]. Furthermore, AI policy and strategies emerge across Latin America (Mexico, Colombia, Argentina, Uruguay, Chile, Peru, and Brazil) [106]; the African Union Continental AI Strategy [107] along with respective national strategies of Mauritius, Egypt, Benin, Rwanda, Senegal, Lesotho, and Kenya; Middle East (UAE, Qatar, Jordan, Saudi Arabia, and Oman) [108]; India (#AIforAll) [9]; and most ASEAN nations (Singapore, Indonesia, Malaysia, the Philippines, Vietnam, and Thailand) [77].

C. The Cambodian Banking Context

Cambodia's financial sector comprises two distinct regulatory sub-sectors: the non-bank financial sub-sector (regulated by the Non-Bank Financial Services Authority) and the banking sub-sector (overseen by the National Bank of Cambodia as central bank). The banking sub-sector encompasses 59 commercial banks, 7 specialized banks, 4 deposit-taking microfinance institutions (MDIs), 85 non-deposit-taking microfinance institutions (MFIs), 89 rural credit institutions, 12 financial lease institutions, 30 payment service institutions (PSIs), 4 third-party processors, 1 credit bureau, 12 audit firms, 5 representative offices, and 3,393 money changers [12]. Key prudential indicators for deposit-taking institutions reflect total capital adequacy at 21.8%, liquidity coverage at 139.3%, return on assets at 1.0%, return on equity at 5.0%, and non-performing loans at 8.9% [12].

To integrate previously isolated payment services, the central bank implemented a series of nationwide interbank clearing systems: the National Clearing System in 2012, the FAST instant retail payment system in 2016, the Online Banking System in 2016, the Cambodia Shared Switch in 2018, the Retail Pay System in 2019, and the Bakong blockchain payment system in 2020 [14, 16]. Cross-border QR payment connectivity has expanded to 8 international jurisdictions: Thailand, Laos, Vietnam, South Korea, Malaysia, China, Singapore, and Japan [16]. In capital markets, the NBC Platform (commenced in 2017 for interbank liquidity operations) was expanded in 2022 to enable government bond trading alongside with corporate stock market operated by the Cambodia Securities Exchange [109].

Despite the absence of a National AI Strategy, Cambodian banking institutions are testing AI solutions across operations: Sathapana Bank deployed Finbots.ai's CreditX platform for scorecards [110]; ABA Bank integrated NAVI virtual assistant [111]; ACLEDA Bank automated risk profiling [112]; Wing Bank partnered with Scienaptic Systems for AI credit decisioning and Khmer voicebots [113, 114]; Credit Bureau Cambodia deployed ML risk scoring [115]; and the central bank partnered with JICA on an AI liquidity forecasting proof-of-concept [54].

D. Theoretical Foundations

To maintain a solid theoretical foundation, this research synthesizes three foundational framework lenses. Diffusion of Innovations (DOI) Theory evaluates how perceived attributes of innovation—relative advantage, compatibility, complexity, trialability, and observability—govern adoption velocity and organizational assimilation patterns across social systems and firm networks [116].

Technology-Organization-Environment (TOE) Framework serves as the primary structural taxonomy, categorizing adoption determinants across internal technological attributes, internal organizational capabilities, and external environmental dynamics [117]. Beyond the prevalence of the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) in individual AI adoption studies, the TOE framework is primarily utilized in corporate IT adoption research [118–120]. Technology includes internal and external technologies relevant to an organization's activities [117]. The factors include the innovation's complexity, compatibility with current systems, and perceived relative advantage, as well as the adopting organization's technological infrastructure. Internal qualities and resources make up the organisational context [117]. Size, operational scope, managerial structure, financial and human resources, and organisational culture are important. Organisations operate in an external environment [117]. The factors include competitive pressures from established and emerging industry participants, industry characteristics like regulatory level and innovation pace, outside technology support infrastructure, technology suppliers, consulting firms, and government policies and regulations. The TOE framework possesses a robust theoretical foundation, aligns with established theories such as Diffusion of Innovation theory, and has been utilized in numerous empirical investigations [118, 119, 121–123].

Digital Transformation Theory conceptualizes AI adoption not as an isolated IT upgrade, but as an enterprise-wide strategic transformation. Venkatraman [124] delineates five transformation levels ranging from localized exploitation and internal integration to business process redesign, network redesign, and business scope redefinition. Furthermore, the TOP (Technology, Organization, People) framework [125] and the Digital Transformation Canvas [126] emphasize that sustainable digital transformation requires the harmonized alignment of strategic purpose, operational pillars (processes, people, platforms, partners), value creation (products,

performance, planet), and risk protection mechanisms (data security, privacy).

E. Conceptual Framework

Synthesizing the theoretical framework with empirical literature, 25 specific research hypotheses were formulated across the TOE contexts.

1) *Technological Context Drivers and Barriers:* The hurdles to entry for banks have been significantly lowered due to the continuous development and availability (TAVA) of advanced AI tools, platforms, and accessible cloud-based AI services [10, 127]. The commercial accessibility of pre-integrated cloud platforms, open-source machine learning models (TensorFlow, PyTorch), foundational LLM and APIs lowers technical entry barriers. Technical compatibility (TCOM) is the extent to which a new technology matches established structures, procedures, infrastructures, values, norms, experiences, and the information-sharing desires of potential adopters or social systems [116]. The degree to which AI aligns with existing core banking IT architectures, middleware, and data standards minimizes operational disruption and installation expense [128]. Relative advantage (TADV) represents how much an innovation is better than its predecessor [116]. Perceived operational superiority of AI over manual legacy processes—such as chatbots, service personalisation, fraud detection, predictive analytics, and risk management—promotes institutional adoption [8, 127, 129, 130]. Nevertheless, technical complexity (TCOX) of technologies is expected to discourage adoption [116, 120]. AI system integration hurdles, lack of technical expertise, algorithmic opacity, and data prerequisites act as potential technical inhibitors [128]. The direct and indirect costs of innovations (TCOS) often prevent their adoption, especially when they exceed an organization's resource capabilities [131]. Substantial capital expenditures for GPU hardware, cloud infrastructure, specialized talent, and continuous maintenance impede resource-constrained firms [132–134]. On this basis, we put forth the following hypotheses.

   H1a: Technological availability is significantly and positively related to AI applications adoption.

   H1b: Technical compatibility is significantly and positively related to AI applications adoption.

   H1c: Relative advantage is significantly and positively related to AI applications adoption.

   H2a: Technical complexity is significantly and negatively related to AI applications adoption.

   H2b: Cost is significantly and negatively related to AI applications adoption.

2) *Organizational Context Drivers and Barriers:* Top management, generally the CEO, must be imaginative to pioneer innovation. Innovativeness is the amount to which a person accepts new ideas before others in a system [116]. Leader innovation is linked to early and rapid acceptance [116]. Other organisational members cannot accelerate information system adoption or technology integration without the CEO's innovation (OTMI) [120]. In the disruptive banking business, banks need a clear vision and an innovative attitude to integrate new technologies like AI [135]. Technological knowledge involves understanding present and emerging technologies, their mechanisms, manufacturing processes, and practical applications for goal achievement. Top management that understands technical innovation (OTMK) is more likely to adopt technology aggressively [136]. Higher level of education increases innovation receptivity [137, 138]. Major organisational transformation requires top management support (OTMS) for resource allocation and service integration [139]. It was found that consistent and continuous managerial assistance is necessary for information system adoption and acceptability [140–143]. Recent studies [9, 128, 144] found that top management's commitment to AI as a strategic priority and allocation of financial, technological, and human resources for AI initiatives predicts AI adoption. Therefore, the subsequent hypotheses are formulated.

   H1d: Top management's innovativeness is significantly and positively related to AI applications adoption.

   H1e: Top management's technology knowledge is significantly and positively related to AI applications adoption.

   H1f: Top management's support is significantly and positively related to AI applications adoption.

   Larger organizational size (OOSI) enables economies of scale that enhance adoption capacity by allowing institutions to absorb upfront experimentation costs and capture greater returns when scaling enterprise solutions [145–149]. Consequently, major banking institutions are significantly more inclined to incorporate AI solutions as central components of their long-term strategic plans than smaller institutions [33, 150]. Organizational slack (OOSL) represents the uncommitted financial, technical, and human resources available to an organization for innovation adoption [116]. Securing competitive advantages through AI requires adequate uncommitted funding and resource buffers to support both initial technology acquisition and continuous enterprise-wide integration [22, 144, 146]. An organization's technical readiness depends on employing specialized talent (OETS) who possess deep knowledge of technological innovations [116, 136, 151]. Enterprise AI deployment requires establishing specialized roles—such as data scientists and machine learning engineers—demanding dedicated upskilling programs to adapt the workforce to changing operational needs [9, 60, 132]. Familiarity gained through peer networks, expert evaluations, and

media sources reduces novelty and perceived adoption risks [116, 131, 152–154]. High familiarity with innovation (OFWI), along with awareness and trust actively promote AI adoption, whereas knowledge gaps and mistrust create formidable barriers to deployment [51, 132]. Hence, the following hypotheses are proposed.

H1g: Organization size is significantly and positively related to AI applications adoption.

H1h: Organizational slack is significantly and positively related to AI applications adoption.

H1i: Employees' technology skills are significantly and positively related to AI applications adoption.

H1j: Familiarity with the innovation is significantly and positively related to AI applications adoption.

Effective communication processes (OCOP) facilitate idea exchange, minimize organizational silos, and allow leadership to convey a compelling vision for technology integration [116, 131, 150, 155, 156]. Effective communication mitigates workforce disruption and directly addresses employee fear regarding job displacement, thereby securing buy-in for AI adoption [22, 157, 158]. A broader operational scope increases investment in novel technologies to manage demand aggregation, inventory, and search costs [118, 159, 160]. A bank's business scope (OSOB) defines specific domain requirements—such as risk management, customer service, and regulatory compliance—that dictate which AI applications are deployed to meet business goals [9, 10, 144, 161, 162]. Interconnectedness (OINT) across internal units and external networks enables the rapid flow and exchange of innovative ideas throughout a social system [116]. Robust collaboration frameworks with business partners, research institutions, and regulators facilitate multi-disciplinary knowledge sharing essential for AI development [10, 22, 163]. Segmenting an organization into distinct sub-units creates specialized demands that drive the adoption of core technologies to resolve coordination challenges [151]. Functional differentiation (OFUD) fosters specialized sub-unit competencies and governance structures that allow AI capabilities to be tailored to specific operational functions across the enterprise [22, 161, 164, 165]. External integration (OEXI), also known as system openness, enable organizations to exchange information across their borders and tap into external expertise [116, 151]. Strategic alliances with FinTech companies, service providers, and international partners supply critical AI infrastructure and specialized solutions that banks lack internally [58, 128, 166]. These result in the following proposed hypotheses.

H1k: Effective communication processes are significantly and positively related to AI applications adoption.

H1l: The scope of business is significantly and positively related to AI applications adoption.

H1m: Interconnectedness is significantly and positively related to AI applications adoption.

H1n: Functional differentiation is significantly and positively related to AI applications adoption.

H1o: External integration is significantly and positively related to AI applications adoption.

Nonetheless, the adoption of AI in the banking industry is constrained by certain organizational factors. Concentrating decision-making power among a limited leadership group promotes structural inertia and bureaucratic layers that inhibit organizational innovativeness [116, 128]. While centralized strategy sets clear executive vision, rigid centralized control (OCEN) generally hinders the rapid, scalable integration of complex AI technologies [22, 144, 151]. Formalization (OFOR) emphasizes strict adherence to established rules, standard procedures, and bureaucratic structures, which correlates negatively with organizational innovativeness [116]. Rigid administrative practices constrain timely AI scaling and frequently restrict applications to routine human labor replacement rather than capability augmentation [22, 163, 167]. Therefore, we proposed the following hypotheses.

H2c: Centralization is significantly and negatively related to AI applications adoption.

H2d: Formalisation is significantly and negatively related to AI applications adoption.

3) *Environmental Context Drivers and Barriers:* External market uncertainty (EMAU)—stemming from rapid technological shifts, economic volatility, competition, customer demand, and regulatory gaps—drives firms to implement adaptive decision-making tools [58, 105, 168, 169]. AI helps financial institutions evaluate market fluctuations, optimize investment strategies, and strengthen real-time risk management during uncertain periods [4, 77, 127, 129]. Intense market competitive pressure (ECOP) from established banks, FinTech startups, and BigTech entrants alters industry rules and forces traditional banks to innovate to protect market share [135, 170–175]. Adopting AI serves as a strategic resource to streamline operations, personalize services, and maintain long-term competitive relevance [6, 130, 176]. Robust technology support infrastructure (ETSI)—including high-speed broadband, scalable data centers, supercomputers, and APIs—is essential to support high computational speeds and big data processing for AI model training [7, 22, 161, 177, 178]. Cloud computing advancements further accelerate implementation timelines and lower upfront infrastructure expenditures across mobile and digital payment channels [161, 177]. Government policies and regulations (EGOP) shape innovation adoption by establishing strategic direction, allocating resources, and building public trust [18, 128, 131, 179, 180]. National AI roadmaps and central bank

regulatory sandboxes reduce compliance uncertainty, encouraging banks to experiment safely within supportive environments [8, 22, 60, 132, 181]. Finally, global uniformity (EGLU) in technical standards and regulations creates a cohesive evolutionary framework that facilitates safe and effective cross-border technology implementation [9, 131, 176, 181, 182]. Adopting international benchmarks, such as the OECD Principles on AI, minimizes regulatory fragmentation, builds public trust, and accelerates global adoption [9, 157, 178]. Therefore, we proposed the following hypotheses.

H1p: Market uncertainty is significantly and positively related to AI applications adoption.

H1q: Competitive pressure is significantly and positively related to AI applications adoption.

H1r: Technology support infrastructure is significantly and positively related to AI applications adoption.

H1s: Government policies are significantly and positively related to AI applications adoption.

H1t: Global uniformity is significantly and positively related to AI applications adoption.

Nevertheless, geographical settings (EGES) dictate resource accessibility, infrastructure quality, talent availability, and spatial communication effects that influence adoption trajectories [116, 131]. Developing economies face structural digital divides and severe talent shortages that impede AI adoption compared to primary investor markets in advanced nations [18, 135, 183, 184]. Thus, another hypothesis is put forward.

H2e: Geographical settings are significantly and negatively related to AI applications adoption.

A thorough literature and theoretical synthesis yielded the study model in Figure 1 that shows the hypothesised correlations between important dimensions relevant to AI adoption in Cambodia's banking sector. This framework guides this empirical study by identifying variables and their expected relationships. It models a modified technology acceptance model framework to address the study's research questions.

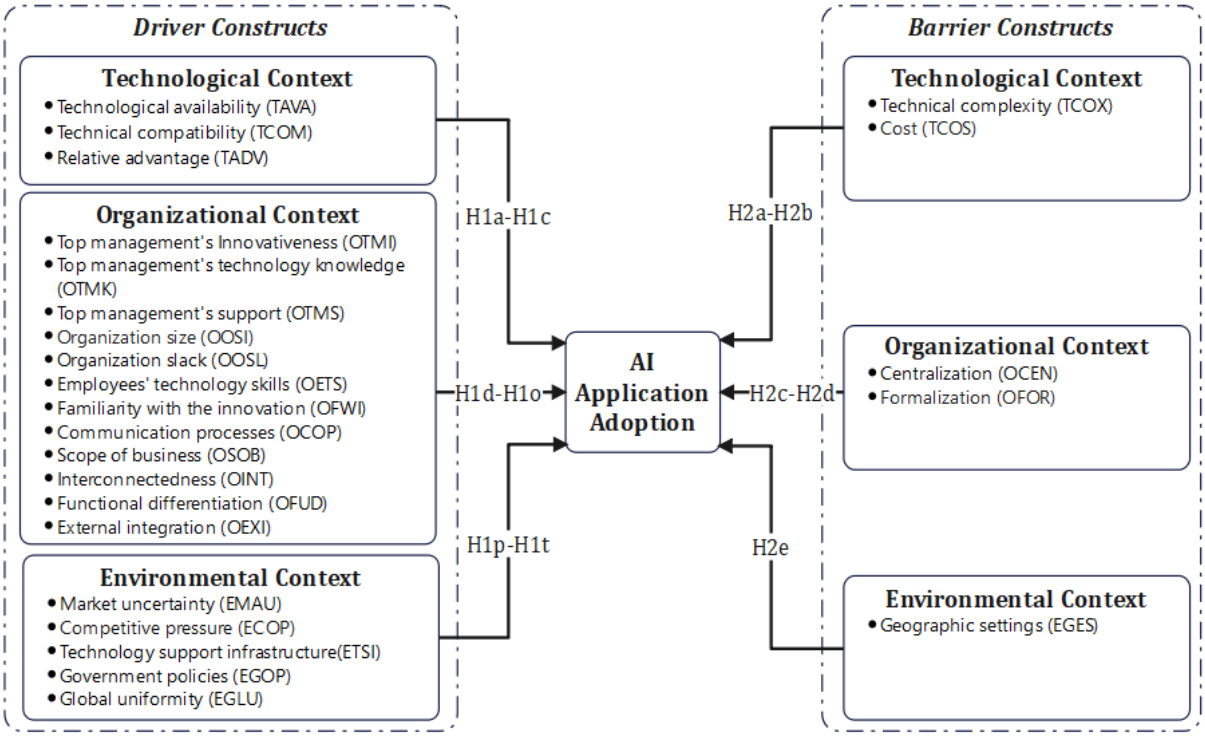


Figure 1 Research Model

III. RESEARCH METHODOLOGY

A. Philosophical Stance and Research Approach

Grounded in a positivist research philosophy, this research employs a structured, deductive reasoning approach to evaluate existing technology adoption frameworks within an understudied emerging market context. Positivism assumes that an objective social reality exists independently of the researcher, allowing empirical phenomena to be measured, quantified, and generalized through formal hypothesis testing [185, 186]. Evaluating competing philosophies, interpretivism was deemed insufficient for statistical hypothesis testing across institutional cohorts, whereas direct/critical realism lacked the quantitative precision required for path modeling [186, 187]. A cross-sectional time horizon was adopted to capture a comprehensive empirical snapshot of organizational AI adoption across the banking industry.

B. Research Strategy and Methods

Evaluating alternative business research strategies—including experimental designs, case studies, action research, grounded theory, ethnography, and narrative analysis—a mixed-methods research strategy using survey paired with

content analysis was selected as optimal. Experimental strategies carry artificiality risks; grounded theory lacks deductive alignment; and ethnography lacks cross-institutional generalizability [186, 188]. Combining quantitative surveys with qualitative semi-structured interviews enables method triangulation, leveraging quantitative breadth with qualitative depth [189].

C. Population and Sample

The target population comprised all formal banking institutions licensed by the National Bank of Cambodia that conduct deposit, credit, and payment operations. Non-deposit taking microfinance institutions, rural credit institutions, money changers, and financial lease institutions were excluded to maintain institutional homogeneity. The sampling frame totalled 101 qualified institutions (59 commercial banks, 7 specialized banks, 4 microfinance deposit-taking institutions, 30 payment service institutions, and 1 credit bureau).

To establish statistical power, Cochran's formula [190] for finite population sample size determination was applied:

$$n = \frac{Z^2 \, x \, p \, x \, (1-p)}{e^2}$$

Where Z = 1.96 (95% confidence level), p = 0.50 (maximum variability assumption), and e = 0.05 (desired margin of error). For the finite population N = 101, applying the finite population correction yields a minimum required sample size of n = 81 institutions. The actual quantitative data collection yielded N = 83 completed questionnaires, satisfying the power calculation requirement.

D. Data Collection and Respondent Profiles

1) *Quantitative Survey:* Structured web-based questionnaires (Google Forms) were distributed to senior management across all 101 target institutions. Follow-up reminder protocols yielded 83 valid responses (82.18% response rate). Sample demographics shown in
2) TABLE I indicate that 67.47% of respondents possessed over 15 years of industry experience; 38.55% were C-Level/SVP/EVP executives; 28.92% were Directors/VPs; and 66.27% represented IT and Digital transformation divisions.

TABLE I. SUMMARY OF QUANTITATIVE DATA DEMOGRAPHY

Demographics	*F*	*RR*	*Demographics*	*F*	*RR*
Current job position			Type of institution		
CEO, President, or equivalent	1	1.20%	Commercial Bank	47	56.63%
C-Level, Senior Vice President, Executive Vice President, or equivalent	32	38.55%	Specialized Bank	7	8.43%
Vice President, Director, or equivalent	24	28.92%	Microfinance Deposit-taking Institution	4	4.82%
Deputy Director, Senior Manager, or equivalent	20	24.10%	Payment Service Institution	24	28.92%
Senior Officer, Officer	6	7.23%	Credit Bureau	1	1.20%
Specific function in the institution			Ownership type of institution		
Management	16	19.28%	Locally incorporated institution	48	57.83%
IT, Digital	55	66.27%	Subsidiary of foreign institution	29	34.94%
Risk, Compliance	7	8.43%	Foreign branch institution	6	7.23%
Operations	4	4.82%	Number of employees		
Retail, Sales	0	0.00%	Under 500	48	57.83%
Corporate, Investment Banking	0	0.00%	501–1000	13	15.66%
Finance	1	1.20%	1001–3000	6	7.23%
Years of professional experience			3001–5000	9	10.84%
< 3 years	3	3.61%	Over 5000	7	8.43%
3–5 years	0	0.00%	Total asset of institution		
6–10 years	9	10.84%	<= $50M	25	30.12%
11–15 years	15	18.07%	$51M–$200M	13	15.66%
> 15 years	56	67.47%	$201M–$999M	25	30.12%
			$1,000–$5,000M	16	19.28%
			> $5,000M	4	4.82%

Note(s): F = Frequency; RR = Response Rate

3) Qualitative *Interviews*: Concurrent qualitative data were gathered via 17 semi-structured, one-on-one interviews with senior executive leaders across 15 banking institutions (quota-sampled across large, medium, and small asset tiers) and 2 senior officials from the banking

regulatory authority, achieving a 77.27% qualitative response rate.

4) TABLE II illustrates the demographic information of qualitative responses.

TABLE II SUMMARY OF QUALITATIVE DATA DEMOGRAPHY

Demographics	*F*	*RR*	*Demographics*	*F*	*RR*
Current job position			Type of institution		
CEO, President, or equivalent	1	5.88%	Commercial Bank	10	62.50%
C-Level, Senior Vice President, Executive Vice President, or equivalent	10	58.82%	Specialized Bank	1	6.25%
Vice President, Director, or equivalent	6	35.29%	Microfinance Deposit-taking Institution	2	12.50%
Deputy Director, Senior Manager, or equivalent	0	0.00%	Payment Service Institution	2	12.50%
Senior Officer, Officer	0	0.00%	Credit Bureau	0	0.00%
Specific function in the institution			Banking supervisory authority	1	6.25%
Management	5	29.41%	Ownership type of institution		
IT, Digital	10	58.82%	Locally incorporated institution	12	80.00%
Risk, Compliance	1	5.88%	Subsidiary of foreign institution	3	20.00%
Operations	0	0.00%	Foreign branch institution	1	6.67%
Retail, Sales	1	5.88%	Number of employees		
Corporate, Investment Banking	0	0.00%	Under 500	6	40.00%
Finance	0	0.00%	501–1000	2	13.33%
Years of professional experience			1001–3000	0	0.00%
< 3 years	0	0.00%	3001–5000	3	20.00%
3–5 years	1	5.88%	Over 5000	4	26.67%
6–10 years	1	5.88%	Total asset of institution		
11–15 years	4	23.53%	<= $50M	2	13.33%
> 15 years	11	64.71%	$51M–$200M	1	6.67%
			$201M–$999M	2	13.33%
			$1,000–$5,000M	7	46.67%
			> $5,000M	3	20.00%

Note(s): F = Frequency; RR = Response Rate

E. Instrument Design, Pretesting, and Pilot Testing

1) *Instrument Scale Architecture:* The survey's section 1 utilized 7-point Likert scales (1 = Strongly Disagree to 7 = Strongly Agree) to measure 25 driver and barrier latent constructs derived from established adoption literature [33, 120, 128, 191–193]. Section 2 measured AI adoption maturity on a 6-point scale, core process integration on an ordinal scale, and functional applications across 24 nominal domains. Section 3 captured organizational demographic profiles.

2) *Pretesting and Content Validity:* Draft instruments underwent pretesting with a panel of 8 academic and banking experts. Content validity was quantified using the Index of Item-Objective Congruence [194], retaining only items achieving IOC ≥ 0.75.

$$IOC = \frac{\sum R}{N}$$

Where $\sum R$= Sum of scores from all specialists for a specific item, and N = Total number of specialists.

3) *Pilot Testing and Reliability:* A pilot study was administered to 30 randomly selected institutions (yielding 24 responses, 80% response rate). Scale reliability was evaluated using Cronbach's alpha ($\alpha \geq 0.70$ benchmark). Four initial scales—Top Management Innovativeness (OTMI, $\alpha = 0.666$), Organization Size (OOSI, $\alpha = 0.605$), and Formalization (OFOR, $\alpha = 0.267$)—fell below thresholds. These constructs underwent targeted item re-wording, electronic skip-logic refinement, and item deletion, elevating all final scale alphas above 0.70 prior to census deployment.

F. Analytical Techniques

Quantitative survey data was analyzed using Partial Least Squares Structural Equation Modeling in SmartPLS 4 [195]. Measurement models were evaluated via Confirmatory Composite Analysis (CCA) for indicator loading reliability ($\lambda \geq 0.708$), internal consistency (Cronbach's $\alpha \geq 0.70$, Composite Reliability CR ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity (Fornell-Larcker criterion

and HTMT < 0.85). Path significance was evaluated via non-parametric bootstrapping with 10,000 resamples.

Content analysis was conducted on qualitative data. Interview transcripts were coded using QDA Miner software, following Elo & Kyngäs' three-phase framework (preparation, organizing, reporting) [196]. Open coding produced 52 initial codes, synthesized into 25 final categories across 2 primary research themes.

G. Ethical Compliance and Data Protection

The research protocol complied strictly with ethical research guidelines established by the Selinus University, the Italian National Research Council, and the Cambodian Research Ethics National Council of Science, Technology and Innovation. The Selinus University Research Ethics Committee approved the research project on December 29, 2025. Survey respondents provided electronic informed consent, and written informed consent was signed by all interview participants. Thus, the consent statement applies uniformly to both interview and survey participants. Absolute institutional anonymity and individual data masking (e.g., P1 Bank, Regulator P16) were enforced to protect proprietary corporate data.

IV. RESULTS

A. Baseline State of AI Adoption and Governance

Descriptive analysis reveals that 63 of 83 surveyed institutions (75.90%) actively utilize AI across various maturity stages, whereas 20 institutions (24.10%) remain non-adopters as illustrated in TABLE III.

TABLE III. STAGES OF AI ADOPTION

Stage of AI adoption	*F*	*RR*
No initiative or plan to use AI	20	24.10%
Research phase	18	21.69%
Plan to implement AI within five years	13	15.66%
Piloting AI use cases	14	16.87%
Implemented minor low-impact AI applications (e.g., administrative tasks, customer inquiries) within the last five years	12	14.46%
Implemented multiple high-impact AI applications (e.g., fraud detection, loan underwriting, customer service bots) within the last five years	6	7.23%
Total	83	100.00%

Regarding strategic roadmaps, 9 institutions (10.84%) maintain a formal AI strategy; 37 institutions (44.58%) are currently developing one; and 37 institutions (44.58%) possess no formal roadmap. Functional deployment spans 24 business domains, led by customer support (47.50%), IT software development (42.50%), transaction fraud prevention (40.00%), credit risk underwriting (40.00%), customer relationship management (40.00%), cybersecurity (37.50%), and business intelligence analytics (37.50%). Figure 2 exhibits the areas of AI implementation.

Core business process integration remains fragmented: 51.81% report zero AI implementation; 12.05% operate in isolated silos; 22.89% achieve partial integration; 9.64% medium integration; 2.41% large integration; and only 1.20% demonstrate full enterprise integration. Looking forward, 73.49% of institutions plan future AI deployments over the next five years, prioritizing BI analytics (51.81%), customer support (50.60%), and financial crime/AML prevention (49.40%).

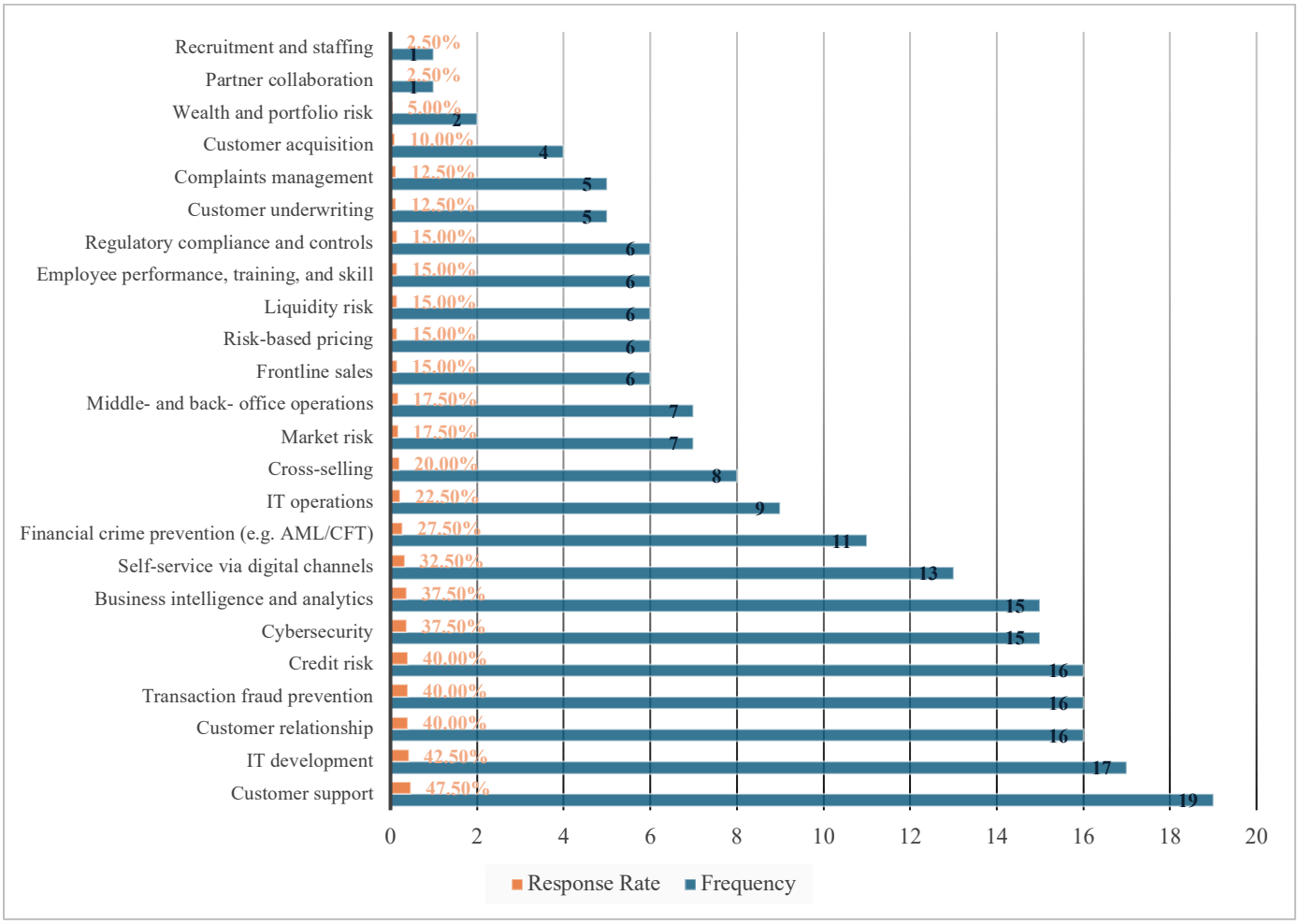


Figure 2 Areas of AI implementation

Regarding risk governance, 56 institutions (67.47%) implemented formal measures for responsible AI such as prioritizing regulatory compliance (46.99%), ethical frameworks (44.58%), employee ethics training (38.55%), data privacy controls (32.53%), human-in-the-loop oversight (27.71%), customer education (27.71%), model explainability (22.89%), and bias mitigation (18.07%).

Planning for the next five years, there increase in AI deployment across 24 business domains, led by business intelligence and analytics (51.81%), customer support (50.60%), financial crime prevention (e.g., AML/CFT) (49.40%), transaction fraud prevention (46.99%), customer relationship (44.58%), cybersecurity (44.58%).

B. Quantitative Measurement Model Assessment

Confirmatory Composite Analysis (CCA) confirmed the statistical robustness of all reflective measurement models in SmartPLS 4. The results of validity and reliability at the item level and at the construct level are highlighted in the following, with details in TABLE IV, Table V and Table VI.

1) Indicator Reliability: All retained outer loadings exceeded the 0.708 benchmark (minimum loading λ = 0.723), demonstrating that latent constructs explain over 50% of indicator variance.

2) Internal Consistency: Cronbach's alpha values ranged from 0.743 to 0.929, and Composite Reliability (CR) scores ranged from 0.729 to 0.966 (EGES revised to CR = 0.884 after removing item EGES3, λ = 0.371), surpassing the 0.70 threshold.

3)

TABLE IV CONVERGENT VALIDITY AND RELIABILITY

CS	*Latent variable*	*Indicator*	*CA α*	*CR ρ_C*	*AVE*	*OL*	*R^2*
Technological context	TAVA		0.82	0.915	0.843		
		TAVA1				0.887	0.96
		TAVA2				0.948	0.979
	TCOM		0.828	0.896	0.743		
		TCOM1				0.888	0.978
		TCOM2				0.798	0.913
		TCOM3				0.896	0.973
	TADV		0.816	0.907	0.83		
		TADV1				0.965	0.983
		TADV2				0.854	0.985
	TCOX		0.908	0.954	0.911		
		TCOX1				0.934	0.981
		TCOX2				0.974	0.973
	TCOS		0.772	0.864	0.764		
		TCOS1				0.744	0.979
		TCOS2				0.987	0.936

Organizational context	OTMI		0.818	0.914	0.841		
		OTMI1				0.95	0.994
		OTMI2				0.883	0.967
	OTMK		0.847	0.929	0.867		
		OTMK1				0.939	0.991
		OTMK2				0.923	0.98
	OTMS		0.874	0.94	0.887		
		OTMS1				0.955	0.99
		OTMS2				0.928	0.977
	OOSI		0.822	0.918	0.849		
		OOSI1				0.911	0.969
		OOSI2				0.931	0.989
	OOSL		0.819	0.889	0.802		
		OOSL1				0.791	0.96
		OOSL2				0.989	0.959
	OETS		0.743	0.885	0.794		
		OETS1				0.867	0.934
		OETS2				0.914	0.984
	OFWI		0.829	0.92	0.852		
		OFWI1				0.906	0.977
		OFWI2				0.94	0.982
	OCOP		0.915	0.959	0.921		
		OCOP1				0.967	0.983
		OCOP2				0.952	0.995
	OSOB		0.866	0.937	0.882		
		OSOB1				0.941	0.983
		OSOB2				0.936	0.986
	OINT		0.764	0.895	0.809		
		OINT1				0.899	0.973
		OINT2				0.9	0.97
	OFUD		0.929	0.966	0.934		
		OFUD1				0.971	0.995
		OFUD2				0.961	0.988
	OEXI		0.831	0.922	0.855		
		OEXI1				0.934	0.983
		OEXI2				0.915	0.98
	OCEN		0.818	0.729	0.728		
		OCEN1				0.735	0.968
		OCEN2				0.745	0.979
	OFOR		0.781	0.893	0.807		
		OFOR1				0.957	0.98
		OFOR2				0.836	0.961
Environmental context	EMAU		0.89	0.947	0.9		
		EMAU1				0.942	0.984
		EMAU2				0.956	0.994
	ECOP		0.779	0.871	0.921		
		ECOP1				0.826	0.97
		ECOP2				0.871	0.96
		ECOP3				0.799	0.982
	ETSI		0.9	0.9	0.909		
		ETSI1				0.952	0.992
		ETSI2				0.955	0.987
	EGOP		0.903	0.954	0.911		
		EGOP1				0.961	0.989
		EGOP2				0.948	0.977
	EGLU		0.911	0.957	0.918		
		EGLU1				0.952	0.992
		EGLU2				0.964	0.988
	EGES		0.762	0.884	0.793		
		EGES1				0.957	0.963
		EGES2				0.819	0.966

Note(s): CS = Construct, CR = Composite Reliability, AVE = Average Variance Extracted, CA = Cronbach's alpha, OL = Outer Loading, R2 = R-squared

4) *Convergent Validity:* Average Variance Extracted (AVE) values ranged from 0.728 to 0.934, far exceeding the 0.50 benchmark.
5) *Discriminant Validity:* Fornell-Larcker evaluation confirmed that the square root of AVE for each construct exceeded all off-diagonal correlations. All HTMT ratios remained safely below the conservative 0.85 threshold (ranging from 0.067 to 0.849).
6) *Collinearity:* Structural VIF values ranged between 1.666 and 2.980 (Tolerance > 0.336), confirming the total absence of multicollinearity distortions (VIF < 3.0).

TABLE V HETEROTRAIT–MONOTRAIT (HTMT) (DISCRIMINANT VALIDITY)

	ECOP	EGES	EGLU	EGOP	EMAU	ETSI	OCEN	OCOP	OETS	OEXI	OFOR	OFUD	OFWI	OINT	OOSI	OOSL	OSOB	OTMI	OTMK	OTMS	TADV	TAVA	TCOM	TCOS
EGES	0.572																							
EGLU	0.754	0.594																						
EGOP	0.576	0.418	0.676																					
EMAU	0.817	0.368	0.566	0.446																				
ETSI	0.846	0.643	0.708	0.504	0.616																			
OCEN	0.662	0.706	0.505	0.513	0.444	0.598																		
OCOP	0.797	0.463	0.503	0.426	0.652	0.591	0.574																	
OETS	0.742	0.661	0.563	0.406	0.508	0.537	0.559	0.779																
OEXI	0.8	0.585	0.606	0.385	0.569	0.719	0.699	0.679	0.84															
OFOR	0.665	0.694	0.46	0.378	0.482	0.546	0.849	0.629	0.657	0.735														
OFUD	0.78	0.503	0.742	0.43	0.595	0.723	0.419	0.541	0.719	0.843	0.511													
OFWI	0.806	0.617	0.569	0.328	0.572	0.591	0.557	0.846	0.848	0.845	0.742	0.782												
OINT	0.786	0.599	0.61	0.453	0.598	0.723	0.583	0.777	0.836	0.796	0.757	0.798	0.808											
OOSI	0.568	0.585	0.583	0.508	0.599	0.534	0.579	0.497	0.481	0.46	0.527	0.517	0.426	0.487										
OOSL	0.466	0.626	0.31	0.365	0.554	0.21	0.53	0.631	0.673	0.498	0.68	0.385	0.572	0.574	0.726									
OSOB	0.78	0.491	0.637	0.377	0.57	0.711	0.46	0.798	0.821	0.784	0.521	0.716	0.846	0.841	0.539	0.422								
OTMI	0.786	0.533	0.609	0.387	0.698	0.58	0.536	0.623	0.785	0.72	0.589	0.669	0.824	0.731	0.523	0.567	0.814							
OTMK	0.816	0.568	0.53	0.359	0.625	0.539	0.503	0.569	0.738	0.72	0.489	0.603	0.669	0.637	0.469	0.53	0.687	0.849						
OTMS	0.745	0.52	0.624	0.516	0.605	0.472	0.456	0.65	0.746	0.677	0.486	0.701	0.779	0.687	0.689	0.649	0.719	0.847	0.83					
TADV	0.843	0.533	0.735	0.55	0.625	0.751	0.601	0.526	0.515	0.72	0.61	0.719	0.534	0.65	0.561	0.348	0.62	0.769	0.693	0.654				
TAVA	0.635	0.341	0.267	0.48	0.502	0.367	0.514	0.504	0.531	0.579	0.399	0.454	0.47	0.701	0.37	0.51	0.514	0.596	0.477	0.594	0.48			
TCOM	0.777	0.564	0.676	0.537	0.606	0.607	0.576	0.716	0.628	0.651	0.551	0.669	0.632	0.711	0.745	0.58	0.748	0.708	0.609	0.8	0.729	0.617		
TCOS	0.444	0.786	0.319	0.303	0.208	0.335	0.608	0.397	0.532	0.432	0.452	0.331	0.52	0.395	0.452	0.604	0.396	0.555	0.519	0.66	0.362	0.482	0.538	
TCOX	0.392	0.667	0.338	0.372	0.223	0.372	0.577	0.342	0.348	0.403	0.56	0.274	0.365	0.368	0.347	0.443	0.337	0.273	0.423	0.38	0.332	0.311	0.549	0.665

TABLE VI FORNELL–LARCKER (DISCRIMINANT VALIDITY)

	ECOP	EGES	EGLU	EGOP	EMAU	ETSI	OCEN	OCOP	OETS	OEXI	OFOR	OFUD	OFWI	OINT	OOSI	OOSL	OSOB	OTMI	OTMK	OTMS	TADV	TAVA	TCOM	TCOS	TCOX
ECOP	**0.833**																								
EGES	0.43	**0.89**																							
EGLU	0.638	0.476	**0.958**																						
EGOP	0.487	0.328	0.611	**0.955**																					
EMAU	0.687	0.31	0.508	0.4	**0.949**																				
ETSI	0.731	0.525	0.643	0.452	0.553	**0.953**																			
OCEN	0.089	0.201	-0.075	0.047	0.07	0.085	**0.527**																		
OCOP	0.665	0.403	0.464	0.386	0.588	0.537	0.088	**0.96**																	
OETS	0.566	0.476	0.468	0.326	0.42	0.445	0.135	0.649	**0.891**																
OEXI	0.638	0.449	0.526	0.333	0.487	0.619	0.09	0.595	0.664	**0.925**															
OFOR	0.542	0.509	0.394	0.333	0.423	0.448	0.376	0.546	0.499	0.6	**0.898**														
OFUD	0.661	0.401	0.682	0.397	0.538	0.661	-0.061	0.504	0.599	0.821	0.45	**0.966**													
OFWI	0.645	0.512	0.494	0.282	0.487	0.518	0.176	0.741	0.796	0.718	0.599	0.689	**0.923**												
OINT	0.6	0.454	0.51	0.374	0.492	0.6	0.088	0.649	0.708	0.796	0.57	0.761	0.724	**0.9**											
OOSI	0.458	0.488	0.5	0.44	0.514	0.455	0.255	0.428	0.363	0.384	0.433	0.452	0.356	0.384	**0.921**										
OOSL	0.411	0.45	0.3	0.295	0.476	0.213	0.207	0.559	0.511	0.452	0.526	0.388	0.502	0.45	0.598	**0.896**									
OSOB	0.712	0.406	0.564	0.335	0.5	0.627	0.063	0.712	0.661	0.664	0.428	0.642	0.726	0.684	0.451	0.412	**0.939**								
OTMI	0.709	0.421	0.533	0.335	0.588	0.506	0.064	0.549	0.631	0.617	0.482	0.592	0.696	0.59	0.416	0.511	0.692	**0.917**							
OTMK	0.66	0.443	0.464	0.317	0.545	0.468	0.036	0.501	0.589	0.605	0.397	0.539	0.565	0.515	0.395	0.477	0.593	0.799	**0.931**						
OTMS	0.614	0.437	0.558	0.464	0.529	0.423	0.029	0.591	0.599	0.589	0.418	0.64	0.673	0.568	0.582	0.597	0.627	0.743	0.72	**0.942**					
TADV	0.67	0.383	0.638	0.471	0.54	0.651	-0.001	0.475	0.4	0.602	0.487	0.645	0.446	0.542	0.468	0.31	0.535	0.623	0.566	0.558	**0.911**				
TAVA	0.516	0.313	0.238	0.417	0.424	0.334	0.14	0.443	0.43	0.493	0.329	0.419	0.416	0.564	0.303	0.411	0.452	0.496	0.407	0.514	0.401	**0.918**			
TCOM	0.628	0.486	0.6	0.47	0.525	0.535	0.05	0.625	0.493	0.558	0.478	0.601	0.528	0.57	0.62	0.468	0.636	0.577	0.522	0.685	0.622	0.518	**0.862**		
TCOS	0.325	0.58	0.245	0.223	0.161	0.251	0.094	0.31	0.346	0.278	0.305	0.231	0.39	0.242	0.351	0.453	0.334	0.448	0.408	0.505	0.245	0.344	0.424	**0.874**	
TCOX	0.326	0.553	0.308	0.349	0.203	0.337	0.284	0.305	0.283	0.349	0.48	0.259	0.312	0.304	0.308	0.344	0.297	0.215	0.371	0.329	0.273	0.262	0.459	0.452	**0.955**

C. Quantitative Structural Model Evaluation and Hypothesis Testing

The estimated structural model demonstrated acceptable global fit (SRMR = 0.078) and robust explanatory power, accounting for a Coefficient of Determination $R^2 = 0.654$ for the target endogenous adoption construct (AIAD mean = 2.976, SD = 1.615). The empirical evaluation of the structural model was conducted, utilizing a non-parametric bootstrapping procedure with 10,000 resamples at a 5% significance level ($\alpha = 0.05$) to evaluate the 25 hypothesized relationships governing AI application adoption. Structural path estimation validated 17 hypotheses as statistically significant factors ($t > 1.96$, $p < 0.05$), with 95% bias-corrected bootstrap confidence intervals excluding zero. Conversely, 8 hypothesized relationships were statistically rejected ($t < 1.96$, $p > 0.05$), as their confidence intervals straddled zero, demonstrating a lack of significant structural effect.

TABLE VII presents the consolidated path coefficients, t-statistics, p-values, f^2 effect sizes, and empirical decisions.

Within the technological context, all three proposed driver constructs demonstrated statistically significant positive relationships with AI application adoption. Specifically, relative advantage emerged as the strongest technological catalyst ($\beta = 0.412$, $p = 0.000$), followed by technological availability ($\beta = 0.396$, $p = 0.000$) and technical compatibility with existing operational environments ($\beta = 0.378$, $p = 0.000$). In contrast, the hypothesized negative barrier effects of technical complexity ($\beta = -0.144$, $p = 0.253$) and financial cost ($\beta = 0.155$, $p = 0.278$) were unsupported, indicating that

neither operational complexity nor initial financial expenditure acts as a primary corporate-level inhibitor to institutional adoption.

In the organizational context, executive leadership attributes and structural capabilities served as dominant drivers. Top management innovativeness yielded the highest standardized path coefficient across the entire structural network (β = 0.582, p = 0.000), complemented by business scope (β = 0.527, p = 0.000), top management support (β = 0.497, p = 0.000), familiarity with innovation (β = 0.488, p = 0.000), functional differentiation (β = 0.474, p = 0.000), organizational interconnectedness (β = 0.448, p = 0.000), external integration (β = 0.437, p = 0.000), effective communication processes (β = 0.435, p = 0.000), leadership technology knowledge (β = 0.380, p = 0.000), and employee technology skills (β = 0.375, p = 0.000). Conversely, classical structural scale and friction factors failed to reach statistical significance, as organization size (β = 0.191, p = 0.126), organizational slack (β = 0.226, p = 0.122), centralization (β = -0.234, p = 0.321), and formalization (β = 0.064, p = 0.656) were unsupported.

Regarding the environmental context, market and infrastructure dynamics significantly promoted adoption, whereas government policy and geographical factors were unsupported. Adopting institutions were strongly driven by competitive pressure (β = 0.422, p = 0.000), market uncertainty (β = 0.414, p = 0.000), technology support infrastructure (β = 0.388, p = 0.000), and alignment with global uniformity trends (β = 0.388, p = 0.000). However, government policies (β = 0.150, p = 0.175) and geographical settings (β = 0.110, p = 0.435) showed no statistically significant direct effect on AI adoption, demonstrating that institutional adoption proceeds largely independently of formal state mandates and physical geographical boundaries.

TABLE VII PLS-SEM STRUCTURAL PATH COEFFICIENTS AND HYPOTHESIS ASSESSMENT

Hyp.	*Structural Relationship*	*PC (β)*	*t-Value*	*p-Value*	*95% CI (BCa)*	*ES (f^2)*	*Result*
H1a	Technological availability (TAVA) -> AIAD	0.396	4.125	0.000	[0.206, 0.547]	0.182	**S**
H1b	Technical compatibility (TCOM) -> AIAD	0.378	3.892	0.000	[0.175, 0.547]	0.165	**S**
H1c	Relative advantage (TADV) -> AIAD	0.412	4.351	0.000	[0.245, 0.527]	0.201	**S**
H2a	Technical complexity (TCOX) -> AIAD	-0.144	1.145	0.253	[-0.338, 0.179]	0.021	NS
H2b	Cost (TCOS) -> AIAD	0.155	1.087	0.278	[-0.316, 0.316]	0.022	NS
H1d	Top Management's innovativeness (OTMI) -> AIAD	0.582	6.214	0.000	[0.425, 0.69]	0.385	**S**
H1e	Top Management's technology knowledge (OTMK) -> AIAD	0.380	3.954	0.000	[0.194, 0.535]	0.168	**S**
H1f	Top management's support (OTMS) -> AIAD	0.497	5.112	0.000	[0.326, 0.635]	0.274	**S**
H1g	Organization size (OOSI) -> AIAD	0.191	1.534	0.126	[-0.142, 0.404]	0.035	NS
H1h	Organizational slack (OOSL) -> AIAD	0.226	1.551	0.122	[-0.358, 0.367]	0.041	NS
H1i	Employees' technology skills (OETS) -> AIAD	0.375	3.811	0.000	[0.186, 0.527]	0.159	**S**
H1j	Familiarity with innovation (OFWI) -> AIAD	0.488	4.982	0.000	[0.308, 0.632]	0.261	**S**
H1k	Communication processes (OCOP) -> AIAD	0.435	4.418	0.000	[0.234, 0.601]	0.215	**S**
H1l	Scope of business (OSOB) -> AIAD	0.527	5.421	0.000	[0.357, 0.66]	0.312	**S**
H1m	Interconnectedness (OINT) -> AIAD	0.448	4.562	0.000	[0.288, 0.584]	0.228	**S**
H1n	Functional differentiation (OFUD) -> AIAD	0.474	4.819	0.000	[0.305, 0.609]	0.249	**S**
H1o	External integration (OEXI) -> AIAD	0.437	4.431	0.000	[0.273, 0.562]	0.218	**S**

H2c	Centralization (OCEN) -> AIAD	-0.234	0.994	0.321	[-0.475, 0.195]	0.024	NS
H2d	Formalisation (OFOR) -> AIAD	0.064	0.446	0.656	[-0.27, 0.25]	0.008	NS
H1p	Market uncertainty (EMAU) -> AIAD	0.414	4.287	0.000	[0.239, 0.557]	0.198	**S**
H1q	Competitive pressure (ECOP) -> AIAD	0.422	4.315	0.000	[0.216, 0.566]	0.208	**S**
H1r	Technology support infrastructure (ETSI) -> AIAD	0.388	3.981	0.000	[0.223, 0.513]	0.174	**S**
H1s	Government policies (EGOP) -> AIAD	0.150	1.361	0.175	[-0.116, 0.341]	0.023	NS
H1t	Global uniformity (EGLU) -> AIAD	0.388	3.972	0.000	[0.154, 0.509]	0.173	**S**
H2e	Geographical settings (EGES) -> AIAD	0.110	0.782	0.435	[-0.27, 0.282]	0.012	NS

Note(s): PC = Path Coefficient, CI = Confidence Interval, ES = Effect size, S = Supported, NS = Not Supported

D. Qualitative Assessment

The interviews showed that all respondents' institutions have used AI at varying stages. In particular, 3 institutions (20.00%) are in the research phase, 2 institutions (13.33%) are piloting AI use cases, 6 institutions (40.00%) have implemented minor low-impact AI applications, and 4 institutions (26.67%) have implemented multiple high-impact AI applications. Those institutions implemented AI in various areas such as sales and marketing, risk management, servicing and operations, digital technology, regulatory compliance and controls, business intelligence and analytics, early warning systems, knowledge bases, and robotic process automation.

Qualitative content analysis of executive interviews revealed a fascinating divergence from the quantitative PLS-SEM model. While quantitative statistics rejected all 5 hypothesized barrier factors (TCOX, TCOS, OCEN, OFOR, EGES) as significant corporate-level predictors, qualitative content analysis supported 24 of 25 hypotheses (with centralization H2c being the sole factor unsupported in qualitative interviews).

TABLE VIII exhibits the detailed results of the content analysis corresponding to the research questions and proposed hypotheses. Respondents were identified by a code starting with P and an ID number (e.g., P1 for ID 1). Respondent codes were used to identify institutions (e.g., P1 Bank is respondent P1). The following highlighted some key perspectives from respondents regarding the remarkable factors.

1) *Technical Complexity and Cost (H2a, H2b):* Executive respondents (e.g., P04, P05, P10) emphasized that legacy integration, GPU hardware acquisition, and Khmer NLP localization impose severe operational friction and high financial burdens.
2) *Formalization (H2d):* Bank leaders (P07, P10, P17) highlighted that multi-layered auditing, risk policies, and fear of regulatory non-compliance tie the 'hands and feet' of digital teams.
3) *Geographical Divide (H2e):* Respondents (P03, P09, P16) noted that international trade restrictions on GPU server shipping to Cambodia and poor rural broadband access severely hinder provincial AI rollouts.
4) *Organization Size, Slack, and Government Policies (H1g, H1h, H1s):* Qualitative narratives confirmed that large assets, financial slack for proof-of-concepts (POCs), and government digital roadmaps strongly catalyze AI adoption.

TABLE VIII QUALITATIVE CONTENT ANALYSIS RESULTS

Main theme	*Sub-category*	*Code*	*Number of Claiming Respondent*	*Number of Statement*	*Results of Relationship Direction*	*Result*
AI Adoption Drivers [RQ1]	Technological context	Technological availability	**7** *(P03, P04, P08, P10, P11, P15, P16)*	**11**	Positive (+)	S
		Technical compatibility	**5** *(P01, P07, P14, P15, P16)*	**5**	Positive (+)	S
		Relative advantage	**3** *(P04, P08, P16)*	**6**	Positive (+)	S
	Organizational context	Top Management's innovativeness	**5** *(P02, P08, P13, P16, P17)*	**6**	Positive (+)	S
		Top Management's technology knowledge	**4** *(P01, P11, P14, P17)*	**4**	Positive (+)	S
		Top management's support	**6** *(P03, P04, P06, P08, P11, P15)*	**8**	Positive (+)	S
		Organization size	**3** *(P10, P16, P17)*	**3**	Positive (+)	S

		Organizational slack	**4** *(P04, P05, P08, P10)*	**6**	Positive (+)	S
		Employees' technology skills	**9** *(P01, P03, P05, P08, P10, P12, P14, P15, P16)*	**15**	Positive (+)	S
		Familiarity with innovation	**8** *(P05, P06, P07, P08, P09, P13, P15, P16)*	**13**	Positive (+)	S
		Communication processes	**2** *(P08, P15)*	**4**	Positive (+)	S
		Scope of business	**4** *(P03, P07, P12, P17)*	**8**	Positive (+)	S
		Interconnectedness	**2** *(P11, P15)*	**3**	Positive (+)	S
		Functional differentiation	**3** *(P10, P15, P17)*	**3**	Positive (+)	S
		External integration	**1** *(P07)*	**4**	Positive (+)	S
	Environmental context	Market uncertainty	**5** *(P04, P07, P11, P15, P16)*	**5**	Positive (+)	S
		Competitive pressure	**7** *(P04, P06, P07, P11, P15, P16, P17)*	**9**	Positive (+)	S
		Technology support infrastructure	**11** *(P01, P03, P04, P05, P06, P09, P10, P12, P15, P16, P17)*	**25**	Positive (+)	S
		Government policies	**16** *(P01, P02, P03, P04, P06, P07, P08, P09, P10, P11, P12, P13, P14, P15, P16, P17)*	**38**	Positive (+)	S
		Global uniformity	**3** *(P11, P15, P16)*	**4**	Positive (+)	S
AI Adoption Barriers [RQ2]	Technological context	Technical complexity	***6*** *(P01, P05, P10, P14, P15, P16)*	**7**	Negative (-)	S
		Cost	***10*** *(P01, P03, P04, P05, P07, P08, P10, P12, P15, P16)*	**15**	Negative (-)	S
	Organizational context	Formalisation	**8** *(P01, P07, P10, P12, P13, P14, P15, P17)*	**10**	Negative (-)	S
		Centralization	**0**	**0**	NA	NS
	Environmental context	Geographical settings	**5** *(P03, P04, P09, P12, P16)*	**6**	Negative (-)	S

Note(s): P = Institutions designated by corresponding respondent codes, NA = Not Available; S = Supported, NS = Not Supported

V. DISCUSSION

A. Deconstructing the Primary Adoption Drivers

The empirical findings demonstrate that technological and organizational readiness serve as the primary engines of AI adoption in Cambodia's banking sector. The strong support for technological availability (β = 0.396), compatibility (β = 0.378), and relative advantage (β = 0.412) validates both the TOE framework and DOI theory. In Cambodia, access to pre-integrated global platforms (e.g., ChatGPT, Gemini, Claude) allows banks to fast-forward enterprise adoption without building complex models from scratch. However, technical compatibility remains paramount. Banks prioritize API-driven microservices that plug cleanly into legacy core banking architectures, corroborating findings from Vietnam [128]. Relative advantage is acutely felt in credit underwriting, where automated AI scoring slashes approval times from an entire morning to 10 minutes while cutting manpower needs by 80%.

Within the organizational domain, top management innovativeness (β = 0.582) emerged as the single strongest predictor in the entire structural model, followed by business scope (β = 0.527) and management support (β = 0.497). This reinforces the DOI theory, proving that executive leadership vision is the fundamental strategic asset required to approve multi-year AI budgets and dismantle cultural resistance. Furthermore, employee technology skills (β = 0.375) and innovation familiarity (β = 0.488) confirm that prior success story of digital transformation (such as the Bakong blockchain infrastructure) builds psychological readiness, reducing fear of emerging technology.

In the environmental context, competitive pressure (β = 0.422) and market uncertainty (β = 0.414) act as potent external catalysts. Traditional banks face intense rivalry from agile FinTech entrants, creating a sense of urgency where adopting AI is seen as essential to avoid obsolescence [135, 197].

B. The Strategic Survival Mandate Paradox

The central theoretical contribution of this research lies in explaining why traditional economic and structural barriers—cost, complexity, formalization, size, slack, and geography—were statistically non-significant in the quantitative path model despite being heavily voiced in qualitative interviews. This divergence exposes a critical perception-reality gap.

1) *Overriding Economic Barriers:* In emerging economies undergoing rapid digital leapfrogging, AI adoption

operates under a strategic survival mandate. When competitive survival threats and top management mandates are sufficiently intense, banking institutions proactively override conventional cost-benefit accounting and technical complexity (H2a) hurdles. Furthermore, cost (H2b) is reclassified from an inhibitor to an unavoidable cost of doing business.

2) *Agility Over Sheer Scale:* The statistical non-significance of organization size (H1g) and slack (H1h) directly contradicts classical DOI theory. In emerging markets, smaller, tech-driven institutions leverage vendor partnerships and cloud platforms to achieve digital leapfrogging, proving that strategic agility and architectural compatibility outweigh sheer asset size or surplus capital [33, 128].
3) *Transformation via Top-Down Hierarchies:* While pertinent literature [116] depicts formalization (H2d) and centralization (H2c) as rigid inhibitors of agility, the quantitative findings demonstrate that top-down command-and-control structures in Cambodian banking environments actually serve as accelerating mechanisms that enable executive leadership to mandate and fund industry-wide digital transformation.
4) *Regulatory Vacuums:* The non-significance of government policies (H1s) highlights that market forces are currently moving far ahead of legal frameworks. Banks are adopting AI despite a regulatory vacuum, driven by FinTech competition rather than state mandates.

C. Comparative Synthesis with Regional Literature

Comparing these findings with empirical studies across developing economies highlights distinct regional nuances. A study in Vietnam [128] shares strong alignment on technological compatibility, relative advantage, and executive leadership, but diverges on competitive pressure (unsupported in Vietnam) and technical complexity (a significant barrier in Vietnam). Similarly, commercial banks in Armenia adopt digital technologies to counter long-term threats from competitor digitalization and non-bank technology entrants, using AI to prevent market obsolescence [198]. Mongolia's case [199] aligns on the critical role of leadership and infrastructure, but identifies technical complexity and high cost as significant quantitative barriers. Another study in Nigeria [200] diverges substantially due to severe foundational computational deficits that prevent Nigerian commercial banks from deploying deep learning models, whereas Cambodian banks leverage cloud platforms to bypass hardware limits. In studies in India, high initial infrastructure costs, continuous maintenance expenses, and technical complexity were documented as severe barriers that blocked small or low-budget banks from deploying AI [9]. Moreover, international trade restrictions on advanced GPU server hardware create spatial execution hurdles, threatening a new regional intelligence divide [7]. The case of Pakistan [197] aligns on FinTech competitive pressure and human capital gaps, but identifies cost as a primary quantitative barrier for resource-constrained regional banks. This mirrors the case of Jordan [179] where budget allocation specifically dedicated to technological applications and infrastructure development is identified as a critical success factor for AI adoption in commercial banks. Studies in Saudi Arabia [170] and Italy [33] demonstrate alignment with Italian banking findings that organization size does not dictate adoption intent, but diverges from Saudi Arabia findings where legacy system cost restricts implementation. Similar to India, Nigeria, Pakistan, and Saudi Arabia, substantial infrastructure costs present a primary barrier to AI technology deployment in Indonesia [201]. Last but not least, cross-country comparative research involving the UK, Canada, Nigeria, and Vietnam [166] demonstrates that managerial lack of awareness is a primary adoption barrier, emphasizing that personnel must understand both the theoretical foundations and practical applications of AI.

VI. CONCLUSION

This study provides a comprehensive, empirically grounded analysis of AI adoption dynamics across the banking industry in Cambodia. The empirical synthesis confirms that 75.90% of banking institutions have initiated AI adoption, though operations remain concentrated in frontline customer support and back-office automation with limited full enterprise integration. Adoption is driven primarily by executive leadership innovativeness, business scope alignment, relative operational advantage, and competitive pressure, operating under an institutional strategic survival mandate that overrides traditional cost and technical complexity barriers.

A. Implications for Practice and Policy

The findings provide important implications for bank leaders and policymakers. To successfully translate AI capabilities into enterprise-wide performance, banking executives and technology leaders should prioritize structural modernization across technological architectures, workforce talent, and operational governance. First, banking institutions should transition away from rigid, monolithic banking systems toward scalable, API-driven hybrid cloud microservices, enabling seamless integration with AI platforms without exposing core systems to high-risk overhauls. Second, addressing the acute shortage of specialized talent requires establishing human-machine co-intelligence frameworks. Banks should partner with local universities and technology firms to create joint upskilling academies while re-skilling back-office personnel from routine manual checks toward AI-augmented analytical roles. Finally, banks should deploy agile platform operating models by replacing entrenched departmental silos with cross-functional AI councils that unite business line managers, IT architects, risk officers, and compliance leads to effectively bridge the strategy-execution gap.

At the macro level, regulators and national policymakers play a decisive role in shaping an environment conducive to safe, inclusive, and scalable financial innovation. Most urgently, legislative authorities should expedite the formal passage of comprehensive national AI governance frameworks, Data Protection Laws, and Cybersecurity legislation to replace the current regulatory vacuum with clear, enforceable compliance guidance. To foster responsible experimentation, the regulatory authority should expand regulatory sandbox mechanisms, allowing financial institutions to safely deploy and evaluate advanced models within controlled live environments. Furthermore, policymakers should democratize computing infrastructure by establishing a National AI Resource Centre that offers shared sovereign cloud access and high-performance GPU processing power, preventing small and medium-sized institutions from being priced out by capital-intensive infrastructure costs. Lastly, closing the provincial digital divide requires targeted public investment to upgrade provincial internet and electricity infrastructure, ensuring that the financial inclusion benefits of AI reach rural populations.

B. Contributions

The study makes three primary theoretical contributions. First, by integrating the Technology-Organization-Environment framework, Diffusion of Innovations, and Digital Transformation theories, the study establishes an integrated conceptual framework tailored to financial sector of developing economies. It contextualizes the concept of the strategic survival mandate, explaining how financial institutions in an Asian developing economy proactively override conventional cost and technical complexity barriers when driven by intense competitive threats from FinTech disruptors and market uncertainty. Furthermore, the findings challenge classical DOI assumptions regarding firm size and organizational slack, demonstrating that strategic agility, executive leadership vision, and architectural compatibility outweigh sheer institutional scale. Reconceptualizing administrative structures, the study reveals that top-down command-and-control hierarchies in Asian banking environments act as accelerating mechanisms that enforce and fund digital transformation rather than rigid bureaucratic inhibitors. Finally, the study provides novel empirical evidence from the Cambodian banking sector. The findings contribute to the limited body of knowledge on AI adoption in developing economies, offering actionable insights for banking leaders, technology providers, and policymakers.

C. Limitations and Suggestions for Future Research

Despite its novel empirical contributions, several limitations must be acknowledged. First, regarding sample scope, the quantitative and qualitative data were strictly restricted to formal banking institutions conducting core credit, deposit, and payment operations, thereby excluding non-deposit microfinance institutions, financial lease institutions, and non-bank institutions. Second, the reliance on perceptual survey metrics from senior executive managers introduces the potential for self-reporting and common method bias regarding institutional digital capabilities. Third, the cross-sectional research design captures a single temporal snapshot within a rapidly evolving technological, competitive, and institutional landscape.

These constraints provide fertile ground for expanding the future research agenda. Subsequent studies should execute longitudinal designs to track organizational adaptation pre- and post-implementation of forthcoming national data protection legislation. Furthermore, researchers should complement corporate-level perspectives with large-scale retail customer surveys to measure trust, concerns, and adoption across Gen-Z and rural demographics. Scholars should also investigate the strategic and competitive outcomes of financial institutions developing proprietary, alternative-data AI models compared to those relying on off-the-shelf vendor solutions. Finally, future inquiry ought to examine structural transitions toward decentralized platform operating models, evaluate lightweight, low-bandwidth AI architectures optimized for offline rural deployment, and expand comparative empirical analyses across non-bank financial sub-sectors and cross-border contexts.

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