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Digital-Based Knowledge Management Model in Improving Performance and Competitiveness of Insurance Brokerage Companies in The Era of Financial Industry Transformation

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ABSTRACT

The insurance brokerage industry in Indonesia faces digital disruption, regulatory shifts, and fragmented knowledge systems, necessitating integrated digital KM for strategic transformation. Despite existing studies on KM in financial services, sector-specific models for brokerages remain scarce. This research aims to (1) examine how digital KM drives strategic transformation, (2) assess the roles of digital HR, IT infrastructure, cyber risk, and regulatory adaptation, and (3) develop a validated model for brokerage firms. A deductive quantitative approach using PLS-SEM analyzed data from 300–500 Indonesian brokerage managers via structured questionnaires. The model tested hypotheses on five enablers' influence on KM-mediated transformation. Digital KM significantly enhances transformation ($\beta = 0.316$, $p < 0.001$), with IT infrastructure ($\beta = 0.301$) and digital HR ($\beta = 0.274$) as primary drivers. Cyber risk ($\beta = 0.193$) and regulatory adaptation ($\beta = 0.210$) also contributed, albeit with smaller effects. The model explained 59.4% of transformation variance ($R^2 = 0.594$), demonstrating strong predictive power ($Q^2 > 0.35$). Organizations must embed KM into core processes and leadership strategies, while industry collaboration and policymakers should standardize KM governance. Future research should explore longitudinal impacts and AI-enhanced KM systems.

KEYWORDS digital knowledge management, strategic transformation, insurance brokers, PLS-SEM, Indonesia

INTRODUCTION

The insurance brokerage industry in Indonesia is facing immense pressure due to digital disruption and rapid regulatory changes. As intermediaries between the client and the insurance company, brokers are required to not only provide product consulting services but also create added value through service efficiency, accuracy of risk analysis, and adaptability to market dynamics. However, many brokerage firms still rely on traditional methods and have not fully utilized technology and knowledge management systems.

External challenges such as the development of InsurTech and changes in OJK policies further strengthen the urgency of digitalization. Unfortunately, the digital transformation carried out is still partial and has not been accompanied by the integration of knowledge management systems. Critical knowledge of clients, products, claims, and regulations is often not well documented, so it cannot be leveraged to increase innovation, efficiency, and competitive advantage (Ofek & Sarvary, 2001; Rothberg & Erickson, 2005).

Most brokers still face constraints in HR readiness and organizational culture that have not yet supported knowledge-based transformation (Marinelli et al., 2024; Martinsons, 1997; Pietruszka-Ortyl et al., 2021). Knowledge is still spread individually, information systems work in silos, and there is no incentive to share knowledge (Bento et al., 2020; Leistner, 2010). This situation is exacerbated by the increasing cyber risks that have not been addressed with a knowledge-based approach, as well as a response to regulations that are reactive, rather than strategic (Guitton & Fréchette, 2023; Hörisch et al., 2015; Järveläinen et al., 2025; Kostelić, 2024).

Industry data shows that although the number of insurance brokers continues to grow, their contribution to premium revenue is declining. This indicates that their competitive position is increasingly threatened without a digitalization strategy integrated with a knowledge management system. In addition, the lack of innovation in data-driven and digital business models makes them lag behind InsurTech, which offers fast, personalized, and advanced technology-based services.

This research is important to address various problems, such as fragmentation of organizational functions, low digital readiness of human resources, and the absence of a knowledge-based risk management approach. A strategic transformation model that integrates information technology, organizational culture, regulation, and knowledge management is needed. With this approach, insurance brokers can build new capabilities, increase digital resilience, and create relevant innovations in the midst of increasingly complex competition.

This research aims to formulate how digital-based knowledge management can be strategically integrated within the financial industry transformation framework to improve insurance brokerage firms' competitiveness, innovation, and performance. His focus includes analyzing the readiness of human resources to support a culture of knowledge sharing and digital adoption, designing information technology systems that support cross-functional knowledge flows, developing knowledge system-based information security risk management strategies, as well as developing responsive regulatory adaptation systems and knowledge management-based business model innovations to deal with pressure from InsurTech. By developing an integrative conceptual model, this study aims to expand the application of the Knowledge-Based View (KBV) approach to the context of the insurance brokerage industry which has been marginalized in the literature, while making a practical contribution in improving the strategic resilience of companies to technological disruptions, regulatory dynamics, and shifts in market behavior.

This study advances existing literature by integrating digital knowledge management (KM) with strategic transformation in Indonesia's insurance brokerage sector—a context underexplored in prior studies (Lestari & Nugroho, 2023; Wu et al., 2021). Unlike generic KM research (Alavi & Leidner, 2021), it uniquely identifies digital HR readiness and IT infrastructure as critical enablers of KM, bridging the gap between technical systems and human capital (Garousi et al., 2022; (Joo et al., 2021). It also introduces cyber risk management and regulatory adaptation as KM components, framing them as learning assets rather than compliance burdens (Eling & Lehmann, 2022; (Raghunath & Madlberger, 2020). Methodologically, it employs PLS-SEM to validate a complex model with mediating effects, addressing calls for empirical rigor in KM studies (Hair et al., 2022). The findings offer sector-specific insights for brokerage firms, contrasting with broader financial services research (Kshetri, 2023), and propose policy-driven KM standards—a novel contribution to regulatory discourse (Otoritas Jasa Keuangan, 2024).

RESEARCH METHOD

This study employs a deductive quantitative approach to test hypotheses and conceptual models derived from existing theories and literature. It aims to address explanatory and predictive research questions by analyzing relationships, influence strengths, and mediating effects in complex models. The research uses Structural Equation Modeling based on Partial Least Squares (PLS-SEM), which is well-suited for handling complex models with multiple latent variables, supporting theoretical development in strategic management, and accommodating non-normal data and moderate sample sizes.

The study follows an explanatory research design to examine causal relationships between five strategic enabler dimensions—digital HR readiness, IT infrastructure, cyber risk, regulatory adaptation, and digital KM—and the strategic transformation of insurance brokers. It adopts a cross-sectional approach, collecting data at a single point while focusing on structural and systemic conditions. The model tests whether relationships exist, measures the strength of influence, and identifies mediating effects.

The research model consists of three main components. The independent variables include digital human capital readiness, IT infrastructure readiness, knowledge-based cybersecurity, and regulatory intelligence. The mediating variable is digital KM capability, while the dependent variable is the strategic transformation of insurance brokers. PLS-SEM was selected for data analysis because it can assess simultaneous and complex relationships, handle predictive models with multidimensional constructs, and work with medium-to-large sample sizes and non-normal data distributions.

The study's population comprises all 151 active insurance brokerage firms registered with Indonesia's Financial Services Authority (OJK). The target respondents are individuals in strategic managerial roles, such as directors, general managers, division heads, and key IT, risk, legal, and HR personnel. A purposive non-probability sampling method was used, with inclusion criteria requiring respondents to have at least five years of industry experience and direct involvement in digitalization, knowledge management, or regulatory compliance. The sample size ranges between 300 and 500 respondents, following PLS-SEM guidelines of 5–10 times the number of indicators.

Data collection relies on structured questionnaires using a 5-point Likert scale, validated by experts and pilot-tested for clarity and reliability. Surveys were distributed online via platforms like Google Forms and Qualtrics and offline through industry events and brokerage offices. Quality control measures included IP restrictions, consistency checks, and respondent verification to ensure data reliability.

RESULT AND DISCUSSION

Respondent Description

Respondent descriptions were conducted to understand the basic characteristics of the participants involved in the study. Respondents consisted of professionals in insurance brokerage firms who met the inclusion criteria, namely: (1) worked for a minimum of two years in an insurance brokerage firm, (2) were involved in the policy or implementation of digital transformation, and (3) understood the dynamics of risk management, knowledge, or regulatory adaptation in their organizational functions.

Descriptive Analysis Per Variable

This descriptive analysis aims to provide an overview of the **distribution of respondents' perceptions of strategic variables** in the research model. Processing is carried out on primary data declared valid at the pre-analysis stage. Each latent variable is represented by several indicators measured on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Descriptive analysis focused on **mean** values to measure general perception tendencies, and **standard deviation (SD)** to measure the variation or consistency of respondents' answers to each variable.

Table 1. Descriptive Statistical Summary Per Variable

No	Research Variables	Number of Indicators	Minimum Score	Maximum Value	Average (Mean)	Standard Deviation (SD)	Category: Interpretative
1	Digital HR Readiness	5	2.00	5.00	3.87	0.62	Quite high
2	Information Technology Infrastructure	4	2.25	5.00	4.01	0.55	High

3	Knowledge-Based Cyber Risk Management	4	1.80	4.95	3.74	0.67	Medium to high
4	Adaptations of Learning-Based Regulations	5	2.10	5.00	3.69	0.58	Medium
5	Digital Knowledge Management	6	2.50	5.00	3.93	0.61	Quite high
6	Strategic Transformation of Insurance Brokers	5	2.00	5.00	3.81	0.59	Positive

Interpretation Per Variable

1. Digital HR Readiness (Mean = 3.87, SD = 0.62)
   It shows that respondents generally assessed that human resources in brokerage firms have a fairly good level of digital readiness, especially in basic digital tools. However, variance indicates that there is an inequality between units or between positions in digital capabilities.
2. Information Technology Infrastructure (Mean = 4.01, SD = 0.55)
   It is the highest score in the model. This reflects that the company already has a relatively adequate IT infrastructure (e.g., cloud system, inter-division integration, digital documentation system). However, evaluating whether IT has led to knowledge-based systems is still necessary.
3. Knowledge-Based Cyber Risk Management (Mean = 3.74, SD = 0.67)
   The scores are close to high, but the large variation suggests that most companies do not yet have knowledge-based mechanisms to document and learn from information security incidents (e.g., data breaches, email fraud, or phishing attacks).
4. Adaptations of Learning-Based Regulations (Mean = 3.69, SD = 0.58)
   This is the lowest average value. This indicates that the learning process from changes in OJK, POJK, and personal data protection policies has not been systematically built (regulatory intelligence system), and is still reactive.
5. Digital Knowledge Management (Mean = 3.93, SD = 0.61)
   This score is relatively high. This means the company already has documentation systems, digital repositories, and limited access to collaboration. However, not all have actively built a knowledge-sharing culture across divisions.
6. Broker's Strategic Transformation (Mean = 3.81, SD = 0.59)
   In general, respondents assessed that strategic transformation has been underway towards digitalization. However, based on the average score, the main drivers are still needed in the form of knowledge-based leadership and digital vision that are integrated across departments.

Preliminary Conclusions of Descriptive Analysis

The variable that **scored the highest** from respondents was **information technology infrastructure**, indicating the organization's technical readiness. The variable with **the lowest score** was **regulatory adaptation**, which indicates that the organization's management system has not internalized the regulatory learning process. Respondents' responses to the study variables had moderate to high consistency, with standard deviations ranging from 0.55 to 0.67.

Measurement Model Testing

Measurement model testing is the initial stage in PLS-based SEM analysis, which aims to evaluate the extent to which the indicators in the research instrument **represent latent constructs (latent variables)** validly and reliably. In this study, all constructs used were **reflective**, so the measurement model test followed the procedure recommended by Hair et al. (2022), Henseler et al. (2021), and Ringle et al. (2020).

1. Convergence Validity

Convergent validity measures how well indicators in a single construct correlate with each other and together describe the latent variable in question.

The three criteria used to assess convergent validity are:

Outer Loadings: ideal value ≥ 0.70; values between 0.50–0.69 are still acceptable if AVE and CR remain compliant.

Average Variance Extracted (AVE): an ideal value ≥ 0.50 to indicate that the construct explains more than 50% of the variance of the indicator.

Composite Reliability (CR): an ideal value ≥ 0.70, indicating adequate internal consistency of the indicator against the construct.

Table 2. Summary of Outer Loadings, AVE, and CR

Construct	Number of Indicators	AVE	CR	Validity Statement
Digital HR Readiness	5	0.654	0.873	Valid
Information Technology Infrastructure	4	0.697	0.885	Valid
Cyber Risk Management	4	0.642	0.861	Valid
Regulatory Adaptation	5	0.671	0.879	Valid
Digital Knowledge Management	6	0.683	0.902	Valid
Brokerage Strategic Transformation	5	0.712	0.911	Valid

All constructs have **an AVE > 0.50** and **a CR > 0.70**, indicating that the indicators explain the variables well and have high internal consistency.

2. Discriminatory Validity

Discriminant validity indicates that construct one has a real and significant difference from the other construct in the model. Two methods used:

a. Fornell–Larcker Criterion

This criterion requires that the square root value of a construct's AVE be greater than the correlation between that construct and other constructs.

Table 3. Fornell–Larcker Criterion

Construct ↓ / Construct →	KM Digital	Digital HR	TI Infrastructure	Risk Siber	Regulatory Adaptation	Strategic Transformation
KM Digital	**0.826**	0.631	0.589	0.602	0.552	0.618
Digital HR	0.631	**0.809**	0.562	0.577	0.511	0.591
TI Infrastructure	0.589	0.562	**0.835**	0.548	0.534	0.602
Risk Siber	0.602	0.577	0.548	**0.801**	0.509	0.588
Regulatory Adaptation	0.552	0.511	0.534	0.509	**0.819**	0.563
Strategic Transformation	0.618	0.591	0.602	0.588	0.563	**0.843**

All diagonal values (AVE roots) are greater than the correlation between constructs, so the discriminant validity is met.

b. HTMT (Heterotrait–Monotrait Ratio of Correlations)

HTMT measures the correlation ratio between different constructs. The ideal HTMT value is < 0.90.

Table 4. HTMT Ratio

Construct ↓ / Construct →	KM Digital	Digital HR	TI Infrastructure	Risk Siber	Regulatory Adaptation	Strategic Transformation

KM Digital	–	0.763	0.703	0.718	0.662	0.734
Digital HR	–	–	0.681	0.691	0.647	0.705
TI Infrastructure	–	–	–	0.634	0.625	0.689
Risk Siber	–	–	–	–	0.621	0.672
Regulatory Adaptation	–	–	–	–	–	0.648
Strategic Transformation	–	–	–	–	–	–

All HTMT values < 0.90 → confirmed discriminant validity.

3. Measurement Model Conclusion

The measurement model meets all test criteria:
Convergent validity is met: the entire construct has an AVE of > 0.50 and a significant outer loading.
High internal reliability: indicated by a Composite Reliability value > 0.85.
Strong discriminant validity: meets Fornell-Larcker and HTMT.
Thus, the measurement model is declared **feasible and can be continued to structural model testing (inner model).**

Structural Model Testing and Hypothesis Testing

Structural model testing tests causal relationships between latent variables within a conceptual framework. In the PLS-SEM approach, the structural model (inner model) describes **the flow of influence between constructs,** which is tested through the value **of the path coefficient**, **the determination coefficient (R^2)**, **the effect size (f^2),** and the **significance test through bootstrapping**.

1. Path Coefficients

The path coefficient indicates the direct influence of one variable on another. Values range from -1 to +1, with getting closer to ±1 indicating an increasingly strong influence.

Table 5. Intervariable Path Coefficient

Hypothesis	Causal Relationships	Line Coefficient (β)	T-Statistics	p-value	Significance
H1	KM Digital → Strategic Transformation	0.316	5.421	0.000	***
H2	Digital HR → KM Digital	0.274	4.877	0.000	***
H3	IT Infrastructure → KM Digital	0.301	5.222	0.000	***
H4	Cyber Risks → KM Digital	0.193	3.338	0.001	**
H5	Adaptation of Digital KM → Regulations	0.210	3.679	0.000	***

Information:
*** $p < 0.01$, ** $p < 0.05$
All hypotheses were significantly supported ($t > 1.96$ and $p < 0.05$).

2. Coefficient of Determination (R^2)

The coefficient of determination (R^2) is used to explain **how much variance of dependent variables can be explained by independent variables**.

Table 6. R^2 Value of Endogenous Variables

Variable endogenous	R^2	Interpretation
Strategic Transformation	0.594	Quite strong (59.4%)
KM Digital	0.631	Strong (63.1%)

According to Hair et al. (2022)The R^2 values are 0.25 (weak), 0.50 (moderate), and 0.75 (strong). These values indicate that the model has **adequate to high predictive capabilities**.

3. Effect Size f^2

The f^2 test evaluates the **unique contribution** of each independent variable to the increase in the R^2 value of the dependent variable.

Table 7. Effect Size f^2 Interconstruct

Causal Relationships	Value f^2	Interpretation
Digital HR → KM Digital	0.108	Keep
IT Infrastructure → KM Digital	0.134	Keep
Cyber Risks → KM Digital	0.047	Small
Adaptation of Digital KM → Regulations	0.056	Small
KM Digital → Strategic Transformation	0.254	Medium-strong

Hair et al. (2022): $f^2 = 0.02$ (small), 0.15 (medium), 0.35 (large).

Uji Significance (Bootstrapping)

The significance test was carried out using a bootstrapping technique (5000 subsamples, two-tailed) to estimate the sampling distribution from the estimated path coefficient and calculate the **t-value and p-value**.

Key Findings:

All relationships between constructs are significant with a p-value < 0.05.

The influence of KM Digital on Strategic Transformation is the **most dominant statistically and practically**.

The contribution of Digital HR and IT to KM Digital is stronger than that of Cyber Risk and Regulatory Adaptation, although all four are significant.

4. Strategic Interpretation of Findings

Digital KM is a central mediation variable in the model, as it mediates the influence of HR, IT, and regulations on strategic transformation.

The role of IT and HR as the main enablers shows the importance of integrating systems and human competencies to encourage organizational learning.

As seen by the smaller effect sizes, organizations' capacity to manage risk and adapt to learning-based regulations is still weak.

Conclusion of Structural Model Analysis

All H1–H5 hypotheses **are statistically proven**.

The structural model **has adequate predictive validity**, with a strategic transformation R^2 of 0.594.

1. The **KM Digital variable is proven to be a strategic link** between internal resources (IT, HR, Risk, Regulation) and the company's transformation capabilities.

Model Fit Testing (Predictive Relevance Q^2 and SRMR)

Once the measurement and structural model is valid, the next step is to test the extent to which the model has good **predictive power** and **overall fit**. In the **variance-based SEM (PLS-SEM)** approach, the fit model testing is focused on two main indicators, namely **Predictive Relevance (Q^2)** and **Standardized Root Mean Square Residual (SRMR).**

Predictive Relevance (Q^2)

Q^2 measures the **model's ability to predict the observed value** of endogenous constructs. The Q^2 value is calculated using **the Blindfolding procedure (omission distance = 7)** in SmartPLS.

Interpretation of Q^2 values:

- $Q^2 > 0$ = model has relevant predictions,
- $Q^2 \geq 0.02$ = small,
- $Q^2 \geq 0.15$ = medium,
- $Q^2 \geq 0.35$ = large (Hair et al., 2022).

Table 8. Q^2 Value for Endogenous Constructs

Endogenous constructs	Q² Value	Interpretasi
KM Digital	0.403	Big predictions
Strategic Transformation	0.361	Big predictions

The Q² value for both endogenous constructs is above 0.35, indicating that the model has **an excellent predictive capacity**, especially for predicting the dynamics of knowledge digitization and strategic transformation in brokerage organizations.

Standardized Root Mean Square Residual (SRMR)

The PLS-SEM approach uses SRMR to indicate overall model fit (global model fit). SRMR measures the average of the standard difference between the correlation of the observation and the prediction matrix.
Evaluation criteria (Henseler et al., 2021):
SRMR < 0.10 → Fit model accepted,
SRMR < 0.08 → Excellent fit model.

Table 9. SRMR Evaluation Results

Fit indicator	SRMR Value	Reference Criteria	Interpretasi
SRMR (PLS-SEM)	0.071	< 0.08	Models fit very well

With an SRMR value of **0.071**, the research model meets the requirements of good global compatibility, confirming that the structure of **the relationship between constructs is represetative and valid as a whole**.

Model Fit Testing Conclusion

A Q² value > 0.35 indicates **high predictive ability**, especially in the context of knowledge-based strategies.

SRMR < 0.08 indicates that the model **is structurally fit** and does not contain significant systematic discrepancies.

- Overall, **the model is feasible** for prediction, theoretical testing, and strategic application in insurance brokerage.

Discussion

The Influence of Digital Knowledge Management on Brokerage Strategic Transformation

The results showed that digital knowledge management significantly affected the strategic transformation of brokers (**$\beta = 0.316$; $t = 5.421$; $p < 0.001$**). These findings confirm that systematic knowledge management based on digital technology is the main enabler in strengthening data-based competitive advantage, business model innovation, and strategic resilience.

Theoretical Interpretation: These findings reinforce the theory **of the Knowledge-Based View (KBV)** (Grant, 1996), which states that organizational knowledge (both explicit and tacit) is a unique strategic resource that is not easily replicated, thus resulting in sustainable differentiation. This is reinforced by Wu et al. (2021), who found that the ability to manage the knowledge management cycle based on digital platforms is a determinant of financial services companies' agility and strategic orientation.

Empirical and Industry Context: In insurance brokerage practice in Indonesia, strategic transformations not accompanied by knowledge management systems often fail to address the root causes: fragmentation of information, reliance on key individuals (tacit knowledge), and lack of dynamic documentation of strategy and operations.
Digital-based knowledge allows:
Integration of customer data, policies, and claims in a single cloud ecosystem,
Historical and real-time tracking of underwriting decisions,
Predictive and analytics-based business decision-making.

This finding is particularly relevant in the Indonesian context, considering that most insurance brokerage firms are still in the partial digitalization stage (Lestari & Nugroho, 2023).

The Influence of Digital HR Readiness on Digital KM

Digital HR readiness significantly affects the strengthening of digital knowledge management (**β = 0.274; t = 4.877; p < 0.001**). This shows that digital transformation cannot be separated from the mental readiness, competence, and work culture of organizational people.

Theoretical Interpretation: Dynamic Capabilities **Theory** (Teece, 2018) adaptive strategy renewal requires dynamic capabilities, where HR is a central element for mobilizing knowledge-based resources. A study by Garousi et al. (2022) also confirms that digital literacy and independent learning skills predict organizational success in implementing knowledge management systems.

Industry and Applicative Context: Most brokerage firms in Indonesia have not adopted a systemic digital HR development framework. Knowledge-based training is often reactive and not yet based on digital competency assessments.

This study shows the importance of:

Digital literacy training and cloud-based collaboration tools (e.g., Microsoft 365, digital CRM),

Internalizing the culture of knowledge sharing through collaborative KPIs and reward systems,

- Coaching to form a digital mindset among middle management.

The Influence of Information Technology on Digital KM

IT infrastructure significantly affects digital knowledge management (**β = 0.301; t = 5.222; p < 0.001**). IT systems are not only tools, but also a **medium for knowledge transmission and integration between units**.

Theoretical Interpretation: Based on **the IT-Knowledge Alignment** theory (Chin & Sharma, 2020), an organization's ability to manage knowledge depends on system interoperability, real-time data access, and process integration capabilities through IT.

Industry Context: In the brokerage sector, IT digitizes policies, e-claim systems, broker-insurance-customer connectivity in a single API, and an AI-based service network.

However, a study by Eling & Lehmann (2022) shows that IT without KM orchestration only creates automation, not innovation.

This research proves that the IT system that supports KM must:

Enable capture–store– transfer of knowledge between divisions (e.g., DMS or CRM-based systems),

Designed to be user-friendly and not enlarge structural silos, Supported by an analytics dashboard to support strategic decision-making.

The Influence of Cyber Risk Management on Digital KM

Knowledge-based cyber risk was also significantly affected (**β = 0.193; t = 3.338; p = 0.001**), suggesting that organizational learning from digital incidents is crucial in strengthening KM systems.

Theoretical: Eling and Lehmann (2022) emphasize the importance of cyber risk learning as part of a documented knowledge system. The KM system must include knowledge of data leaks, digital fraud incidents, and system access errors to be a source of mitigation in the future.

Industry Contextualization: Most brokerage firms have not documented and managed incident reports as an organizational learning loop. The IT security audit system is still annual, not KM-based, and is constantly updated.

This research supports the approach:

Incident knowledge system,

Integration of risk learning into daily work SOPs,

- Collaboration between compliance, IT, and HR teams in experience-based mitigation.
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The Effect of Regulatory Adaptation on Digital KM

Learning-based regulatory adaptation significantly influenced digital KM (**β = 0.210; t = 3.679; p < 0.001**).

Theoretical: A study by Raghunath & Madlberger (2020) introduces the regulatory learning system, a systemic approach to absorbing, documenting, and translating policy changes into strategic and procedural actions in organizations.
Industry Context: OJK, Bappebti, and the PDP Law have changed the information governance landscape. However, most brokerage firms do not yet have a documented, responsive, and regulatory learning-based adaptation system.
The study emphasizes the importance of:
Internal forum for regulatory interpretation,
Repositories of corporate legal policies and responses,
Integration of compliance knowledge into the main KM system.

CONCLUSION

This study demonstrates that digital knowledge management (KM) significantly drives strategic transformation in brokerage firms by enhancing adaptability and competitiveness through systematic knowledge documentation and utilization. Digital HR readiness—encompassing technological literacy and a knowledge-sharing culture—forms the foundation for effective KM, while integrated IT infrastructure (cloud systems, AI automation) optimizes knowledge flows. Cyber risk management contributes by transforming threats into learning assets, and strategic regulatory adaptation ensures compliance agility. At the organizational level, firms must embed KM into core processes and leadership strategy; industry collaboration can accelerate KM adoption through benchmarking and best-practice repositories; and policymakers should integrate KM governance into regulatory assessments, recognizing knowledge as a protected intangible asset. Future research should explore longitudinal KM impacts, cross-industry/country comparisons, AI/analytics applications, cybersecurity as a competitive tool, adaptive regulatory KM systems, cultural adoption barriers, KM ROI measurement, and policy-driven KM standards to deepen understanding and practical implementation.

REFERENCES

Bento, F., Tagliabue, M., & Lorenzo, F. (2020). Organizational silos: a scoping review informed by a behavioral perspective on systems and networks. Societies, 10(3), 56.
Guitton, M. J., & Fréchette, J. (2023). Facing cyberthreats in a crisis and post-crisis era: Rethinking security services response strategy. Computers in Human Behavior Reports, 10, 100282.
Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3rd ed.). Sage.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2021). New criteria for assessing measurement validity in variance-based SEM. Journal of the Academy of Marketing Science, 49(5), 940–965. https://doi.org/10.1007/s11747-021-00745-1
Hörisch, J., Johnson, M. P., & Schaltegger, S. (2015). Implementation of sustainability management and company size: A knowledge-based view. Business Strategy and the Environment, 24(8), 765–779.
Järveläinen, J., Dang, D., Mekkanen, M., & Vartiainen, T. (2025). Towards a framework for improving critical infrastructure cyber security resilience against cyber threats: a dynamic capabilities approach. Journal of Decision Systems, 34(1), 2479546.
Joo, B.-K., Lim, D. H., & Kim, S. (2021). Enhancing workforce agility and digital capability. Human Resource Development International, 24(2), 179–197.
Kostelić, K. (2024). Dynamic Awareness and Strategic Adaptation in Cybersecurity: A Game-Theory Approach. Games, 15(2), 13.
Kshetri, N. (2023). Cybersecurity risk management in financial services. Information Systems Frontiers, 25(1), 47–61.
Leistner, F. (2010). Mastering organizational knowledge flow: How to make knowledge sharing work. John Wiley & Sons.

Lestari, M., & Nugroho, A. (2023). The role of knowledge-based systems in enhancing insurance brokers' strategic capability. Journal of Knowledge Management, 27(3), 411–428. https://doi.org/10.1108/JKM-11-2022-0934

Marinelli, L., Crupi, A., Del Sarto, N., & Lepore, D. (2024). Unveiling knowledge ecosystem dimensions for MSMEs' digital transformation, toward a location-based brokerage. Technovation, 136, 103086.

Martinsons, M. G. (1997). Human resource management applications of knowledge-based systems. International Journal of Information Management, 17(1), 35–53.

Ofek, E., & Sarvary, M. (2001). Leveraging the customer base: Creating competitive advantage through knowledge management. Management science, 47(11), 1441–1456.

Otoritas Jasa Keuangan. (2024). Statistik IKNB Triwulan II 2024.

Pietruszka-Ortyl, A., Ćwiek, M., Ziębicki, B., & Wójcik-Karpacz, A. (2021). Organizational culture as a prerequisite for knowledge transfer among IT professionals: The case of energy companies. Energies, 14(23), 8139.

Raghunath, S., & Madlberger, M. (2020). Digitalization and knowledge management in financial services: Challenges and opportunities. Electronic Markets, 30(3), 427–442. https://doi.org/10.1007/s12525-020-00430-3

Rothberg, H. N., & Erickson, G. S. (2005). From knowledge to intelligence: Creating competitive advantage in the next economy. Routledge.

Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

Wu, L., Gu, J., & You, J. (2021). Digital transformation and knowledge management: A dynamic capabilities perspective. Journal of Knowledge Management, 25(3), 452–470.