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Organisational Readiness for AI Contact Center Adoption in Indonesian Banking

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ABSTRACT

Artificial intelligence (AI) is transforming customer service operations in banking, with contact centers as a primary deployment. This study examines the causal structure of organisational readiness factors for AI contact center adoption in Indonesian banking and develops a scenario planning framework to guide implementation strategy across institutional contexts. The research employs a sequential multi-method design: ten in-depth interviews (IDI) across six functional domains (contact center operations, product management, regulatory and risk, technology and AI, compliance, and customer perspective); reflexive thematic analysis to identify and consolidate implementation factors; DEMATEL (Decision-Making Trial and Evaluation Laboratory) causal analysis by eight domain experts; MICMAC structural classification; and four-scenario strategic planning. Thematic analysis of interview transcripts consolidated 10 final factors using discriminant validity criteria. DEMATEL analysis ($n = 8$; normalisation parameter $s = 33.875$; significance threshold $\alpha = mean(T) + 1 \cdot SD = 0.8259$) identified 19 significant causal relationships. The 10 factors were categorised within the Technology-Organisation-Environment (TOE) framework. DEMATEL causal analysis revealed that all five Cause factors ($r-c > 0$) belong to these dimensions: FIN, MAN, PEL, KOM, and NAS, while the Effect factors belong to these dimensions: AKU, KEA, DAT, INF, and REG. AI Response Accuracy is the most structurally central factor, confirming its role as the convergence point of all causal investment pathways. MICMAC structural analysis classified Financial Readiness, Management Commitment, and Agent Competency as Driving variables; Technology Infrastructure, AI Response Accuracy, and Data Security as Relay amplifiers; Data Availability and Regulatory Compliance as Output indicators; and HR Training and Customer Readiness as Autonomous variables. CLD analysis identified five reinforcing loops (R1–R5) and one balancing loop (B1). The scenario planning framework constructs a two-axis matrix: Organisational Readiness ($X = FIN \times 0.55 + MAN \times 0.45$, weights proportional to $r-c$ magnitudes) and

Ecosystem Support (Y = NAS). Four scenarios are mapped against KBMI institutional profiles: Scenario A (Optimal Transformation, KBMI IV), Scenario B (Independent Innovation, KBMI III), Scenario C (Ecosystem-Led Adoption, Digital banks), and Scenario D (Pre-Adoption, KBMI I–II conventional banks). The principal finding is that AI contact center implementation in Indonesian banking is fundamentally an organisational challenge that manifests as a technology challenge. Financial readiness and management commitment must precede technology selection; data quality and AI accuracy are outputs of organisational investment, not independent prerequisites. These findings invert the conventional technology-first implementation narrative and provide empirically grounded, KBMI-stratified guidance for banking practitioners, regulators, and future research.

Keywords: Artificial Intelligence; Contact Center; DEMATEL; Scenario Planning; Indonesian Banking; Toe Framework; Organisational Readiness

INTRODUCTION

The growth of artificial intelligence (AI) has transformed how industries operate. In ASEAN, digitalization has become the base of banking strategy. Malaysia, Singapore, Thailand, and Indonesia have implemented comprehensive digital banking that leverage AI for personalization, fraud detection, and customer service automation. Notably, 91% of bank boards globally have formally approved Generative AI programs, signaling that AI is no longer an experimental initiative but a strategic imperative (Kreger, 2025).

Artificial Intelligence (AI) has become one of the most transformative forces in the global financial industry. By the end of 2024, approximately 78% of banking institutions worldwide had integrated AI into at least one core business function, up from 55% in 2022 (McKinsey Global Institute, 2024). Global AI investment in financial services reached USD 35 billion in 2023 and is projected to exceed USD 64 billion by 2028 (MarketsandMarkets, 2024). Banks increasingly utilize AI to improve operational efficiency, personalize customer experiences, and enhance decision-making, making AI a key component of strategic development (Lazo & Ebardo, 2023).

Indonesia’s economic growth is supported by several major sectors. According to Badan Pusat Statistik (BPS, 2025), manufacturing remains the largest contributor to GDP, while the financial services sector recorded consistent growth of 4.74% between 2023 and 2024. Banking plays a central role within the financial services industry, with total banking assets exceeding IDR 11,000 trillion in 2024, making its performance critical to national financial stability.

Increasing competition has accelerated digital transformation in banking, requiring institutions to deliver more personalized, responsive, and convenient services. Besides developing innovative digital products, banks must also improve service quality because customer satisfaction depends not only on products but also on service excellence. As banking products become increasingly complex, organizations need knowledgeable customer service agents supported by advanced internal technologies.

To enhance customer service, banks have adopted technologies such as AI-powered chatbots, automation, mobile banking applications, and advanced security systems. However, these innovations require substantial investments in technology, human resources, and regulatory compliance, with implementation challenges varying according to institutional size and customer segments.

Indonesia classifies commercial banks under the KBMI (Kelompok Bank berdasarkan Modal Inti) framework introduced through POJK No. 12/POJK.03/2021, replacing the previous BUKU classification. Banks are categorized into four capital tiers (KBMI I–IV), ranging from small digital and private banks to the country's four largest banks (BRI, BCA, Mandiri, and BNI). Capital strength influences banks' capacity to invest in technology, develop human resources, and meet regulatory requirements. KBMI III and IV banks also face stricter governance, risk management, and AI governance requirements under OJK Circular Letter No. 11/SEOJK.03/2022 and the OJK AI Governance Guidelines (2023). Indonesian banks are further divided into conventional and digital banks, with digital banks operating primarily through digital channels as recognized by POJK No. 12/POJK.03/2021.

AI has become an important enabler of customer service transformation. Applications such as chatbots, machine learning, natural language processing (NLP), robotic process automation (RPA), fraud detection, risk assessment, and intelligent contact centers improve service efficiency and customer experience. AI can streamline inbound call handling, support customer service agents with real-time knowledge management, reduce Average Handling Time (AHT), improve response accuracy, and allow human agents to focus on more complex issues (Andrade & Tumelero, 2022; Wang et al., 2023). Effective implementation, however, depends on aligning AI capabilities with customer needs and designing intuitive user interactions (Meng et al., 2025).

Despite these advantages, AI implementation presents several challenges, including data privacy, cybersecurity, regulatory compliance, workforce resistance, customer trust, and the need for continuous human oversight (Al-Baity, 2023; Ghandour, 2021; Rahman et al., 2023). AI systems also require large volumes of high-quality data to achieve robust performance, increasing concerns regarding data protection and potential breaches (Nguyen et al., 2023). Furthermore, integrating AI with legacy banking systems is technically complex and costly because it requires interoperability, secure data exchange, and alignment with existing business processes (Schwaeke et al., 2025; Madanchian & Taherdoost, 2025).

Overall, while AI offers significant opportunities to improve personalization, operational efficiency, and service quality in banking, successful implementation requires banks to address technological, organizational, regulatory, and ethical challenges. Accordingly, this study aims to bridge this gap by developing scenario planning frameworks that help Indonesian banks anticipate multiple AI implementation pathways and formulate appropriate strategic responses.

RESEARCH METHOD

Research Design

This study adopts a qualitative research approach to develop recommendations for AI implementation in banking contact centers. The research begins by identifying the planning scope through observation to understand the key issues and driving forces influencing AI adoption. Previous studies indicate that customer trust and social influence are critical determinants of AI acceptance (Mei et al., 2025), while service quality, employee skills, and organizational commitment significantly influence users' acceptance of AI-based customer service systems (Almuraqab et al., 2024). In addition, organizational readiness—including top management support, employee capability, and internal technological competence—is essential for successful AI implementation (Wang et al., 2023).

Potential influencing factors will first be identified through in-depth interviews. Subsequently, experts will evaluate these factors using a DEMATEL questionnaire to identify causal relationships among them. Scenario outputs will then be organized into decision matrices that compare scenario probability, resource requirements, implementation complexity, expected operational improvements, and risk levels to support managerial decision-making.

The CLD development is guided by five key questions: (1) which relationships are most important in the system; (2) what intermediate factors exist; (3) what is the polarity of each relationship; (4) where delays occur; and (5) whether any important factors have been omitted. These questions facilitate the identification of the system's initial feedback loops.

Data Collection Method

The study employs a qualitative approach using In-Depth Interviews (IDI) combined with DEMATEL-based causal questionnaires. Semi-structured interviews will be conducted with stakeholders selected according to their knowledge, experience, roles, and responsibilities to capture diverse perspectives. This approach enables researchers to consider organizational, environmental, social, and cultural contexts that may influence AI implementation.

Following the interviews, experts will complete a DEMATEL questionnaire to validate the identified driving forces and examine the causal relationships among influencing factors.

Data Analysis Method

Interview data will be analyzed using thematic analysis, while DEMATEL (Decision-Making Trial and Evaluation Laboratory) will be employed to examine direct and indirect causal relationships among the identified factors (Fearnley, 2022). Thematic analysis will identify recurring themes and patterns from interview transcripts, whereas DEMATEL will model the interrelationships among factors based on expert perceptions from diverse backgrounds, providing a comprehensive understanding of the drivers of AI implementation.

RESULT AND DISCUSSION

Business Solution

The DEMATEL causal structure provides direct empirical grounding for business solutions that reframes the AI contact center implementation challenge. Rather than begin with technology selection, the causal evidence indicates that implementation success requires leading with organizational readiness. This section will translate the DEMATEL findings into a strategic implementation framework.

AI Implementation Framework for Indonesian Banking Contact Centers

Based on the DEMATEL causal structure, this research proposes a three-tier Implementation Readiness Framework for AI contact center deployment in Indonesian banking. The framework organizes the 10 factors into sequentially interdependent groups corresponding to their causal roles, moving from upstream organizational foundations to downstream technical outcomes.

Strategic Foundation (FIN, MAN)

Two of the strongest Cause factors form the organizations side that must be established before any implementation activity can proceed effectively. FIN (Financial Readiness) requires not only capital allocation for initial acquisition but also multi-year operational budget commitment covering licensing, maintenance, retraining, etc. MAN (Management Support & Commitment) requires board-level AI strategy and KPI alignment. Banks in KBMI I–II categories with constrained capital budgets may need to phase tier 1 beginning with management commitment before capital allocation.

Capability Development (PEL, KOM, NAS, REG)

This tier encompasses the human capability development and environmental alignment activities that translate organizational commitment into operational readiness. PEL (Human Resource Training Programs) must be designed as continuous learning systems with tiered curricula spanning technical AI operation. KOM (Human Resource Competencies in AI Utilization) development requires redesigning agent role frameworks to achieve AI collaboration skills and higher-order customer service competencies. NAS (Customers Readiness and Acceptance) requires proactive customer education and transparent AI disclosure. REG (Regulatory Compliance, AI Risk Management and Governance) must be addressed as an architectural decision at deployment design stage, not retrofitted post-implementation. Especially, as we know, OJK has released their AI governance guidance back in 2025. Banks should comply with the regulator's “rule” if they want to implement the subject being regulated.

Technical Outcomes (INF, DAT, KEA, AKU)

The four Effect factors represent the technical outcome, which are the set of capabilities that organizations achieve as a result from tier 1 and tier 2 investments. INF (Technology Infrastructure) decisions should be driven by regulatory data residency requirements, scalability projections, and total cost of ownership analysis across on-premise, cloud, and hybrid architectures. DAT (Data Availability and Quality) requires sustained governance investment: pipeline, knowledge base curation, and model retraining. KEA (Data Security and Access Control) implementation should follow both regulatory standards and industry best practices for AI-specific threats. AKU (AI Accuracy and Response Reliability) should be measured continuously from pilot phase with deployment thresholds defined in advance based on the bank's risk tolerance.

Scenario Planning for AI Contact Center Implementation

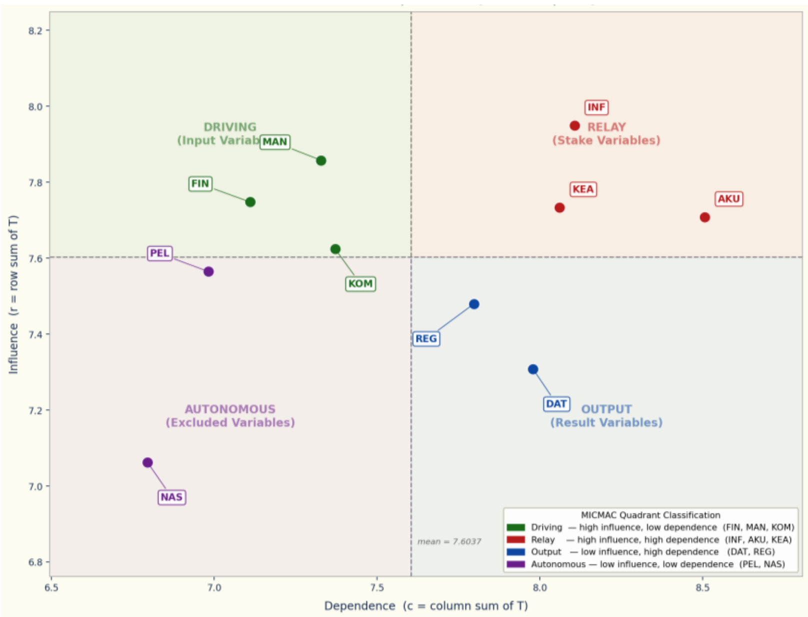

Figure 2 MICMAC Structural Classification: AI Contact Center Implementation Factors

To capture the strategic diversity of implementation contexts across Indonesian banking institutions, this research develops a scenario planning model derived from the two orthogonal causal dimensions identified by DEMATEL. The scenario matrix is constructed along two axes: The Organizational Readiness axis (X-axis), defined by the combined strength of two internal Cause factors (FIN+MAN), PEL (HR Training), despite ranking as the second-strongest Cause factor by r−c magnitude (r−c = 0.582), is deliberately excluded from the X-axis composite. The MICMAC structural analysis positions PEL in the Autonomous quadrant (low influence, low dependence) indicating that training investment operates as a structurally independent co-condition rather than a systemic driver that propagates through the causal network. PEL cannot function as a differentiating axis because it does not accumulate organically from financial capacity or management commitment: a bank with strong FIN and MAN must still separately commit to training investment, meaning

PEL must be explicitly managed regardless of scenario position. Second, the scenario matrix is designed to identify where institutions start, not every action they must take. PEL is a universal action item for all four scenarios; FIN and MAN are the structural variables that determine which scenario an institution inhabits. Including PEL in the X-axis would conflate a context variable with a prescription variable, and reduce the discriminant validity of the axis construct.

The Ecosystem Support axis (Y-axis) is defined by NAS (Customer Readiness and Acceptance). Three converging structural properties justify this selection. First, NAS is classified as a Cause factor ($r-c = +0.266$), confirming that it exerts net positive influence on implementation outcomes rather than being shaped by them. Second, MICMAC analysis positions NAS in the Autonomous quadrant (low influence, low dependence), indicating that it operates largely outside the bank's direct organisational control: unlike FIN or MAN, which management can mobilise through internal decisions, NAS reflects the digital literacy, AI acceptance propensity, and channel behaviour of the bank's customer segment, variables that are shaped by demographic, socioeconomic, and market-level forces external to the institution. Third, NAS has no significant outgoing edges in the causal network ($T_{ij} < \alpha$ for all NAS→Effect pairs), confirming that its influence on implementation is distal and environmental rather than direct and mechanistic. These three properties make NAS the appropriate representative of the ecosystem dimension: it captures the demand-side boundary condition that defines how much implementation ambition is strategically warranted, independent of the organisational readiness the X-axis measures.

The axis weights for the composite scores are derived directly from the DEMATEL $r - c$ values, which quantify each factor's net causal contribution to the implementation system. For the Organizational Readiness axis (X-axis), the DEMATEL analysis yields FIN an $r - c$ score of 0.63801 and MAN an $r - c$ score of 0.52976. Expressed as proportional weights within the top driver: FIN accounts for $0.63801 \div (0.63801 + 0.52976) = 54.6\%$ of combined causal output, and MAN accounts for 45.4%. Rounding to one decimal place for operational simplicity produces weights of 0.55 for FIN and 0.45 for MAN, reflecting FIN's marginally stronger net causal role as the primary resource-enabling driver from which all subsequent capability and technical investment flows.

For the Ecosystem Support axis (Y-axis), NAS is used as the sole component. REG is intentionally excluded from the Y-axis even though it is still an environment factor. This decision is taken on the following grounds: under OJK Regulation No. 12/POJK.03/2021 and OJK Circular Letter No. 11/SEOJK.03/2022, a clear and enforced AI governance framework is already in place for Indonesian commercial banks. The structural role of B1 loop also further supports the exclusion of REG from the scenario Y-axis because regulatory compliance is a system governor that responds to deployment decisions, not an independent variable that differentiates institutional readiness. REG's negative r-c means REG is an Effect Factor not a Cause. A bank that uses AI has to comply, but a bank that doesn't use AI doesn't have to comply. Thus, REG acts as a compliance gate and not as a distinguishing variable that moves across institutions. This is also supported by the DEMATEL result that REG is an Effect factor (r-c = -0.3178), i.e. regulatory compliance posture is reactive to organisational investment rather than independently determining it. Conversely, NAS captures the external market demand condition that individual banks have limited direct control over and that varies materially across KBMI groups and market segments. The composite axis scores are therefore: Organizational Readiness (X) = (FIN × 0.55) + (MAN × 0.45); Ecosystem Readiness (Y) = NAS. Each component factor is assessed on a 1–10 ordinal scale constructed from secondary institutional data proxies, producing axis composite scores ranging from 1.0 to 10.0. The scenario quadrant boundary is set at the midpoint value of 5.0.

To position Indonesian banking institutions within the scenario matrix, this research applies the OJK KBMI classification (Kelompok Bank berdasarkan Modal Inti — Bank Groups by Core Capital) as the primary institutional stratification variable. Under OJK Regulation No. 12/POJK.03/2021, banks are classified into four capital tier groups based on core capital (modal inti): KBMI I (below Rp 6 trillion), KBMI II (Rp 6–14 trillion), KBMI III (Rp 14–70 trillion), and KBMI IV (above Rp 70 trillion). These tiers are meaningful proxies for AI implementation context because core capital determines not only the absolute investment capacity available for technology acquisition, but also the operational sophistication, regulatory reporting complexity, and customer segment characteristics that collectively shape both organizational readiness and ecosystem conditions. The four KBMI tiers therefore represent four structurally distinct implementation contexts that map directly onto the two-axis scenario matrix structure.

Each KBMI group is assigned researcher-constructed ordinal scores on a 1–10 scale for each of the three component factors, derived from secondary institutional data. FIN scores are indexed to core capital capacity and technology investment intensity, drawn from OJK Statistik Perbankan Indonesia Q4-2023: KBMI I and KBMI II Conventional scores 2 (capital-constrained; technology investment typically below 1% of operating expenses); Digital Banks, being differentiate from each KBMI classification, scores 3 (moderate capital; more technology projects feasible); KBMI III scores 3-6 (sufficient capital for enterprise-scale AI deployment but depends on the type of bank); KBMI IV scores 9 (large capital base enabling sustained multi-year AI platform investment). MAN scores reflect AI governance and digital transformation maturity derived from bank annual reports 2023, capturing indicators such as the presence of a dedicated AI or digital governance structure, board-level technology strategy, and existing AI deployment track record: KBMI I-II Conventional Banks score 3, Digital Banks as they have more digital savvy customers produce systematically higher MAN scores relative to its KBMI I, II, III peers, which are predominantly regional banks operating branch-heavy service models, therefore they scored 6. KBMI III score 4-7 depends on the type of banks as national private banks are started to get into AI adoption as well, and KBMI IV is 8. REG is excluded from the axis scoring as it functions as a universal compliance gate rather than a differentiating variable (see axis weight rationale above). NAS scores reflect the digital literacy and AI service acceptance propensity of each group's primary customer segment, derived from BI Consumer Payment Survey 2022 and digital banking penetration data from annual reports: KBMI I-II Conventional Banks, which predominantly serve mass-market and rural segments, score 2.5, while Digital Banks and KBMI III-IV serving predominantly urban and digitally-active segments, score 5-9, and KBMI III BPD, score 4. Applying the composite formulas X = (FIN × 0.55) + (MAN × 0.45) and Y = NAS produces the following ordinal estimates as shown in table 1.

Table 1. Ordinal of Each KBMI Classifications

Classification	FIN	MAN	NAS	X	Y
KBMI I-II Conventional	2	3	2.5	2.45	2.5
Digital Banks	4	5	9	4.35	9.0
KBMI III National Banks	6	7	5	6.45	5.0
KBMI III BPD	3	4	4	3.45	4.0
KBMI IV	9	8	9	8,55	9.0

Table 2. Contact Center Implementation Scenario Planning Matrix

Scenario	Position	Operational Description	Strategic Recommendation
A OPTIMAL TRANSFORMATION	High Org Readiness High Ecosystem Support	Full-scale AI deployment with end-to-end automation of routine interactions; proactive model expansion; human-AI collaboration as standard operating model.	Leverage position; pursue differentiation; benchmark against regional best practice.
B INDEPENDENT INNOVATION	High Org Readiness Low Ecosystem Support	Selective deployment prioritizing internal efficiency gains; agent-assist AI before customer-facing AI; invest in regulatory engagement and customer education to build ecosystem support over 24–36 months.	Lead regulatory dialogue; use proven use cases to build customer trust; design for modular expansion as ecosystem matures.
C ECOSYSTEM-LED ADOPTION	Low Org Readiness High Ecosystem Support	Compliance-driven minimum viable AI deployment; prioritize organizational capability building; seek consortium models or BaaS partnerships to bridge financial gaps; focus on	Build financial and management foundation; consider phased deployment co-funded through vendor partnership; target KBMI progression.

		regulatory-required use cases first.	
D PRE-ADOPTION	Low Org Readiness Low Ecosystem Support	Pre-adoption phase: AI implementation not yet viable at scale. Focus entirely on foundation building, regulatory literacy, and pilot programs of strictly limited scope to build organizational confidence.	No major deployment. Invest in readiness. Establish pilot with 1-2 use cases to generate internal evidence base for future investment decisions.

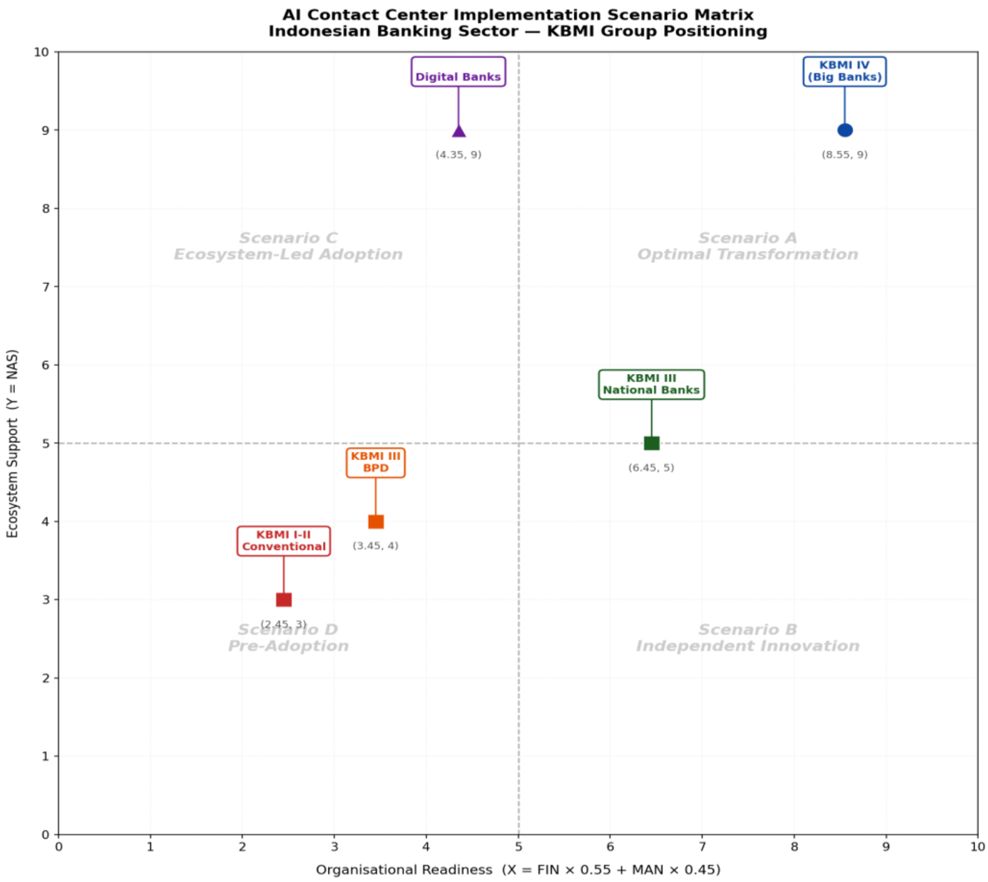

Figure 2. AI Contact Center Implementation Scenario Matrix - Indonesian Banking Sector KBMI Group Positioning

Figure 1maps Indonesian banking institutions by KBMI group onto the four-quadrant scenario matrix, using secondary data proxies for organizational readiness and ecosystem support. Scenario A represents the target state for any AI contact center strategy, where strong organizational readiness is matched by a supportive regulatory environment and customer market. Scenario B represent organizational capability that presented by the existence of AI deployments, but ecosystem maturity remains a constraint requiring active management.

Scenario C represent the Digital Banks which coming from KBMI I, II, and III yet they have a different customers base who more digital savvy, indicating they need a different approach compared to conventional banks, putting the Digital Banking into Ecosystem-Led Adoption scenario. Scenario D represent the dominant context for KBMI I-II Conventional institutions, where capital limitations constrain organizational readiness before ecosystem factors are even relevant.

Implementation Plan

The implementation plan presented in this section operationalizes the Three-Tier Implementation Readiness Framework into a sequenced, time-bounded roadmap. The sequencing logic is entirely derived from the DEMATEL causal structure: factors with higher positive $r - c$ scores (stronger Causes) must be addressed before the factors they drive can be effectively developed. This causal sequencing principle ensures that implementation investments are made in the order of their systemic impact, minimizing the risk of technical capability investments failing due to insufficient organizational preconditions.

Phased Implementation Roadmap

Table 3. Phased AI Contact Center Implementation Roadmap

Phase	Primary Factors	Key Activities	Success Metrics
Phase 1 Foundation	FIN MAN REG	1. Formalize AI implementation strategy with board-level endorsement 2. Allocate multi-year budget envelope covering 3-years 3. Appoint dedicated AI implementation owner with cross-functional authority 4. Conduct regulatory gap assessment (OJK, BI, UU PDP requirements) 5. Establish AI governance framework and accountability structure 6. Select 2–3 initial use cases with defined accuracy thresholds	AI Strategy Document Budget Approval Governance Framework Regulatory Compliance Map
Phase 2 (12-30 months) Optimization & Scale	INF DAT KEA AKU	1. Implement data quality governance: pipeline design, curation schedule, retraining cadence 2. Deploy full security architecture (RBAC, encryption, AI-specific threat controls) 3. Scale AI deployment to full use case portfolio based on pilot accuracy evidence 4. Establish AI Center of Excellence	Data Governance Score Security Audit Pass

		for continuous model improvement 5. Expand customer-facing AI as AKU thresholds are achieved per use case type 6. Contribute to regulatory dialogue based on operational evidence	
Phase 3 (0-6 months) Capability Development	PEL KOM NAS	1. Launch tiered agent AI literacy training program 2. Design and deploy infrastructure (on-premise/cloud/hybrid) per regulatory requirements 3. Develop customer education and disclosure materials 4. Pilot AI deployment with controlled customer group 5. Establish continuous feedback loop	Training Completion Rate ≥ 80% AKU ≥ 70% Infrastructure Deployed Customer NPS Baseline

The implementation roadmap should be calibrated to the institutional context of the implementing bank as the Indonesian banking sector is very heterogeneous in capital capacity, technology maturity, and human resource capability among KBMI groups (OJK Regulation No. 12/POJK.03/2021). Each group guided by DEMATEL begins with the following priority actions. Figure IV.5 places each of the KBMI groups in the scenario matrix and thus provides an empirical basis for selecting a strategy for each institution.

Core Tier Banks/Digital Bank/Average Resource: Scenario A, B, or C

These institutions have sufficient capital to fund full implementation.

Priority 1: Establish a complete AI governance and cross-functional implementation ownership with director-level accountability.

Priority 2: Set measurable, use-case-specific accuracy targets before technology selection, using these targets to drive vendor evaluation (AKU).

Priority 3: Invest in AI literacy at scale, targeting contact center staff and customers.

The risk for groups with bigger capital is organizational satisfaction. With financial capacity available, the failure mode is underinvestment in management commitment and training while over-investing in technology platforms before the organizational foundation is solid.

Conventional/Smaller Regional Banks: D

These institutions face binding capital constraints that make full-scale AI implementation non-viable in the near term.

Priority 1: Determine if investment in AI contact centers is compatible with the current capital budget and if not, identify partnership models (vendor revenue share, consortium deployment or Banking as a Service intermediation) to adopt AI capabilities without owning the infrastructure outright (FIN).

Priority 2: Develop internal regulatory capacity to understand OJK requirements before making architecture decisions (REG).

Priority 3: Deploy one narrowly scoped AI use case (e.g., FAQ automation through existing digital channels) to build organisational experience and generate internal evidence without large capital commitment.

FIN and MAN are the most important in project sustainability context. The finding shows that these two will be a problem due to the lack of commitment in budget after initial deployment or leadership disengagement after pilot phase if there is no commitment. The focus of the proposed framework on organisational foundation first and then technical investment is specifically designed to avoid these failure modes. Banks that finish Phase 1 (strategic foundation) before Phase 3 (technical outcomes) are on track to realise the DEMATEL network's primary objective: enduring, quantifiable AI response accuracy that mirrors the company's brand and fosters long-term customer trust.

If the proposed framework is implemented as described, the expected outcomes across a 36-month implementation cycle include: AI response accuracy (AKU) reaching the bank's pre-defined deployment threshold for standard use cases; measurable AI resolution of routine contact center interactions; agent capacity reallocation toward complex, high-value cases requiring human judgment and emotional intelligence; full regulatory compliance across OJK, Bank Indonesia, and UU PDP requirements; and measurable improvement in customer satisfaction scores driven by faster resolution of routine queries and higher-quality human interaction for complex cases. These outcomes collectively constitute the operational definition of AI contact center implementation success as described by the expert participants of this research.

CONCLUSION

This study aims to identify and map the causal structure of factors influencing the implementation of Artificial Intelligence (AI) in Indonesian banking contact centers. Using a sequential mixed-methods approach, the research combines in-depth interviews with DEMATEL causal network analysis based on the Technology–Organization–Environment (TOE) framework. The main findings are summarized as follows.

Ten Critical Factors and Their Identification

The study identified 10 critical factors influencing AI implementation in banking contact centers. Initially, 15 key factors were extracted through thematic analysis of ten expert interviews and evaluated using four DEMATEL selection criteria: identifiability, bidirectional influence capacity, conceptual distinctness, and expert assessability. After consolidating conceptually overlapping factors, the final variables were grouped into five dimensions: Technology Capabilities (DAT, INF, AKU), Governance and Ethical Frameworks (REG, KEA), Organizational Capabilities (PEL, FIN, MAN), Customer Acceptance (NAS), and Operational Effectiveness (KOM).

The Causal Structure: Organizational Primacy over Technology

DEMATEL analysis involving eight experts (n = 8; s = 33.8750; threshold α = 0.8259) identified 19 significant causal relationships among 90 possible factor pairs. The results revealed that the primary Cause factors are organizational, human, and market-related variables (FIN, MAN, PEL, KOM, NAS), whereas the Effect factors consist of technology outcomes and governance constraints (AKU, DAT, REG, KEA, INF).

These findings indicate that AI implementation in Indonesian banking is primarily driven by organizational decisions and capabilities, rather than by technological readiness alone. Technology-related outcomes—including system accuracy, data quality, infrastructure, security, and governance—are achieved through organizational investment and commitment rather than serving as initial prerequisites.

Within the TOE framework, the Organization dimension (FIN, MAN, PEL, KOM) functions as the principal driver of AI implementation. The Environment dimension positions Customer Acceptance (NAS) as the market-driven causal factor and Regulation (REG) as a governance constraint. Meanwhile, the Technology dimension (INF, DAT, AKU, KEA) represents the implementation outcomes that organizations must develop through effective organizational capabilities and strategic investment.

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