The Role of Business Process Capability and AI Adoption in SMEs

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Abstrak– Organisasi semakin banyak mengadopsi kecerdasan buatan (AI) untuk meningkatkan efisiensi dan daya saing; namun, usaha kecil dan menengah (UKM) sering menghadapi tantangan dalam mewujudkan potensi manfaatnya. Studi ini menyelidiki peran mediasi kapabilitas manajemen proses bisnis (BPM) dalam hubungan antara adopsi AI dan kinerja proses di antara UKM di Kalimantan Timur, Indonesia. Desain penelitian kuantitatif digunakan menggunakan metode survei dan wawancara. Populasi studi terdiri dari UKM yang memanfaatkan platform e-commerce, dengan purposive sampling digunakan untuk memilih responden yang berpengalaman dalam adopsi digital. Sebanyak 105 respons valid dianalisis menggunakan Structural Equation Modeling (SEM) dengan WarpPLS. Adopsi AI diukur melalui lima dimensi: akuisisi data, wawasan kognitif, keterlibatan kognitif, dukungan keputusan, dan teknologi kognitif, sementara kapabilitas BPM mencakup empat dimensi: literasi data, literasi inovasi, literasi pelanggan, dan literasi digital. Kinerja proses dinilai melalui dimensi efektivitas dan efisiensi. Hasil penelitian menunjukkan bahwa adopsi AI tidak secara langsung meningkatkan kinerja proses tetapi secara signifikan meningkatkan kapabilitas BPM, yang pada gilirannya memengaruhi kinerja proses secara positif. Lebih lanjut, kapabilitas BPM sepenuhnya memediasi hubungan antara adopsi AI dan kinerja proses. Temuan ini menyoroti bahwa AI saja tidak dapat menciptakan nilai bisnis tanpa kapabilitas BPM yang kuat. Studi ini berkontribusi pada teori dan praktik dengan menerapkan Resource-Based View (RBV) untuk menunjukkan bagaimana UKM dapat mencapai kinerja proses yang berkelanjutan melalui manajemen sumber daya yang strategis

Kata Kunci: Adoption AI, Proses Bisnis, Kapabilitas, Kinerja, Resource-Based View

Abstract– Organizations are increasingly adopting artificial intelligence (AI) to improve efficiency and competitiveness; however, small and medium enterprises (SMEs) often face challenges in realizing its potential benefits. This study investigates the mediating role of business process management (BPM) capabilities in the relationship between AI adoption and process performance among SMEs in East Kalimantan, Indonesia. A quantitative research design was employed using survey and interview methods. The study population consisted of SMEs utilizing e-commerce platforms, with purposive sampling used to select respondents experienced in digital adoption. A total of 105 valid responses were analyzed using Structural Equation Modeling (SEM) with WarpPLS. AI adoption was measured through five dimensions: data acquisition, cognitive insight, cognitive engagement, decision support, and cognitive technology, while BPM capabilities encompassed four dimensions: data literacy, innovation literacy, customer literacy, and digital literacy. Process performance was assessed through the dimensions of effectiveness and efficiency. The results showed that AI adoption did not directly improve process performance but significantly improved BPM capabilities, which in turn positively influenced process performance. Furthermore, BPM capabilities fully mediated the relationship between AI adoption and process performance. These findings highlight that AI alone cannot create business value without robust BPM capabilities. This study contributes to theory and practice by applying the Resource-Based View (RBV) to demonstrate how SMEs can achieve sustainable process performance through strategic resource management.

Keywords: AI Adoption, Business Process, Capabilities, Performance, Resource-Based View

1. INTRODUCTION

The use of artificial intelligence (AI) is becoming more widespread among organizations worldwide to enhance their business performance and remain competitive. Artificial Intelligence has the potential to supplement or substitute human workers in management tasks, such as decision-making and strategy analysis. Despite its various benefits, many companies and SMEs still find it challenging to effectively utilize AI for operational improvements [1]. This underscores the value of understanding how AI can impact business processes and results.

In this study, SMEs in East Kalimantan, Indonesia, are the focus of attention. The research is conducted on them. SMEs face greater challenges in investing in high-tech digital solutions due to their limited resources, unlike large corporations. They are expected to remain flexible and competitive despite digital transformation and global market conditions. The National Capital Region (IKN), where East Kalimantan is located, is a suitable location for this research due to its focus on efficiency and resource utilization. The outcome is that SMEs in this area encounter both opportunities and obstacles in utilizing AI and other digital technologies for their business objectives.

The research examines three closely related factors: AI adoption, BPM capability, and process performance. By utilizing AI, businesses can enhance their creativity, flexibility and data-driven decision-making abilities, leading to better overall performance [2], [3]. The benefits may not be realized unless the organization has exceptional BPM proficiency. An organization can design, analyze, and improve its internal processes through BPM capability. This capability is crucial for helping companies navigate digital transformation, promoting the adoption of new technologies, and improving the customer experience [4]. Hence, the implementation of BPM might be instrumental in connecting AI to improved business outcomes.

Despite extensive research on the effectiveness of business processes [5], there has been little attention given to the correlation between AI, BPM capability, and process performance in small and medium-sized enterprises. Instead of examining the strategic integration of AI and BPM, most current research concentrates on exploring their respective frameworks, methods, and models. According to previous studies, the implementation of AI without considering BPM can have a detrimental effect on company performance [3], [6]. Innovation and automation in BPM have shown a significant impact on decision-making and organizational outcomes [7]. Examining the impact of AI on process performance through BPM capability is still important.

The gap is addressed by examining how BPM capability bridges the gap between AI adoption and process performance in SMEs in East Kalimantan. This study is exceptional because it focuses on SMEs in e-commerce who are facing digital transformation challenges in urban environments. This research seeks to determine the extent of BPM maturity in relation to the impact of AI on SME processes. ". These findings are expected to add value to theory by extending the RBV to how strategic resources such as AI and BPM capabilities impact process performance.

Artificial Intelligence (AI) is the adoption of artificial intelligence based on AI resources: data, infrastructure and skills, human knowledge [8]. [9] defines AI adoption as the process of an organization effectively tapping into and harnessing AI resources to drive innovation. AI has five fundamental features from a business perspective: collecting and processing information; understanding data; communicating with customers; acting on their insights; using AI in decision-making; and leveraging AI technologies.

In practical use, AI can assist organizations in identifying patterns, comprehending customer behavior, integrating chatbots into customer service, and developing recommendation systems using data. AI is primarily employed to automate tasks, increase productivity, and make better decisions. The impact of AI adoption is not always evident. Research indicates that AI can boost company performance [10], [11]. Other studies yield mixed results, with [3], [10]. According to [12], AI adoption can lower a company's market value, but [7] did not demonstrate any significant connection between AI adoptement and company performance. Despite their differences, these findings suggest that we must learn more about the role of AI in creating value in processes.

H1: Business process performance is positively impacted by the use of artificial intelligence (AI).
H2: The capabilities of BPM are positively impacted by AI adoption.

The systematic approach of coordinating and enhancing work processes to ensure consistency, efficiency [13] is known as BPM. Variability, repetition, the level of knowledge required for tasks, and their interdependence are all factors that determine the nature of these processes [14]. Six crucial areas of capability, including adherence to organizational strategy, strong governance, effective methods, integration of information technology and human resources, and cultivating a supportive organizational culture, are essential for the successful implementation of BPM [15] to support digital transformation, BPM capability is necessary to rethink existing processes and foster innovation. In addition to its technical advantages, BPM fosters a culture that prioritizes continuous improvement, as stated by [5]. According to previous studies, organizations benefit from BPM-based innovation [16]. Additionally, BPM expertise facilitates customer experience management by improving data literacy and understanding of customer needs, which helps organizations adapt to changing environments [4].

H3: BPM capabilities are beneficial for the business process performance.

Effectiveness and efficiency are the two main factors that determine process performance [5]. Effectiveness refers to the degree of effectiveness in achieving the desired outcomes, while efficiency is defined as the proportionate use or misuse of resources during the process [17]. The effectiveness of a digital transformation process is heavily reliant on an organization's ability to embrace new technologies, regulate innovation in regulated ways, and maintain high operational quality.

H4: The relationship between AI adoption and business process performance is mediated by the utilization of capabilities in BPM.
H5: There is a total effect between AI adoption and process performance

This study is grounded in the theoretical framework of the Resource-Based View (RBV). A. The use of valuable, rare, and impractical resources that are hard to duplicate or replace in a company is considered by RBV as an important factor in the company's competitive advantage. Knowledge-based improvement by way of technology and organizational resources is the primary objective of RBV in information systems [18]. The adoption of AI and BPM capabilities is regarded as strategic resources that can provide SMEs with a sustainable competitive edge, according to this research.

2. RESEARCH METHODS

2.1 Pre-Research

This study used a questionnaire consisting of three sections: (1) BPM Capabilities; (2) AI Adoption; and (3) Process Performance. The questionnaire was developed by building on previous theoretical foundations to ensure content validity. For all constructs, existing measurement instruments established in previous research were used in this study. The measurement of BPM capabilities used the updated BPM Capabilities framework [15], which focused on four updated BPM capability areas within the Human pillar: Data Literacy, Innovation Literacy, Customer Literacy, and Digital Literacy.

To measure AI Adoption, a construct developed by [9] was used. This questionnaire is a second-order construct consisting of five dimensions: Data Acquisition and Pre-processing, Cognitive Insights, Cognitive Engagement, Cognitive Decision Aid, and Cognitive Technology. To measure process performance, a construct developed by [5] was used. This second-order construct consists of two dimensions: Effectiveness (results-oriented) and Efficiency (economy-oriented).

2.2 Data Collection

A population is the total number of elements to be investigated, while a sample is a portion of the population perceived to represent the entire population being studied [19]. The population considered in this study was SMEs using e-commerce in East Kalimantan Province. In cross-sectional data collection, the main characteristics of the target sample were: length of business, business size, experience using AI, and market reach [3], [16].

The sampling technique in this study used a non-probability technique, meaning that each member of the population does not have an equal chance of being selected, and the researcher does not know the exact population size [19]. The sampling method used in this study was purposive sampling, which uses the researcher's judgment in selecting cases for a specific purpose. The design, measurement items, and questionnaire were developed following the guidelines [20]. A newly developed model for AI adoption and BPM capabilities with a structured questionnaire, which represents the proposed research model, was used.

2.3 Data Analysis

This study was cross-sectional, meaning data was collected at a single point in time [19]. The survey used a combined data collection method, using an online questionnaire and face-to-face interviews to answer research questions. The survey was conducted from May to July 2025. The survey consisted of closed-ended questions in the form of a questionnaire. Respondents completed the questionnaire directly, allowing them to choose from among the alternative answers provided by the researcher. The questionnaire was used to measure the constructs being analyzed: AI Adoption, Business Process Management Capability, and Perceived Process Performance.

The questionnaire consisted of three sections. The first section contained statements about respondents' willingness to complete the questionnaire. The second section contained statements about the constructs being analyzed using a Likert scale of 1-5 (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree). The third section contained demographic characteristics such as: length of business, business size, length of time using AI, and business reach. The questionnaire was distributed through interviews and online-based Google Forms. The online questionnaire was chosen to provide respondents with a sense of security and comfort when completing the questionnaire [19]. Furthermore, according to [19], the internet can facilitate the process of reaching respondents. Therefore, the online questionnaire was used by researchers to increase the number of respondents.

Partial least squares structural equation modeling (PLS-SEM) was used to test the research hypotheses using WarpPLS 8.0 software [21]. PLS-SEM has been used in business research to test theories represented in complex models [22]. WarpPLS is more suitable for models with non-linear relationships and researchers who want to explore complex interactions between variables. WarpPLS software was used in this study in two stages. First, an assessment of the developed reflective and formative measurement model (internal model) was conducted, and then an evaluation of the structural model (external model) was conducted by establishing the relationships between the latent variables in the research model [23].

Table 1. Operational Definition of Variables

Variable	Dimension / Indicator	Source
AI Adoption (X1)	Data Acquisition & Processing (DACQ), Cognitive Insights (CI), Cognitive Engagement (CE), Cognitive Decision Assistance (CDA), Cognitive Technology (CT)	[9]
BPM Capability (X2)	Data Literacy (DL), Innovation Literacy (IL), Customer Literacy (CL), Digital Literacy (DGL)	[7], [15]
Process Performance (Y)	Effectiveness (EFE), Efficiency (EFI)	[5]

3. RESULTS AND DISCUSSIONS

3.1 Results

3.1.1 Respondent Characteristics

The study used an organizational unit of analysis to examine the perceptions of SME management. Data were collected using offline surveys and interviews. The total number of respondents was 113, but eight respondents were eliminated due to data indicating outliers. The study used 105 respondents who met the threshold determined based on the ten-times rule of thumb [24]. Table 2 shows the proportion of businesses operating for more than 5 years (37%) and less than 5 years (63%). SMEs have been using technology for more than 2 years (57%) in their operations.

Table 2. Respondent Characteristics

	Frequency (n = 105)	Percentage
1. Gender		
Male	47	45
Female	58	55
2. Respondent Age		
< 30 years	41	39
30 – 39 years	26	25
40 – 49 years	25	24
> 50 years	13	12
3. Length of Business		
< 1 year	16	15
1 - 5 years	50	48
> 5 years	39	37
4. Length of Technology Adoption		
6 months to <1 year	19	18
1 year to <2 years	26	25
more than 2 years	60	57

(Source: Data processed 2025)

AI Adoption. AI adoption is reflected by five dimensions. Data Acquisition and Pre-processing consists of four items, such as: "We collect data from our existing systems for analysis." Cognitive Insight consists of three items, such as: "We use digital tools to see trends in sales data." Cognitive Engagement consists of three items, such as: "Our customers can interact with digital systems (such as the web, social media, or apps)." Cognitive Decision Aid consists of four items, such as: "We use systems to provide product price recommendations (such as dynamic pricing)." Cognitive Technology consists of three items, such as: "We use online services (cloud) to store and access business data." All items use a scale ranging from 1 = strongly disagree to 5 = strongly agree.

BPM Capability. Focuses on the core Human element, formed by four dimensions. Data Literacy consists of three items, such as: "I know how to read and understand business data reports (e.g., sales or customer reports) for decision-making." Innovation Literacy consists of three items, such as: "I know how to find new ideas to develop my business." Customer Literacy consists of three items, such as: "I understand who my business's main customers are." Digital Literacy consists of four items, such as: "I understand the role of technology in helping business development." All items are scaled from 1 = strongly disagree to 5 = strongly agree.

Process Performance. This variable is formed by two dimensions: Effectiveness and Efficiency. Effectiveness consists of five items, such as: "The work processes in my business produce products or services that meet customer expectations." Efficiency consists of five items, such as: "The work processes in my business do not waste a lot of time." All items are scaled from 1 = strongly disagree to 5 = strongly agree.

Control Variables. This study has four demographic control variables: age, gender, length of business, and length of technology use. Control variables are used to assess external variables that confound the hypothesized relationships. Table 3 presents the study's descriptive statistics, consisting of minimum, maximum, mean, and standard deviation values.

Table 3. Descriptive Analysis Results

Variable	N	Min	Max	Mean	Std. Deviation
AI Adoption	105	1	5	3.9	1,076
Business Process Management Capability	105	1	5	4.3	0,769
Process Performance	105	2	5	4.3	0,786

(Source: Data processed 2025)

3.1.2 Validity and Reliability Test

This study used WarpPLS for validity and reliability testing. Convergent validity testing based on outer loading is considered valid if the outer loading value is >0.7. The higher the outer loading, the stronger the relationship between the indicator and its latent variable. The outer loading measurement results have a strong correlation with the latent variable it represents. However, in the cognitive engagement variable, there is one item with a fairly strong correlation. An outer loading value of >0.6 is acceptable as the minimum limit for convergent validity in this study. All indicator measurements are valid. Discriminant validity testing based on Average Variance Extracted (AVE) is considered valid if the value is >0.5. The higher the AVE, the better a latent variable or construct is in explaining the variance of its indicators. The AVE measurement results for all items are >0.5. The Fornell-Larcker criterion is also used to ensure that the measurement model used has discriminant validity. The criterion used is that the square root of the AVE must be higher than the correlation between latent variables in the same column. The results of the discriminant validity test indicate that the designed instrument has good discriminant validity based on the Fornell-Larcker approach and cross-loading values. Composite reliability (CR) is used to measure the extent to which items in the questionnaire are correlated with each other and measure the same concept internally. The CR value must be > 0.7 [24]. The higher the CR, the better the composite item reliability. The results of the questionnaire item testing indicate measurement consistency and reliability. Therefore, the measurement model of this study is valid and reliable. This model is ready for further analysis. Table 4 shows the results of the outer model testing.

Table 4. Outer Model Test Results

<table>
<tr><th>Indicator</th><th>Item</th><th>Outer loading</th><th>Ket</th><th>AVE</th><th>Fornell-Larcker</th><th>Composite Reliability</th><th>Ket</th><th>P-value</th></tr>
<tr><td rowspan="4">Data Acquisition and Processing</td><td>DACQ1</td><td>0,801</td><td>valid</td><td rowspan="4">0,694</td><td rowspan="4">0,833</td><td rowspan="4">0,901</td><td rowspan="4">reliable</td><td rowspan="4">< 0,001</td></tr>
<tr><td>DACQ2</td><td>0,841</td><td>valid</td></tr>
<tr><td>DACQ3</td><td>0,833</td><td>valid</td></tr>
<tr><td>DACQ4</td><td>0,856</td><td>valid</td></tr>
<tr><td rowspan="3">Cognitive Insight</td><td>CI1</td><td>0,757</td><td>valid</td><td rowspan="3">0,681</td><td rowspan="3">0,825</td><td rowspan="3">0,865</td><td rowspan="3">reliable</td><td rowspan="3">< 0,001</td></tr>
<tr><td>CI2</td><td>0,856</td><td>valid</td></tr>
<tr><td>CI3</td><td>0,859</td><td>valid</td></tr>
<tr><td rowspan="3">Cognitive Engagement</td><td>CE1</td><td>0,808</td><td>valid</td><td rowspan="3">0,609</td><td rowspan="3">0,780</td><td rowspan="3">0,822</td><td rowspan="3">reliable</td><td rowspan="3">< 0,001</td></tr>
<tr><td>CE2</td><td>0,870</td><td>valid</td></tr>
<tr><td>CE3</td><td>0,647</td><td>valid</td></tr>
<tr><td></td><td>CDA1</td><td>0,857</td><td>valid</td><td>0,698</td><td>0,836</td><td>0,902</td><td>reliable</td><td>< 0,001</td></tr>
</table>

Indicator	Item	Outer loading	Ket	AVE	Fornell-Larcker	Composite Reliability	Ket	P-value
Cognitive Decision Aid	CDA2	0,845	valid					
	CDA3	0,776	valid					
	CDA4	0,860	valid					
Cognitive Technology	CT1	0,853	valid	0,649	0,806	0,846	reliable	< 0,001
	CT2	0,851	valid					
	CT3	0,705	valid					
Data Literacy	DL1	0,817	valid	0,723	0,850	0,887	reliable	< 0,001
	DL2	0,874	valid					
	DL3	0,859	valid					
Innovation Literacy	IL1	0,898	valid	0,723	0,850	0,887	reliable	< 0,001
	IL2	0,817	valid					
	IL3	0,834	valid					
Customer Literacy	CL1	0,833	valid	0,686	0,828	0,867	reliable	< 0,001
	CL2	0,867	valid					
	CL3	0,782	valid					
Digital Literacy	DGL1	0,879	valid	0,736	0,858	0,918	reliable	< 0,001
	DGL2	0,877	valid					
	DGL3	0,849	valid					
	DGL4	0,826	valid					
Effectiveness	EFE1	0,853	valid	0,706	0,840	0,923	reliable	< 0,001
	EFE2	0,824	valid					
	EFE3	0,815	valid					
	EFE4	0,833	valid					
	EFE5	0,876	valid					
Efficiency	EFI1	0,863	valid	0,719	0,848	0,927	reliable	< 0,001
	EFI2	0,870	valid					
	EFI3	0,874	valid					
	EFI4	0,848	valid					
	EFI5	0,782	valid					

(Source: Data processed 2025)

3.1.3 Structural Model Analysis

Model fit is used to assess how well the model represents the relationships between observed variables. A model is considered fit if the Average Path Coefficient (APC), Average R-squared (ARS), and Average Adjusted R-squared (AARS) values are significant at P <0.001. Average Variance Inflation Factor (AVIF) and Average Full Collinearity VIF (AFVIF) are considered good if <3.3, but tolerable if <5. The Tenenhaus goodness-of-fit (GoF) value is considered low if ≥0.10, moderate if >0.25, and good if ≥0.36 [25]. The APC test result is 0.245, p = 0.002, indicating that the average path coefficient is statistically significant. ARS = 0.493, p <0.001, and AARS = 0.475, p <0.001 indicate that the average coefficient of determination is quite high and significant. A GoF value of 0.662 indicates strong model strength (GoF >0.36). AVIF values of 1.339 and AFVIF = 1.883 indicate no multicollinearity issues in the model (ideal standard <3.3). The model can be concluded to have excellent structural and predictive fit.

The next stage of interpreting the results is testing the inner model or structural model by testing the hypothesis and the coefficient of determination (R-square). Testing is performed using a t-test. If the obtained p-value is <0.10 (α=10%), the effect is insignificant. If the p-value is <0.05 (α=5%), the effect is significant. If the p-value is <0.01 (α=1%), the effect is very significant. Table 5 shows the results of the inner model testing.

Table 5. Inner Model Test Results

Hypothesis	Path Coefficient (β)	*P-value*	*R-square*
Direct Effect			
H1: AAI → PP	(0,020)	0,417	
H2: AAI → BPMC	0,692***	<0.001	0,479
H3: BPMC → PP	0,695***	<0.001	0,507
Control			
Gender → PP	0,095	0,161	
Usia → PP	0,065	0,251	
Lama Usaha → PP	(0,059)	0,271	
Lama Adopsi Teknologi → PP	(0,091)	0,170	
Indirect Effect			
H4: AAI → BPMC → PP	0,481***	<0.001	
Total Effect			
H5: AAI → PP	0,460***	<0.001	

N=105; sig***p=<0,01; sig** p=<0,05

(Source: Data processed 2025)

3.1.4 Hypothesis Testing

Table 5 shows the coefficient values for the influence of each exogenous variable on the endogenous variable, along with the p-value for each coefficient. The results of the hypothesis testing are as follows: AI adoption has a negative effect on Process Performance, with a Path Coefficient value of 0.020 and is insignificant with a p-value of 0.417. AI adoption does not directly affect Process Performance. The first hypothesis in this study is rejected.

AI adoption has a positive effect on Business Process Management Capability, with a Path Coefficient value of 0.692 and is highly significant, with a p-value <0.001. The relationship between these two variables is unidirectional, meaning that better AI adoption will improve Business Process Management Capability. The second hypothesis in this study is accepted.

Business Process Management Capability has a positive effect on Process Performance, with a Path Coefficient value of 0.695 and is highly significant, with a p-value <0.001. The relationship between these two variables is unidirectional, meaning that better Business Process Management Capability will improve Process Performance. The third hypothesis in this study is accepted.

AI has a positive mediating effect on PP through Business Process Management Capability with a Path Coefficient of 0.481 and is highly significant, with a p-value <0.001. The total effect of AI adoption on Process Performance is positive with a Path Coefficient of 0.460 and is highly significant, with a p-value <0.001. The effect of AI Adoption on Process Performance is fully mediated by Business Process Management Capability. The control variables gender, age, length of business, and length of technology adoption do not show a significant effect on Process Performance.

The R-square value indicates the extent to which the independent variables explain the variance of the dependent variable. Based on the results of the structural model test in Figure 1, the R-square value for the latent variable Business Process Management Capability is 0.479, meaning AI Adoption explains 47.9% of the variance in the dependent variable digital behavior. Meanwhile, the R-square value for the latent variable Process Performance is 0.507, meaning AI Adoption and Business Process Management Capability explain 50.7% of the variance in the dependent variable Process Performance.

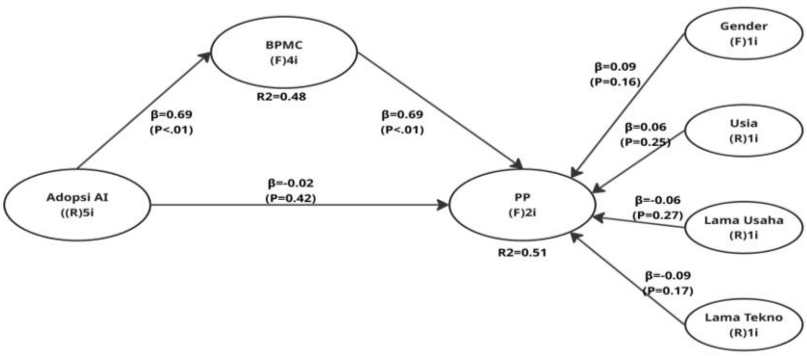

Figure 1. Structural Model Test Results

3.2 Discussion

This SEM model shows that AI Technology Adoption significantly improves BPM Capability, and BPM Capability significantly improves Organizational Process Performance. The effect of AI Adoption on Process Performance occurs indirectly through BPM Capability. The control variables of gender, age, business tenure, and technology adoption period do not have a significant impact.

3.2.1 AI Adoption and Process Performance

These findings indicate that the implementation of AI alone is not sufficient to drive improvements in the effectiveness and efficiency of business processes. This is consistent with the research by [12], which states that AI investment can actually reduce a company's market value when it is not accompanied by organizational readiness to manage change. AI adoption includes data acquisition and processing capabilities, namely the ability to collect and prepare data from various sources for analysis. Cognitive insight is also necessary as the ability to use AI technology to find patterns and meaning in data. Organizations are also required to have cognitive engagement, namely the ability to support interactions between humans and computers assisted by AI. Conversely, studies by [10] and [3] found that AI adoption has a positive impact on creativity and organizational performance, especially when organizations are able to utilize technology strategically. Thus, these differing findings emphasize that the benefits of AI can only be realized when organizations have mature internal processes to support the integration of this technology.

3.2.2 AI Adoption and BPM Capabilities

The results of the analysis imply that the use of AI promotes the strengthening of data literacy, innovation literacy, customer literacy, and digital literacy, which are important pillars in BPM [7], [15]. The study by [7] also confirms that AI adoption can improve process automation, organizational learning, and innovation, there by strengthening BPM capabilities. AI adoption also needs to be supported by cognitive decision support, which is the ability to use technology to aid decision making. In addition, cognitive technology integration is necessary as the ability to combine AI technology with other devices and services. For SMEs in East Kalimantan, data acquisition and processing, cognitive insights, cognitive engagement, cognitive decision support, and cognitive technology serve as catalysts that enable organizations to manage business processes in a more adaptive, responsive, and data-driven manner.

3.2.3 BPM Capabilities and Process Performance

These results show that BPM maturity can improve process effectiveness and efficiency, which is in line with the findings of [5] regarding the contribution of BPM culture and methods to process performance. The research by [15] also confirms that BPM is an important prerequisite for successful digitalization, as it is capable of aligning organizational strategies, governance, and technology. Organizations need to be supported by resources with data literacy, referring to knowledge of data analysis techniques, data privacy and security, and corporate data assets related to business processes. In addition, knowledge support regarding innovation techniques and techniques for analyzing customer needs and preferences when interacting in an omni-channel environment is important to support organizational process performance. Digital literacy also plays a role in supporting performance improvement through knowledge of the mechanisms underlying the digital economy. In the context of SMEs, strengthening BPM through data literacy, innovation literacy, customer literacy, and digital literacy is key to responding to changes in market demand and increasing competitiveness in the digital era.

3.2.4 Mediation of BPM Capabilities on Process Performance

An important finding from this study is the full mediation of BPM capabilities in the relationship between AI adoption and performance. These results reinforce the Resource-Based View (RBV) perspective that technology will only create competitive advantage if it is managed through organizational capabilities [18], [26]. In other words, AI does not directly improve process performance, but contributes through enhancing BPM capabilities that enable innovation and organizational learning [7]. Data literacy, innovation literacy, customer literacy, and digital literacy shape BPM capabilities to improve organizational process performance, both in terms of results and economic value. Therefore, BPM functions as a connecting mechanism that transforms the potential of AI technology into tangible improvements in business process performance.

4. CONCLUSION

This study confirms that AI adoption does not directly impact process performance, but significantly improves BPM capabilities. Furthermore, BPM capabilities are proven to be a determining factor in improving process performance and fully mediate the relationship between AI adoption and process performance. These findings reinforce the Resource-Based View (RBV) perspective that technology only creates business value when leveraged through appropriate organizational capabilities.

The limitations of this study are SMEs that use e-commerce applications as a sales medium operating in East Kalimantan Province. The BPM capability variable only focuses on the BPM capability area in the Human pillar. Therefore, future studies can expand the research object and measure BPM capabilities from the pillars of strategic alignment, governance, methods, information technology, and culture.

Practically, the study's findings imply that SMEs in East Kalimantan need to position BPM as a key foundation in their digitalization processes. AI adoption must be accompanied by increased data literacy, innovation literacy, customer literacy, and digital literacy to transform the technology's potential into operational effectiveness and efficiency. Therefore, SME development strategies should focus not only on technology investment but also on strengthening organizational capabilities to achieve sustainable competitive advantage.

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