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Integration of Knowledge Management Capability (KMC) mediated by AI Capability and Organizational Learning Agility for Sustainable Competitive Advantage in the Digital Era in Binjai City MSMEs

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ABSTRACT
This research seeks to examine the function of HR Analytics as a moderating variable in the integration model of This study aims to examine the influence of Knowledge Management Capability, AI Capability, and Organizational Learning Agility on Sustainable Competitive Advantage in organizations using the Resource-Based View and Dynamic Capability approaches. Analysis was conducted using PLS-SEM to assess the direct and indirect effects between variables. The results show that AI Capability has a significant positive effect on Sustainable Competitive Advantage (36.1%), confirming that the use of AI plays a crucial role in building long-term competitiveness. In addition, Knowledge Management Capability is the most dominant variable, with a very strong influence on AI Capability (85.1%), and has a significant impact on Organizational Learning Agility (22.8%) and Sustainable Competitive Advantage (33.2%). This study also found that Knowledge Management Capability influences Sustainable Competitive Advantage indirectly through AI Capability (30.7%), which is the strongest mediating pathway, and through Organizational Learning Agility (14.3%). These findings confirm that knowledge management is a fundamental element in strengthening technological capabilities and learning agility, which ultimately enhances sustainable competitive advantage. This research provides theoretical contributions to the development of a knowledge-based integration model as well as practical implications for organizations in designing sustainable digital transformation strategies.

Keywords: Knowledge Management Capability, Sustainable Competitive Advantage, AI Capability, Organizational Learning Agility, SEM-PLS

INTRODUCTION

The acceleration of digital transformation has changed the pattern of business competition, especially for digital SMEs that now operate in a data-driven ecosystem. The Knowledge-Based View (Grant, 1996) emphasizes that knowledge is a strategic resource that is difficult to imitate. However, recent literature shows that Knowledge Management Capability (KMC) needs to transform into an intelligent system based on artificial intelligence (AI) to generate adaptive insights (Zhang et al., 2025). In this context, digitalization is no longer optional, but a prerequisite for maintaining sustainable competitive advantage.

This phenomenon is particularly relevant for digital MSMEs in Binjai City, which is rapidly developing as a hub for creative economic activity in North Sumatra. Despite the significant contribution of local MSMEs to the city's economy, many businesses still face a digital capability gap and struggle to integrate knowledge with intelligent technology, as is the case with other MSMEs in Indonesia (Setiawan & Rahmawati, 2025). Yet studies show that AI can strengthen the dynamics of knowledge management, automate decision-making, and increase organizational learning agility (Cheng & Lee, 2025; Yusoff et al., 2025). Without this adaptability, Binjai's MSMEs risk being left behind in increasingly data-driven regional

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competition.

However, previous research has been limited to the direct relationship between KMC and sustainable competitive advantage (Nguyen et al., 2024; Jang et al., 2023), while the layered mediation role of AI and organizational learning agility (OLA) in the context of digital MSMEs, particularly in developing cities like Binjai, has not been widely empirically tested. In fact, Huang & Park (2025) emphasized that competitive advantage is difficult to achieve without transforming knowledge into tangible adaptive capabilities. Therefore, this study integrates KBV, Dynamic Capability Theory (Teece, 2007), and the concept of learning agility (De Meuse, 2019) to test a more comprehensive KMC–AI–OLA–SCA model. This model is expected to explain how digital MSMEs in Binjai City can utilize AI as a cognitive mechanism that transforms knowledge into sustainable competitive advantage.

Table 1. Condition of Digital MSMEs in Binjai City in 2025

No	Digital Readiness Indicators for Binjai City MSMEs	Number of MSMEs (n)	Percentage (%)	Short Description
1	Total MSMEs (all sectors)	110	100%	Population basis of the study
2	MSMEs that have used basic digital platforms (social media, e-commerce)	68	61.8%	The majority are still at the initial digitalization level.
3	MSMEs that have a simple knowledge management system (sales records, customers, SOPs)	42	38.1%	Not yet integrated with smart technology
4	MSMEs with a digital capability gap (minimal use of digital technology)	55	50%	The main challenges of the Binjai MSME sector
5	MSMEs that have used AI-based technology (recommendations, chatbots, simple analytics)	12	10.9%	AI adoption is very low
6	MSMEs that have high potential for AI adoption (stable internet access, young human resources, digital-native businesses)	30	27.2%	Potential segmentation for research
7	MSMEs that demonstrate high organizational learning agility (based on learning speed & adaptation indicators)	25	22.7%	Agility is still low in most MSMEs
8	MSMEs that have implemented digital-based product/service innovations	20	18.1%	Strong correlation with readiness for AI

Source: 2025 Binjai City MSME Statistics Report. Binjai City Cooperatives, SMEs, and Trade Service.

This table shows that of the 110 MSMEs in Binjai City, most are still in the early stages of digitalization, with 61.8% only using basic digital platforms and only 10.9% starting to adopt AI-based technologies. This finding confirms the existence of a significant digital capability gap, in accordance with the phenomenon described by Setiawan & Rahmawati (2025). Furthermore, the low levels of organizational learning agility (22.7%) and digital innovation (18.1%) reinforce the urgency of the KMC–AI–OLA–SCA model to help Binjai MSMEs improve their adaptive capabilities in facing data-driven competition.

LITERATURE REVIEW

Sustainable Competitive Advantage (SCA)

Sustainable Competitive Advantage (SCA) refers to an organization's ability to create and

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sustain valuable, rare, difficult-to-imitate, and non-substitutable advantages (Barney, 1991; Teece, 2007). In the digital economy, SCA is increasingly determined by organizational knowledge, innovation, and learning agility rather than traditional physical resources (Choi & Kim, 2025). Recent research suggests that SCA is dynamic, evolving through organizational adaptation to digital technologies and market changes (Rahman & Karim, 2025). Organizations that leverage data, develop artificial intelligence (AI), and integrate organizational learning have a greater chance of sustaining these advantages (Zhang et al., 2025). According to Huang & Park (2025), SCA in the digital era is influenced by three main dimensions: innovation capability, knowledge utilization, and market responsiveness, which together shape the strategic outcomes of the integration of KMC, AI Capability, and OLA.

Artificial Intelligence Capability (AI Capability)

Artificial Intelligence Capability (AI Capability) describes the extent to which an organization is able to integrate artificial intelligence into business processes and knowledge management to create strategic value (Cheng & Lee, 2025). From a Knowledge-Based View perspective, AI Capability is considered a new form of dynamic capability because it strengthens the KMC function through automation, prediction, and adaptive learning (Nguyen & Pham, 2025). Research by Rahman & Karim (2025) explains that AI Capability consists of four indicators, namely AI infrastructure, AI skills & competence, AI integration, and AI data intelligence. The strategic role of AI as a mediator lies in its ability to increase the effectiveness of organizational learning while accelerating the company's response to changes in the business environment (Huang & Park, 2025), thereby strengthening the relationship between KMC and OLA.

Organizational Learning Agility (OLA)

Organizational Learning Agility (OLA) is an organization's ability to quickly acquire, process, and apply new knowledge in the face of environmental uncertainty (De Meuse, 2019; Yusoff et al., 2025). Within the KBV framework, OLA functions as a knowledge conversion capability that enables organizations to transform knowledge into strategically valuable adaptive actions. According to Setiawan & Rahmawati (2025), OLA has three main dimensions: learning speed, adaptability, and experimentation, which respectively reflect an organization's capacity to learn quickly, adapt flexibly, and dare to experiment. OLA mediates the relationship between AI Capability and SCA by transforming technology-based insights into relevant strategic decisions (Huang & Park, 2025). Therefore, in digital organizations, OLA is a form of strategic agility that directly influences sustainable competitiveness.

Knowledge Management Capability (KMC)

Knowledge Management Capability (KMC) is an organization's ability to effectively create, disseminate, and apply knowledge to support innovation and performance (Grant, 1996; Lee & Kim, 2025). In the context of KBV, KMC is seen as a key foundation for determining competitive advantage due to its inherent difficulty for other organizations to imitate. KMC consists of three core dimensions: knowledge acquisition, knowledge sharing, and knowledge application, which collectively enable organizations to develop a superior knowledge base. The

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integration of KMC with artificial intelligence has the potential to transform data into strategic insights that strengthen decision-making and innovation (Zhang et al., 2025). Thus, KMC is not only a source of internal advantage but also a key catalyst in the integrative KMC–AI–OLA–SCA model.

Conceptual Framework

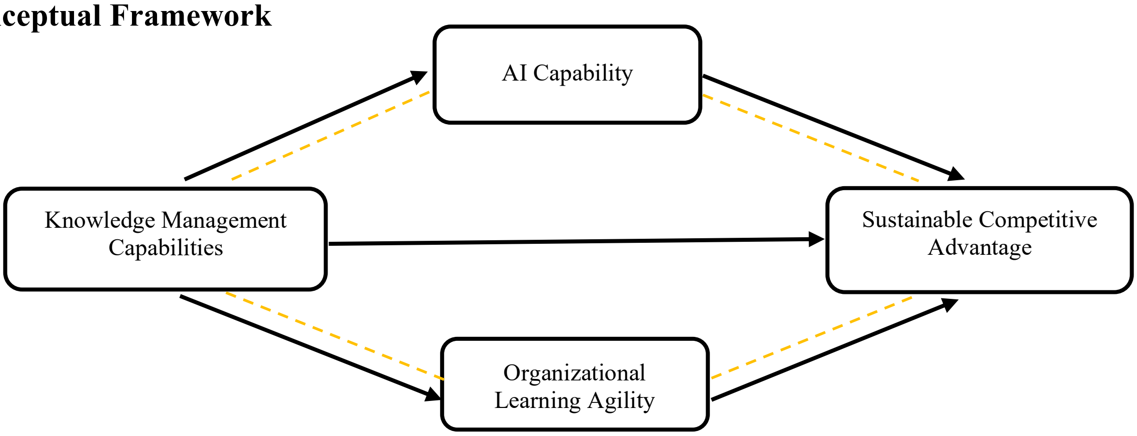

Figure 1: Conceptual Framework
Source: Researcher, 2025

METHODS

The research analysis was conducted using a quantitative approach. The research was conducted on MSMEs in Binjai City. The sample used in the study was 70 MSMEs in Binjai City. The sampling method utilized a nonprobability sampling technique in the form of accidental sampling, namely saturated sampling. One of the data collection methods used was a questionnaire. The list of questions in the questionnaire was arranged in the form of closed questions that were relevant to the focus of the research and were designed so that respondents could answer them quickly, so that the filling process was more efficient and less time-consuming.

Quantitative data analysis is a research approach that assesses the relationship between variables through statistical testing or calculations based on primary data and questionnaire responses. In this study, the analysis process was carried out using SmartPLS 4.1.1.2 software. The method applied was Partial Least Squares-based structural equation modeling (PLS-SEM) to quantitatively test and understand the relationship between variables through Structural Equation Modeling analysis.

RESULTS AND DISCUSSION

RESULT

Outer Model

The outer loading value is the initial step in the Outer Model analysis and is considered satisfactory if its value exceeds 0.7 (Hair et al., 2019). This value reflects a good level of convergent validity, meaning the indicator accurately represents the latent variable. Thus, it contributes to improving the quality, accuracy, and consistency of the

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measurement results in the model used.

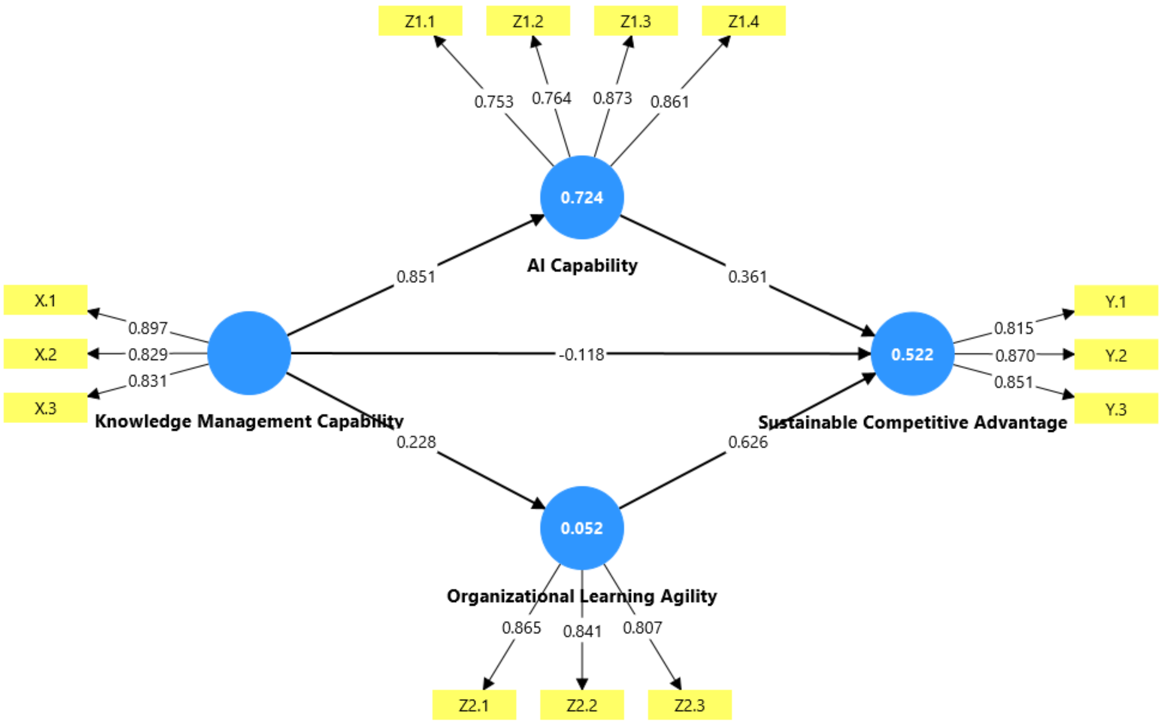

Figure 2. Outer Model
Source: SmartPLS 4.1.1.2 data processing, 2025

All indicators are declared valid because their outer loading values exceed the minimum limit of 0.7, as shown in Figure 2.

Outer Loading

The outer loading values of the indicators on the latent variables in this study consistently averaged above 0.7, consistent with recommended standards. These results are detailed in Table 2.

Table 2. Outer Loading Values

	AI Capability	*Knowledge Management Capabilities*	*Organizational Learning Agility*	*Sustainable Competitive Advantage*
X.1		*0.897*		
X.2		*0.829*		
X.3		*0.831*		
Y.1				*0.815*

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Y.2				***0.870***
Y.3				***0.851***
Z1.1	***0.753***			
Z1.2	***0.764***			
Z1.3	***0.873***			
Z1.4	***0.861***			
Z2.1			***0.865***	
Z2.2			***0.841***	
Z2.3			***0.807***	

Source: SmartPLS 4.1.1.2 data processing, 2025

Construct Reliability and Validity Test

All variables in this study were proven reliable and valid, as indicated by Cronbach's Alpha and composite reliability values above 0.70, and an AVE value above 0.50. This indicates that each indicator adequately represents its construct, making AI Capability, Knowledge Management Capability, Organizational Learning Agility, and Sustainable Competitive Advantage suitable for further analysis.

Table 3. Values Construct Reliability And Validity

	Cronbach's alpha	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*
AI Capability	*0.830*	*0.849*	*0.887*	*0.663*
Knowledge Management Capabilities	*0.812*	*0.815*	*0.889*	*0.727*
Organizational Learning Agility	*0.788*	*0.793*	*0.876*	*0.702*
Sustainable Competitive Advantage	*0.801*	*0.802*	*0.883*	*0.715*

Source: SmartPLS 4.1.1.2 data processing, 2025

Fornell-Larcker Criterion Test

The correlation results between latent variables show that the diagonal value (bold) is the root of the Average Variance Extracted (AVE) in table 4, which is greater than the correlation value between other variables in the same row or column.

Table 4. Value Fornell-Larcker Criterion

	AI Capability	*Knowledge Management Capabilities*	*Organizational Learning Agility*	*Sustainable Competitive Advantage*
AI Capability	*0.814*			
Knowledge Management Capabilities	*0.851*	*0.853*		
Organizational Learning Agility	*0.202*	*0.228*	*0.838*	
Sustainable Competitive Advantage	*0.387*	*0.332*	*0.673*	*0.846*

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Cross Loading Test

The results of the cross-loading analysis in Table 5 show that the loading value of each indicator on the latent variable it measures (shown in bold) is higher than the loading value on the other latent variables. This condition confirms that discriminant validity has been met properly, because each indicator more dominantly represents its own construct compared to other constructs in the model.

Table 5. Value Cross Loading Test

	AI Capability	*Knowledge Management Capabilities*	*Organizational Learning Agility*	*Sustainable Competitive Advantage*
X.1	*0.733*	***0.897***	*0.184*	*0.280*
X.2	*0.669*	***0.829***	*0.224*	*0.224*
X.3	*0.767*	***0.831***	*0.177*	*0.337*
Y.1	*0.370*	*0.329*	*0.566*	***0.815***
Y.2	*0.335*	*0.272*	*0.501*	***0.870***
Y.3	*0.279*	*0.241*	*0.628*	***0.851***
Z1.1	***0.753***	*0.584*	*0.088*	*0.271*
Z1.2	***0.764***	*0.646*	*0.146*	*0.162*
Z1.3	***0.873***	*0.783*	*0.176*	*0.351*
Z1.4	***0.861***	*0.738*	*0.229*	*0.439*
Z2.1	*0.223*	*0.269*	***0.865***	*0.584*
Z2.2	*0.176*	*0.172*	***0.841***	*0.566*
Z2.3	*0.101*	*0.120*	***0.807***	*0.540*

Source: SmartPLS 4.1.1.2 data processing, 2025

Inner Model

The Inner Model aims to examine the influence of direct and indirect relationships between the variables used and to test hypotheses based on the significance of the values obtained.

Analysis of the Coefficient of Determination (R-square)

The coefficient of determination analysis of the R-square value shows that the model is able to explain 72.4% of the variation in AI Capability, which indicates a strong level of explanatory power. Meanwhile, Organizational Learning Agility has an R-square value of 5.2%, which indicates that the predictor variables only have a very low influence on this variable. Meanwhile, Sustainable Competitive Advantage has an R-square value of 52.2%, which means that more than half of the variation can be explained by the model, so it is included in the moderate to strong category. The Adjusted R-square value that is not much different from the R-square in all constructs indicates that the model is stable and does not experience overfitting.

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Table 6. Value Coefficient of Determination (R-square)

	R-square	*Adjusted R-square*
AI Capability	*0.724*	*0.722*
Organizational Learning Agility	*0.052*	*0.043*
Sustainable Competitive Advantage	*0.522*	*0.508*

Source: SmartPLS 4.1.1.2 data processing, 2025

Hypothesis Testing

Based on the results of the SEM path analysis using SmartPLS version 4.1.1.2, internal testing was conducted to determine the relationship between constructs. The T-statistic and probability values indicate how well the hypothesis was tested. If the T-statistic value is greater than the T-table value, it indicates that the hypothesis is accepted. This hypothesis test includes direct and indirect effect testing.

Table 7. Test Results Direct Effect

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*
AI Capability -> Sustainable Competitive Advantage	*0.361*	*0.353*	*0.118*	*3,072*	*0.002*
Knowledge Management Capability -> AI Capability	*0.851*	*0.854*	*0.042*	*20,289*	*0,000*
Knowledge Management Capability -> Organizational Learning Agility	*0.228*	*0.231*	*0.085*	*2,671*	*0.008*
Knowledge Management Capability -> Sustainable Competitive Advantage	*0.332*	*0.334*	*0.087*	*3,833*	*0,000*
Organizational Learning Agility -> Sustainable Competitive Advantage	*0.626*	*0.629*	*0.058*	*10,757*	*0,000*

Source: SmartPLS 4.1.1.2 data processing, 2025

The results of the table above show that all paths in the model have a positive and significant influence. AI Capability is proven to increase Sustainable Competitive Advantage with a coefficient of 0.361, T value = 3.072, and p = 0.002, which means that the use of AI effectively strengthens the company's long-term competitive advantage. On the other hand, Knowledge Management Capability is the strongest foundation in the model, seen from its very large influence on AI Capability (0.851; T = 20.289; p = 0.000). This capability also increases learning agility (0.228; T = 2.671; p = 0.008) and even contributes directly to sustainable competitive advantage (0.332; T = 3.833; p = 0.000), thus indicating that knowledge management is a strategic resource that plays a role in various aspects of organizational performance according to the RBV view.

In addition, Organizational Learning Agility is a strong predictor of competitive

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advantage, with a coefficient of 0.626, T value = 10.757, and p = 0.000, which indicates that organizational agility in learning and adapting has a major contribution in creating sustainable advantages. Overall, this model illustrates that sustainable competitive advantage is formed through the synergy between knowledge capabilities, AI capabilities, and learning agility, where Knowledge Management Capability is the starting point that strengthens the other two variables, thus creating a strategic impact on the sustainability of the company's competitiveness.

Table 8. Test Results Indirect Effect

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*
Knowledge Management Capability -> Organizational Learning Agility -> Sustainable Competitive Advantage	*0.143*	*0.144*	*0.052*	*2,719*	*0.007*
Knowledge Management Capability -> AI Capability -> Sustainable Competitive Advantage	*0.307*	*0.300*	*0.100*	*3,082*	*0.002*

Source: SmartPLS 4.1.1.2 data processing, 2025

The results of the table above on the mediation pathway show that Knowledge Management Capability significantly influences Sustainable Competitive Advantage through Organizational Learning Agility with a mediation coefficient of 0.143, a T value of 2.719, and p = 0.007. This finding indicates that part of the influence of Knowledge Management Capability on sustainable competitive advantage works through increasing organizational learning agility. In other words, companies that are able to manage knowledge effectively will be more agile in learning, adapting, and responding to change, and this agility then strengthens their sustainable competitive advantage.

Furthermore, the second mediation pathway shows that Knowledge Management Capability also influences Sustainable Competitive Advantage through AI Capability, with a mediation coefficient of 0.307, a T-value of 3.082, and p = 0.002. The higher value of this coefficient than the mediation pathway through learning agility indicates that the use of AI is a stronger mediation mechanism. This means that the better a company manages knowledge, the higher the AI capabilities it can develop, and ultimately the greater the competitive advantage it can achieve. Overall, these two pathways demonstrate that knowledge capability not only has a direct influence but also works through two strategic mechanisms: learning agility and AI capability to create sustainable competitive advantage.

CONCLUSION

The Influence of AI Capability on Sustainable Competitive Advantage

The results of the study indicate that AI Capability has a positive and significant effect on Sustainable Competitive Advantage with a coefficient of 0.361, which means that AI

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capability contributes 36.1% in increasing sustainable competitive advantage. This finding confirms that the higher the company's ability to utilize AI for analytics, prediction, automation, and decision-making, the greater the company's ability to create differentiation that is difficult for competitors to imitate. This is in line with the literature stating that the use of AI is one of the main drivers of competitive advantage in the digital era and Industry 5.0.

The Influence of Knowledge Management Capability on AI Capability

Knowledge Management Capability's influence on AI Capability was recorded as the strongest in the model, with a coefficient of 0.851, equivalent to an 85.1% direct influence contribution. This means that companies with strong knowledge management capabilities through knowledge acquisition, knowledge sharing, and knowledge utilization practices will be much more capable of developing mature AI capabilities. These results emphasize that the quality of internal knowledge and the ability to manage it are foundational to optimizing artificial intelligence technology.

The Influence of Knowledge Management Capability on Organizational Learning Agility

The effect of Knowledge Management Capability on Organizational Learning Agility showed a coefficient of 0.228, contributing a 22.8% effect. This finding indicates that companies with good knowledge management practices are more agile in learning and adapting to changes in the business environment. Google, IBM, and Toyota, for example, demonstrate that structured knowledge accelerates an organization's ability to explore and exploit new knowledge, a hallmark of learning agility.

The Influence of Knowledge Management Capability on Sustainable Competitive Advantage

In addition to the indirect effect through mediators, Knowledge Management Capability was also shown to have a direct effect on sustainable competitive advantage with a coefficient of 0.332, or a 33.2% contribution. This indicates that knowledge is a strategic asset that not only supports technological and learning processes but also directly influences sustainable competitiveness. According to RBV theory, valuable, rare, and difficult-to-imitate knowledge is a core resource for achieving long-term competitive advantage.

The Influence of Organizational Learning Agility on Sustainable Competitive Advantage

Organizational Learning Agility has a significant influence on Sustainable Competitive Advantage, with a coefficient of 0.626, meaning learning agility contributes 62.6% of the direct influence on increasing sustainable competitive advantage. This is one of the largest influences in the model. This finding confirms that companies that are able to learn quickly, adapt, and react dynamically to the business environment will excel in creating competitive advantages that are difficult for competitors to replicate.

The Influence of Knowledge Management Capability on Sustainable Competitive Advantage Organizational Learning Agility

The indirect effect through learning agility shows a coefficient of 0.143, meaning 14.3%

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of the impact of Knowledge Management Capability on Sustainable Competitive Advantage is channeled through increased learning agility. This means that good knowledge management not only directly increases competitive advantage but also strengthens it through organizational learning mechanisms. In other words, the more effectively a company manages knowledge, the higher the organization's learning agility, which ultimately further enhances sustainable competitive advantage.

The Influence of Knowledge Management Capability on Sustainable Competitive Advantage Through AI Capability

The mediation pathway through AI Capability shows a coefficient of 0.307, indicating that 30.7% of the influence of Knowledge Management Capability on Sustainable Competitive Advantage is channeled through AI Capability. This makes the AI mediation pathway the strongest compared to the pathway through learning agility. These results emphasize that Knowledge Management Capability is a primary prerequisite for the formation of effective AI Capability, and that AI capability then becomes a crucial driver of a company's competitive advantage.

RECOMMENDATIONS

Based on the findings that Knowledge Management Capability is a key variable that has a strong influence on AI Capability and Organizational Learning Agility, further research is recommended to explore more deeply the antecedent factors that shape knowledge management capability, such as organizational culture, leadership quality, and internal technology readiness. This exploration will provide a more comprehensive picture of the strategic foundations needed by companies to continuously improve knowledge-based capabilities. Furthermore, considering that the mediation pathway through AI Capability has the largest indirect effect on Sustainable Competitive Advantage, further researchers can expand other technology variables such as big data analytics capability, digital innovation capability, or machine learning readiness to see whether other digital technologies have a more significant impact on shaping long-term competitive advantage.

It is also recommended that future research use a longitudinal approach to capture the dynamics of changes in AI Capability and Organizational Learning Agility on company competitiveness over time. This is important because AI capabilities and learning agility are adaptive and tend to evolve annually. Furthermore, expanding the research object to other industries, such as logistics, manufacturing, or banking, could enrich the generalizability of these findings, as each industry has different digital transformation characteristics. Future researchers could also incorporate moderating variables, such as strategic alignment, digital leadership, or environmental turbulence, to test the conditions under which Knowledge Management Capability, AI Capability, and Learning Agility work more strongly or less strongly in influencing sustainable competitive advantage. Thus, further research will be able to provide a deeper and more contextual understanding of the AI-agility knowledge management integration model in building sustainable competitive advantage.

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