

Organizational Readiness In Artificial Intelligence Implementation: The Role of Digital Transformation In Bank Indonesia

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Abstract.

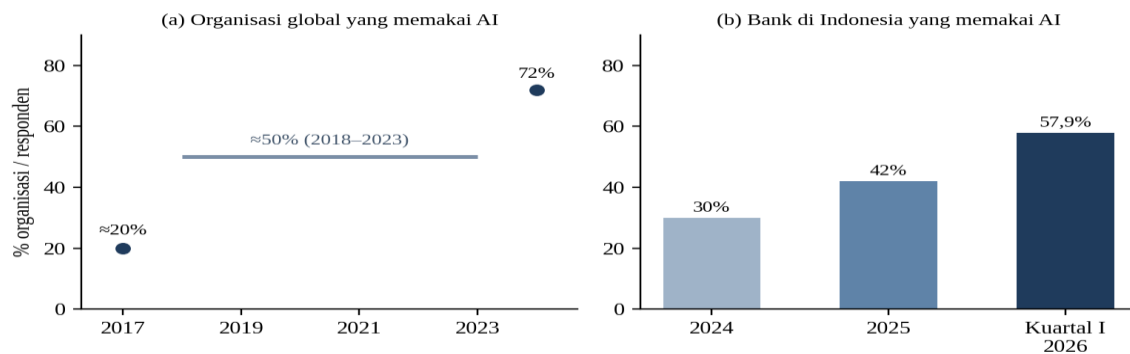
This study analyzes the relationship between digitalization, structural transformation, and carbon emission intensity in six ASEAN countries, namely Indonesia, Malaysia, Thailand, the Philippines, Vietnam, and Cambodia. The study uses annual panel data for the period 2004–2024, with the main estimation period covering 2010–2024. Carbon emission intensity is used as the dependent variable, while the number of internet users, industry value added, urban population, GDP per capita, international trade, and services sector value added are used as independent variables. All variables are transformed into natural logarithms so that the coefficients can be interpreted as elasticities. Estimation is conducted using the Fixed Effects Model with period fixed effects and Panel EGLS with period weights following model selection tests. The results show that digitalization, proxied by the number of internet users, has a positive but statistically insignificant relationship with carbon emission intensity. In contrast, industry value added, urban population, GDP per capita, and international trade have positive and significant relationships. Services sector value added has a negative and significant relationship with carbon emission intensity. These findings indicate that structural transformation toward the services sector is associated with lower emission intensity, while industrial expansion, urbanization, economic growth, and trade are associated with increased carbon emission intensity in the countries examined.

Keywords: carbon intensity; digitalization; structural transformation; trade and urbanization.

I. INTRODUCTION

The adoption of artificial intelligence (AI) by organizations has increased sharply in recent years. McKinsey reported that 72 percent of respondents to its global survey in early 2024 stated that their organizations were using AI, after that figure held at around 50 percent for six years (Singla et al., 2024). Dstry Damayanti, who was then the Senior Deputy Governor of Bank Indonesia (BI), cited the data at the Banking AI Day forum on September 9, 2024. He said the figure was up from about 20 percent seven years earlier and placed the financial sector, including central banks, as one of the fastest users of AI (Bisnis.com, 2024; Infobanknews, 2024). This surge demands broader readiness than technology. Uren and Edwards (2023) concluded from a qualitative study of AI experts that the readiness of people, processes, and data is necessary in addition to technological readiness to achieve long-term operational success.

Indonesian banking is among the earliest and most aggressive sectors to adopt AI (Infobanknews, 2026). A Perbanas survey with IBM noted that the adoption rate of AI in banking will increase from around 30 percent in 2024 to 42 percent in 2025 and 57.9 percent in the first quarter of 2026 (Figure 1) (Putri, 2026). The Financial Services Authority (OJK) launched the Indonesian Banking Artificial Intelligence Governance on April 29, 2025 as a complement to the banking digital transformation acceleration policy (Financial Services Authority, 2025). BI schedules the implementation of the Indonesian Payment System Blueprint (BSPI) 2030 in stages in 2025–2030 through five main initiatives (Bank Indonesia, 2024). BI Deputy Governor Filianingsih Hendarta stated that BSPI 2030 will strengthen the capacity of fraud detection systems, including through AI technology (Kontan.co.id, 2025).

**Fig. 1***AI adoption in Indonesia's global and banking organizations*

Note. Panel (a) used McKinsey global survey data; the 2017 figure (about 20%) came from Destry Damayanti's statement and McKinsey said that adoption remained around 50% in 2018–2023. Panel (b) used the Perbanas–IBM survey. The two panels used different samples and definitions so that they could not be directly compared. Source: Singla et al. (2024); Infobanknews (2024); Putri (2026).

BI is taking an active position in this transformation. BI's Digital Innovation Master Plan sets a target to become a leading digital central bank by 2025 (Bank Indonesia, n.d.). Globally, central banks have long used machine learning for statistics, macroanalysis, payment system supervision, and supervision, while newer generations of techniques demand infrastructure, expertise, and attention to data quality and privacy (Araujo et al., 2024). At the July 2026 EMEAP meeting, Governor Perry Warjiyo stated that BI is gradually implementing AI through strengthening data and metadata quality, governance, human resource capabilities, and innovation (Bank Indonesia, 2026). BI's mandate over rupiah and financial system stability makes its policy decisions have a direct impact on banking. A study of Islamic banking in West Nusa Tenggara shows that inflation is suppressing bank profitability and that regulators need to maintain economic stability to sustain the performance of the sector (Aprizal et al., 2025).

Technology ownership and policy roadmap do not guarantee successful implementation. Jöhnk et al. (2021) compiled five categories of AI readiness factors from interviews with 25 experts and asserted that organizations need to assess their assets, capabilities, and commitments before adopting AI. Holmström (2022) offers an AI readiness framework that links AI to digital transformation, and Hradecky et al. (2022) examine the readiness of organizations to adopt AI in the Western European exhibition sector. The gap between access and usage also emerges at the user level of digital financial services. Duasa and Wiranatakusuma (2025) report on the persistent gap between refugees' access to and use of digital financial tools in Malaysia, resulting in the need for policies to simplify the registration process and strengthen digital financial literacy.

Organizational readiness is multidimensional. Silva et al. (2025) designed a 20-dimensional digital readiness assessment model that centered the perspective of general employees, and they criticized the previous model for reflecting the views of senior management as it largely reflected the views of senior management. A survey by banking Gfrerer et al. (2021) showed that managers and employees have similar perceptions of attitudes and empowerment towards change, but differ significantly in perceptions of individual readiness, competencies, and innovation barriers. Ahmed et al. (2024) found that organizational culture, resources, change management competencies, and employee attitudes have a significant influence on digital transformation readiness in Malaysian manufacturing. Rafferty et al. (2013) place change readiness as a multilevel construct that can be examined at the individual, group, and organizational levels. Readiness research therefore needs to capture more than one layer of the organization.

Authorities and industry players in Indonesia emphasize this non-technical aspect. OJK reminds that the results of AI analysis should not be the sole basis for bank decisions, including in lending (Putri, 2026). Infobanknews notes that strengthening governance and regulations is considered important to maintain customer security, accountability, and trust amid new risks due to AI (Infobanknews, 2026). The governors

of the central bank EMEAP in July 2026 emphasized that AI adoption must be accompanied by strengthening governance, supervision, and risk mitigation (Bank Indonesia, 2026). The study of the public sector maps the meaning of digital transformation as well as the applications and challenges of AI specifically in public institutions (Mergel et al., 2019; Wirtz et al., 2019).

Central banks are different from commercial banks. The mandate of monetary policy and financial system stability demands public accountability and prudence, so the logic of profit-oriented transformation and market speed cannot be simply moved. Fernandez and Rainey (2006) compiled the success factors of organizational change specifically for the public sector, and Kuipers et al. (2014) mapped the change management literature in public organizations. Destry Damayanti emphasized at the 20th BMEB Conference that geoeconomic fragmentation, digital transformation, and systemic risks make sectoral policy approaches no longer adequate (CNBC Indonesia, 2026). Araujo et al. (2024) added that collaboration between central banks, for example through knowledge sharing and expertise pooling, keeps central banks at the forefront of AI development.

The study of readiness for AI and digital transformation is dominated by a survey-based quantitative approach. Rivai P et al. (2025) measured individual readiness for change at Bank Jago through PLS-SEM with a questionnaire to 387 permanent employees. Ahmed et al. (2024) combined a survey of 357 respondents with interviews with 20 key informants in the Malaysian manufacturing sector. Chatterjee et al. (2021) tested the adoption of AI in manufacturing and production companies with an integrated TAM-TOE model. Gfrerer et al. (2021) also used a survey of the banking industry to compare the perceptions of managers and employees.

Some studies took a qualitative path. Jöhnk et al. (2021) interviewed 25 AI experts and compiled readiness factors and indicators. Uren and Edwards (2023) conducted a *cross-sectional* qualitative study with a purposive sample of AI experts from research, development, and business functions, and proposed an AI adoption model that extends the *lens of people–process–technology* with a data dimension. Both studies produced useful frameworks, but the samples came from practitioners across industries and did not focus on central banks or policy-mandated public institutions. Creswell and Poth (2018) place qualitative research as an approach to examining the meanings that actors attach to phenomena, and Tsoukas and Chia (2002) view organizational change as an ongoing process.

In Indonesia, the study of banking digital readiness is centered on commercial banks and digital banks, such as Bank Jago (Rivai P et al., 2025). BI provides policy direction documents such as the Digital Innovation Master Plan (Bank Indonesia, n.d.) and BSPI 2030 (Bank Indonesia, 2024). These documents explain directions and targets, but do not examine how leaders articulate readiness or how employees interpret it. This gap is important because BI is the country's only monetary authority, with a different institutional structure, bureaucratic culture, and accountability mechanisms than commercial banks. Theoretical gaps also exist. Multidimensional digital readiness models (Silva et al., 2025) and AI readiness frameworks (Holmström, 2022) are developing for companies and SMEs, and throughout the author's search there has been no adequate effort to adapt them to organizations whose goals are systemic stability and public trust. The logic of successful digital transformation in such organizations is likely to differ, as speed and efficiency can clash with the principles of prudence and oversight mandates.

Based on these gaps, this study aims to explore the readiness of BI organizations in implementing AI through digital transformation policies. This study examines how readiness is reflected in leadership statements and policy documents, with attention to the dimensions of human resources, processes, and governance, not only technological aspects. The qualitative approach was chosen because *readiness* at the level targeted in this study is a process of organizational meaning that develops over time (Creswell & Poth, 2018; Tsoukas & Chia, 2002), and document analysis allows a reading of the process (Bowen, 2009).

This research makes two contributions. Theoretically, it expands the literature on organizational readiness and digital transformation to policy-mandated public institutions, a domain that is less often worked on than the private sector and SMEs (Fernandez & Rainey, 2006; Kuipers et al., 2014). Practically, his findings can be an input for BI and related authorities, including the OJK, in designing strengthening

organizational readiness that is in line with the character of the central bank (Financial Services Authority, 2025), so that AI-based transformation runs without sacrificing public prudence and accountability.

II. LITERATURE REVIEW

2.1 Organizational Readiness Theory for transformation

The grand theory that is the basis of the analysis of this research is *Organizational Readiness for Change Theory*. Armenakis et al. (1993) distinguish readiness *for change* from *resistance to change* and assert that readiness is formed by the beliefs, attitudes, and intentions of organizational members towards change, so it is not the same as the absence of rejection. Weiner (2009) extends this idea to the organizational level by defining organizational *readiness for change* as a multilevel and multifaceted construct that relies on two core elements: *change commitment*, which is the collective determination of organizational members to implement change, and *change efficacy*, which is collective belief in the organization's ability to implement it. Shea et al. (2014) make these two elements the basis *for the Organizational Readiness for Implementing Change* (ORIC) measure, and Rafferty et al. (2013) examine readiness as a multilevel construct at the individual, group, and organizational levels.

Weiner (2009) places change valence and contextual factors as determinants of readiness. Change valence refers to the extent to which organizational members assess change as valuable and relevant to their interests. Contextual factors include structural, cultural, and resource conditions that enable or hinder change. Holt et al. (2007) developed a readiness scale that includes change-specific efficacy, change suitability, management support, and personal benefits, while Armenakis et al. (1993) explained that change messages shape readiness. This study uses four elements, namely commitment, efficacy, valence, and contextual factors, as analytical categories. The implementation of AI is organizational change, so the readiness that is studied is the collective readiness of organizational members to accept and implement the change.

2.2 Digital Transformasi

The second concept is digital transformation. Vial (2019) defines digital transformation as a process when digital technology creates disruption that triggers an organization's strategic response to change its value creation path, while managing structural changes and organizational barriers. Verhoef et al. (2021) distinguish three stages, namely digitization, digitalization, and digital transformation, and the last stage demands a change in business models and organizational capabilities as a whole. Warner and Wäger (2019) describe digital transformation as a process of continuous strategic renewal and building dynamic capabilities. Mergel et al. (2019) offer a definition of digital transformation based on interviews with experts in the public sector. From this framework, the research derives five analytical aspects: digital strategy, digital capability, digital leadership, digital culture, and process transformation.

2.3 Adoption of Artificial Intelligence

The third concept, *artificial intelligence adoption*, provides specific context to the changes studied. Dwivedi et al. (2021) map AI as a multidisciplinary phenomenon that influences organizational decision-making, innovation, and stakeholder relations, as well as demands attention to human governance and collaboration and AI. The OECD Council's recommendations on artificial intelligence affirm accountability, transparency, and responsible governance as principles of AI development (OECD, 2019). Mikalef and Gupta (2021) conceptualize and measure organizational AI capabilities, while Wirtz et al. (2019) map the applications and challenges of AI in the public sector. In this study, AI becomes a context and trigger for change whose organizational readiness is studied, and is not treated as a dependent variable whose success is measured.

2.4 Organizational Commitment and Learner Organization

The concept of organizational commitment helps to understand how attachment to the organization strengthens the acceptance and sustainability of change. Meyer and Allen (1991) identified three components of commitment: *affective commitment*, which is emotional attachment to the organization; *continuance commitment*, which is the calculation of the profit-loss of leaving the organization; and *normative commitment*, which is a sense of moral obligation to survive. Herscovitch and Meyer (2002) extend the three-component model to commitment to organizational change. This study uses the three components as a

supporting perspective to read the commitment to change as reflected in the leadership statement and policy direction, without measuring the individual commitment of employees.

The concept of learning organization is used as a supporting perspective to understand the capacity of the organization to respond to and sustain change. Senge (1990) defines a learning organization as an organization that continues to expand its capacity to create desired outcomes through a shared mindset, team learning, and shared vision. This perspective is in line with the view of Tsoukas and Chia (2002) that organizational change takes place as an ongoing process. This study views organizational learning, knowledge sharing, and competency improvement as aspects that help interpret the policies and public statements analyzed.

The five concepts do not stand in line as independent theories. *Readiness for change* is the main framework, digital transformation and AI adoption are the context of change, and *organizational commitment* and *organizational learning* function as supporting concepts to understand factors related to organizational readiness.

2.5 Previous Research

Table 1 summarizes the most relevant studies. The three studies are discussed in more detail as they provide direct methodological and conceptual comparisons to this study.

Table 1
Summary of relevant previous studies

Studies	Context and methods	Key findings	Loopholes in this research
Jöhnk dkk. (2021)	Cross-industry; in-depth interviews with 25 AI experts, triangulated with literature	Five categories of AI readiness factors and their indicators; organizations need to assess assets, capabilities, and commitments	A sample of practitioners across industries; not public institutions or central banks
Uren dan Edwards (2023)	AI experts from research, development, and business functions; cross-sectional qualitative studies, purposive samples	AI (people, process, technology, data) adoption model; people, process, and data readiness is needed in addition to technology	expert level; not studying central banks
Ahmed dkk. (2024)	Malaysian manufacturing; mixed methods (survey of 357 participants, interviews of 20 key informants)	Organizational culture, resources, change management competencies, and employee attitudes affect digital transformation readiness	The private sector; focus on digital transformation, not AI in public institutions
Rivai P dkk. (2025)	Bank Jago (bank digital); kuantitatif, kuesioner 387 pegawai tetap, PLS-SEM	Organizational learning becomes the strongest mediator between disruptive technology and individual readiness	commercial banks; individual level; non-central banks
Gfrerer dkk. (2021)	Banking industry; surveys	Perceptions of attitudes and empowerment are similar; individual readiness, competencies, and barriers to innovation differ significantly between managers and employees	Not a central bank; not a study of policy discourse
Silva dkk. (2025)	SMEs; design science; 20-dimensional model based on the perspective of public servants	The previous model reflects the views of senior management	SMEs; not public institutions

Source: compiled by the authors from the referenced study.

The first study is a study by Jöhnk et al. (2021) that mapped an organization's AI readiness factors through in-depth interviews with 25 AI experts, then trivialized it with scientific literature and practitioners. The study compiles five categories of readiness factors along with actionable indicators, and confirms that organizations need to assess their assets, capabilities, and commitments for specific AI adoption goals. Its relevance to this study lies in a methodological precedent: qualitative interviews can map AI readiness

factors. The qualitative study of Uren and Edwards (2023) leads to the same conclusion, namely that the readiness of people, processes, and data is necessary in addition to technological readiness, and Holmström (2022) links AI readiness to digital transformation.

The second research is a study by Ahmed et al. (2024) on digital transformation readiness in Malaysia's manufacturing sector. The mixed-method design combined a survey of 357 participants with semi-structured interviews with 20 key informants to examine the interaction of organizational culture, resources, change management competencies, and employees' attitudes towards readiness. These four factors have a significant effect on digital transformation readiness. This study combines dynamic capability theory (Warner & Wäger, 2019), resource-based view, and change management. Its relevance for this study lies in the affirmation that human culture and competence, which are covered in organizational commitment and learning organization, determine readiness in proportion to technical readiness. Silva et al. (2025) added that organizational structure, culture, and technological readiness need to be assessed together.

The third research is a study by Rivai P et al. (2025) in a national context, which examines the influence of disruptive technology on organizational culture, transformational leadership, organizational learning, and individual readiness for change at Bank Jago, a digital bank in Indonesia. A structured questionnaire to 387 permanent employees was analyzed with PLS-SEM. The three variables mediated the influence of disruptive technology on individual readiness, and organizational learning became the strongest mediator. This study validates the role of organizational learning in Indonesia's digital banking and at the same time becomes a direct methodological comparator, because this study takes a qualitative path in institutionally different institutions. Gfrerer et al. (2021) complement the banking picture with evidence that the perception of manager and employee readiness can differ significantly.

2.6 Research Analysis and Gaps

The three previous studies have clear similarities and differences. All three agree that organizational readiness for technology-based change cannot be reduced to technical readiness, as it involves culture, competence, and learning processes (Ahmed et al., 2024; Jöhnk et al., 2021; Rivai P et al., 2025). The first study took a qualitative path on practitioners across industries, the second study combined quantitative and qualitative methods on manufacturing, and the third study was fully quantitative on commercial digital banks. All three did not examine policy-mandated public institutions such as central banks, and two of them did not explicitly place AI as a context of change.

Another similarity is seen at the level of analysis. Banking survey studies show that perceptions of digital readiness differ between managers and employees (Gfrerer et al., 2021), and many models of readiness assessments reflect the views of senior management (Silva et al., 2025). Readiness at the leadership level and at the executive level cannot therefore be treated as the same thing.

Empirically, research space is available to assess the readiness of AI in central banks, especially BI, by examining how that readiness is reflected in leadership statements and public policy documents. This approach differs from studies that measure individual perceptions through surveys and interviews (Table 1). The literature on organizational change in the public sector has compiled success factors and mapped the findings specific to public institutions (Fernandez & Rainey, 2006; Kuipers et al., 2014), but throughout the authors' research it has not been applied to AI readiness in central banks. Methodologically, the dominance of quantitative approaches in Indonesian banking studies, such as in Bank Jago, leaves room for a qualitative approach that is able to explain the mechanisms behind readiness rates.

This gap is also theoretical. Existing AI readiness models and AI capabilities (Holmström, 2022; Mikalef & Gupta, 2021) as well as digital transformation frameworks (Verhoef et al., 2021; Vial, 2019) have not been explicitly tailored to institutions oriented towards systemic stability and public accountability, throughout the authors' search. The integration of these five research concepts in this context is important because the logic of change success in publicly mandated organizations is likely to be different: change valence, for example, is not solely determined by competitive advantage, but by the extent to which change is perceived to support the credibility and policy prudence that are at the core of the central bank's identity.

2.7 Conceptual Framework

Based on the synthesis of these theories and gaps, this study compiles a conceptual framework with the theory of organizational readiness to change as the main analytical umbrella (Figure 2). Four categories, namely change commitment, change efficacy, change valence, and contextual factors, were used to examine the indications of BI's readiness for AI-based change in leadership public statements and policy documents (Holt et al., 2007; Shea et al., 2014).

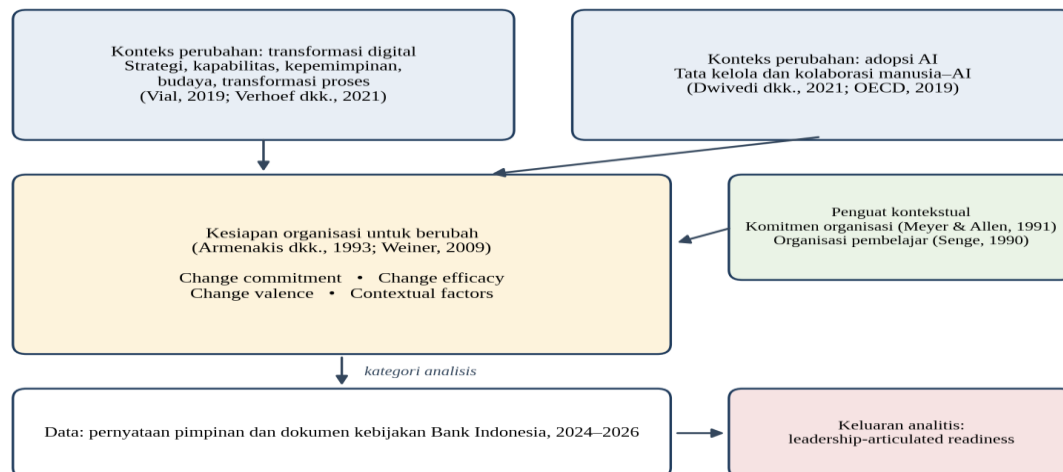


Fig. 2 *Conceptual framework of the research*

Source: compiled by the author based on Armenakis et al. (1993), Weiner (2009), Vial (2019), Verhoef et al. (2021), Dwivedi et al. (2021), Meyer and Allen (1991), and Senge (1990).

Digital transformation and AI adoption are positioned as a context of change that is not measured by success. Aspects of strategy, capability, leadership, culture, and process transformation explain the arena in which change takes place (Mergel et al., 2019), while the principles of human-AI governance and collaboration explain the nature of the changes faced (Dwivedi et al., 2021; OECD, 2019). Organizational (Meyer & Allen, 1991) and learning organizations (Senge, 1990) are positioned as contextual reinforcers that influence variations in change efficacy and change commitment between individuals and between work units.

This framework places readiness as a construct that is dynamically formed through the interaction of four categories of readiness, the context of digital transformation and AI, and the commitment factor and learning capacity. Since the data is limited to leadership statements and policy documents, the analytical output is leadership-articulated readiness, which is distinguished from the collective readiness of the organization as a multilevel construct (Rafferty et al., 2013).

III. RESEARCH METHODS

3.1 Design and Paradigm

This study uses a qualitative approach with the constructivism-interpretivism paradigm, which views the reality of the organization as the result of social constructions that are continuously negotiated by actors in it (Creswell & Poth, 2018). Readiness, in the framework of Weiner (2009), is formed by the beliefs, attitudes, and shared meanings of organizational members, so it is not enough to be reduced to a single score. The researcher does not attempt to objectively establish the level of readiness of BI. The researcher examines how readiness for AI-based change is reflected in leaders' public statements and policy documents. The design is in the form of a single case study on BI (Yin, 2018). This choice is consistent with previous AI readiness studies that used interviews and qualitative studies (Jöhnk et al., 2021; Uren & Edwards, 2023).

3.2 Data Sources and Selection Criteria

Data in the form of public statements of BI leaders and policy documents published in 2024–2026 and reported by national media or officially published by BI and the government (Table 2). Direct interviews

with high-ranking BI officials were not available during the study period, so official public statements were analyzed as an articulation of institutional attitudes. Statements or documents are selected when (a) related to AI, digital transformation, or the continuity of digital policies, (b) they come from official BI officials or documents, or from the government for leadership transition events, and (c) can be traced to public sources. OJK documents and other news reports are treated as supporting context and are not encoded as primary data (Bowen, 2009).

3.3 Analytical Techniques

The analysis of the document (Bowen, 2009) was performed by framework-based deductive coding. Four categories of readiness became the initial code, and each statement or policy was mapped to that category along with its indicators and inference limits (Table 3). This procedure follows the logic of thematic analysis (Braun & Clarke, 2006). Validity is maintained by examining statements on more than one source when available (Yin, 2018), distinguishing direct quotes from media paraphrasing, and stating inference limits on each finding.

IV. RESULTS AND DISCUSSION

This section analyzes public statements and official documents for 2024–2026 (Table 2; Figure 3). The corpus includes the news of BI's leadership transition after the resignation of Governor Perry Warjiyo on July 25, 2026 (Detik.com, 2026; Presidential Secretariat, 2026), Destry Damayanti's statement at Banking AI Day on September 9, 2024 (Bisnis.com, 2024; Infobanknews, 2024) and at the 20th BMEB Conference on July 31, 2026 (CNBC Indonesia, 2026), Perry Warjiyo's statement at the EMEAP meeting on July 23–24, 2026 (Bank Indonesia, 2026), statement by the Head of the Payment System Policy Department, Dicky Kartikoyono, on the Proactive Risk Management initiative in early 2024 (Investortrust.id, 2024), as well as the BSPI 2030 document (Bank Indonesia, 2024).

Table 2 Public Statements & official documents for 2024–2026

No.	Date	Resources and forums	Relevant content	Source
1	9 Sep 2024	Banking AI Day; Destry Damayanti	AI is used by BI to process granular data; BI as a user and regulator	(Bisnis.com, 2024; Infobanknews, 2024)
2	1 Agu 2024	Launch of BSPI 2030	Five key initiatives; phased implementation 2025–2030	(Bank Indonesia, 2024; Warta Ekonomi, 2024)
3	Awal 2024	Online discussion; Dicky Kartikoyono	proactive risk management; limitations of manual supervision	(Investortrust.id, 2024) (perlu diverifikasi)
4	23 Okt 2025	PRIMA Executive Gathering 2025; Filianingsih Hendarta	BSPI 2030 strengthens cyber resilience and fraud detection, including with AI	(Kontan.co.id, 2025)
5	23–24 Jul 2026	EMEAP Meeting; Perry Warjiyo	Gradual adoption of AI: data and metadata, governance, HR capabilities, innovation	(Bank Indonesia, 2026)
6	25–27 Jul 2026	Perry's resignation Warjiyo; RDG 26 Jul	Destry Damayanti becomes Acting Governor (Article 50 paragraph 2 of the BI Law)	(Detik.com, 2026; detikFinance, 2026; Sekretariat Presiden, 2026)
7	31 Jul 2026	20th BMEB Conference; Destry Damayanti	Integration of policy instruments; digital finance research agenda and AI	(CNBC Indonesia, 2026)

Note. OJK (Financial Services Authority, 2025) documents and other news are used as supporting contexts. Source: compiled by the author.



Fig. 3. *Timeline of events and statements analyzed, 2024–2026*

Note. Dicky Kartikoyono's statement (early 2024) was not included because the date and source have not been verified. Sources: Bank Indonesia (2024); Infobanknews (2024); Financial Services Authority (2025); Kontan.co.id (2025); Bank Indonesia (2026); Presidential Secretariat (2026); CNBC Indonesia (2026).

4.1 Thematic findings

The first theme is *change efficacy*, which is an indication of confidence in the organization's capacity to implement AI-based changes (Shea et al., 2014). The strongest indicator came from Perry Warjiyo at the EMEAP meeting on July 23–24, 2026. He stated that BI is implementing AI gradually through strengthening the quality of data and metadata, governance, human resource capabilities, and innovation, while maintaining data sovereignty and strategic infrastructure. He also emphasized that "the success of AI adoption does not only depend on technology, but also on synergy between people, processes, and good governance" (Bank Indonesia, 2026, para. 2). This statement mentions the capabilities that are being built, so that it becomes a more direct indicator of efficacy than a statement of needs. The experience of other central banks shows that the use of AI does demand new infrastructure and expertise (Araujo et al., 2024).

Dicky Kartikoyono was quoted as stating that BI "cannot manually supervise real-time transactions or real-time fraud" in an online discussion at the end of February 2024 (Investortrust.id, 2024). This statement acknowledges the limitations of conventional supervision and accompanies the Proactive Risk Management initiative. Recognition of limitations marks the need for change more clearly than confidence in capability, so this study reads it as an indicator of efficacy only when accompanied by initiatives that build technical capacity (Holt et al., 2007). This statement represents a single official and cannot be read as a collective attitude of all leaders.

The second theme is *change valence*, which is the extent to which leaders view AI-based change as valuable for the strategic interests of institutions (Weiner, 2009). At Banking AI Day on September 9, 2024, Destry Damayanti mentioned the financial sector, including central banks, as the main driver of digital transformation and stated that BI has begun to utilize AI in its activities (Infobanknews, 2024). He explained that BI puts itself in two positions, as a user and as a regulator, and uses AI to process highly granular data to support policy formulation (Bisnis.com, 2024). At the 20th BMEB Conference in Bali, July 31, 2026, Destry stated that geoeconomic fragmentation, digital transformation, and systemic risks make sectoral approaches inadequate and demand the integration of monetary policy, macroprudential, payment systems, financial markets, and fiscal coordination. It also designated the deepening of digital financial studies, including AI, as one of the four priority research agendas (CNBC Indonesia, 2026). Both statements show the positive value of AI for institutional needs. The comparison needs to be careful: the 2024 industry forum and the 2026

research conference have different audiences and goals, and AI is only one topic in the 2026 statement. This study therefore does not conclude that there is a shift in rhetoric about AI.

The third theme, *contextual factors*, appears to be the transition of leadership in the midst of the research period. Perry Warjiyo resigned voluntarily for personal reasons on July 25, 2026. The government received a letter of resignation on July 26, and the Board of Governors Meeting on the same day appointed Senior Deputy Governor Destry Damayanti as Acting Governor based on Article 50 paragraph 2 of the Bank Indonesia Law (detikFinance, 2026; Presidential Secretariat, 2026). Destry stated that BI continues to carry out all its duties and authorities, including maintaining rupiah exchange rate stability, payment system, and financial system stability (Detik.com, 2026; detikFinance, 2026). In the perspective of contextual factors, this statement indicates the absence of an explicit change in the direction of digital policy at the level of post-transition public statements. These findings do not prove that the structural and internal conditions of the organization are stable, as the statement of continuity is a prevalent institutional communication in sudden succession.

The fourth theme, change commitment, is reflected in the continuity of the payment system policy direction. BSPI 2025 is followed by BSPI 2030 which was launched on August 1, 2024 and implemented in stages in 2025–2030 through five main initiatives (Bank Indonesia, 2024; Warta Ekonomi, 2024). In October 2025, Deputy Governor Filianingsih Hendarta stated that BSPI 2030 will strengthen payment infrastructure along with data infrastructure to increase cyber resilience and fraud detection capacity, including with AI (Kontan.co.id, 2025). The sustainability of this horizon shows a policy commitment to a long-term digital agenda that does not depend on a single official. Commitment to change can be based on affective attachment, cost calculation, or normative obligations (Herscovitch & Meyer, 2002), and policy documents do not indicate which components are dominant in employees. This study therefore does not conclude the extent to which these commitments are understood and implemented at the organizational level.

The four themes are interrelated in the institutional narrative that appears consistent (Table 3). The statement on capability building supports efficacy, Destry's statement supports valence, the statement of continuity supports context stability, and BSPI 2030 supports long-term policy commitments. This consistency comes from a corpus that is entirely in the form of official communication, so selection bias and audience effects cannot be ruled out (Bowen, 2009).

Table 3
Synthesis of findings by readiness category

Category	Indicators in the data	Source	Inference limits
Change efficacy	Gradual implementation of AI through data and metadata quality, governance, and HR capabilities; recognition of the limitations of manual oversight	D5, D3	Leadership statements, not real capability measures; D3 citations need source verification
Change valence	Gradual implementation of AI through data and metadata quality, governance, and HR capabilities; recognition of the limitations of manual oversight	D1, D7	Forums are different; do not show a shift in rhetoric about AI
Contextual factors	Leadership transition July 25–27, 2026; statement of continuity of duties and authority	D6	Continuity statements are not evidence of internal stability
Change commitment	BSPI 2025 followed by BSPI 2030; AI in fraud detection	D2, D4	Policy commitment, not employee commitment; affective, continuous, and normative components are not observed

Sumber: analisis penulis.

4.2 Theory-Based Interpretation

These findings show that all four categories of readiness are present simultaneously in the articulation of leadership policies, in line with the view that readiness is shaped by the beliefs and values articulated by influential figures (Armenakis et al., 1993). True readiness, however, must be reflected at the collective level (Weiner, 2009) and multilevel (Rafferty et al., 2013). The data of this study are limited to

high-ranking officials, so the readiness identified is more accurately called leadership-articulated readiness than organizational readiness in the full sense.

This distinction is met with the criticism of Silva et al. (2025) that many readiness models reflect the views of senior management and do not centralize the perspective of general employees. Gfrerer et al. (2021) show that banking managers and employees differ significantly in the perception of individual readiness, competencies, and innovation barriers. A similar pattern may exist at BI, but the data of this study cannot be confirmed. The precedent places that possibility on the agenda for further research.

Destry's 2024 statement emphasizes the use of AI, while the 2026 statement emphasizes policy integration. This distinction is consistent with the view that digital transformation does not stop at the application of technology to existing processes and can drive broader changes to processes and capabilities (Verhoef et al., 2021). Such transformation takes place as a sustained strategic renewal (Warner & Wäger, 2019) and as a strategic response to disruption (Vial, 2019). The difference in forums makes this study not define the stages of BI's digital transformation.

AI is best understood as a context for triggering change. Perry and Destry's statement places AI as an instrument for productivity, efficiency, oversight, and policy formulation, in line with the emphasis that the value of AI lies in its contribution to decision-making and governance (Dwivedi et al., 2021). The principles of accountability and transparency (OECD, 2019) and the AI readiness framework that links AI to digital transformation (Holmström, 2022) provide a similar foundation.

Compared to Jöhnk et al. (2021), who compiled the AI readiness factors from interviews with 25 experts, the BI corpus shows that leaders recognize governance, data quality, and human capabilities as prerequisites, so that non-technical aspects emerge from the initial discourse. The character of a central bank mandated by stability and public accountability may explain this, but this study does not test this explanation. Regarding the finding of Rivai P et al. (2025) that organizational learning is the strongest mediator, this study cannot confirm or refute because the data does not reach the individual level. The limitations themselves are a comparative note: the analysis of public discourse was not able to reveal the dynamics of individual readiness reached by the survey study through 387 respondents. Ahmed et al. (2024) show that the culture and competence of change management have a significant effect, and that aspect is also beyond the reach of the data.

Practically, BI and OJK need to build a readiness assessment mechanism that reaches implementing employees in various units and levels, so that the articulation of leadership readiness is not the only indicator of transformation success. Without this mechanism, the gap between policy ambition and implementation capacity is difficult to detect early. An Islamic banking study from UMY shows that banks need to improve liquidity efficiency and financing risk management, while regulators maintain economic stability (Aprizal et al., 2025). The study of access to digital financial services shows that policies need to close the gap between access and use through simpler processes and stronger literacy (Duasa & Wiranatakusuma, 2025). The sustainability of BSPI 2030 in the post-transition statement shows that a long-term blueprint can maintain policy direction, but this study has not tested whether blueprints are more resilient to leadership change than initiatives that depend on specific officials' preferences.

Theoretically, this study offers a distinction between leadership-articulated readiness, which is readiness that is reflected in leadership statements and policies, and organizational readiness in the full sense, which is readiness that includes the collective perception of organizational members. This distinction is important because leadership statements can give the impression of high readiness even though they represent a single layer of multilevel constructs (Rafferty et al., 2013). The data also do not show disruptions to the digital agenda due to leadership transitions, so the allegation that the central bank's digital transformation stages can be disrupted by non-economic contextual factors cannot be supported and is not put forward as a contribution. Methodologically, document analysis allows an examination of institutions whose internal activities are not fully open, with an epistemic limit that public discourse is a curated representation and is not the same as a complete portrait of organizational readiness (Bowen, 2009).

This research has limitations that need to be acknowledged. First, all data is sourced from public statements and news reports, so the consistency between public discourse and internal practice cannot be verified. Second, all sources come from high-ranking officials, so the voices of implementing employees are not represented. Third, as a single case study, these findings are not statistically generalized and contribute as analytical generalizations that need to be tested in other contexts. Follow-up research needs to be triangulated through interviews with employees across levels and work units, ideally with official research permission from BI, as well as comparing readiness patterns with other central banks that have mapped their AI applications (Araujo et al., 2024).

V. CONCLUSION

This article explores the readiness of BI organizations to implement AI through the ongoing digital transformation process. Analysis of the leadership's public statements and policy documents for 2024–2026 shows that the four categories of readiness are reflected in the data. Change efficacy is reflected in Governor Perry Warjiyo's statement on the gradual implementation of AI through data quality, governance, and human resource capabilities, as well as from the recognition of the limitations of manual supervision in Proactive Risk Management initiatives. Change valence is reflected in the affirmation of the use of AI in 2024 and the agenda of policy integration and digital financial research in 2026. Contextual factors appear to be stable at the level of public statements after the leadership transition, and change commitment is reflected in the continuity of BSPI 2025 to BSPI 2030. This readiness has only been identified at the level of leadership discourse, so the question of how employees and work units interpret readiness has not been answered.

Theoretically, this study reinforces the proposition that readiness is multidimensional and offers a distinction between leadership-articulated readiness and organizational readiness in the full sense. In practical terms, the results recommend that BI and OJK should not make the articulation of leadership readiness the only indicator of transformation success, and build an assessment mechanism that reaches out to implementing employees. Methodologically, document analysis and public discourse can be a middle way to examine closed institutions when access to interviews is limited, with epistemic limits that public discourse is a curated representation.

The limitations of this study include reliance on public statements and news reports, representation of high-ranking officials only, and a single case study design. Further research needs to be triangulated through direct interviews with employees across levels and work units at BI, ideally with official research permission, to test whether gaps between leadership discourse and executive employee experience also occur, and compare readiness patterns with other countries' central banks to reinforce analytical generalizations.

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