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LEVERS OF CONTROL AND DIGITAL INNOVATION IN THE INDONESIAN BANKING SECTOR: A HYBRID SEM-ANN APPROACH

Abstract

This study aims to analyze the relationship between management control systems and digital innovation in the Indonesian banking sector through the theory of levers of control (LOC). Unlike previous studies that often assume linear relationships and analyze LOC in aggregate, this study adopts a disaggregated approach and hybrid methods to provide a more comprehensive understanding. The methodology integrates partial least squares structural equation modeling (PLS-SEM) and artificial neural network (ANN) using data from 76 chief financial officers (CFOs) of commercial banks in Indonesia (response rate 77.55%). The PLS-SEM results showed that the belief system (β = 0.234), boundary system (β = 0.231), and interactive control system (β = 0.281) were positively related to digital innovation, with the interactive control system as the most consistent dimension, while the diagnostic control system did not show a significant linear relationship (p = 0.066). The ANN analysis complements these findings by showing that the interactive control system has the highest level of predictive importance, followed by the diagnostic control system, boundary system, and belief system. These findings suggest that PLS-SEM and ANN provide complementary insights, where PLS-SEM describes linear relationships based on theoretical models. In contrast, ANN describes the relative contribution of each predictor to the model's predictive ability. Overall, interactive control systems are the most consistent LOC dimension related to digital innovation and illustrate the added value of a hybrid approach for a more comprehensive understanding of the role of management control systems in digital transformation in the banking sector.

Keywords management control system, levers of control, digital innovation, commercial banking, PLS-SEM, artificial neural network (ANN)

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INTRODUCTION

The increasingly digitized business environment has changed how organizations create and maintain a competitive advantage (Tran, 2023). In the banking sector, this transformation is taking place very quickly due to the demands of efficiency, security, and changes in customer behavior, which increasingly depend on digital services (Setiawan & Prakoso, 2024). In this context, digital innovation is no longer optional, but rather a fundamental element in organizational operations and strategies.

As one of the largest economies in Southeast Asia, the banking sector in Indonesia has experienced a significant digital acceleration in recent years, reflected in the sharp increase in digital transactions, where the value of digital banking transactions has increased by almost 300% in the last five years (Bank Indonesia, 2025). However, this acceleration has not always been matched by stable banking per-

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formance. Meanwhile, profitability fluctuated between 1.5% and 2.7% during 2020–2025 (Financial Services Authority/OJK, 2025). This raises fundamental questions about how organizations manage digital transformation to stay aligned with their strategic goals. Digital innovation is not only concerned with the adoption of technology, but also relies on internal mechanisms that govern how strategies are implemented in a dynamic environment.

Therefore, the management control system (MCS) becomes a key element as it connects strategy with operational implementation. However, in practice, the need to encourage innovation often conflicts with the need to maintain stability and control. This tension between flexibility and control is becoming increasingly complex in the digital context, where change is rapid, and uncertainty is increasing.

Although the role of MCS in supporting organizational change has long been recognized, there is still a limited understanding of how the control mechanism works in the context of digital innovation, particularly in the banking industry of developing countries. In addition, it is unclear how different control mechanisms can simultaneously support innovation exploration while maintaining organizational discipline. Based on these conditions, the scientific problem that arises is how organizations can balance the need for digital innovation with the need for control through their internal mechanisms, as well as the role of these mechanisms in influencing the innovation process in a dynamic and high-risk environment.

1. LITERATURE REVIEW AND HYPOTHESES

Digital innovation has been recognized as a key determinant of an organization's competitive advantage in an increasingly digitized and dynamic business environment. The literature shows that digital innovation not only improves operational efficiency but also enables new business models, improved customer experience, and the development of data-driven services (Minakshi et al., 2026; Faiz et al., 2024; Kim et al., 2021). In banking, digital innovation is becoming increasingly crucial amid intense competitive pressures, financial technology (fintech) disruptions, and demand for fast, secure, and integrated services. In addition, banks in developing countries have a strategic role in driving financial inclusion and economic growth, so the ability to effectively manage digital innovation is critical (Abdurrahman, 2025; Al-Ansi et al., 2024).

However, most previous research has focused on technological determinants of digital innovation, such as infrastructure readiness, information system adoption, and technological capabilities (Fayad et al., 2025; Lavanya & Rajkumar, 2024; Wang et al., 2024). This approach tends to ignore the role of internal managerial mechanisms, specifically how MCS shapes organizational behavior in driving innovation. In fact, digital innovation is essentially the result of complex organizational processes, which involve strategic decision-making, risk management, and cross-functional coordination (Schrader et al., 2025). Thus, there is an important gap in the literature regarding how MCS affects digital innovation.

The management accounting literature confirms that MCS not only serves as a control tool to ensure the achievement of objectives, but also as a mechanism that allows organizations to adapt and innovate amid environmental uncertainty (Baird et al., 2019; Truant et al., 2024). Thus, the Levers of Control (LOC) developed by Simons (1995) became one of the most widely used theoretical approaches to explain how organizations balance the need between control and innovation. LOC consists of four main dimensions: belief system, boundary system, diagnostic control system, and interactive control system, each with a different but complementary role in directing organizational behavior.

The LOC theory explains that the belief system encourages the search for opportunities to achieve the core values of the organization (Simons, 1995). This system serves as a positive driver that inspires employees to innovate and explore. In the context of belief systems, the organization's strategic values and aspirations form a shared purpose that encourages creativity and the courage to take risks. Organizations with a strong digital vision are able to inspire innovative employee onboarding and encourage the exploration of new technologies (Wang, 2022). Belief systems create a meaningful framework for digital innovation, thus providing intrinsic motivation in pursuing experimentation and development of new services.

Simons (1995) also emphasizes that the search for opportunities in innovation can pose business risks. The LOC theory argues that MCS must balance the tension between growth and control. Innovation for growth needs to be balanced with control to ensure profitable growth (Baird et al., 2019; Simons, 2000). The boundary system defines the scope of exploration through risk limits, compliance rules, and operating standards that keep digital initiatives within a secure regulatory framework. In the banking industry, highly regulated by OJK regulations, data protection regulations, and risk management, the boundary system is becoming critical. Clear boundaries can reduce the cost of irrelevant experiments, speed up iterative processes, and increase the focus of innovation efforts (Caccamo et al., 2023; Ringgaard et al., 2025).

Baird et al. (2019) emphasize the importance of using diagnostics to ensure innovation effectiveness because interactive use alone is not enough. Diagnostic control systems provide performance monitoring and evaluation tools essential to implementing digital innovation. Through measurable indicators, organizations can ensure that digital initiatives remain consistent with strategy, operational efficiency, and performance goals. Several studies have found that diagnostic control systems can increase innovation effectiveness because performance control provides the focus and clarity needed in the digitalization process (Phan et al., 2023; Weber et al., 2024). However, these benefits only arise when diagnostic systems are used, enabling, not coercive.

In managing the tension between digital innovation and the achievement of predictable goals, the use of interactive MCS supports the development of ideas and creativity. Managers use interactive control systems to encourage opportunity search, stimulate outbursts, and develop new strategic initiatives (Boussaidi & Korbi, 2025; Chrusciak et al., 2025; Najda-Janoszka et al., 2025). Henri (2006) argued for a match between the need for innovation and the use of an organic control system. The need for interaction and information processing capacity required for innovation capabilities is likely to be supported by the use of interactive MCS. Through the provision of an agenda and a forum for face-to-face dialogue and debate, interactive use of MCS allows top management to send signals and focus the organization's attention on their preferences (Simons, 1995). By encouraging dialogue, debate, and exchange of information, interactive use contributes to the dissemination of knowledge necessary during innovation decision-making (Rogers, 1962). Therefore, the use of interactive MCS expands information processing capacity and encourages interaction, which ultimately boosts the spread of innovation.

Among the four levers of LOC, the interactive control system is the closest mechanism to innovation. This system encourages strategic discussions, two-way learning, cross-functional dialogue, and intensive collaboration between business and technology units. Organizations that enable interactive control tend to have higher agility, faster iteration speeds, and better technology sensing capabilities than those that rely solely on diagnostic controls (Phan et al., 2023; Weber et al., 2024). In digital banking, interactive control systems play an important role as a trigger for the exploration of new technologies.

Although LOC theory has been widely used to explain the relationship between control systems and innovation, most previous research has still focused on testing the interdimensional relationships of LOC using a linear approach based on a theoretical model. This approach provides an important understanding of the significance of relationships between constructs, but tends to place each dimension of the LOC as a stand-alone predictor in the structural model. In complex and dynamic digital innovation, such approaches may not yet fully capture the variation in the relative contribution of each control mechanism to innovation performance. In addition, most studies are still limited to an inferential approach, so they have not provided much additional perspec-

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tive in terms of the model's predictive capabilities. Therefore, a more comprehensive approach is needed to combine theory-based analysis and prediction-based approaches to gain a more comprehensive understanding of LOC dimensions in digital innovation.

This study aims to examine the impact of four LOC dimensions on digital innovation in the banking sector. Based on the literature review, the following hypotheses were proposed:

H1: *There is a positive relationship between belief systems and digital innovation.*

H2: *There is a positive relationship between boundary systems and digital innovation.*

H3: *There is a positive relationship between diagnostic control systems and digital innovation.*

H4: *There is a positive relationship between the interactive control system and digital innovation.*

2. METHOD

This study uses a quantitative approach with a survey method conducted from July to October 2025 to examine the relationship between the dimension of LOC and digital innovation in the banking industry, especially commercial banks in Indonesia. The research population includes all 98 commercial banks registered and supervised by the Financial Services Authority (OJK) as of 2025. The research sample consists of commercial banks in Indonesia, which include state-owned banks (BUMN), regional development banks (BPD), and national private commercial banks. The purposive sampling technique was used with the following criteria:

1) having an active level of adoption of digital innovations;

2) providing adequate data related to organizational activities through annual reports or other official sources; and

3) operating fully as a commercial bank during the observation period.

These criteria ensure the empirical relevance and consistency of the regulatory context.

The research respondents are chief financial officers (CFOs), responsible for financial management and control systems. This position has a strategic understanding of management control practices, organizational policies, and involvement in the bank's digital transformation process and strategic decision-making, so they can provide relevant information. A total of 76 valid responses were collected and deemed suitable for further analysis, with a response rate of 77.55%. This sample size meets the minimum requirements for PLS-SEM analysis and aligns with previous research in the banking industry and executive-level management studies (Rapina et al., 2024; Yunita et al., 2024) with limited respondent access. Thus, the sample size is adequate for the purpose of this analysis.

Prior to the widespread distribution of the questionnaire, the research instruments were tested on a limited basis to ensure the clarity of the questions and the suitability of the banking industry context. The construct of digital innovation is measured using integrative instruments adapted from Yu et al. (2025). This instrument includes six statements: quantity, quality, scope, openness, iteration, and agency. The LOC construct is measured through four dimensions: boundary system, beliefs system, diagnostic control system, and interactive control system. These four dimensional systems are measured using an instrument developed by Widener (2007), which consists of eighteen statements. All items were measured on a five-point Likert scale. Appendix A presents a complete description of the measurement items in this study.

This study adopts an integrative approach by combining partial least squares structural equation modeling (PLS-SEM) and artificial neural network (ANN). This approach allows testing theory-based structural relationships through PLS-SEM and evaluating the predictive ability and relative importance of independent variables to dependent variables using ANN (Ali et al., 2026; Fitriyani & Ratmono, 2024). The analysis was carried out in two stages; the first stage used PLS-SEM through SmartPLS software version 4.0 to evaluate the measurement model as well as test the relationships between constructs within the proposed theoretical framework. The second stage used ANN through SPSS version 27 to complement the analysis with a prediction-based approach, particularly in assessing model performance and identifying the relative importance of independent variables.

3. RESULTS

Table 1 shows the demographic features of the research sample. The demographic profile of the respondents in this study (n = 76) showed the dominance of male participants at 65.79% (n = 50), while female participants comprised 34.21% (n = 26). In terms of age, the majority of respondents were in the mature age category, where 50.00% were 50 years old and above, and 39.47% were in the 40–49 age range, while none of the respondents were under 30 years old. Educational backgrounds were dominated by Bachelor's (64.47%) and Master's (34.21%) graduates, with only 1.32% holding a Doctoral degree. Furthermore, the professional profile of respondents reflects a high level of seniority, as evidenced by the majority of respondents (59.21%) having more than 15 years of work experience. In comparison, only 5.26% have less than 5 years of service. Collectively, this composition indicates that the research data are sourced from individuals who are mature in age, have higher education backgrounds, and possess extensive professional experience in their fields.

Because data were collected through the same survey instrument and from one respondent in each organization, this study has the potential for common method bias (CMB). According to Podsakoff et al. (2012), CMB can be minimized through both procedural and statistical approaches. Procedurally, this study applies several preventive measures, namely ensuring the anonymity of respondents, emphasizing that there are no right or wrong answers, and using several reverse-coded items (Leong et al., 2020). Furthermore, statistically, the test was carried out using Harman's single-factor test through exploratory factor analysis without rotation via SPSS. The results showed that the largest single factor explained only 41.19% of the total variance, below the 50% threshold. These results indicate that common method bias was not the dominant threat in this study, although its existence cannot be completely ruled out.

In addition, to ensure that the data collected are truly representative, the study conducted non-response bias testing. Initial respondents and final responders were compared, and final responders were treated as non-respondents (Armstrong & Overton, 1977). Final responders are defined as those who return the questionnaire only after the second follow-up reminder. As shown in Table 2, the assessment showed a p-value of > 0.05, indicating no significant difference in the mean scores of the two groups. Therefore, the data show that non-response bias was not a significant risk in this study, suggesting the results are valid for further analysis and that the data are representative.

3.1. PLS-SEM results

The first step in PLS-SEM analysis is to assess the measurement model and ensure it meets the re-

Table 1. Demographic characteristics

Demographic variable	Category	Frequency (n)	Percentage (%)
Gender	Male	50	65.79%
	Female	26	34.21%
Age	Less than 30 years	0	0.00%
	30–39 years	8	10.53%
	40–49 years	30	39.47%
	50 years and above	38	50.00%
Education Level	Bachelor's degree	49	64.47%
	Master's degree	26	34.21%
	Doctoral degree	1	1.32%
Years of Experience	Less than 5 years	4	5.26%
	5–10 years	8	10.53%
	11–15 years	19	25.00%
	More than 15 years	45	59.21%

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Table 2. Non-response bias test: Early respondents and late respondents

Construct	Early respondents (n = 12)	Late respondents (n = 64)	p-value
Belief system	3.54	4.02	0.053
Boundary system	3.54	3.88	0.099
Diagnostic control system	3.50	3.94	0.169
Interactive control system	3.71	3.86	0.414
Digital innovation	3.89	3.97	0.750

Table 3. Reliability and convergent validity

Construct	Number of Indicators	Composite Reliability	Cronbach's Alpha	Loading range	AVE
Belief system	4	0.782	0.768	0.709–0.795	0.587
Boundary system	4	0.837	0.815	0.708–0.833	0.640
Diagnostic control system	4	0.747	0.743	0.717–0.775	0.559
Interactive control system	6	0.861	0.851	0.712–0.837	0.574
Digital innovation	6	0.883	0.876	0.719–0.821	0.616

quirements for reliability and construct validity (Hair et al., 2022). As shown in Table 3, the composite reliability and Cronbach's alpha coefficient are above the standard 0.70, thus crossing the threshold of internal consistency reliability (Hair et al., 2022). Regarding convergent validity, each indicator showed a statistically significant charge ($p < 0.05$) and exceeded the 0.70 threshold. In addition, the AVE value of each construct is greater than 0.50, indicating convergent validity at a high level.

To assess the discriminant validity, this study used the Fornell–Larcker criteria and the heterotrait–monotrait ratio (HTMT). The results in Table 4 show that the square root of the average variance extracted (AVE) for each construct (shown diagonally) is greater than its correlation with the other constructs, so that the Fornell–Larcker criteria are met (Hair et al., 2022; Nitzl, 2016). Furthermore, Table 5 shows that most HTMT values are below the recommended threshold. Nevertheless, the boundary system-diagnostic control system (0.881) and diagnostic control system–interactive control system (0.852) construct pairs exceed or are very close to the conservative threshold of 0.85. These findings indicate a conceptual proximity between the constructs, which is understandable given that the four constructs are dimensions of the theoretically interrelated levers of control (LOC) framework. Henseler et al. (2015) state that a looser threshold of 0.90 can still be applied to constructs that have con-

Table 4. Discriminant validity tests: Fornell–Larcker

Construct	Belief System	Boundary system	Diagnostic control system	Interactive control system	Digital Innovation
Belief system	(0.766)	0.489	0.515	0.517	0.593
Boundary system	0.489	(0.800)	0.707	0.584	0.647
Diagnostic control system	0.515	0.707	(0.748)	0.678	0.670
Interactive control system	0.517	0.584	0.678	(0.758)	0.669
Digital Innovation	0.593	0.647	0.670	0.669	(0.785)

Table 5. Discriminant validity tests: HTMT

Construct	Boundary system	Belief System	Diagnostic control system	Interactive control system	Digital Innovation
Boundary system					
Belief system	0.609				
Diagnostic control system	0.881	0.668			
Interactive control system	0.693	0.634	0.852		
Digital Innovation	0.732	0.705	0.788	0.756	

Table 6. Model fit indices

Fit Indicator	Result	Criteria
R-Squared (ID)	0.607	≥ 0.5 (moderate), ≥ 0.75 (substantial)
Adjusted R-Squared (ID)	0.585	≥ 0.5 (moderate), ≥ 0.75 (substantial)
Full Collinearity VIF	1.504–2.603	< 5
Outer VIF (VIF Indicator)	1.218–2.968	< 5

ceptual proximity. Therefore, although the HTMT results show conceptual overlap in some construct pairs, the overall HTMT value remains below the 0.90 threshold, so discriminant validity can still be considered adequate. However, these results need to be interpreted carefully, considering two construct pairs exceed the conservative threshold of 0.85 (Hair et al., 2022).

The next step in the PLS-SEM process is to evaluate the structural model in terms of predictive accuracy and model suitability. The criteria set by R-squared and Adjusted R-squared in Table 6 indicate that the model is adequate; this suggests that the exogenous construct of the model explains most of the variation in the dependent endogenous variables. In addition, a multicollinearity examination using the full collinearity variance inflation factor (VIF) showed that all constructs showed a VIF value of less than 5. Therefore, the structural model has no collinearity problems, maintaining the reliability of the path estimation.

Figure 1 presents the results of the structural model, where the significance of the relationships between constructs is evaluated based on path coefficient values, t-statistics, and p-values from the bootstrapping procedure. Table 7 summarizes the hypothesis testing results. The findings show that three of the four control constructs have a positive and statistically significant relationship with digital innovation. Among the three constructs, the interactive control system has the largest path coefficient ($\beta = 0.281$), followed by the belief system ($\beta = 0.234$) and the boundary system ($\beta = 0.231$). In contrast, the diagnostic control system showed no statistically significant association with digital innovation ($p = 0.066$).

3.2. Artificial neural network analysis

Once the evaluation of the PLS-SEM structural model is complete, the next stage in the SEM–ANN framework is to construct the ANN model using the independent constructs that have been evaluated in the previous stage, as shown in Figure 2. In this hybrid approach, PLS-SEM evaluates the relationships between constructs within the proposed theoretical model. Furthermore, ANN complements the analysis by evaluating the predictive performance of the model and identifying the relative importance of each predictor to digital innovation. Thus, the combination of PLS-SEM and ANN provides a complementary approach, where PLS-SEM tests theory-based models, while ANN evaluates the relative predictive contribution of each LOC dimension.

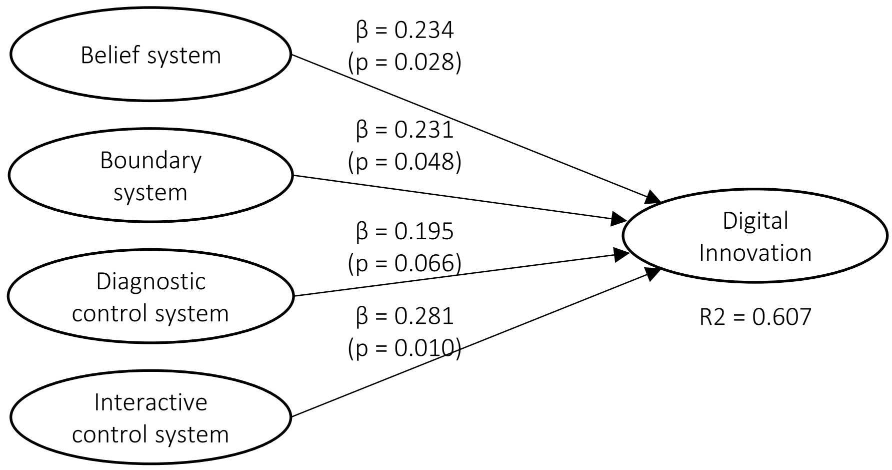

Figure 1. Structural model

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Table 7. Path coefficients and p-values

Structural/hypothesized paths	Parameter (β)	t-statistic	p-value	Results
Belief system → Digital innovation	0.234	2.197	0.028	Supported
Boundary system → Digital innovation	0.231	1.978	0.048	Supported
Diagnostic control system → Digital innovation	0.195	1.837	0.066	Not Supported
Interactive control system → Digital innovation	0.281	2.561	0.010	Supported

The ANN results in Table 8 show a variation in the Root Mean Square Error (RMSE) value between the ten model specifications, which reflects the characteristics of the stochastic-based learning process in ANN. At the training stage, RMSE ranged from 0.378 to 0.601, with an average of 0.514 and a standard deviation of 0.064. Meanwhile, at the testing stage, the RMSE ranged from 0.50 to 0.93, with an average of 0.67 and a standard deviation of 0.130. The difference in performance between training and testing data is common in ANN modeling because the model generalizes to data not used during training. A relatively larger variation in the testing stage also showed the effect of initial weight initialization and data sharing on modeling results. Therefore, this study used ten training processes (multiple runs) and reported average scores to reduce the influence of variation due to random initialization. Thus, variation between runs reflects the stochastic characteristics of the ANN algorithm. Therefore, the ANN results are interpreted as a complementary predictive analysis of PLS-SEM, while the interpretation of the predictor's relative importance level is based on the average value obtained from the entire run.

Table 8. Root mean square error for ANN model

Neural Network	Training	Testing
ANN specification-1	0.5108022	0.50
ANN specification-2	0.4800298	0.93
ANN specification-3	0.5674266	0.52
ANN specification-4	0.523759	0.59
ANN specification-5	0.4904995	0.66
ANN specification-6	0.5527785	0.86
ANN specification-7	0.5650221	0.68
ANN specification-8	0.6014797	0.60
ANN specification-9	0.4740517	0.70
ANN specification-10	0.3786177	0.70
Mean	0.5144467	0.67
Standard deviation	0.0635506	0.13

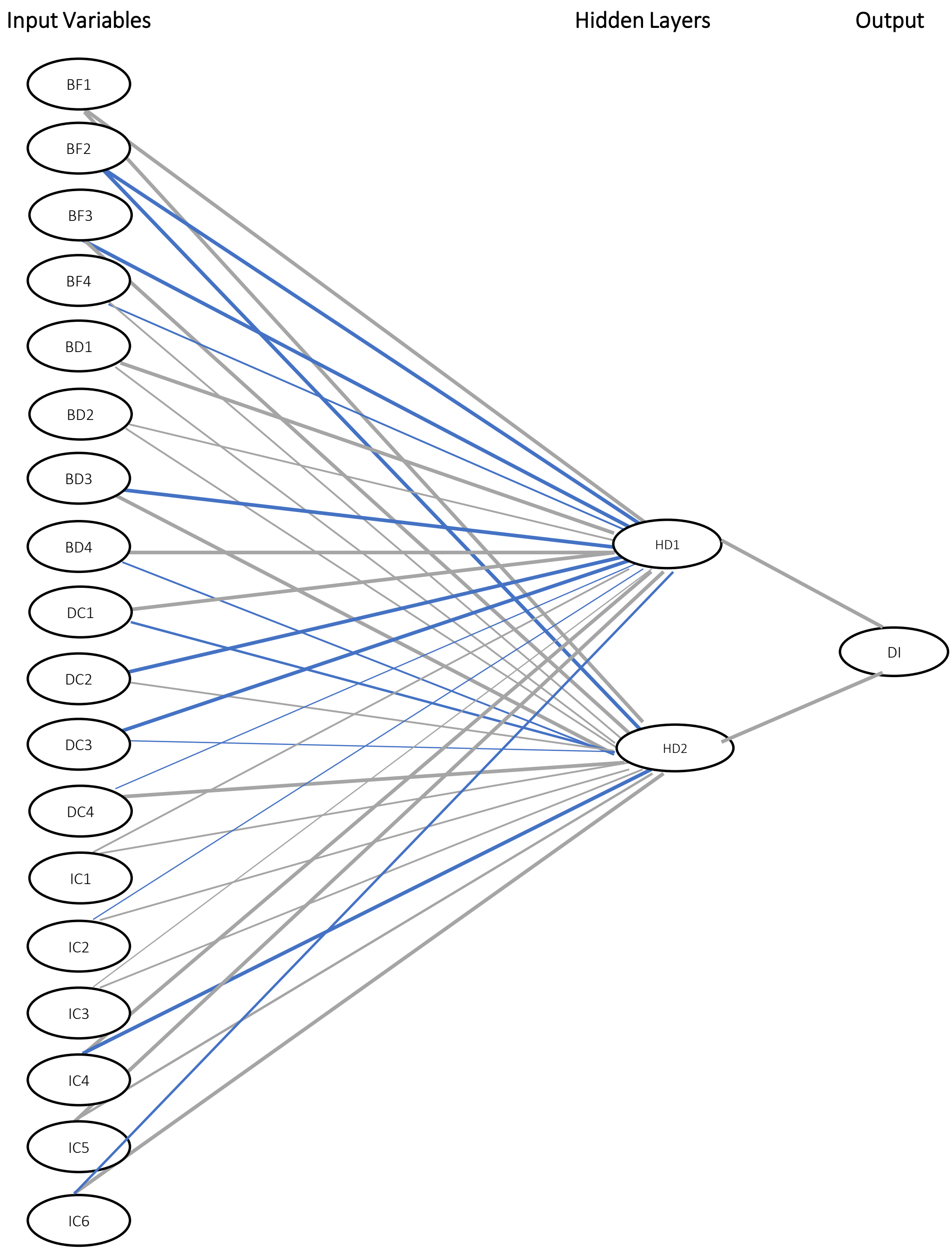
Note: BF = Belief System; BD = Boundary System; DC = Diagnostic Control system; IC = Interactive Control System; DI = Digital Innovation; HD = Hidden Layers.

Table 9 presents the sensitivity analysis showing normalized importance of each predictor, which is calculated based on the average results of ten ANN trainings. The normalized importance value describes the relative contribution of each predictor to the model's predictive ability, so it is used to sort the predictive importance level of variables. The results show that the interactive control system has the highest level of predictive importance (100%), followed by the diagnostic control system (71.7%), the boundary system (62.6%), and the belief system (34.7%).

Table 9. Sensitivity analysis of ANN model

Factor description	Importance	Normalized importance
Belief system	0.129	34.7%
Boundary system	0.233	62.6%
Diagnostic control system	0.267	71.7%
Interactive control system	0.372	100.0%

Table 10 presents a comparison of PLS-SEM and ANN results to provide an overview of the relative contribution of each dimension of the LOC based on both analysis approaches. In PLS-SEM, the comparison is based on the magnitude of the path coefficient as an indication of the strength of the relationship between constructs in the structural model, while in the ANN it is based on the value of normalized relative importance as a measure of relative contribution to the predictive performance of the model. The comparison results show differences in the order of relative importance between the two methods. The interactive control system ranks first in both approaches. In contrast, the belief system has the second-largest path coefficient in PLS-SEM but ranks fourth based on normalized relative importance in ANN. Meanwhile, the diagnostic control system did not show a statistically significant relationship with PLS-SEM, but ranked second based on normalized relative importance in ANN. The boundary system ranks third in both methods. These differences suggest that PLS-SEM and ANN provide complementary perspectives, where PLS-SEM emphasizes the evaluation of relationships between constructs



Note: BF = Belief System; BD = Boundary System; DC = Diagnostic Control System; IC = Interactive Control System; DI =Digital Innovation; HD = Hidden Layers.

Figure 2. Artificial neural network (ANN) model

within a theoretical framework, while ANN highlights the relative contribution of predictors to the model's predictive capabilities.

Regarding the hypothesis testing results, H1, H2, and H4 are supported, as belief system, boundary system, and interactive control system exhibit positive and statistically significant relationships with digital innovation. In contrast, H3 is not supported because diagnostic control system does not exhibit a statistically significant relationship with digital innovation. These results are based on the PLS-SEM analysis, whereas the ANN results are used to assess the relative predictive importance of the LOC dimensions rather than to determine hypothesis acceptance or rejection.

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Table 10. Comparison between PLS-SEM and ANN findings

IV	PLS-SEM			ANN		
	Total Effect	Finding	Ranking (PLS)	Ranking (ANN)	ANN results: Normalized relative importance (%)	Matched or Not
BF	0.234	Sig	2	4	34.7%	Not
BD	0.231	Sig	3	3	62.6%	Matched
DC	0.195	Sig	4	2	71.7%	Not
IC	0.281	Sig	1	1	100%	Matched

Note: BF = Belief System; BD = Boundary System; DC = Diagnostic Control System; IC = Interactive Control System.

4. DISCUSSION

The test results show that the belief system is positively related to digital innovation. Empirically, the relationship shows a path coefficient of β = 0.234 with a *p*-value of 0.028. These findings are consistent with LOC theory, which views the belief system as a mechanism for communicating the organization's core values, vision, and strategic direction to build a shared understanding of its goals. In the context of the digital transformation of the Indonesian banking sector, these findings indicate that the alignment of organizational values with the direction of digital transformation is related to the creation of an environment that is more supportive of the implementation of digital innovation. Thus, consistent communication of values and strategic goals can provide a foundation for organizations to direct digital innovation initiatives. These findings support Wang (2022), who shows that belief systems play a role in aligning organizational strategic goals with innovation activities. However, our results provide an additional perspective to the findings of Henri (2006), who did not confirm a significant relationship between dynamic tension and innovation. This insignificance is likely due to the non-inclusion of the belief system as an integral part of the LOC (Baird et al., 2019).

Furthermore, the test results showed that the boundary system had a positive and statistically significant relationship with digital innovation (β = 0.231; *p* = 0.048). These findings indicate that the existence of strategic boundaries and risk management mechanisms is related to digital innovation in the banking sector. Under strict regulations, the boundary system provides clarity on behavioral limits and acceptable risk levels, so that organizations have a reference in carrying out various digital innovation initiatives. Thus, well-defined boundaries not only serve as a control mechanism, but can also support the implementation of digital innovations within an appropriate governance framework. These findings are consistent with Simons (1995), Caccamo et al. (2023), and Ringgaard et al. (2025), who show that boundary systems are related to innovation effectiveness in a high-regulation context. On the other hand, our results provide an additional perspective to the findings of Bisbe and Otley (2004). They did not find a significant relationship between the use of MCS and innovation because they focused more on interactive control systems, while our study evaluated the four dimensions of LOC separately to identify the contribution of each control mechanism to digital innovation.

The findings on interactive control systems showed a positive and statistically significant relationship with digital innovation (β = 0.281; *p* = 0.010). These findings indicate that interactive control systems are the most consistent LOC dimension related to digital innovation. Within the LOC framework, the interactive control system facilitates communication, organizational learning, and information exchange in the face of strategic uncertainties (Simons, 1995, 2000). Therefore, in the context of Indonesia's banking digital transformation, this mechanism relates to the ability of organizations to respond to environmental changes and implement digital innovations. This result is also strengthened by the ANN analysis, which places the interactive control system as the predictor with the highest level of relative importance in the predictive model. These findings support Simons (1995, 2000) and previous empirical research that showed a positive relationship between interactive control systems and innovation (Boussaidi & Korbi, 2025; Chrusciak et al., 2025; Najda-Janoszka et al., 2025).

In contrast to other LOC dimensions, the diagnostic control system did not have a statistically significant relationship with digital innovation in the PLS-SEM analysis (β = 0.195; *p* = 0.066). This finding is inconsistent with Simons' (1995) levers of control theory and the empirical evidence documented by Widener (2007) and Phan et al. (2023). This indicates that, in the linear model tested, the diagnostic control system did not show a significant direct relationship with digital innovation. This result is understandable, as diagnostic control systems focus more on monitoring target achievement, performance evaluation, and control based on predetermined standards, so their role in digital innovation may not be directly visible. Nevertheless, ANN analysis shows that diagnostic control systems have a fairly high level of relative predictive importance (71.7%), ranking second in predictive models. These differences in findings show a difference in perspective between the inferential-based PLS-SEM approach and the predictive-based ANN.

Overall, our findings show that the PLS-SEM and ANN approaches provide a complementary perspective in understanding the relationship between LOC dimensions and digital innovation. PLS-SEM identifies relationships between constructs within theoretical models, while ANN indicates the relative contribution of each dimension to the model's predictive power. The integration of the two approaches provides a more comprehensive understanding than using either method separately. The findings of this study also provide additional empirical support for the argument of Baird et al. (2019) regarding the importance of paying attention to the differences in the style of using management control systems in explaining the variation in the results of previous research. In addition, our results show a difference in perspective between inferential and predictive approaches in explaining the relationship between control mechanisms and digital innovation. Therefore, further research should use a longitudinal design or analysis methods explicitly designed to test more complex relationships, so that the interactions between LOC dimensions can be understood in more depth.

CONCLUSION

This study aims to analyze the relationship between the dimensions of levers of control (LOC) and digital innovation in the Indonesian banking sector using a hybrid approach of partial least squares structural equation modeling (PLS-SEM) and artificial neural network (ANN).

The results showed that the interactive control system, belief system, and boundary system had a significant positive relationship with digital innovation. In contrast, the diagnostic control system showed no significant relationship in the PLS-SEM model. The ANN analysis complements these findings by showing that the interactive control system has the highest level of relative predictive importance, followed by the diagnostic control system, boundary system, and belief system. These findings suggest that PLS-SEM and ANN provide complementary perspectives, where PLS-SEM explains relationships based on theoretical models, while ANN measures the relative contribution of each predictor to the model's predictive ability.

This study makes a theoretical contribution by showing that PLS-SEM and ANN hybrid approaches can lead to a more comprehensive understanding of the relationship between LOC dimensions and digital innovation. From a practical perspective, the interactive control system is the most consistent LOC dimension related to digital innovation, so it should be a focus when designing management control systems in the banking sector.

This paper has some limitations. It is limited to banks selected through purposive sampling techniques with the criteria of having actively adopted digital innovations, so the generalization of findings needs to be done carefully. Further research is suggested involving a more diverse sample and using a research design that allows for more complex relationship testing.

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APPENDIX A

Table A1. Measurement items

Statements	Source(s)
Levers of Control	
Beliefs System	
Organizations have formal documents such as a statement of vision, mission, creed, or corporate values that clearly define the organization's values, goals, and strategic direction	Widener (2007)
Top management rarely conveys the core values of the organization to all employees through various communication media **(reverse coded (RC))**	
All employees understand and recognize the core values that are the basis of organizational behavior in achieving strategic goals	
An organization's mission statement is able to arouse the enthusiasm and motivation of employees to support the achievement of organizational goals	
Boundary System	
The organization has established a code of ethics or code of business conduct that is consistently implemented across all parts of the organization	Widener (2007)
Management clearly communicates to all employees about areas or types of actions that must be avoided	
Organizations do not have clear policies regarding risks that need to be avoided in decision-making and operational activities **(reverse coded (RC))**	
All employees understand the behavioral boundaries that have been set and use them as a guide in working	
Diagnostic Control System	
Organizations do not utilize performance measurement systems to monitor the achievement of strategic objectives **(reverse coded (RC))**	Widener (2007)
Regularly perform organizational performance results compared to predefined performance targets and standards	
Organizations use performance measurement systems to identify discrepancies between actual and target outcomes, and take corrective actions where needed	
Performance measurement reflects the key success factors that the organization has established and is used to ensure alignment of activities with the strategy	
Interactive Control System	
Top management routinely pays attention to performance measurement systems as part of the strategic decision-making process	Widener (2007)
Top management is directly involved in interpreting the information generated from the performance measurement system	
Operational managers actively and routinely use performance measurement systems in carrying out their functions and responsibilities	
Discussions about the results and analysis of performance measurement systems are conducted openly and involve various levels of management	
Information from performance measurement systems is used to support strategic dialogues and respond to the dynamics of the business environment	
Work units in these organizations do not actively utilize information from performance measurement systems to achieve shared goals **(reverse coded (RC))**	
Digital Innovation	
The bank is actively developing new digital services, the number of which continues to increase over time	Yu et al. (2025)
The bank's digital innovations have improved service efficiency and strengthened its reputation and competitive position in the market	
Digital innovation is carried out in various bank service functions, such as credit, savings, payments, and customer service	
Banks actively collaborate with external parties (such as fintech or startups) in developing digital innovations	
Banks rarely update digital service features, despite receiving feedback from users **(reverse coded (RC))**	
The bank's digital innovation is primarily initiated from internal initiatives, not just based on the recommendations of technology vendors	

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