ASEAN INTERNATIONAL SANDBOX CONFERENCE

ASEAN International Sandbox Conference 2025 AISC Proceedings, Volume 7, 2025
https://aseansandbox.org

# Selecting Technologies for Sustainable Digital Transformation in Commercial Banks: An Integrated Delphi - ANP Approach

Ha Viet Le
Department of Information Technology, Thuongmai University, Hanoi, Vietnam
Email: levietha@tmu.edu.vn

## Abstract

Sustainable digital transformation has become a global strategic priority because organisations face pressure to meet environmental, social, and governance (ESG) standards. This study developed an integrated evaluation framework to help commercial banks (CBs) select and prioritise technology applications that improve the effectiveness of sustainable digital transformation. We used the Delphi method and conducted in-depth interviews with 18 senior executives at CBs in Vietnam to identify nine evaluation criteria and reach consensus. Risk level had the highest weight. This result reflected the sector's caution about cybersecurity challenges. We applied the analytic network process (ANP) to model interdependencies among the criteria and derive technology priorities. The main finding indicated a rollout in decreasing priority: Artificial intelligence, cloud computing, big data, robotic process automation, blockchain, and Internet of Things. Sensitivity analysis confirmed that, if the weight of the environmental criterion increased, cloud computing could overtake artificial intelligence. This finding affirmed the role of cloud infrastructure in supporting green objectives. Theoretically, the study extended the TOE framework and Dynamic Capabilities by integrating ESG criteria into the technology selection model. It also advanced a Delphi–ANP procedure that handled nonlinear dependencies. In practice, the study provided a staged technology roadmap and underscored the need for data governance to help banks balance short-term economic gains with long-term sustainability responsibilities.

***Keywords:*** *artificial intelligence, cloud computing, commercial banks, sustainable digital transformation*

## 1. Introduction

Sustainable digital transformation (STD) in commercial banks is regarded as a global strategic priority. Within this agenda, banks needed to deploy new technologies to meet ESG standards (Alshdaifat et al., 2024; Soomro et al., 2025). STD restructured banking operations and redefined relationships with customers, creating new requirements for social responsibility and sustainability (Al-Ansi et al., 2024; Nwachukwu et al., 2025). In developing markets, more than 90% of financial transactions were conducted through digital channels, reflecting rapid and profound digitalisation (Bueno et al., 2024). However, prior studies have shown that selecting and integrating new technologies to achieve STD remains a complex challenge (Amiri et al., 2023; Wang, Hu, & Guan, 2025). Legacy systems were a major constraint due to their outdatedness, inflexibility, and difficulty of integration. Technology investment decisions were multi-criteria and interdependent problem in which the value of each technology could be amplified or offset by the presence of complementary technologies (Wang et al., 2025). Artificial Intelligence (AI), Big Data, and Cloud Computing applications faced challenges in data governance, privacy, and algorithmic bias, with ethical and legal implications (Rane et al., 2024). Migrating core banking to the cloud offered flexibility but posed significant data-security risks (Subramanian & Jeyaraj, 2018). These barriers were compounded by accumulated "technical debt," which increased integration cost and complexity. Therefore, to deploy new technology applications, banks need a decision framework that prioritises technologies aligned with their digital transformation strategy.

Although many studies examined the effects of individual technologies on bank performance, significant research gaps persisted. First, existing studies used linear or simple hierarchical decision models that did not capture interdependencies and feedback loops among criteria and technologies in the complex Fintech ecosystem (Wang et al., 2025). Second, despite the growing importance of ESG, sustainability criteria were seldom systematically and quantitatively integrated into banking technology-selection models (Fahad & Bulut, 2024). Many studies confirmed that ESG objectives often held lower priority than financial and risk objectives when allocating technology budgets (Saeedi & Ashraf, 2024). Third, most studies focused on developed markets and overlooked challenges specific to emerging economies, including evolving regulation, limited financial resources, and digital skills gaps. In addition, a methodological gap remained in combining structured expert consensus with network-analytic techniques to prioritise technology choices under uncertainty (Beiderbeck et al., 2021).

This study aimed to develop a framework to prioritise the deployment of technology applications in CBs. We used the Delphi method and conducted in-depth interviews with 18 senior executives at CBs in Vietnam to identify and reach consensus on the evaluation criteria (Barrios et al., 2021; Beiderbeck et al., 2021). We then applied ANP to model the interdependencies among the requirements and determine the optimal priority order of new technologies based on the validated criteria (Saaty, 2008). This approach differed from prior studies by combining structured expert knowledge with quantitative multi-criteria analysis and by integrating ESG factors into strategic technology decision-making (Makki & Alqahtani, 2022). The study extended the TOE and DC frameworks to the context of technology selection for STD, particularly by integrating ESG criteria into technology assessment. It also developed a methodological framework combining Delphi and ANP to address complex decisions involving interdependent criteria. In practice, the results provided a specific, evidence-based roadmap for CBs to prioritise technology investments and balance short-term economic benefits with long-term sustainability goals (Syarifuddin, 2024; Vaidya, 2022).

The paper is structured as follows. Section 2 reviews theoretical foundations and related studies and discusses baseline frameworks and the state of technology adoption in banking. Section 3 details the research methods and explains the rationale and procedures for the integrated Delphi-ANP model. Section 4 reports the results from both the Delphi and ANP stages, including criterion weights and the ranking of technologies. Section 5 discusses the findings and presents theoretical and practical implications. Finally, Section 6 concludes with the main insights, limitations, and directions for future research.

## 2. Objectives

This study aimed to develop an integrated evaluation framework that combines the Technology–Organization–Environment (TOE) model with Dynamic Capabilities (DC) theory to achieve two research objectives:

1. To identify the criteria for selecting new technologies in the digital transformation of commercial banks.
2. To analyze the prioritization of technologies implemented in the digital transformation of commercial banks.

TOE offers a structured lens for identifying criteria for new technology implementation. It posits that adoption decisions depend on three contexts: technology (compatibility, complexity), organisation (resources, implementation capability), and environment (competitive pressure, regulation) (Baker, 2012). In banking, TOE has been used to study the deployment of cloud computing and fintech initiatives (Makki & Alqahtani, 2022). A recognised limitation of TOE is its largely static view, which does not capture the co-evolution of technology and organisational structures in volatile financial settings. DC theory focuses on the firm's ability to sense opportunities, seize resources, and reconfigure internal capabilities to sustain competitive advantage under change (Al-Ansi et al., 2024). Prior research used DC to explain how banks mobilise these capabilities to innovate and adapt (Mikalef et al., 2020).

Combining TOE and DC creates mutual reinforcement. TOE specifies what criteria to consider when implementing new technology. DC clarifies how these technologies convert into strategic value. This combination balances strict compliance demands in the regulatory environment (the E context in TOE) with the urgent need to build dynamic capabilities that enable rapid response to Fintech innovation. Therefore, technology choices should serve capability building rather than only immediate operational needs. Together, these concepts yield a synthetic theoretical framework for assessing and guiding STD in CBs, addressing technological and strategic complexity simultaneously (Al-Ansi et al., 2024; Patrício et al., 2024).

## 3. Materials and Methods

### *3.1. Research design*

The study combined the Delphi and ANP methods to address two questions: the technology selection criteria and the priority order for deployment in the STD process. First, the study used the Delphi method to identify the technology selection criteria. Delphi provided a structured process for collecting and refining expert opinions to reach consensus on evaluation criteria in complex contexts (Beiderbeck et al., 2021). Technological factors and evaluation criteria in the banking ecosystem were not linearly independent. They showed mutual dependencies and feedback loops. Therefore, the study applied ANP to model these network relationships and to convert qualitative judgments into quantitative weights.

We conducted interviews with 18 senior banking leaders in Vietnam. We selected the panel purposively to ensure diversity and representation, including managers from state-owned CBs, joint-stock CBs, and foreign banks. The interviewees held a range of professional roles, from CEO/Deputy CEO to Chief Information Officer (CIO) / Chief Technology Officer (CTO), and Chief Risk Officer (CRO). This diversity was necessary to ensure that the final evaluation framework was not biased by the culture of a single organizational type or the perspective of a single functional area, and that it reflected the sector's challenges and priorities.

*3.2. Delphi Method*

We implemented the Delphi method through an iterative interview process to reach consensus on the determinants of effective STD and to ensure the evaluation framework aligned with industry practice (Beiderbeck et al., 2021). We conducted Delphi anonymously and independently to minimize bias from group pressure or authority in complex multi-criteria evaluation settings. Table 1 below presents the panel demographics and demonstrates diversity across bank types (dominant state-owned banks, TMCPs, and foreign banks).

**Table 1** Demographic statistics of the expert panel (n = 18)

| Item | Group | Quantity | Percentage (%) |
|---|---|---|---|
| Gender | Male | 13 | 72.22% |
| | Female | 5 | 27.78% |
| Age range | <=40 | 6 | 33.33% |
| | 40-50 | 8 | 44.44% |
| | >=50 | 5 | 27.78% |
| Job position | CEO/Deputy | 6 | 33.33% |
| | CIO/CTO | 4 | 22.22% |
| | CRO | 3 | 16.67% |
| | Head of Digital Banking | 3 | 16.67% |
| | Chief Operating Officer | 2 | 11.11% |
| Bank type | State-Owned Commercial Bank | 5 | 27.78% |
| | Joint Stock Commercial Bank | 10 | 55.56% |
| | Foreign bank in Vietnam | 3 | 16.67% |
| Experience | <= 10 years | 7 | 38.89% |
| | 10-20 years | 8 | 44.44% |
| | >=20 years | 3 | 16.67% |
| Education level | Master | 11 | 61.11% |
| | PhD | 7 | 38.89% |

The Delphi procedure comprised two rounds. Drawing on the literature review and the industry context, the research team developed a list and working definitions for the criteria; Round 1 collected open and semi-structured feedback, which we then synthesized, standardized, and returned anonymously for expert revision in Round 2. The Delphi process was iterative and aimed for high consensus on the evaluation framework. To quantify consensus and strengthen methodological robustness, we used a 5-point Likert scale for the dimensions "relevance–feasibility–coordination". To ensure that the final results accurately reflected expert agreement, we calculated the coefficient of variation (CV) for each criterion. We computed CV as the standard deviation (lower values preferred) divided by the criterion's mean. A criterion was accepted only when CV $\leq$ 0.20, consistent with Delphi practice. CV was calculated from the mean and standard deviation of the ratings to provide an objective measure of convergence. To ensure that the criteria base was well-grounded and could feed directly into the quantitative model, we implemented Delphi as a complementary mechanism to ANP.

*3.3 ANP method*

We used ANP to build the criteria–alternative network from the Delphi inputs; to collect pairwise comparisons on the 1–9 scale; to test consistency (C·R) and compute the supermatrix; to derive limit weights; and to run robustness checks through sensitivity scenarios (Saaty, 2008). During matrix adjustment, we used the consistency ratio (C·R), calculated as C·R = (C·I)/(R·I), as the reference. We accepted C·R < 0.10. This approach ensured fit to the Vietnamese context (based on the panel of 18 banking leaders and the nine agreed criteria) while maintaining international ANP standards for handling interdependence and feedback in multi-criteria decision-making. The ANP network had three layers, as shown in Figure 1: (i) the goal layer, "technology deployment priority for STD"; (ii) the criteria cluster with the nine Delphi-agreed criteria; and (iii) the alternatives cluster with six technologies: AI, Cloud, Big Data, RPA, Blockchain, and IoT. With this network, ANP allowed criteria to interact within and across clusters and reduced "double counting" of weights when dependencies existed.

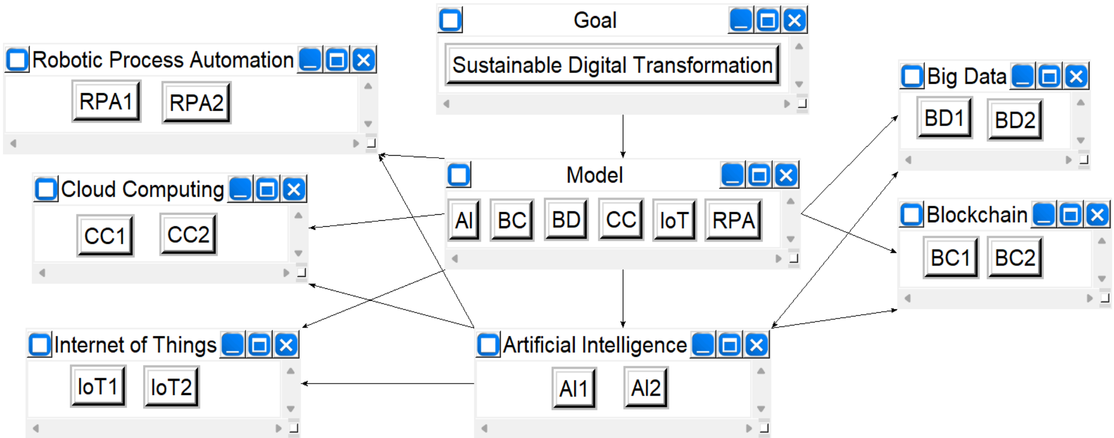


**Figure 1** ANP network structure in the SuperDecisions software

After building the ANP network, the expert panel used Saaty's 9-point scale to conduct pairwise comparisons of the relative importance of each criterion. The study ran three layers of assessment: (a) the relative importance among criteria; (b) the relative contribution of each technology for each criterion; and (c) the dependency arcs among criteria, where applicable. The judgment matrices for each observed criterion and technology reflected mutual influence. We tested each matrix for C·R < 0.10. If the condition held, the error lay within an acceptable range. If it exceeded the threshold, experts reviewed their judgments to restore consistency. Because each matrix arises from pairwise comparisons within a factor group, maintaining consistency across the full system of criteria can be difficult and affect subsequent eigenvector and eigenvalue calculations. Therefore, we checked the consistency of each judgment matrix to keep errors within acceptable limits. We entered the comparison matrices into SuperDecisions 2.10 to: (1) create the unweighted supermatrix; (2) perform cluster normalization to obtain the weighted supermatrix; and (3) raise the matrix to powers until convergence to derive the limit matrix, from which we extracted the global priority vector for the six technologies (Syarifuddin, 2024).

After deriving the weights from the limit matrix, we conducted a sensitivity analysis to assess the stability of the technology ranking under strategic shifts in the criteria weight allocation. We designed three scenarios that emphasized risk (risk_up), cost (cost_up), and environment (env_up). This design is related directly to banking governance. When the organization temporarily prioritized cost, cost-saving technologies could rise in rank, whereas an environmental emphasis highlighted green infrastructure and sustainable development. Phần này cần cung cấp đủ chi tiết để các nhà nghiên cứu có đủ trình độ có thể sao chép toàn bộ nghiên cứu. Cần đưa vào các giao thức cho các phương pháp mới, nhưng cũng có thể tham khảo các giao thức đã được thiết lập tốt.

## 4. Results and discussion

*4.1. Delphi analysis results*

The study selected twelve initial criteria to evaluate STD for CBs: risk level, cost efficiency, information security, implementation capability, environmental impact, customer experience, data governance, system interoperability, scalability, regulatory compliance, integration with legacy systems, and technology readiness.

**Table 2** Delphi analysis results for technology selection criteria

| No. | Criteria | $\bar{X}$ | S | CV | Description |
|---|---|---|---|---|---|
| 1 | Risk exposure | 4.78 | 0.43 | 0.09 | Potential for financial loss, operational disruption, or reputational damage arising from the adoption and integration of new technology, including compliance, cybersecurity, and operational risks (Nwachukwu et al., 2025). |
| 2 | Cost efficiency | 4.56 | 0.51 | 0.11 | The extent to which a technology helps optimize operational costs, reduce transaction costs, and deliver a quantifiable return on investment (ROI) within a defined timeframe (Vaidya, 2022). |
| 3 | Information security | 4.83 | 0.38 | 0.08 | The technology's capability to protect the integrity, confidentiality, and availability of customer data and transaction data against unauthorized access and attacks (Subramanian & Jeyaraj, 2018). |
| 4 | Implementation capability | 4.67 | 0.49 | 0.10 | The organization's readiness in terms of resources (personnel, finance), processes, and IT infrastructure to successfully integrate and operate a new technology solution (Al-Ansi et al., 2024). |
| 5 | Environmental impact | 4.22 | 0.65 | 0.15 | The technology's contribution to reducing the bank's carbon footprint, optimizing energy efficiency, and supporting green finance initiatives (Rane et al., 2024). |
| 6 | Customer experience | 4.72 | 0.46 | 0.10 | The technology's ability to create seamless, personalized, and convenient customer interactions across digital channels, thereby enhancing satisfaction and loyalty (Nwoke, 2024). |
| 7 | Data governance | 4.61 | 0.5 | 0.11 | The technology's capacity to consistently, accurately, and in compliance with privacy regulations support data collection, storage, management, and use throughout the entire data lifecycle (Rane et al., 2024). |
| 8 | System interoperability | 4.39 | 0.61 | 0.14 | The technical and operational ability of a new technology to exchange data and integrate seamlessly with existing legacy systems and third-party platforms, avoiding the creation of data silos (Al-Ansi et al., 2024). |
| 9 | Scalability capacity | 4.50 | 0.51 | 0.11 | The technology's ability to accommodate growth in transaction volume, user numbers, and service diversity without degrading performance or incurring unreasonable cost increases (Hasan, Popp, & Oláh, 2020). |

*Note: Mean ($\bar{X}$), standard deviation (S), coefficient of variation (CV)*

After two rounds of the Delphi process, the study again collected and synthesized feedback from 18 experts, achieving a 100% response rate. The experts did not object to the original evaluation dimensions; however, they proposed adjustments to specific criteria within each dimension. The initial STD criteria identified from the literature review were reduced to nine in the final round. The requirements - regulatory compliance, integration with legacy systems, and technology readiness - were removed due to overlap with other criteria or difficulties in collecting quantitative data. Notably, the experts refined the wording of specific criteria and reached consensus that these nine criteria provided a comprehensive assessment of technology adoption (Barrios et al., 2021; Beiderbeck et al., 2021). The criteria listed in Table 4.2 provide a multidimensional and comprehensive perspective for evaluation and serve as the basis for the subsequent ANP analysis stage.

Table 2 shows that each criterion met the specified standard with a CV below 0.20, indicating high agreement among experts on the validity of these nine criteria. The criteria “information security” and “risk level” had the lowest coefficients of variation (0.08 and 0.09, respectively), indicating near-unanimous expert agreement on their validity (Beiderbeck et al., 2021). The standard deviations of the remaining seven criteria ranged from 0.40 to 0.65, showing that most ratings were close to the mean and reflecting basic consensus among the experts (Barrios et al., 2021). Notably, the “environmental impact” criterion had the highest CV (0.15), suggesting varied expert views on the priority of sustainability in Vietnam’s banking sector, consistent with studies that show ESG objectives often rank below core financial and risk goals (Fahad & Bulut, 2024).

**Table 3** Evaluation framework for technology applications

| Technology | Evaluation Criterion | Measurement Content |
|---|---|---|
| Artificial Intelligence | Risk Level | Cumulative success rate of CBs using AI technology to prevent default risk in the current year. |
| | Customer Experience | Cumulative number of customers served through the bank's intelligent investment advisory service and chatbot. |
| Cloud Computing | Deployment Capability | Degree of core system migration to the cloud and the number of applications deployed on the cloud platform. |
| | Information Security | Cumulative number of data security risks encountered during data transmission on the cloud. A higher number indicates weaker data security capability. |
| Big Data | Environmental Impact | Reduction in energy consumption and carbon emissions from using CBs's cloud infrastructure compared to the previous year. |
| | Data Governance | Number of times customer data is integrated and governed using the big data technology. |
| | Cost-Effectiveness | Reduction in operating costs based on big data analysis between the previous year and the current year for CBs. |
| Robotic Process Automation | Resource Efficiency | Number of personnel replaced achieved through RPA. |
| | System Integration Capability | Degree of RPA integration with existing systems and the number of processes automation. |
| Blockchain | Scalability | Cumulative number of cross-border payment transactions executed using the blockchain technology. |
| | Data Security & Privacy | Support for private transactions and ensuring data security. |
| Internet of Things | Data Processing & Analysis Capability | Ability to process real-time data streams at the edge, integrating AI/ML to provide warnings and predictions. |
| | Connectivity Protocol Support | Compatibility with multiple connectivity standards, such as 5G, Wi-Fi, LoRaWAN, NB-IoT, MQTT, and CoAP to suit different deployment environments. |

Through a comprehensive literature review and an iterative Delphi process, the study systematically identified six main evaluation dimensions in Table 3: AI, Cloud Computing, Big Data, RPA, Blockchain, and IoT. These dimensions primarily assessed how these technologies improved operational efficiency through innovation in financial products and services (Amiri et al., 2023; Wang et al., 2025). The framework balanced operational, strategic, technological, and environmental objectives, and integrated ESG criteria into technology evaluation (Al-Ansi et al., 2024; Saeedi & Ashraf, 2024). The Delphi results provided a "consensus-filtered" input for the subsequent ANP analysis, in which the final weights for each criterion were determined via pairwise comparisons.

*4.2. ANP analysis results*

Experts conducted pairwise comparisons of the relative importance of the factors using Saaty's 9-point scale. We then constructed the judgment matrices and verified their consistency to ensure errors were within acceptable bounds. Specifically, we calculated the consistency ratio (CR) and required CR < 0.10. If a matrix did not meet this condition, we adjusted it using the Random Index (RI) (Syarifuddin, 2024). The consistency test results for the main judgment matrices are reported in Table 4.

**Table 4** Consistency verification of the judgment matrices

| Judgment matrix | Consistency Ratio (CR) |
|---|---|
| Comparison between criteria | 0.085 |
| Technology by risk level | 0.071 |
| Technology by cost-effectiveness | 0.064 |
| Technology by information security | 0.079 |
| Technology by deployment capability | 0.088 |
| Technology by environmental impact | 0.053 |
| Technology by customer experience | 0.081 |
| Technology by data governance | 0.066 |
| Technology by system integration capability | 0.049 |
| Technology by scalability | 0.058 |

Table 4 indicates that all consistency ratios are below 0.10, showing a high level of consistency in expert judgments. After the matrices passed the test, we formed the unweighted supermatrix. We then applied column-wise normalization to obtain the weighted supermatrix and raised it to successive powers until convergence to derive the limit matrix. The values in the limit matrix represent the global priority weights of the technologies.

**Table 5** Consistency check results for each judgment matrix

| Judgment matrix | Goal | Aggregated criteria | AI | Cloud | Big Data | RPA | Blockchain | IoT |
|---|---|---|---|---|---|---|---|---|
| CR | 0.078 | 0.082 | 0.019 | 0.022 | 0.010 | 0.029 | 0.012 | 0.008 |

*Note: Because the order of each interdependent matrix at the subnetwork level is less than 3, their consistency ratio (CR) equals 0.*

Table 5 shows that the consistency ratio (CR) for all judgment matrices was below 0.10, indicating satisfactory consistency and confirming that the matrices were acceptable. After all matrices passed the consistency test, we created the unweighted supermatrix. However, the unweighted supermatrix only captured the interdependencies among criteria and did not account for their weights. To address this, we normalized each column to obtain the weighted supermatrix. We then raised the weighted supermatrix to successive powers until it converged, producing the limit matrix. The elements in each column of the limit matrix no longer changed materially, indicating that the system had reached a stable state. We could then determine the aggregated weights of the criteria, as presented in Table 6.

**Table 6** Results of technology priority weight computation

| Technology | Normalized Weight | Rank | Application |
|---|---|---|---|
| Artificial Intelligence | 0.298 | 1 | Credit risk management, fraud detection, biometric eKYC, personalized experience |
| Cloud Computing | 0.295 | 2 | Platform infrastructure, scalability, reducing IT costs, supporting the ESG environment |
| Big Data | 0.172 | 3 | Customer behavior analysis, data-driven risk management, and a platform for AI |
| Robotic Process Automation | 0.155 | 4 | Automating back-office processes, reducing operational errors, and short-term cost optimization |
| Blockchain | 0.048 | 5 | Cross-border payments, trade finance, supply chain transparency |
| Internet of Things | 0.031 | 6 | ATM predictive maintenance, collateral asset monitoring, and selective applications |

The results show a clear stratification in priority. AI (0.2982) and Cloud Computing (0.2949) formed the top tier. AI ranked first because it enhanced credit scoring, fraud detection, eKYC –biometrics, and portfolio personalization, applications already proven in banking. Cloud Computing ranked highly as the foundational infrastructure. It provides the compute required for advanced analytics, scales resources flexibly, lowers infrastructure costs, and raises service availability, with positive ESG effects when paired with robust digital infrastructure governance (Chen, You, & Chang, 2021). Big Data (0.1724) and RPA (0.1552) constituted the second tier. Big Data provided input to AI models and supported data-driven decision-making (Hasan et al., 2020). RPA scored well for improving operational efficiency and reducing errors in back-office processes. Big Data also strengthened risk management and operational performance through transaction and behavioral analytics, consistent with the data–dynamic capability argument (Mikalef et al., 2020). Blockchain (0.0483) and IoT (0.0310) had markedly lower priority. Despite potential in specialized areas such as trade finance and cross-border payments, Blockchain deployment remained limited due to ecosystem and integration barriers (Shahid et al., 2025).

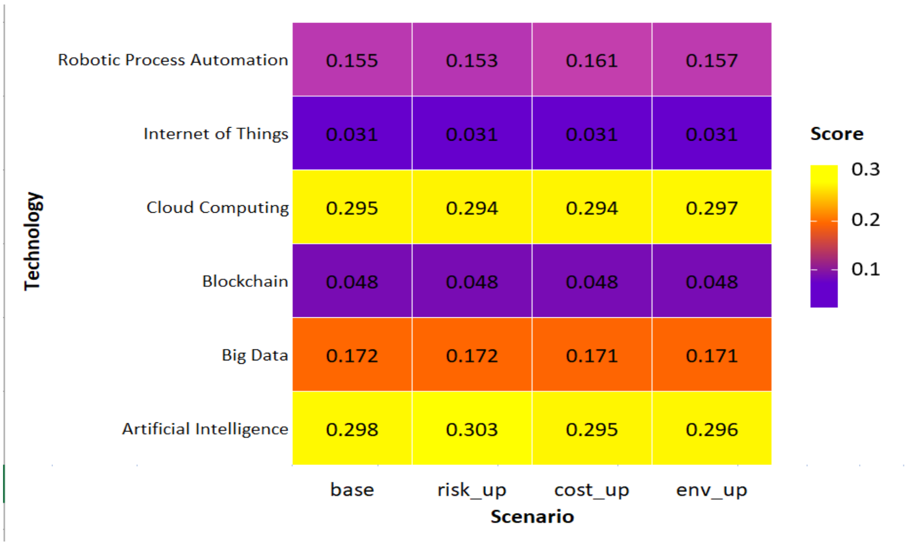


**Figure 2** Sensitivity of global priority scores to changes in criterion weights

We conducted a sensitivity analysis to assess the ANP model's stability when criterion weights change. We simulated three scenarios: higher priority for risk level (risk_up), cost efficiency (cost_up), and environmental impact (env_up), relative to the base scenario (base). The results in Figure 2 confirm that the model is highly stable. In most scenarios, the technology ranking did not change materially. AI and Cloud Computing consistently ranked first and second. In the "cost_up" scenario (increased priority for cost efficiency), the RPA score rose slightly (from 0.155 to 0.161), reflecting its direct link to cost optimization; however, the overall ranking remained unchanged. The most notable shift appeared in the "env_up" scenario (increased priority for environmental impact), where Cloud Computing (0.297) surpassed AI (0.296) to take first place. This highlights the role of optimized cloud infrastructure in improving energy efficiency and supporting green development goals. The overall stability confirms the robustness of the prioritization model and indicates that AI and Cloud Computing are foundational to STD despite modest shifts in strategic emphasis.

*4.3 Discussion*

*4.3.1 Technology selection criteria for sustainable digital transformation*

The Delphi analysis revealed strategies for selecting new technologies in bank digital transformation. The most salient finding is the prioritization of pragmatic and defensive criteria, which reflects a cautious approach focused on foundational issues. The results show that risk exposure ranked first with the highest weight (0.16), followed by implementation capability (0.15). This pattern indicates that executives prioritize controlling operational, compliance, and security risks arising from new technologies while ensuring the organization has sufficient ability to implement transformation projects successfully. This prioritization aligned with prior studies that emphasized risk governance and the challenges of integrating new technologies into complex legacy systems.

In contrast, aspirational and future-oriented criteria received much lower weights. Notably, environmental impact ranked seventh (0.08), whereas system interoperability ranked last (0.05).

This hierarchy is not merely a strategic choice; it also signals the current stage of development of Vietnam's banking industry. The emphasis on risk and implementation capability suggests that organizations remain in a "foundation-consolidation" phase, focusing on core challenges such as responding to competitive pressure from Fintech firms, modernizing legacy IT infrastructure, and complying with increasingly complex regulations. Before banks can fully pursue a comprehensive sustainability agenda aligned with international practice, they need to secure stability and safety in core operations. This creates a noticeable "sustainability gap." While international academic literature increasingly treats environmental, social, and governance (ESG) factors as integral to financial strategy and risk management, the expert panel in this study positioned them as secondary concerns. This discrepancy indicates a potential vulnerability as global capital standards and regulatory regimes become increasingly closely aligned with ESG goals.

In addition, the very low weight assigned to system interoperability (0.05) exposes a paradox and a serious long-term risk. The top-priority technologies in the ANP analysis (AI, Cloud, Big Data) are inherently data and network-dependent; they deliver maximum value only when systems can communicate seamlessly. Prioritizing isolated deployments without commensurate attention to interoperability reflects a silo-based approach. This is a typical recipe for new forms of "technical debt," where large integration costs and data fragmentation later offset early gains from standalone projects. Consequently, the experts' focus on immediate implementation capability may inadvertently create a more complex and costly integration challenge in the future, which runs counter to the vision of an integrated and comprehensive digital ecosystem outlined in studies such as Al-Ansi et al. (2024).

The above weighting structure arose from: (i) compliance and security pressures when moving core systems to the cloud and opening APIs, which led banks to prioritize risk and safety (Subramanian & Jeyaraj, 2018); (ii) legacy systems that raise implementation difficulty, which increased the weight on capability to execute; (iii) market pressure for digital experience (eKYC, hyper-personalization), which placed the customer experience criterion on par with security; and (iv) ESG-E, despite its growing visibility, has not yet become the engine of IT budgets unless policy levers or incentives exist. These dynamics are evident in Vietnam: the number of eKYC accounts has increased rapidly, and large banks have reported cases of core-to-cloud migration and process automation.

*4.3.2 Priority order for deploying technologies in sustainable digital transformation*

The ANP analysis identified a clear and structured priority order for technology deployment. This result reflects a logical strategic roadmap that aligns with the priorities established in the Delphi phase. The analysis showed that AI (0.298) and Cloud Computing (0.295) form a dominant foundational pair in the highest-priority tier. A secondary tier includes Big Data (0.172) and RPA (0.155). By contrast, Blockchain (0.048) and the IoT (0.031) were not deployed in many cases. This result aligned with prior research that identified AI, Cloud, and Big Data as a pillar triad with strong complementarities in modern finance. AI (the intelligence) and Cloud Computing (the engine) are prerequisites for bank digital transformation, while Big Data (the fuel) powers them.

Specifically, in AI applications, the highest weight reflected its role in improving credit scoring (Shahid et al., 2025; Nwoke, 2024), fraud detection (Nwachukwu et al., 2025; Hasan et al., 2020; Pradhan & Gain, 2025), biometric eKYC, and portfolio personalization (Pundareeka Vittala et al., 2024). Banks deployed Cloud Computing as a foundational infrastructure. It provides compute capacity for advanced analytics, elastic scalability, lower infrastructure costs, and higher service availability; it also has positive ESG effects when paired with green digital infrastructure governance (Hasan et al., 2020; Mikalef et al., 2020). Big Data supplied inputs to AI models and supported data-driven decision-making, strengthening risk governance and operational performance through transaction and customer behavior analytics (Hasan et al., 2020; Mikalef et al., 2020). RPA was valued for improving operational efficiency and reducing errors in back-office processes, although gains depended on the degree of process re-engineering and integration with AI and Cloud (Patrício et al., 2024). Blockchain and IoT received much lower priority, reflecting limited deployment due to ecosystem and integration barriers.

The proposed deployment roadmap is: (1) build intelligent and scalable infrastructure (AI on Cloud); (2) optimize existing processes and exploit data assets (RPA and Big Data); and (3) explore disruptive, ecosystem-level technologies (Blockchain, IoT) once the foundation is solid (Makki & Alqahtani, 2022; Wang et al., 2025). This approach indicates a deliberate strategy, rather than a chaotic technology race. Although Blockchain had been widely studied for its digital transformation benefits, banks placed Blockchain applications last in their sequence. This pattern reflects a realistic assessment of a nascent ecosystem and legal uncertainty in emerging markets such as Vietnam.

A new finding emerged when comparing the ANP results with the technology-selection criteria. AI, which depends heavily on input data, ranked first. In contrast, data governance, the foundation for effective AI, ranked only fifth, with a weight of 0.12. This inconsistency shows that banks appear more attracted to value-generating AI applications than to the foundational, less visible work of building robust data-governance frameworks. The value of big-data analytics capability does not arise directly; it is mediated by other organizational capabilities, suggesting that technology alone is insufficient. Therefore, deprioritizing data governance controls is a significant latent risk in Vietnamese banks' digital transformation strategies. Without elevating the strategic importance of data governance, prioritized investments in AI and Big Data may not deliver the expected return on investment (ROI). They may even create new risks related to data quality, algorithmic bias, and privacy. A notable nuance is that Cloud can outrank AI when banks increase the weight on environmental criteria (the env_up scenario in the sensitivity analysis), due to its advantages in energy efficiency and green infrastructure governance. If ESG goals move to the forefront, the cloud becomes a more critical lever for reducing the carbon footprint and improving resource efficiency.

*4.3.3 Theoretical contributions*

The study's unique contribution is the development and empirical testing of an integrated Delphi-ANP model tailored to evaluating technology choices for STD. Although combined Delphi-ANP models have been used to assess Fintech innovation in general, this study is among the first to integrate sustainability criteria (environmental impact) explicitly and to apply this analytical framework to the banking sector in an emerging economy. In doing so, the study addressed the gap left by the absence of system-oriented frameworks to model interdependencies among criteria and by the limited incorporation of ESG factors into technology-selection models.

In addition, the study extended the TOE and DC theories. The ANP model operationalized complex, non-linear interactions among Technology characteristics (the six evaluated technologies), the Organizational context (implementation capability, data governance), and the Environmental context (risk exposure). Moreover, the study enriched the dynamic capabilities view by providing a structured decision tool that helps organizations "sense" (via Delphi expert consensus), "seize" (by prioritizing technologies with ANP), and "reconfigure" their technological and operational assets. The results provided empirical evidence that technology selection was closely linked to the building and development of these dynamic capabilities.

*4.3.4 Practical contributions and managerial implications*

The findings provide practical implications for multiple stakeholders in the banking–finance ecosystem, including bank leadership, regulators, and technology vendors. The integrated Delphi–ANP approach not only ranked technology priorities but also identified governance, legal, and collaboration prerequisites for systematic investment decisions, strategy formulation, and risk management. Multi-stakeholder coordination helps banks overcome system-level barriers such as technology infrastructure constraints, talent shortages, and limited system interoperability (Wang et al., 2025).

For commercial banks, the study proposes a structured, capability-staged technology roadmap to help them shift from ad hoc adoption to a comprehensive digitalization strategy. The ANP results indicated that AI and Cloud Computing are foundational technologies that build an "intelligent infrastructure" for STD; Big Data and RPA support operational optimization and decision-making; and Blockchain and IoT should be deployed selectively in later phases after the ecosystem and regulatory framework mature (Mikalef et al., 2020; Wang et al., 2025). Accordingly, the proposed investment roadmap includes the following phases:

1) Prioritize AI in risk management, cybersecurity, and personalization of customer experience.
2) Build a "core-on-cloud and data lakehouse" infrastructure to ensure flexibility and ESG compliance.
3) Expand Big Data applications for marketing and credit scoring.
4) Apply RPA to improve process productivity.
5) Pilot Blockchain for cross-border payments, reconciliation, and trade finance.
6) Use IoT for collateral monitoring and ATM maintenance

The Delphi results also revealed a "data governance paradox": the "data governance" criterion received only a moderate weight (0.12) even though AI and Big Data ranked highest. This imbalance warns that banks may invest heavily in AI without a robust data foundation, which can lead to algorithmic bias, privacy breaches, and reputational harm (Rane et al., 2024). Therefore, Chief Data Officers (CDOs) and Chief Information Officers (CIOs) should elevate data governance to a board-level strategic priority rather than treat it as a technical issue.

For regulators: The study showed that a flexible, innovation-oriented legal framework is a prerequisite to balance technology development with system stability. Policies should clarify data privacy, information security, and ethical standards when applying AI in credit scoring or customer service, similar to GDPR (Makki & Alqahtani, 2022; Pradhan & Gain, 2025). The low weights for environmental impact (0.08) and system interoperability (0.05) indicate a short-term focus on financial and core risk objectives. However, delaying investments in interoperability will lead to siloed systems, data fragmentation, and high future integration costs, thereby limiting the value of the digital ecosystem (Al-Ansi et al., 2024). Regarding sustainability, the sensitivity analysis revealed an important insight: as environmental weight increases, cloud computing overtakes AI. This suggests that banks should leverage cloud migration not only for operational efficiency (Hasan et al., 2020; Al-Ansi et al., 2024; Syarifuddin, 2024) but also as a strategic lever to improve energy efficiency and support green finance goals (Rane et al., 2024; Fahad & Bulut, 2024).

For technology vendors and consultants: The study suggests that solution providers should adjust their value propositions and market messages to align with Vietnamese banks' priorities: risk reduction, security assurance, cost optimization, and implementation simplicity. Proposals such as “AI for credit risk control” or “secure, ESG-compliant cloud migration” are more persuasive than offerings that only emphasize novelty (Pundareeka Vittala et al., 2024; Shahid et al., 2025). Firms that can deliver integrated solutions, combining AI-as-a-Service on a secure cloud with strategic data advisory, will hold a sustainable competitive advantage in a rapidly transforming financial market.

## 5. Conclusion

In the current wave of banking digital transformation oriented toward environmental, social, and governance standards, this study develops an integrated evaluation framework to help CBs select suitable deployment technologies. The study used Delphi to conduct in-depth interviews with 18 senior executives at Vietnamese CBs to identify technology selection criteria. It then used ANP to model interdependencies among the requirements and to rank technology priorities. The Delphi analysis showed that bank leaders prioritized three groups of factors in technology decisions: risk (reflecting caution about cybersecurity and regulatory challenges); implementation capability and information security (ensuring sufficient resources to transform legacy IT infrastructure); and customer experience (in a market that faces competition from fintech firms). The ANP analysis produced a clear priority order. Based on these criteria, the study established an optimal technology roadmap. AI and Cloud Computing form an inseparable pair of pillars. They provide the foundation for an optimization layer comprising Big Data and RPA. And exploratory technologies such as Blockchain and IoT should follow. Sensitivity analysis confirmed the model’s stability across scenarios. It indicated that, when the environmental weight increases, Cloud Computing can overtake AI, underscoring the role of cloud infrastructure in supporting sustainability objectives. Theoretically, the study extends the TOE framework and the dynamic capabilities theory by integrating ESG criteria into the technology selection model. It also develops a combined Delphi–ANP methodology that can model interdependencies among criteria. Practically, the study provides a staged technology roadmap for CBs, particularly in emerging markets, that helps balance short-term economic efficiency with long-term sustainability goals.

The study has limitations. First, the sample focused on Vietnamese CBs with 18 experts, which may limit generalizability to markets with different regulatory contexts and levels of technological maturity. Second, the research used a cross-sectional design and did not capture how technology priorities shift over time as technologies mature and regulatory environments evolve. Third, although ANP can model complex dependencies, the specification of these relationships still relies on expert judgment. Future research will broaden the survey to other regions to test the framework's generalizability, conduct longitudinal surveys to track changes in technology priorities over time. Future research will incorporate additional quantitative methods, such as structural equation modeling, to validate causal relationships and analyze data governance challenges in deploying AI and Big Data in commercial banks.

## 6. Acknowledgements

The author gratefully acknowledges the eighteen senior banking leaders in Vietnam who served as the expert panel for the Delphi and ANP procedures. Their time, insights, and constructive feedback were essential to defining the technology selection criteria and validating the prioritisation framework. To preserve confidentiality and reduce potential organisational bias, their names and institutions are not disclosed; all participants consented to be thanked anonymously. The author also thanks the executives and departments that facilitated interview scheduling and provided access to non-sensitive operational insights within state-owned commercial banks, joint-stock commercial banks, and foreign banks operating in Vietnam.

The author gratefully acknowledges administrative assistance with data collection and interview transcript preparation, as well as constructive feedback from seminar participants and anonymous reviewers on this manuscript. This research received no external funding. If individual contributors wish to be named, the author will do so upon written consent and in accordance with the conference's policy.

## References

Al-Ansi, A. M., Garad, A., & Jaboob, M. (2024). Unraveling the complexities of financial innovation and digital transformation within banking systems. *Multidisciplinary Reviews*, *7*(11), 2024265. https://doi.org/10.31893/multirev.2024265

Alshdaifat, S. M., Aziz, N. H. A., Alhasnawi, M. Y., Alharasis, E. E., Al Qadi, F., & Al Amosh, H. (2024). The Role of Digital Technologies in Corporate Sustainability: A Bibliometric Review and Future Research Agenda. *Journal of Risk and Financial Management*, *17*(11), 509. https://doi.org/10.3390/jrfm17110509

Amiri, M., Hashemi-Tabatabaei, M., Keshavarz-Ghorabaee, M., Antucheviciene, J., Šaparauskas, J., & Keramatpanah, M. (2023). Evaluation of Digital Banking Implementation Indicators and Models in the Context of Industry 4.0: A Fuzzy Group MCDM Approach. *Axioms*, *12*(6), 516. https://doi.org/10.3390/axioms12060516

Baker, J. (2012). The Technology–Organization–Environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information Systems Theory* (Vol. 28, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

Barrios, M., Guilera, G., Nuño, L., & Gómez-Benito, J. (2021). Consensus in the Delphi method: What makes a decision change? *Technological Forecasting and Social Change*, *163*, 120484. https://doi.org/10.1016/j.techfore.2020.120484

Beiderbeck, D., Frevel, N., Von Der Gracht, H. A., Schmidt, S. L., & Schweitzer, V. M. (2021). Preparing, conducting, and analyzing Delphi surveys: Cross-disciplinary practices, new directions, and advancements. *MethodsX*, *8*, 101401. https://doi.org/10.1016/j.mex.2021.101401

Bueno, L. A., Sigahi, T. F. A. C., Rampasso, I. S., Leal Filho, W., & Anholon, R. (2024). Impacts of digitization on operational efficiency in the banking sector: Thematic analysis and research agenda proposal. *International Journal of Information Management Data Insights*, *4*(1), 100230. https://doi.org/10.1016/j.jjimei.2024.100230

Chen, X., You, X., & Chang, V. (2021). FinTech and commercial banks' performance in China: A leap forward or survival of the fittest? *Technological Forecasting and Social Change*, *166*, 120645. https://doi.org/10.1016/j.techfore.2021.120645

Fahad, S., & Bulut, M. (2024). Structural and Digital Transformation of the Financial Industry: A Futuristic Approach for Sustainable and Green Digitalization. *Muslim Business and Economics Review*, *3*(2), 314–333. https://doi.org/10.56529/mber.v3i2.305

Hasan, M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data*, *7*(1), 21. https://doi.org/10.1186/s40537-020-00291-z

Makki, A. A., & Alqahtani, A. Y. (2022). Modeling the Enablers to FinTech Innovation in Saudi Arabia: A Hybrid Approach Using ISM and ANP. *Systems*, *10*(5), 181. https://doi.org/10.3390/systems10050181

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Nwachukwu, P. S., Chima, O. K., & Okolo, C. H. (2025). Digital transformation in banking: Impact of technological innovation and an integrated framework for customer relationship success. *Gulf Journal of Advance Business Research*, *3*(9), 1245–1283. https://doi.org/10.51594/gjabr.v3i9.158

Nwoke, J. (2024). Digital Transformation in Financial Services and FinTech: Trends, Innovations and Emerging Technologies. *International Journal of Finance*, *9*(6), 1–24. https://doi.org/10.47941/ijf.2224

Patrício, L., Varela, L., & Silveira, Z. (2024). Integration of Artificial Intelligence and Robotic Process Automation: Literature Review and Proposal for a Sustainable Model. *Applied Sciences*, *14*(21), 9648. https://doi.org/10.3390/app14219648

Pradhan, R., & Gain, N. (2025). Leveraging AI for sustainability in banking: A systematic review of integrated approaches. *International Journal of Engineering Technologies and Management Research*, *12*(6). https://doi.org/10.29121/ijetmr.v12.i6.2025.1624

Pundareeka Vittala, K. R., Ahmad, S. S., Seranmadevi, R., & Tyagi, A. K. (2024). Emerging Technology Adoption and Applications for Modern Society Towards Providing Smart Banking Solutions, In *Advances in Medical Technologies and Clinical Practice* (315-329). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5261-8.ch018

Rane, N. L., Rane, J., & Paramesha, M. (2024). Artificial Intelligence and business intelligence to enhance Environmental, Social, and Governance (ESG) strategies: Internet of things, machine learning, and big data analytics in financial services and investment sectors. *Trustworthy Artificial Intelligence in Industry and Society* (pp. 82-133). Deep Science Publishing. https://doi.org/10.70593/978-81-981367-4-9_3

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, *1*(1), 83. https://doi.org/10.1504/IJSSCI.2008.017590

Saeedi, M., & Ashraf, B. N. (2024). The Role of Technology in Promoting Green Finance: A Systematic Literature Survey and the Development of a Framework. *Journal of Risk and Financial Management*, *17*(10), 472. https://doi.org/10.3390/jrfm17100472

Shahid, S., Ahmed, S., Nabi, G., Murtaza, M., & Solangi, A. (2025). FinTech 4.0 and the Future of Global Finance: Blockchain, Artificial Intelligence, and Big Data as Catalysts of Digital Financial Innovation. *Inverge Journal of Social Sciences*, *4*(3), 364–379. https://doi.org/10.63544/ijss.v4i3.173

Soomro, J. A., Rafi, S. K., & Abbasi, B. A. (2025). Integrating Emerging Technologies with ESG (Environmental, Social and Governance) for Sustainable Business Practices: In *Value Creation and Circular Business Models for Resource Scarcity* (279–304). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-1117-3.ch004

Subramanian, N., & Jeyaraj, A. (2018). Recent security challenges in cloud computing. *Computers & Electrical Engineering*, *71*, 28–42. https://doi.org/10.1016/j.compeleceng.2018.06.006

Syarifuddin, F. (2024). Fostering inclusive welfare and Islamic financing through Islamic social finance digitalization strategy. *Edelweiss Applied Science and Technology*, *8*(4), 583–619. https://doi.org/10.55214/25768484.v8i4.1438

Vaidya, S. R. (2022). Defining the digital banking innovation maturity model: A comprehensive maturity assessment for the digital banking innovation framework. *Journal of Digital Banking*, *7*(1), 46. https://doi.org/10.69554/OLAV3709

Wang, X., Hu, W., & Guan, N. (2025). A Systemic Approach to Evaluating Fintech-Driven Competitiveness in Commercial Banks: Integrating Delphi and ANP Methods. *Systems*, *13*(5), 342. https://doi.org/10.3390/systems13050342