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The Influence Of Human Resources Digital Capabilities On The Business Agility Of Food Processing Msmes With Readiness To Adopt Artificial Intelligence As A Mediating Variable

Iis Azelya[1], Berandi Suharyansyah[2]

[1,2]Management Study Program, Faculty of Economics and Business, Bangka Belitung University

Corresponding Author: azelya@ubb.ac.id[1],berandi@ubb.ac.id[2]

Abstract

This study aims to analyze the influence of human resources (HR) digital capabilities on the business agility of food processing MSMEs, with readiness to adopt artificial intelligence (AI) as a mediating variable. The study used a quantitative explanatory approach with data from 120 respondents measured through 20 five-point Likert scale statements. Data were analyzed using PLS-SEM using SmartPLS 4. Descriptively, all three variables are in the high category, and the results of the measurement model evaluation indicate that all indicators are valid and reliable. The results of the structural model test indicate that HR digital capabilities have a positive and significant effect on AI adoption readiness (β = 0.636; p < 0.001) and on business agility (β = 0.237; p = 0.012), and AI adoption readiness has a positive and significant effect on business agility (β = 0.607; p < 0.001). AI adoption readiness partially mediated the effect of HR digital capabilities on business agility (β = 0.386; p < 0.001). The model explained 60.7% of the variation in business agility. This finding suggests that strengthening digital literacy and culture among business actors needs to be followed by preparing for AI adoption to enable MSMEs to respond quickly to market changes.

Keywords: HR Digital Capabilities; AI Adoption Readiness; Business Agility; Food MSMEs; PLS-SEM

INTRODUCTION

Business competitiveness is increasingly determined by the ability to utilize digital technology, including for micro, small, and medium enterprises (MSMEs) (OECD, 2021). In Indonesia, MSMEs contribute approximately 60.5 percent to the national gross domestic product (Asian Development Bank, 2022). Digital transformation is seen as a

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way for MSMEs to remain relevant and resilient in the face of competition (Kraus et al., 2021). Artificial intelligence (AI) is a crucial part of this transformation, as it can assist with process automation, data analysis, and customer interactions (Davenport & Ronanki, 2018; Harahap et al., 2025).

However, the benefits of AI for MSMEs do not come automatically. A bibliometric and systematic review of 63 Scopus articles from 2020–2024 shows that AI adoption in MSMEs is uneven, with many businesses still in the trial and error stage, and financial constraints, low digital literacy, and weak organizational support are key barriers (Yesuf & Fields, 2025). The same study noted that successful adoption depends on organizational readiness and human capital. On the other hand, AI also raises concerns that machines will replace humans, whereas for small organizations, AI is more appropriately positioned as a tool that enhances human capabilities (Raisch & Krakowski, 2021).

Human readiness is becoming increasingly important as digital maturity is determined more by strategy, work culture, and talent development than by technology itself (Kane et al., 2017). A study of 307 MSMEs in Peru found that digital competencies influence digital transformation, while changes in work culture occur through human resource (HR) management practices (Espina-Romero et al., 2026). Furthermore, most AI maturity models are designed for large companies and are less suited to the conditions of MSMEs, which operate with limited resources, informal governance, and dependency on external parties (Sawang & Sornlertlamvanich, 2026).

These challenges are unique to the archipelago. Bangka Belitung Islands Province has 119,303 active MSMEs with 252,755 workers (Bangka Belitung Islands Provincial Government, tt), and Belitung Regency recorded 20,452 active MSMEs as of December 2021 (ANTARA, 2022). On average, internet access in this province is relatively high, reaching 81.50 percent of the population in 2025, above the national average of 77.63 percent (Central Statistics Agency, 2026). However, nationally, access in rural areas still lags behind urban areas, while inter-island delivery of materials and products depends on transportation schedules and weather. Research in Bangka shows that digital ecosystem support only impacts MSME performance if business actors actively adopt digital business (Purwati et al., 2026). In other island regions, digital transformation of MSMEs has been shown to require technological leadership that understands local conditions (Nengsih et al., 2026; Putra et al., 2025).

For food processing MSMEs, the ability to capture change and respond quickly, or business agility, is crucial because demand is seasonal and the supply of seafood raw materials is unstable (Overby et al., 2006; Zhu, 2020). Research on 142 food and beverage MSMEs in Indonesia found that digital platform capabilities strengthen strategic agility, which in turn increases competitiveness (Henryanto et al., 2025). Conversely,

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research in the Riau Islands found that customer agility was not significantly related to MSME performance (Putra et al., 2025). These inconsistent findings indicate the need for more contextualized studies.

Throughout the author's research, previous research generally addresses parts of the digital capabilities of human resources, AI adoption readiness, and business agility separately, within the context of urban or developed countries. Studies of AI adoption in MSMEs in developing countries are still limited (Yesuf & Fields, 2025), and existing evidence on digital technology and agility in Indonesian food MSMEs has not specifically addressed AI or island regions (Henryanto et al., 2025). This gap underpins this research.

Based on the above description, this study aims to: (1) examine the influence of human resources digital capabilities on AI adoption readiness and business agility; (2) examine the influence of AI adoption readiness on business agility; and (3) examine the role of AI adoption readiness as a mediator. The research results are expected to form the basis for formulating an AI implementation roadmap for island food MSMEs.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Human Resources Digital Capabilities

Digital competence can be viewed at both the individual and organizational levels. At the individual level, the DigComp 2.2 framework views digital competence as a combination of knowledge, skills, and attitudes across five areas: information and data literacy, communication and collaboration, digital content creation, security, and problem-solving (Vuorikari et al., 2022). At the organizational level, digital competence is a set of capabilities that enable an organization to implement and utilize digital technologies, including strategic orientation and the ability to integrate technology into work processes (Espina-Romero et al., 2026).

In MSMEs, these two levels are difficult to separate because business owners often act as both managers and employees. Therefore, this study defines human resource digital capability as the ability of those running a business to use, understand, and adapt digital technology for business purposes, including their readiness to adopt new technologies. From a dynamic capabilities perspective, this capability is the microfoundation that enables organizations to seize opportunities, capitalize on them, and reorganize resources (Teece, 2007). Human resource digital capability is measured through two dimensions: digital literacy and capability, and adoption readiness and culture. The second dimension refers to the view that technological readiness is influenced by optimism and innovativeness, and hampered by discomfort and insecurity (Parasuraman, 2000).

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Readiness for Adopting AI Technology

Individual acceptance of technology is largely explained through the Technology Acceptance Model, which places perceived usefulness and perceived ease of use as key determinants (Davis, 1989). The Unified Theory of Acceptance and Use of Technology adds the role of social influences and enabling conditions, such as the availability of devices, networks, and technical assistance (Venkatesh et al., 2003). At the organizational level, the Technology–Organization–Environment framework explains that technology adoption is influenced by the characteristics of the technology, organizational conditions, and the external environment (Tornatzky & Fleischer, 1990).

Specifically for MSMEs, AI maturity cannot be equated with the number of tools used. It is a configuration of internal capabilities and ecosystem support, influenced by limited resources, informal governance, and the dominant role of owner-managers (Sawang & Sornlertlamvanich, 2026). This study defines AI adoption readiness as the extent to which business actors believe in the benefits of AI, have supporting conditions, and intend to start using it. This construct is measured through two dimensions: perceived benefits of AI, infrastructure readiness, and adoption intention.

Business Agility

Organizational agility is a combination of the ability to perceive environmental changes (sensing) and the ability to respond to them (responding) (Overby et al., 2006). Lu and Ramamurthy (2011) differentiate between market agility and operational agility. From a dynamic capabilities perspective, agility is viewed as the ability to efficiently redirect resources amid uncertainty, noting that agility also has costs (Teece et al., 2016). This study measures business agility through two dimensions: market sensitivity and response speed, and innovation and reconfiguration.

Hypothesis Development

The relationship between human resource digital capabilities and AI adoption readiness. Human capital and AI-related competencies are among the dimensions of AI maturity in MSMEs (Sawang & Sornlertlamvanich, 2026). Low digital literacy is also noted as a major barrier to AI adoption in MSMEs (Yesuf & Fields, 2025). Business owners who are more adept at using digital technology tend to more easily see the benefits of AI and are more confident in using it, in line with the logic of perceived usefulness and ease of use in TAM (Davis, 1989). Research on MSMEs in Peru also found that digital competencies strongly influence digital HR practices and digital transformation (Espina-Romero et al., 2026).

H1: HR digital capabilities (X) have a positive effect on AI adoption readiness (Z).

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The relationship between AI adoption readiness and business agility. Information technology creates digital action options that can be exploited when opportunities or threats arise (Sambamurthy et al., 2003) and strengthens the ability to capture and respond to change (Overby et al., 2006). AI specifically helps MSMEs identify opportunities and read the market through faster analysis (Yesuf & Fields, 2025). In the food and beverage MSME industry in Indonesia, digital platform capabilities have been shown to positively impact strategic agility (Henryanto et al., 2025).

H2: AI adoption readiness (Z) has a positive effect on business agility (Y).

The direct link between HR digital capabilities and business agility. HR digital capabilities don't always require AI to be impactful. Businesses that leverage social media and simple data can capture shifts in customer preferences and respond without AI tools. This aligns with the view that the skills and decisions of people within an organization are the microfoundations of dynamic capabilities (Teece, 2007), as well as the finding that digital competencies directly influence the digital transformation of MSMEs (Espina-Romero et al., 2026).

H3: HR digital capabilities (X) have a positive effect on business agility (Y).

The mediating role of AI adoption readiness. The literature shows a recurring pattern: digital capabilities or support impact business outcomes through intermediary mechanisms. Strategic agility mediates the influence of digital platform capabilities on MSME competitiveness (Henryanto et al., 2025), and digital business adoption mediates the influence of digital ecosystems on MSME performance (Purwati et al., 2026). By the same logic, human resource digital capabilities are thought to strengthen business agility in part by increasing AI adoption readiness.

H4: AI adoption readiness (Z) mediates the effect of HR digital capabilities (X) on business agility (Y).

The research model and four hypotheses are presented in Figure 1. HR digital capability is denoted as X (exogenous variable), AI adoption readiness as Z (mediating variable), and business agility as Y (endogenous variable).

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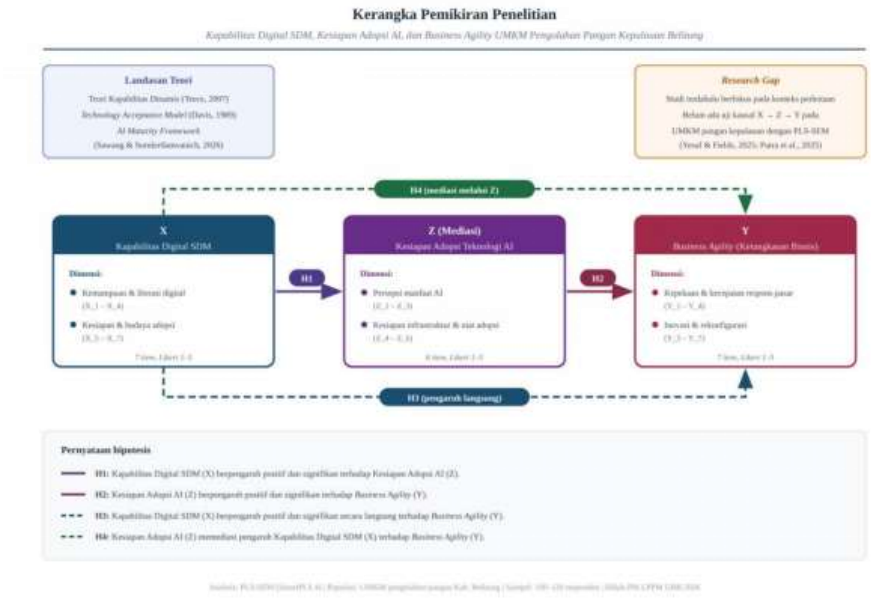


Figure 1. Research Model

RESEARCH METHODS

This study uses a quantitative approach with an explanatory design to examine the causal relationship between HR digital capabilities (X), AI adoption readiness (Z), and business agility (Y). The unit of analysis is food processing MSMEs, with business owners or managers as respondents.

The data analyzed were 120 respondents and were intended to describe the actual condition of MSMEs. With two predictors on the largest endogenous construct, the minimum sample size to detect a moderate effect ($f^2 = 0.15$) at $\alpha = 0.05$ was 68 respondents for a power of 0.80 and 107 respondents for a power of 0.95. Post hoc examination using the inverse square root method (Kock & Hadaya, 2018) showed that the smallest path coefficient in the model ($\beta = 0.237$) required a minimum of 111 respondents at $\alpha = 0.05$ and a power of 0.80, and 153 respondents at a power of 0.90. Thus, the number of 120 respondents was sufficient at a power of 0.80, but not sufficient at a power of 0.90.

The instrument consists of 20 statements with a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). HR digital capability is measured with seven items covering digital skills and literacy as well as adoption readiness and culture, referring to DigComp 2.2 (Vuorikari et al., 2022) and the dynamic capabilities perspective (Teece, 2007). AI adoption readiness is measured with six items covering perceived AI benefits as well as infrastructure readiness and adoption intention, referring to TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and TRI (Parasuraman, 2000). Business

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agility is measured with seven items covering market responsiveness and speed as well as innovation and reconfiguration (Overby et al., 2006; Lu & Ramamurthy, 2011). In software, indicators are labeled KD1–KD7 for X, KA1–KA6 for Z, and BA1–BA7 for Y.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. PLS-SEM was chosen because the study aimed to predict and explain endogenous constructs, the model contained mediation paths, and the sample size was relatively small (Hair et al., 2019). The analysis was conducted in two stages. The first stage was the evaluation of the measurement model through outer loading (≥ 0.708), Cronbach's alpha and composite reliability (0.70–0.95), average variance extracted (AVE ≥ 0.50), and discriminant validity with the Fornell-Larcker criteria and heterotrait-monotrait ratio (HTMT < 0.90) (Hair et al., 2019; Henseler et al., 2015). The second stage is the evaluation of the structural model through the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and the significance test of the path coefficient with bootstrapping [fill in the number of subsamples, for example 5,000] in two directions at $\alpha = 0.05$. The mediation effect is tested through the specific indirect effect and is classified following Zhao et al. (2010).

The PLS-SEM algorithm was run with a path weighting scheme, an initial weight of 1.0, a maximum limit of 3,000 iterations, and a stop criterion of $10.^{-7}$. The algorithm reached convergence in the fourth iteration, well before the maximum limit, so the estimation results were stable. The Cramér-von Mises normality test showed that all indicators were not normally distributed ($p < 0.001$). This condition strengthens the rationale for using PLS-SEM, because this method does not require data normality and tests significance through nonparametric bootstrapping (Hair et al., 2019). For descriptive analysis, the average score was categorized by class length $(5 - 1) / 5 = 0.80$, namely 1.00–1.80 (very low), 1.81–2.60 (low), 2.61–3.40 (moderate), 3.41–4.20 (high), and 4.21–5.00 (very high).

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 presents the average scores for each variable and its dimensions. All three variables are in the high category. AI adoption readiness had the highest average (3.874), followed by business agility (3.752) and human resource digital capability (3.585). At the indicator level, the highest score was for KA5, or the intention to try AI-based tools in the near future (3.933), while the lowest score was for KD5, or the feeling of comfort in trying new technology (3.517). This pattern indicates that respondents' interest in AI is relatively higher than their current digital capabilities.

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The skewness values for all indicators ranged from -0.917 to 0.237, and the excess kurtosis values ranged from -0.638 to 1.092. The distribution of responses tended to be slightly skewed to the left, indicating that more respondents chose agree and strongly agree.

Table 1. Descriptive Statistics of Research Variables

Variables and dimensions	Indicator	Average	Elementary School	Category
HR Digital Capabilities (X)	KD1–KD7	3,585	0.790	Tall
Digital skills and literacy	KD1–KD4	3,569	—	Tall
Readiness and culture of adoption	KD5–KD7	3,606	—	Tall
AI Adoption Readiness (Z)	KA1–KA6	3,874	0.848	Tall
Perceived benefits of AI	KA1–KA3	3,861	—	Tall
Infrastructure readiness and adoption intentions	KA4–KA6	3,886	—	Tall
Business Agility(Y)	BA1–BA7	3,752	0.920	Tall
Market sensitivity and response speed	BA1–BA4	3,729	—	Tall
Innovation and reconfiguration	BA5–BA7	3,783	—	Tall

Note: The dimension mean is the mean of the indicators; SD is calculated from the mean score of the variable per respondent (n = 120). Source: processed data (2026).

Evaluation of Measurement Model

Table 2 shows that all outer loadings are above 0.708, with a range of 0.799 (KD2) to 0.917 (BA3). Thus, each indicator is able to explain more than 50% of the variance in its construct, so all 20 indicators were retained. The indicator VIF values range from 2.836 to 4.993, or below the threshold of 5, so there are no critical collinearity issues at the indicator level (Hair et al., 2019).

Table 2. Outer Loading and VIF Indicators

SmartPLS Label	Item code	*Outer loading*	VIF
BA1	Y_1	0.913	4,671
BA2	Y_2	0.893	3,934
BA3	Y_3	0.917	4,657
BA4	Y_4	0.890	3,662
BA5	Y_5	0.901	4,319

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BA6	Y_6	0.916	4,899
BA7	Y_7	0.909	4,437
KD1	X_1	0.881	3,762
KD2	X_2	0.799	2,836
KD3	X_3	0.900	4,230
KD4	X_4	0.891	4,043
KD5	X_5	0.865	3,832
KD6	X_6	0.899	4,993
KD7	X_7	0.882	4,201
KA1	Z_1	0.895	3,690
KA2	Z_2	0.913	4,438
KA3	Z_3	0.880	3,271
KA4	Z_4	0.892	3,673
KA5	Z_5	0.904	3,902
KA6	Z_6	0.897	3,777

Source: data processed with SmartPLS 4 (2026).

Table 3 shows that Cronbach's alpha (0.949–0.963), rho_A (0.949–0.964), and composite reliability rho_c (0.958–0.970) all exceeded 0.70, indicating that all three constructs are reliable. AVE values ranged from 0.765–0.820, above 0.50, indicating that convergent validity was met. However, composite reliability for all three constructs exceeded 0.95. Hair et al. (2019) cautioned that values this high may indicate redundant items or consistent response patterns, warranting further investigation.

Table 3. Reliability and Convergent Validity

Construct	*Cronbach's alpha*	rho_A	rho_c	AVE
HR Digital Capabilities (X)	0.949	0.949	0.958	0.765
AI Adoption Readiness (Z)	0.951	0.952	0.961	0.804
Business Agility(Y)	0.963	0.964	0.970	0.820

Source: data processed with SmartPLS 4 (2026).

Discriminant validity was tested using two criteria. Based on the Fornell-Larcker criterion (Table 4), the square root of the AVE of each construct (diagonal numbers) was greater than its correlation with other constructs. Based on the HTMT criterion (Table 5), all values were below 0.90, with the highest value of 0.790 between AI adoption readiness and business agility. The cross-loading values also indicated that each indicator had the

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highest loading on its own construct. Thus, discriminant validity was met (Henseler et al., 2015).

Table 4. Fornell-Larcker Criteria

Construct	X	Z	Y
HR Digital Capabilities (X)	0.875		
AI Adoption Readiness (Z)	0.636	0.897	
Business Agility(Y)	0.623	0.757	0.906

Note: The diagonal numbers are the square roots of AVE. Source: processed data (2026).

Table 5. Heterotrait-Monotrait Ratio (HTMT)

Construct	X	Z	Y
HR Digital Capabilities (X)			
AI Adoption Readiness (Z)	0.668		
Business Agility(Y)	0.652	0.790	

Source: data processed with SmartPLS 4 (2026)

Structural Model Evaluation

Before assessing the path coefficients, collinearity between predictors was first examined. The VIF values for the structural model for the HR digital capability and AI adoption readiness pathways to business agility were both 1.681, well below the threshold of 3, indicating no multicollinearity between predictors (Hair et al., 2019).

Table 6 shows that HR digital capabilities explain 40.5% of the variation in AI adoption readiness (R^2 = 0.405), while HR digital capabilities and AI adoption readiness together explain 60.7% of the variation in business agility (R^2 = 0.607). Referring to Hair et al. (2019), both values are in the weak to moderate and moderate categories. The Q^2 values for AI adoption readiness (0.318) and business agility (0.486) are greater than zero, so the model has moderate predictive relevance.

Table 6. Coefficient of Determination and Predictive Relevance

Endogenous constructs	R^2	R^2 adjusted	Q^2
AI Adoption Readiness (Z)	0.405	0.400	0.318
Business Agility(Y)	0.607	0.600	0.486

Note: Q^2 is obtained from the blindfolding procedure (construct cross-validated redundancy). Source: processed data (2026).

*Effect size*Table 7 shows that the influence of HR digital capabilities on AI adoption readiness (f^2 = 0.681) and the influence of AI adoption readiness on business agility (f^2 =

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0.558) is relatively large, while the direct influence of HR digital capabilities on business agility ($f^2 = 0.085$) is relatively small (Cohen, 1988). The SRMR value of 0.042 is below 0.08, which indicates good model fit (Hu & Bentler, 1999; Henseler et al., 2016). The SRMR, d_ULS (0.370), and d_G (0.477) values in the saturated model and the estimated model are identical, because all possible paths between constructs have been estimated so that the structural model is saturated.

Table 7. Effect Size (f^2)

Track	f^2	Category
X → Z	0.681	Big
Z → Y	0.558	Big
X → Y	0.085	Small

Note: 0.02 = small; 0.15 = medium; 0.35 = large (Cohen, 1988). Source: processed data (2026).

Hypothesis Testing

The bootstrapping results in Table 8 and Figure 2 show that all four hypotheses are accepted. HR digital capability has a positive and significant effect on AI adoption readiness (β = 0.636; t = 11.217; p < 0.001), so H1 is accepted. AI adoption readiness has a positive and significant effect on business agility (β = 0.607; t = 4.863; p < 0.001), so H2 is accepted. HR digital capability also has a positive and significant direct effect on business agility (β = 0.237; t = 2.499; p = 0.012), so H3 is accepted.

The indirect effect of HR digital capabilities on business agility through AI adoption readiness is also significant (β = 0.386; t = 4.187; p < 0.001), thus H4 is accepted. Since the direct and indirect effects are both significant and in the same direction, AI adoption readiness acts as a complementary partial mediator (Zhao et al., 2010). The total effect of HR digital capabilities on business agility is 0.623 (0.237 + 0.386), and approximately 62% of this is channeled through AI adoption readiness.

Table 8. Hypothesis Testing Results

Hypothesis	Track	β	Sample mean	Elementary School	t	p	Decision
H1	X → Z	0.636	0.637	0.057	11,217	< 0.001	Accepted
H2	Z → Y	0.607	0.616	0.125	4,863	< 0.001	Accepted
H3	X → Y	0.237	0.228	0.095	2,499	0.012	Accepted

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H4	X → Z → Y	0.386	0.394	0.092	4,187	< 0.001	Accepted

Source: data processed with SmartPLS 4 (2026).

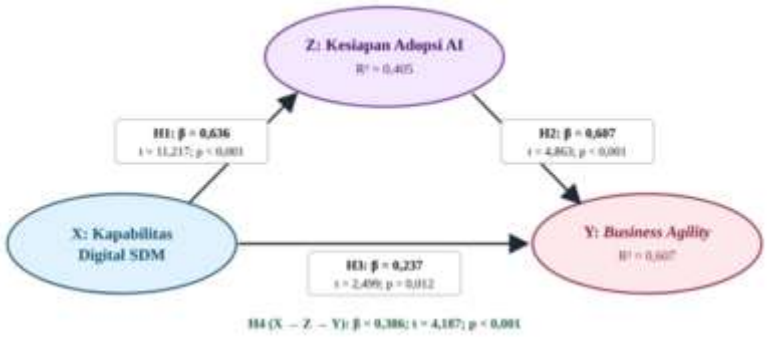


Figure 2. Structural Model Test Results

DISCUSSION

The strongest influence in this model is the influence of human resources' digital capabilities on AI adoption readiness (H1). This finding aligns with the TAM logic that individuals accustomed to using technology will more easily see the benefits and convenience of new technologies (Davis, 1989). This result is also consistent with the findings of Espina-Romero et al. (2026) that digital competence directly influences the digital transformation of MSMEs, as well as with the study by Yesuf and Fields (2025) which places low digital literacy as one of the main obstacles to AI adoption in MSMEs. For food MSMEs, basic skills such as managing a marketplace and reading simple sales data are the entry points before they are ready to try AI-based tools.

AI adoption readiness has been shown to significantly impact business agility (H2). From a dynamic capabilities perspective, readiness to utilize new technologies strengthens a business's ability to recognize opportunities (sensing) and respond to them (seizing) (Teece, 2007; Overby et al., 2006). This finding aligns with Henryanto et al. (2025), who found that digital platform capabilities positively impact the strategic agility of food and beverage MSMEs in Indonesia.

The direct effect of human resource digital capabilities on business agility (H3) is significant, but the effect size is small. This means that business owners' digital capabilities do help them respond to market changes, for example by quickly adjusting promotions on social media, but the majority of their contribution is channeled through their readiness to adopt AI (H4). This mediation pattern aligns with Purwati et al. (2026), who found that digital business adoption acts as an intermediary between the digital ecosystem and the performance of MSMEs in Bangka. The implication is that MSME

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mentoring programs should not stop at digital literacy but should continue with the introduction of simple AI tools relevant to the needs of food businesses.

CONCLUSION

Data analysis shows that HR digital capabilities have a positive and significant effect on AI adoption readiness and business agility, AI adoption readiness has a positive and significant effect on business agility, and AI adoption readiness partially mediates the effect of HR digital capabilities on business agility. The model explains 60.7% of the variation in business agility and has adequate predictive relevance. Descriptively, all three variables are in the high category, with HR digital capabilities as the variable with the lowest score.

Practically, these results suggest that the development of MSMEs' digital capabilities needs to be directed in stages: from basic digital literacy, to readiness to utilize AI, to the ability to respond quickly to market changes. Limitations of this analysis lie in the nature of the data, its cross-sectional design, its composite reliability exceeding 0.95, and its sample size, which is only adequate at 0.80 power for the smallest direct path. Further research is needed to test this model with field data collected through documented quality control procedures.

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