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Digital Leadership, Technology Readiness, AI Adoption, Organizational Agility, and Operational Performance

Intan Rahmatillah* Universitas Pasundan, Indonesia
Sidik Priadana Universitas Pasundan, Indonesia
Yusuf Arifin Universitas Pasundan, Indonesia

***Corresponding author:**
Intan Rahmatillah,
Universitas Pasundan, Indonesia.
✉intan.239010005@mail.unpas.ac.id

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Abstract

Background: Small and medium-sized food service businesses face a practical question: whether their use of artificial intelligence (AI) and their ability to adapt are associated with how they perform operationally. Urban West Java provides a setting in which restaurants and cafés operate across several cities and use AI at different levels of integration.
Objective: This study examined the relationships of digital leadership and technology readiness with AI adoption and organizational agility, and the separate relationships of AI adoption and organizational agility with operational performance.
Methods: A cross-sectional survey used purposive recruitment across nine cities. Eligible businesses had operated for at least one year and had used AI-based technology for at least six months. Structured five-point questionnaires were completed by owners, managers, or key operators, yielding 400 valid responses. The data were analyzed using structural equation modeling.
Results: Digital leadership and technology readiness each showed significant positive associations with AI adoption and organizational agility. Technology readiness had the larger coefficient for AI adoption, whereas digital leadership had the larger coefficient for organizational agility. AI adoption and organizational agility each showed significant positive associations with operational performance and jointly accounted for 90.4% of its estimated variance in the sample.
Conclusion: The findings identify distinct organizational and technological correlates of AI adoption and agility among participating businesses and indicate the need to validate the measures against observed usage and performance.

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INTRODUCTION

Artificial intelligence (AI) can help businesses analyze operational data and automate routine tasks (Astawa & Arsha, 2024; Efendi et al., 2024; Hossain et al., 2024; Nair & Nathiya, 2024). For food service businesses, a practical question is whether these capabilities are associated with operational performance when businesses differ in their leadership, technology readiness, and ability to respond to change.

In McKinsey's 2022 survey, respondents reported AI adoption in at least one business function at about half of their organizations (Chui et al., 2022). In Indonesia, executives identified generative AI as a potential contributor to business reinvention, with anticipated benefits for efficiency and innovation (Indonesia, 2024). These expectations leave open how established AI users incorporate the technology into day-to-day operations.

Micro, small, and medium enterprises (MSMEs) face market pressures that make digital tools relevant to customer service, marketing, and sales forecasting (Dinul Khaq et al., 2024; Firly, 2024; Ikpe, 2024). In this article, small and medium-sized enterprises (SMEs) are the subset of MSMEs within the study's business-size criteria. Santosa and Surgawati (2024) examined AI as a marketing tool among Indonesian MSMEs. Harahap et al. (2025) discussed how AI, particularly chatbots, could support customer service in this broader group.

Indonesia had approximately 4.85 million food and beverage service businesses in 2023. These businesses employed about 9.80 million people and generated Rp998.37 trillion in sales Statistik (2024). These figures describe the national food and beverage service sector, which includes activities beyond the restaurants and cafés sampled here.

The culinary scene in West Java is an important topic worthy of study due to various factors, including its large population, dynamic economic activity, and the rapid growth of restaurants and cafes in urban areas. The cities of Bandung, Bogor, Bekasi, Depok, Cimahi, Cirebon, Tasikmalaya, Sukabumi, and Banjar exemplify the diverse dynamics of the culinary business sector, ranging from themed cafes and modern restaurants to small and medium-sized local businesses. According to data from Open Data West Java, the number of restaurants and cafes in these urban areas is quite high, for example, in the cities of Bekasi, Depok, Tasikmalaya, Bogor, and Bandung (Barat, 2024). Some business owners have already adopted point-of-sale systems, digital ordering, social media promotions, simple chatbots, or online marketplaces. However, the adoption of technologies such as inventory forecasting, sales analysis, product recommendations, and data-driven service personalization remains uneven among business owners.

The adoption of AI in restaurants and cafes does not depend solely on the availability of technology; the role of digital leaders is crucial because they set the direction for transformation, build a digital work culture, and drive the use of data in operational decisions. Digital leadership goes beyond the ability to use technological tools; it also encompasses the ability to shape a digital vision, steer change, empower employees, and create an innovative and adaptive culture (Anam et al., 2024; Mahmood et al., 2024). In the context of SMEs, which generally have limited resources, simple organizational structures, and a high degree of dependence on decisions made by owners or business leaders, digital leadership competencies are particularly important. In the restaurant industry, digital leadership can drive the integration of AI into procurement, production, marketing, customer service, and delivery processes, making operations more responsive to market needs (Sheiko, 2024).

Technology readiness reflects an organization's capacity to provide the infrastructure, data, staff skills, and governance needed to use AI. Tehrani et al. (2024) examined these capabilities in multinational corporations. In smaller food service businesses, using a digital point-of-sale system can indicate a degree of technology readiness. An AI-enabled function, such as predictive demand forecasting, provides a more direct example of AI use.

Organizational agility involves anticipating change and adjusting operating practices in response to it. Prior research has linked AI to faster processing of information and greater adaptive capacity (Guruprasad et al., 2024; Mahama et al., 2024; Ştefan et al., 2024). Agile approaches have also been examined in digital transformation initiatives (Ramljak et al., 2024). The present model treats AI adoption and organizational agility as parallel predictors of operational performance.

Operational performance in this study covers process effectiveness, operational efficiency, customer satisfaction, financial performance, and employee satisfaction and engagement. AI tools can support tasks such as inventory planning and customer service (Harahap et al., 2025; Moeuf et al., 2020). Whether these applications are associated with the broader performance measure is an empirical question.

Based on a preliminary survey of restaurant and café business owners in West Java, there are early indications of this issue. Overall, 61% of respondents are already familiar with AI or machine learning, while the rest are unsure or do not yet understand how to apply these technologies in their businesses. Some respondents have been using these technologies for more than a year, primarily for design, digital promotion, customer communication, marketplaces, and supporting applications such as Canva, WhatsApp Business, Google Ads, Meta Ads, ChatGPT, and certain POS systems. However, the use of these technologies remains largely practical and has not yet fully integrated into core business processes

The preliminary mean scores were 3.15 for operational performance, 3.13 for organizational agility, 3.13 for AI adoption, and 3.09 for technology readiness. Customer satisfaction, radicalness, risk-taking, and external environmental support were among the relatively weak indicators. These observations motivated an examination of the relationships among the constructs in the main survey.

Al-Khatib (2023) examined antecedents of generative AI adoption and its links with exploratory and exploitative innovation. Tehrani et al. (2024) identified dimensions of AI readiness in multinational corporations. Santosa and Surgawati (2024) focused on marketing use among Indonesian MSMEs. This study brings readiness and digital leadership into the same model and estimates AI adoption and organizational agility as separate correlates of operational performance in urban food service SMEs.

This study examined whether digital leadership and technology readiness were associated with AI adoption and organizational agility and whether AI adoption and organizational agility were each associated with operational performance. Its contribution is to estimate these six relationships in a single model for participating small and medium-sized restaurants and cafés in urban West Java.

METHOD

This study used a cross-sectional quantitative survey to examine the relationships among digital leadership, technology readiness, artificial intelligence adoption, organizational agility, and operational performance in small and medium-sized restaurants and cafés in urban West Java. Descriptive analysis summarized respondents and construct scores. Structural equation modeling tested the hypothesized relationships.

Primary data were collected through structured questionnaires administered to owners, managers, or key operators of restaurants and cafés. Respondents were selected for their firsthand knowledge of business management, digital technology, and the use of AI in operations. Interviews and non-participant observations provided contextual information about technology implementation. The questionnaire consisted of closed-ended statements using a five-point Likert scale from “strongly disagree” to “strongly agree.”

Table 1
Research Design Summary

Aspect	Description
Approach	Quantitative
Method	Cross-sectional survey
Nature of Research	Descriptive and hypothesis-testing
Unit of Analysis	Small- and medium-sized restaurants and cafés
Respondents	Owners, managers, or key operators
Location	Urban areas of West Java
Data Collection Technique	Questionnaire, interviews, and observation
Measurement Scale	Likert scale 1-5
Analysis Technique	Descriptive analysis and Structural Equation Modeling (SEM)

The study population comprised restaurants and cafés in Bogor, Sukabumi, Bandung, Cirebon, Bekasi, Depok, Cimahi, Tasikmalaya, and Banjar. Eligible small and medium-sized businesses had operated for at least one year and used AI-based technology for at least six months. Examples included generative functions in ChatGPT, Gemini, or Canva AI, AI-enabled chatbots, and predictive or recommendation functions integrated into restaurant workflows. Routine digital payments, ordering, messaging, and transaction recording were classified as general digital functions unless an AI feature was used.

Article 35 of Government Regulation No. 7 of 2021 specifies business capital of more than Rp1 billion up to Rp5 billion for small businesses and more than Rp5 billion up to Rp10 billion for medium-sized businesses, excluding land and business premises (Republic of Indonesia, 2021). The study used these business-capital categories to define the eligible business sizes.

Respondents were selected using a combination of purposive sampling and proportional allocation by region. Purposive sampling was chosen to ensure that respondents met the research

criteria, particularly regarding business size, location, operational experience, and AI usage. Next, the sample was allocated proportionally according to the number of restaurants and cafes in each city region in West Java. The minimum sample size was determined using Cochran's formula with a 95% confidence level, a 5% margin of error, and a maximum proportion of 0.5. After applying the finite population correction, the minimum required sample size was 370 respondents. In the study, a total of 400 valid data points from respondents were analyzed.

Table 2

Planned Sample Distribution

Region	Planned City Allocation
Bogor City	52
Sukabumi City	14
Bandung City	38
Cirebon City	7
Bekasi City	113
Depok City	69
Cimahi City	13
Tasikmalaya City	59
Banjar City	3
Total	368

Note. The listed city allocations sum to 368. The reported overall planning target was 370, and 400 responses were analyzed (Table 6).

Digital leadership (X_1) and technology readiness (X_2) were exogenous predictors. AI adoption (Y_1) and organizational agility (Y_2) were endogenous in their respective equations and served as parallel predictors of operational performance (Z). The dimensions and questionnaire item codes appear in Table 3.

Table 3

Operationalization of Research Variables

Variable	Dimension	Number of Items	Item Code
Digital Leadership (X_1)	Visionary planning and digital culture	4	P1-P4
	Technology adaptation and innovation support	4	P5-P8
	Digital skills and literacy	4	P9-P12
	Empowerment and employee development	4	P13-P16
Technology Readiness (X_2)	Strategic capability	2	P17-P18
	Organizational culture	2	P19-P20
	Information technology infrastructure	2	P21-P22
	Data security	2	P23-P24
	Business model transformation	2	P25-P26
	Data analytics and governance	2	P27-P28
	Cost-benefit and risk evaluation	2	P29-P30
	Environmental factors	2	P31-P32
AI Adoption (Y_1)	Innovativeness	5	P33-P37
	Strategic anticipation	5	P38-P42
	Risk-taking	5	P43-P47
Organizational Agility (Y_2)	Proactivity	4	P48-P51
	Radicalness	4	P52-P55
	Responsiveness	4	P56-P59
	Adaptability	4	P60-P63
Operational Performance (Z)	Employee satisfaction and engagement	4	P64-P67
	Process effectiveness	4	P68-P71
	Operational efficiency	4	P72-P75

Variable	Dimension	Number of Items	Item Code
	Customer satisfaction	4	P76-P79
	Financial performance	4	P80-P83

The questionnaire contained 83 statements, with item codes and dimensions shown in Table 3. Digital leadership covered digital direction, innovation support, digital skills, and employee development. Technology readiness covered strategic, cultural, technical, security, data governance, and external factors. The AI adoption scale assessed innovativeness, strategic anticipation, and risk-taking in the context of AI. These dimensions capture an orientation toward using AI, so scores may overlap with strategic orientation and do not quantify usage intensity or verified deployment. Organizational agility covered proactivity, radicalness, responsiveness, and adaptability. Operational performance covered employee satisfaction and engagement, process effectiveness, operational efficiency, customer satisfaction, and financial performance.

Data processing was conducted in two stages. The first stage was descriptive analysis, which served to describe the characteristics of the respondents and the patterns of their responses to each variable. Response scores were categorized based on value ranges to reflect levels of digital leadership, technological capabilities, AI adoption, organizational agility, and operational performance.

Structural equation modeling was used to estimate the three equations for AI adoption, organizational agility, and operational performance:

$$Y_1 = \gamma_{11}X_1 + \gamma_{12}X_2 + \zeta_1$$
$$Y_2 = \gamma_{21}X_1 + \gamma_{22}X_2 + \zeta_2$$
$$Z = \beta_{31}Y_1 + \beta_{32}Y_2 + \zeta_3$$

X_1 = digital leadership (KD), X_2 = technology readiness (KT), Y_1 = AI adoption (AKB), Y_2 = organizational agility (KO), and Z = operational performance (KIN). The codes in parentheses identify the same constructs in the original output figures. The γ and β terms denote structural coefficients, and ζ denotes an equation-specific disturbance. In Figure 1, ξ_1, ξ_2, η_1, η_2, and η_3 correspond to X_1, X_2, Y_1, Y_2, and Z, respectively. Its γ_1–γ_4 and β_1–β_2 label the same six paths in equation order.

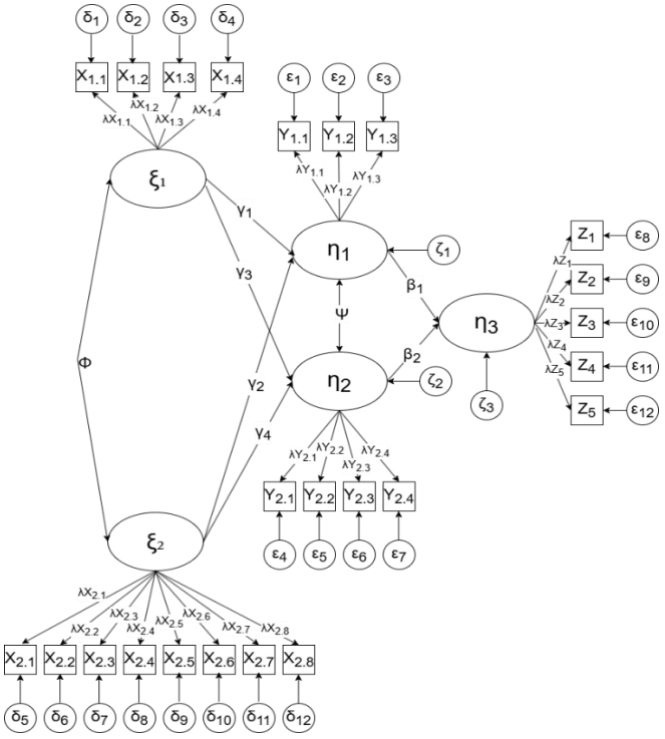

Figure 1. Structural Equation Model

Before testing the hypothesis, the instrument was first tested for validity and reliability. Content validity was assessed through expert review to ensure that the items were consistent with the intended construct. Item validity is measured by comparing the Pearson correlation between item scores and the total score for the construct; an item is considered valid if the correlation value reaches the established significance threshold. Reliability is tested using Cronbach's Alpha, and the minimum acceptable indicator is a value of ≥ 0.70.

The fit of an SEM model is assessed using a series of criteria, including theoretical fit, accuracy of parameter estimates, explanatory power, and predictive power. Goodness-of-fit indicators are measured using indices such as the Chi-Square, RMSEA, CFI, and TLI. In general, a model is considered acceptable if the RMSEA falls within an acceptable range, the CFI and TLI are close to or exceed 0.90, and the direction of the relationships between variables is consistent with the theory. In addition, the model's predictive power is assessed based on the coefficient of determination (R^2) for the endogenous variables.

Table 4
Model Testing Criteria

Testing Aspect	Criteria
Content validity	Items are consistent with the construct based on expert judgment
Item validity	Significant item-total correlation
Reliability	Cronbach's Alpha ≥ 0.70
Model fit	Assessed using Chi-Square, RMSEA, CFI, and TLI
Path significance	The relationship is significant if the statistical value meets the testing threshold
In-sample explanatory power	Assessed from the R^2 value of endogenous constructs

This study examines the direct relationships among the variables in the model by testing hypotheses regarding the effects of digital leadership and technological readiness on AI adoption and organizational agility. Furthermore, AI adoption and organizational agility were tested to assess their impact on operational performance. The results of these tests were used to determine whether the empirical model supports the theoretical framework developed in this study.

RESULTS AND DISCUSSION

Results

The survey covered small and medium-sized restaurants and cafés in the nine West Java cities listed in the Method section. Table 5 presents the capital categories used to describe the business-size scope, including the excluded microenterprise category (Republic of Indonesia, 2021).

Table 5
Business Category Characteristics Based on Government Regulation No. 7 of 2021

Business Category	Business Capital	General Characteristics
Micro Business	Up to IDR 1.000.000.000	Very small business scale, limited number of workers, simple business management, and the use of digital technology is generally still basic.
Small Business	> IDR 1.000.000.000 up to IDR 5.000.000.000	More stable operational capacity, more workers, and starting to use digital technology to support business operations.
Medium Business	> IDR 5.000.000.000 up to IDR 10.000.000.000	More established business scale, more formal management structure, greater investment capability, and relatively higher digital readiness.

The analysis included 400 valid responses from owners, key operators, or senior managers. Table 6 distinguishes the 368 planned city allocations from the 400 analyzed responses. Every city exceeded its listed allocation. Cimahi had the largest absolute difference,

with 22 analyzed responses against 13 planned. The recruitment records needed to establish the reason for that difference were unavailable.

Table 6
Planned Allocations and Analyzed Responses by City

Region (City)	Planned Allocation	Analyzed Responses
Bogor	52	55
Sukabumi	14	15
Bandung	38	41
Cirebon	7	9
Bekasi	113	117
Depok	69	74
Cimahi	13	22
Tasikmalaya	59	62
Banjar	3	5
Total	368	400

The largest business-age group comprised establishments operating for 1–3 years, reported by 155 of 400 respondents (38.75%). Another 121 respondents (30.25%) reported more than 10 years in operation. The sample thus included both newer and established businesses.

Table 7
Respondent Characteristics Based on Business Age

Business Age Category	Frequency	Percentage
1-3 years	155	38.75%
4-6 years	46	11.50%
7-10 years	78	19.50%
More than 10 years	121	30.25%
Total	400	100%

The largest age group comprised respondents aged 35–44 years (185 of 400, 46.25%). A bachelor's degree was the most frequently reported qualification (197 of 400, 49.25%), followed by a master's or doctoral degree (109 of 400, 27.25%).

Table 8
Respondent Characteristics Based on Age

Respondent Age	Frequency	Percentage
Under 25 years	63	15.75%
25-34 years	77	19.25%
35-44 years	185	46.25%
45-54 years	64	16.00%
55 years and above	11	2.75%
Total	400	100%

Table 9
Respondents' Highest Educational Attainment

Highest Educational Attainment	Frequency	Percentage
Junior High School or Lower	0	0.%
Senior High School/Vocational School	6	1.50%
Diploma (D1-D4)	88	22%
Bachelor (S1)	197	49.25%
Postgraduate (S2/S3)	109	27.25%
Total	400	100%

Of the 400 respondents, 176 (44%) reported AI use for 1–2 years and 170 (42.50%) for 6–12 months. The most common frequency was 3–5 times per week, reported by 134 respondents

(33.50%). A majority of respondents (305 of 400, 76.25%) used AI only for selected tasks.

Table 10
Duration of AI Use in Business

Duration of AI Use	Frequency	Percentage
6-12 months	170	42.50%
1-2 years	176	44%
More than 2 years	54	13.50%
Total	400	100%

Table 11
Frequency of AI Use

Frequency of AI Use	Frequency	Percentage
Very rarely, less than 1 time in a month	0	0%
Rarely, 1-3 times in a month	74	18.50%
Sometimes, 1-2 times in a week	126	31.50%
Often, 3-5 times in a week	134	33.50%
Very often, used every day	66	16.50%
Total	400	100%

Table 12
Level of AI Integration in Operations

Level of AI Integration	Frequency	Percentage
Fully integrated with the work system	38	9.50%
Used only for certain tasks	305	76.25%
Still in the trial/pilot project stage	57	14.25%
Total	400	100%

Table 13
Type of AI Access Used

Type of AI Access	Frequency	Percentage
Only free/unpaid version	240	60%
Combination of free and paid	138	34.50%
Paid	22	5.50%
Total	400	100%

Most respondents reported using AI for selected tasks. Free-only access was the most common access category (Table 13).

Instrument validation was conducted by examining validity, reliability, and normality. The validity test results showed that each item in the variables of digital leadership, technological readiness, artificial intelligence adoption, organizational agility, and operational performance had an r-calculated value above the critical r value of 0.30; therefore, all items were deemed valid. The reliability test yielded Cronbach's Alpha values for all variables above 0.70, so it can be concluded that the instrument is reliable.

Table 14
Variable Reliability Test Results

Variable	Cronbach's Alpha	Cut Off	Description
Digital leadership	0.9783	0.7	Reliable
Technology readiness	0.9775	0.7	Reliable
Organizational agility	0.9824	0.7	Reliable
Artificial intelligence adoption	0.9639	0.7	Reliable
Operational performance	0.9607	0.7	Reliable

Normality testing using the one-sample Kolmogorov-Smirnov test yielded p-values for each variable that were all greater than 0.05. For digital leadership, the significance value was

0.089; for technology readiness, 0.077; for artificial intelligence adoption, 0.129; for organizational agility, 0.113; and for operational performance, 0.091. Therefore, it can be concluded that the data are normally distributed.

Scores were classified as very poor (1.00–1.80), poor (1.81–2.60), fair (2.61–3.40), good (3.41–4.20), or very good (4.21–5.00). All five construct means fell in the fair category. Several individual dimensions fell in the good category.

Digital leadership averaged 3.23. Employee empowerment and development had the highest dimension mean (3.40), and technology adaptation and innovation support had the lowest (3.05). Technology readiness averaged 3.34, with strategic capability highest (3.49) and data security lowest (3.12). AI adoption averaged 3.24, with innovativeness highest (3.39) and strategic anticipation lowest (3.14).

Organizational agility averaged 3.27. Radicalness had the highest mean (3.49), and responsiveness had the lowest (3.15). Operational performance averaged 3.13. Customer satisfaction had the highest mean (3.52), and process effectiveness had the lowest (2.86).

Table 15

Descriptive Summary of Research Variables

Variable	Average	Category	Highest Dimension	Lowest Dimension
Digital leadership	3.23	Fair	Employee empowerment and development (3.40)	Technology adaptation and innovation support (3.05)
Technology readiness	3.34	Fair	Strategic capability (3.49)	Data security (3.12)
Artificial intelligence adoption	3.24	Fair	Innovativeness (3.39)	Strategic anticipation (3.14)
Organizational agility	3.27	Fair	Radicalness (3.49)	Responsiveness (3.15)
Operational performance	3.13	Fair	Customer satisfaction (3.52)	Process effectiveness (2.86)

The measurement model analysis indicates that all constructs have adequate factor loadings and t-values above the critical threshold. For the digital leadership variable, the highest factor loading was found in the dimensions of adaptability to technology and support for innovation, at 0.976. For the technological readiness variable, the highest factor loading was found in the dimensions of data analytics and governance, at 0.953. For the artificial intelligence adoption variable, the highest factor loading was in the strategic foresight dimension, at 0.958. Meanwhile, for the organizational agility variable, the highest factor loading was found in the responsiveness dimension, with a value of 0.967. Finally, for the operational performance variable, the highest factor loading was found in the customer satisfaction dimension, at 0.966.

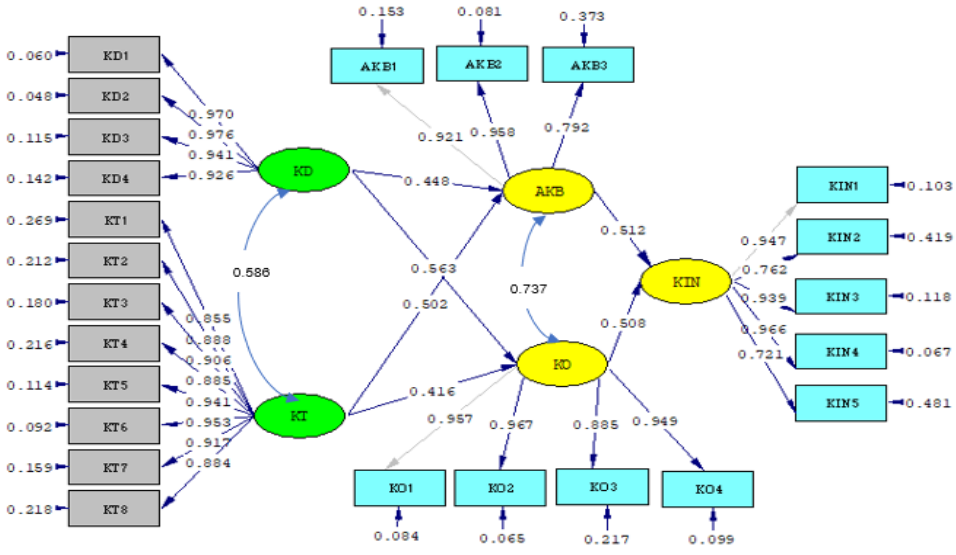

Figure 2. Relationship Structure of All Research Variables

CFI (0.990), TLI/NNFI (0.988), and RMSEA (0.075) met the stated benchmarks. GFI (0.868) and AGFI (0.823) were marginal, and PGFI (0.648) was below the manuscript's stated benchmark. The reported chi-square-related value (2.511) was compared with a ratio benchmark (<3.00), consistent with χ^2/df, but the source output did not establish the statistic's identity. The raw χ^2, degrees of freedom, and the pairing with the reported p-value of 0.087 remain unverified.

Table 16

Goodness of Fit Model Test Results

GoF Measure	Estimate	Test Result	Requirement
Reported χ^2-related value	2.511	Requires confirmation	< 3.00
Reported p-value	0.087	Meets stated criterion (>0.05)	> 0.05
GFI	0.868	Marginal fit	≥ 0.90
RMSEA	0.075	Good fit	< 0.08
ECVI	1.504	Good fit	~ 1
TLI/NNFI	0.988	Good fit	≥ 0.90
NFI	0.986	Good fit	≥ 0.90
AGFI	0.823	Marginal fit	≥ 0.90
IFI	0.990	Good fit	≥ 0.90
CFI	0.990	Good fit	≥ 0.90
PGFI	0.648	Below stated benchmark	≥ 0.90
PNFI	0.800	Good fit	~ 1

Note. Confirmation from the original SEM output is required to establish whether 2.511 represents χ^2 or χ^2/df and whether the reported p-value corresponds to the same model test.

The first structural equation estimated the associations of digital leadership and technology readiness with AI adoption:

$$Y_1 = 0.448X_1 + 0.502X_2, \; R^2 = 0.717$$

Digital leadership and technology readiness jointly accounted for 71.7% of the estimated variance in AI adoption. The technology readiness coefficient (0.502) was larger than the digital leadership coefficient (0.448).

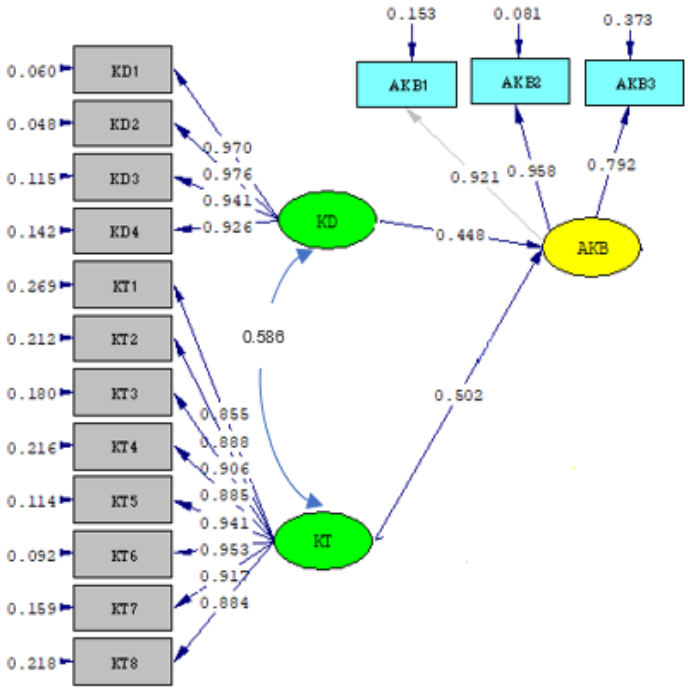

Figure 3. Structural Paths to AI Adoption

Table 17
Decomposition of Explained Variance in AI Adoption

Variable	Path Coefficient	Squared Coefficient	Shared Term	Allocated R^2
Digital Leadership	0.448	20.2%	13.2%	33.3%
Technology Readiness	0.502	25.2%	13.2%	38.4%
Total		45.3%	26.4%	71.7%

Digital leadership (β = 0.448, t = 10.938) and technology readiness (β = 0.502, t = 11.969) were positively associated with AI adoption. Both t statistics exceeded the reported critical value of 1.966. Tables 17–19 decompose predicted variance for two standardized, correlated predictors as $R^2 = b_1^2 + b_2^2 + 2b_1b_2r_{12}$. Each predictor is allocated its squared coefficient and one shared term, $b_1b_2r_{12}$. The shared term arises from predictor correlation and has no mediation interpretation. The table percentages are the reported rounded values and can differ slightly from recomputations based on the displayed coefficients.

The second structural equation estimated the associations of digital leadership and technology readiness with organizational agility:

$$Y_2 = 0.563X_1 + 0.416X_2, \; R^2 = 0.765$$

Digital leadership and technology readiness jointly accounted for 76.5% of the estimated variance in organizational agility. The digital leadership coefficient (0.563) was larger than the technology readiness coefficient (0.416).

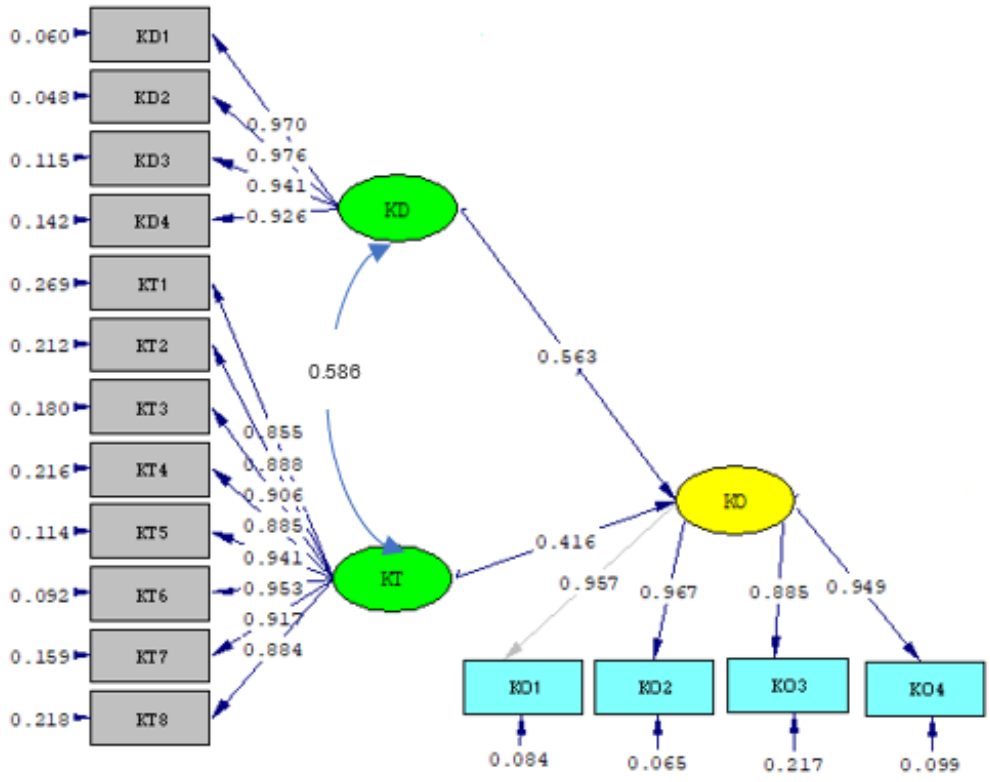

Figure 4. Structural Paths to Organizational Agility

Table 18
Decomposition of Explained Variance in Organizational Agility

Variable	Path Coefficient	Squared Coefficient	Shared Term	Allocated R^2
Digital Leadership	0.563	31.7%	13.7%	45.5%
Technology Readiness	0.416	17.3%	13.7%	31.0%
Total		49.0%	27.4%	76.5%

Digital leadership (β = 0.563, t = 14.482) and technology readiness (β = 0.416, t = 11.461) were positively associated with organizational agility. Both t statistics exceeded the reported critical value of 1.966.

The third structural equation estimated the separate associations of AI adoption and organizational agility with operational performance:

$$Z = 0.512Y_1 + 0.508Y_2, \quad R^2 = 0.904$$

AI adoption and organizational agility jointly accounted for 90.4% of the estimated variance in operational performance in the sample. The high in-sample R^2 should be interpreted alongside the unresolved questions about construct overlap and shared measurement.

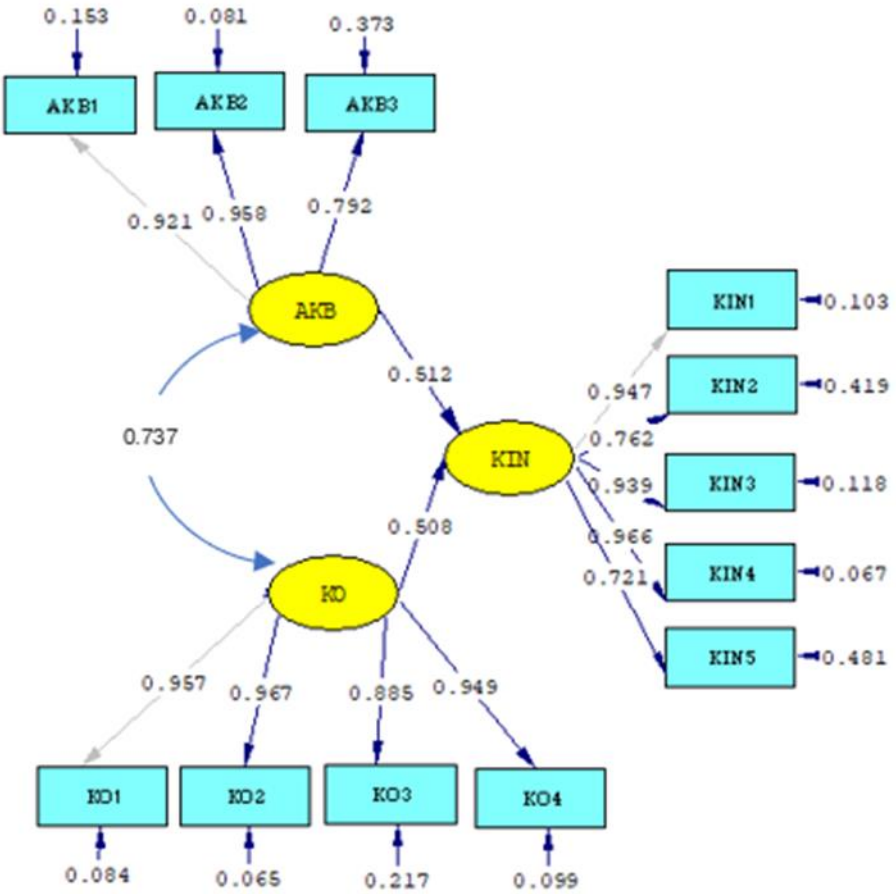

Figure 5. Structural Paths to Operational Performance

Table 19

Decomposition of Explained Variance in Operational Performance

Variable	Path Coefficient	Squared Coefficient	Shared Term	Allocated R^2
Artificial Intelligence Adoption	0.512	26.2%	19.2%	45.4%
Organizational Agility	0.508	25.8%	19.2%	45.0%
Total		52.0%	38.4%	90.4%

AI adoption (β = 0.512, t = 15.502) and organizational agility (β = 0.508, t = 15.865) were positively associated with operational performance. Both t statistics exceeded the reported critical value of 1.966.

Table 20
Summary of Hypothesis Testing Results

Relationship between Variables	Path Coefficient	t Statistic	Critical t Value	Decision
Digital leadership → AI adoption	0.448	10.938	1.966	Significant
Technology readiness → AI adoption	0.502	11.969	1.966	Significant
Digital leadership → Organizational agility	0.563	14.482	1.966	Significant
Technology readiness → Organizational agility	0.416	11.461	1.966	Significant
AI adoption → Operational performance	0.512	15.502	1.966	Significant
Organizational agility → Operational performance	0.508	15.865	1.966	Significant

Table 21
Correspondence of Expected and Estimated Path Signs

Relationship between Variables	Pre-Estimation	Post-Estimation	Suitability
Digital leadership → AI adoption	+	+	Suitable
Technology readiness → AI adoption	+	+	Suitable
Digital leadership → Organizational agility	+	+	Suitable
Technology readiness → Organizational agility	+	+	Suitable
AI adoption → Operational performance	+	+	Suitable
Organizational agility → Operational performance	+	+	Suitable

Table 17. allocated 38.4% of AI adoption variance to technology readiness and 33.3% to digital leadership. Each allocation includes a share of predictor covariance.

The estimated path from technology readiness to AI adoption was numerically larger than the corresponding path from digital leadership. The comparison describes the reported estimates.

Table 18. allocated 45.5% of organizational agility variance to digital leadership and 31.0% to technology readiness.

The estimated path from digital leadership to organizational agility was numerically larger than the corresponding path from technology readiness.

Table 19. allocated 45.4% of operational performance variance to AI adoption and 45.0% to organizational agility. Both allocations include a 19.2% shared term.

Strategic anticipation, responsiveness, and customer satisfaction had the highest displayed loadings for AI adoption, organizational agility, and operational performance, respectively. Loading strength describes the measurement model. The descriptive means summarize the levels reported by respondents.

All six estimated path signs matched the hypothesized positive directions in Table 21.

Discussion

Digital leadership was rated fair. Employee empowerment and development received the highest mean, while technology adaptation and innovation support received the lowest. The latter identifies a potential priority for developing managers' ability to evaluate technologies against operational needs.

Technology readiness was rated fair. Strategic capability had the highest mean, and data security had the lowest. Tehrani et al. (2024) identified data, infrastructure, and organizational capabilities as components of AI readiness in multinational firms. The present results show how selected readiness dimensions were rated in a smaller-business setting.

AI adoption was rated fair. Innovativeness scored highest and strategic anticipation lowest. The pattern is compatible with the reported use of AI for selected tasks, although the orientation-based scale cannot establish which AI features were used or how intensively they were used.

Organizational agility was rated fair. Radicalness had the highest mean and responsiveness the lowest. The difference suggests that respondents rated their capacity for

substantial changes more favorably than their ability to respond rapidly.

Operational performance was rated fair. Customer satisfaction had the highest mean and process effectiveness the lowest. Process effectiveness therefore merits attention in any follow-up assessment using operational records.

Digital leadership and technology readiness were each positively associated with AI adoption. The larger estimated readiness coefficient is consistent with the organizational and technological antecedents examined by (Al-Khatib, 2023). In this sample, the outcome also captured strategic orientation toward AI, which limits direct comparison with measures of actual system use.

Digital leadership and technology readiness were each positively associated with organizational agility. The larger estimated leadership coefficient suggests a role for managerial direction alongside technology capacity. Ramljak et al. (2024) considered agility in digital transformation initiatives, whereas the present analysis examined agility in relation to leadership and readiness in food service SMEs.

AI adoption and organizational agility each showed a positive association with operational performance, with similar estimated coefficients. AI can support the analysis of operational information. Organizational agility can complement this function by enabling teams to act on decisions as conditions change. The model estimated separate paths to performance and did not test how one predictor might transmit the relationship of the other. This distinction is consistent with Venkatesh (2022) research agenda, which distinguishes the factors underlying AI tool adoption and use from the benefits that may follow.

CONCLUSION

This study examined whether digital leadership and technology readiness were associated with AI adoption and organizational agility, and whether AI adoption and organizational agility were associated with operational performance. Among 400 valid responses from owners, managers, and key operators of small and medium-sized restaurants and cafés using AI in nine West Java cities, all six estimated relationships were positive and statistically significant. AI adoption and organizational agility were parallel predictors and jointly accounted for 90.4% of the estimated in-sample variance in operational performance.

The findings apply to the purposively recruited businesses that had used AI for at least six months. Their applicability to microenterprises, non-users of AI, and businesses outside the study cities remains unknown. Future research could use longitudinal designs, record AI functions and usage intensity, and include objective performance measures. Further validation of the AI adoption measure and its separation from the other constructs is needed before drawing stronger conclusions.

Owners and managers can prioritize technology according to operational needs and clarify its intended use for staff. Basic point-of-sale (POS) records, Quick Response Code Indonesian Standard (QRIS) payments, and social media posting are digital functions. Predictive forecasting and AI-enabled review classification are examples of AI functions that businesses could assess for particular operating needs.

Data security was the lowest-rated technology readiness dimension. Managers could consider access controls, two-factor authentication, and organized storage of transaction and inventory records. These are proposed practices whose effectiveness was outside the study's scope.

Businesses could select AI functions according to their resources and the extent of integration into current work. Generating promotional drafts or summarizing reviews may suit a limited pilot, while demand forecasting requires sufficiently complete sales and inventory records. The study did not evaluate an implementation sequence.

Responsiveness was the lowest-rated agility dimension. Managers could pilot rapid-response standard operating procedures (SOPs) for stockouts, order surges, or service delays, specifying staff responsibilities and escalation points. The effect of these procedures would need to be evaluated in practice.

Process effectiveness was the lowest-rated operational performance dimension. Role-specific training could focus on consistent transaction recording, inventory updates, and complaint handling. Businesses could evaluate these practices using routine measures such as

order errors or service delays.

The cross-sectional design captured relationships at one point in time and could not establish temporal order or causality. A longitudinal design could repeatedly measure AI use, organizational practices, and operational performance to assess how these measures change together.

Purposive recruitment and the requirement of at least six months of AI use limit generalization. The sample was restricted to small and medium-sized restaurants and cafés in nine West Java cities. Microenterprises, non-users of AI, and establishments outside those cities were outside the study's scope.

The AI adoption scale may overlap with strategic orientation because it assesses innovativeness, strategic anticipation, and risk-taking. Future validation should examine item and construct separation and use direct indicators such as AI functions deployed, frequency of use, and integration into specific workflows.

Future studies could assess whether competitive pressure, staff data literacy, or financial readiness changes the observed relationships. Objective indicators such as recorded waste, fulfillment times, or sales could supplement respondent ratings of operational performance.

The interviews and non-participant observations supplied context for technology implementation. The reported structural estimates were based on questionnaire responses, leaving possible shared method bias and self-report error. Future mixed-methods research could integrate interview and observation findings systematically and triangulate survey ratings with independent operational records.

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AUTHOR CONTRIBUTION STATEMENT

Intan Rahmatilah conceptualized the study, collected the data, conducted the formal analysis, and prepared the original draft. Sidik Priadana contributed to the research methodology, supervised the study, and critically revised the manuscript. Yusuf Arifin contributed to the interpretation of the findings and revised the manuscript. All authors approved the final version of the manuscript.

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