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Comparative Analysis of Regional Readiness for the Implementation of *Artificial Intelligence* (AI) as a Support for Bank Financing Decision Making in Indonesia

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ABSTRACT

This study examines the level of understanding and awareness of climate change risks among agricultural Micro, Small, and Medium Enterprises (MSMEs) in Merauke Regency, South Papua, and its implications for sustainable accounting practices. A qualitative approach was employed through interviews, observation, and documentation involving 12 agricultural MSMEs in Semangga, Tanah Miring, and Kurik Districts. The findings show that MSME actors have experienced the impacts of climate change, such as floods, droughts, and uncertain seasonal patterns; however, their understanding remains limited and has not been integrated into financial management practices. Most MSMEs still use simple bookkeeping and do not record climate-related losses as business risks. Despite these limitations, MSMEs demonstrate adaptive strategies through planting adjustments, commodity diversification, and social cooperation. This study contributes by highlighting the importance of climate risk awareness and sustainable accounting practices to strengthen the resilience of agricultural MSMEs in vulnerable rural areas.

Keywords: Agricultural MSMEs; Resilience; Climate change; Sustainable accounting; South Papua

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INTRODUCTION

In 2020, the Covid-19 pandemic severely impacted the banking sector due to social restrictions, self-isolation, and lockdown policies. These conditions pushed banks to continue serving customers. Consequently, service digitization became a primary focus, leading to digital transformation that has transformed conventional service patterns into more sophisticated, responsive, and transparent digital services. (Ramadhani and Trimuliani 2024)

The development of Artificial Intelligence (AI) has brought significant changes to the banking industry. The use of AI enables financial institutions to improve operational efficiency, accelerate data analysis processes, and support more accurate, data-driven decision-making. In the banking sector, AI technology has been widely used for credit risk analysis, fraud detection, service personalization, and even customer creditworthiness assessments (Bi and Bao 2024).

Furthermore, digital transformation has become a key agenda for global economic development in the last decade. Developments in information technology, big data analysis, cloud computing, and AI have transformed various industrial sectors, including the financial services and banking sectors. AI is no longer seen as merely a support tool, but rather as a strategic instrument capable of improving operational efficiency, accelerating business processes, and generating more accurate decision-making through *real -time*, large-scale data processing (Bramulya et al. 2025) but also as a financial product recommendation system. The use of AI allows banks to evaluate financing feasibility more objectively compared to conventional methods that still rely on manual analysis (Mawlidy, Primasatya, and Lorensa 2024).

This development can be seen in smartphone usage in Indonesia, which continues to show an upward trend until 2025. The number of national internet users has reached 229.4 million, or approximately 80.66% of the total Indonesian population. Smartphones have become the primary device people use to access the internet, whether for communication, education, work, financial transactions, or digital economic activities. (Muhammad, 2025)

In response to these developments, banks have begun adopting digital banking systems, meaning all banking activities are conducted through information technology to facilitate independent customer transactions. Banking services that utilize information technology include internet *banking, call centers* and *mobile banking.* In Indonesia, the Financial Services Authority (OJK) defines *fintech 2.0 as financial institutions that provide digital financial services, while fintech 3.0* refers to start-ups that utilize technological advances to provide innovative financial products and services. (Bahari 2024)

Data from the Indonesian Internet Service Providers Association (APJII) shows that the number of internet users in Indonesia will reach 221.56 million in 2024, equivalent to 79.5% of the total national population. This figure is an increase from the previous year's 78.19% and demonstrates a consistent growth trend over the past five years. This high internet penetration provides a crucial foundation for the development of digital financial services and the implementation of AI technology in the banking sector ((APJII), 2024).

However, Indonesia's readiness for AI implementation is not uniform across regions. Disparities in human resource quality, societal digitalization, economic capacity, and financial inclusion remain challenges in encouraging equitable AI technology implementation. One indicator that can illustrate society's digital readiness is the Indonesian Digital Society Index (IMDI). In 2025, the national IMDI score was recorded at 44.53, an increase from 43.34 in the previous year. While this trend is positive, it indicates that the Indonesian public's digital readiness remains in the intermediate category, with significant regional differences (Nugraha, 2025).

In addition to digital readiness, the success of AI implementation is also influenced by the quality of human resources, as reflected in the Human Development Index (HDI) and average years of schooling (RLS). The higher the quality of education in a region, the greater the community's ability to adopt new technologies and utilize AI-based systems. Furthermore, regional economic capacity, as reflected in Gross Regional Domestic Product (GRDP), plays a role in providing the resources needed to support digital transformation. Another factor is the level of financial inclusion, which can be represented by banking Third Party Funds (DPK), an indicator of community activity and participation in the formal financial system.

Previous studies have focused primarily on the application of AI in credit risk management, financing feasibility prediction, and the development of machine learning models in the banking sector. However, research examining regional readiness for AI to support bank financing decision-making remains relatively limited, for example in South Papua Province. Mobile phone ownership remains below the national average. The latest data shows that only around 50.08% of the population owns a mobile phone. This figure indicates that half of South Papuans are not yet connected to digital communications technology. ((BPS) 2024)

While large urban areas and the western region have benefited from rapid technological developments, the eastern region continues to face limitations in internet connectivity, technological infrastructure, and skilled human resources. Consequently, there is a research gap in the lack of studies integrating aspects of digitalization, human resource quality, economic capacity, and financial inclusion in assessing regional readiness for AI implementation. Therefore, understanding how AI is implemented in financing decision-making in this context is crucial for identifying opportunities and barriers to digital transformation in specific regions, such as the Underdeveloped, Frontier, and Disadvantaged (3T) regions.

The diffusion of innovation explains how technological innovations spread across organizations and regions, while the technology acceptance model emphasizes the role of perceived usefulness and perceived ease of use in influencing technology adoption (George Noveril Hibur, Ronald PC Fanggidae, and others). Previous studies in Indonesia have largely focused on digital banking adoption, mobile banking acceptance, and customer perceptions of financial technology (Rahmawati, Nur, and Syahnur 2023). Meanwhile, studies specifically investigating AI implementation in the financing decision-making process across regions are still very limited.

Based on these conditions, this study aims to comparatively analyze regional readiness for the implementation of AI to support banking financing decision-making in Indonesia using indicators such as the Indonesian Digital Society Index (IMDI), Human Development Index (HDI), average years of schooling (RLS), Gross Regional Domestic Product (GRDP), and Third Party Funds (TPF). The results are expected to provide an overview of the level of readiness of each region in facing AI-based banking transformation and provide input for the government, regulators, and the banking industry in formulating strategies for developing an AI ecosystem.

LITERATURE REVIEW

Artificial Intelligence (AI) in the Banking Industry

Artificial Intelligence (AI) is a technology that enables computer systems to learn, recognize patterns, predict, and make decisions similar to those performed by humans. In the banking industry, AI has developed into a key technology supporting digital transformation through the use of machine learning, natural language processing, predictive analytics, and intelligent automation. Applications of AI in banking include credit scoring, credit risk analysis, fraud detection, chatbot-based customer service, personalized financial products, and financing decision-making.

The development of artificial intelligence (AI) in the banking sector is accelerating, driven by the increasing volume of financial data to be managed and the need for faster and more accurate decision-making. According to Bramulya et al. (2025), AI can improve the effectiveness of banking services through deeper and more comprehensive data analysis capabilities than conventional methods. Their research indicates that perceived benefits, perceived ease of use, awareness of AI, subjective norms, and trust are factors influencing the sustainability of AI use in the Indonesian banking industry. Furthermore, the implementation of AI plays a role in improving bank operational efficiency and supporting higher-quality, data-driven decision-making.

One of the most rapidly developing applications of AI in the banking sector is in the credit and financing analysis process. In practice, financing decisions require an evaluation of various aspects such as repayment capacity, credit history, customer characteristics, economic conditions, and financing risk level. AI enables all of this information to be analyzed quickly and comprehensively using algorithms that produce more accurate predictions than traditional methods. Various studies have shown that the use of AI and machine learning can increase the effectiveness of credit scoring, reduce the risk of non-performing loans, and expedite the financing approval process (BI 2024).

Based on this description, it is clear that AI has significant potential to improve the efficiency, accuracy, and quality of banking financing decision-making. However, the success of its implementation is determined not only by the availability of technology but also by the readiness of the supporting ecosystem, which includes the quality of human resources, the level of societal digitalization, economic capacity, and the development of the financial sector. Therefore, analyzing regional readiness for AI implementation is crucial to understanding the extent to which a region is able to support artificial intelligence-based banking transformation.

Artificial Intelligence (AI) as a Decision-Making Support System

A Decision Support System (DSS) is a computer-based system designed to help decision-makers address semi-structured to unstructured problems by utilizing data, analytical models, and relevant information. It does not replace humans in the decision-making process, but rather provides information and recommendations that can improve the quality, speed, and accuracy of decisions. In an increasingly complex and dynamic business environment, DSS plays a crucial role in supporting organizational evaluation, planning, and control. With advances in digital technology, DSS have evolved from rule-based systems to platforms that leverage artificial intelligence for more adaptive and predictive analysis (Wahono and Ali 2021).

The integration of Artificial Intelligence (AI) into DSS has transformed the way organizations manage and utilize data in decision-making processes (Setiadi, Zikrillah, and Elfona 2026). AI enables DSS to not only present historical information but also learn from the available data through *machine learning algorithms*, *deep learning*, and other analytical techniques.

In the banking industry, the relationship between AI and DSS is becoming increasingly important as this sector generates vast amounts of data from financial transactions, customer profiles, credit histories, digital activities, and various other economic indicators

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(Fudaili et al. 2025). The system is capable of analyzing multiple variables simultaneously and generating recommendations that can be used by credit analysts and bank management in making financing decisions.

While AI enhances DSS, its implementation still faces challenges such as data quality, algorithm transparency, information security, and ethical considerations in technology use. In this context, the success of AI as a DSS depends not only on technological advancements but also on the readiness of the supporting ecosystem, which includes digital infrastructure, human resource quality, economic capacity, and the level of financial inclusion in a region.

Regional Readiness for *Artificial Intelligence* (AI) Implementation

AI implementation depends not only on technology but also on the readiness of the supporting environment. Regional readiness is a region's ability to provide the resources, infrastructure, human resource capacity, and economic ecosystem for optimal innovation adoption. In digital transformation, regional readiness is crucial because differences in technological progress between regions can be significant. Regions with adequate digital infrastructure, qualified human resources, and strong economic activity are more ready to adopt new technologies than those with limitations (Rawung et al. 2025).

Digital readiness is a key prerequisite for AI implementation. Without adequate digital infrastructure and the ability of communities to utilize technology, AI implementation will be ineffective. This study uses the Indonesian Digital Society Index (IMDI) as an indicator of regional digital readiness, developed by the Ministry of Communication and Digital and encompassing infrastructure/digital ecosystems, digital skills, digital empowerment, and the use of technology in everyday life. Because AI relies on data, connectivity, devices, and user interaction, regions with higher levels of digitalization have a greater opportunity to adopt AI in sectors such as banking (Natalia 2024), making the IMDI a relevant measure of digital readiness in AI implementation.

Furthermore, the quality of human resources (HR) is one of the main factors determining a region's readiness to implement Artificial Intelligence (AI). In this study, human resource quality is represented by the Human Development Index (HDI) and Average Years of Schooling (ARS), which reflect the level of education, health, and community capacity to access knowledge. The higher the HDI and ARS of a region, the greater the community's ability to understand, adopt, and utilize AI-based technology in various economic and social activities. Therefore, these two indicators can be used to describe the level of human resource readiness to support the implementation of AI and digital transformation in a region.

On the other hand, economic capacity and the level of financial inclusion are also important factors in supporting the implementation of Artificial Intelligence (AI). In this study, regional economic capacity is measured through Gross Regional Domestic Product (GRDP), while financial inclusion is proxied through banking Third Party Funds (TPF). GRDP reflects a region's ability to provide resources and technology investment, while TPF indicates the level of community participation in the formal financial system and the availability of data that can be utilized by AI. The higher a region's GRDP and TPF, the greater the readiness of its economy and financial ecosystem to support the implementation of AI in the banking sector.

Conceptual Framework

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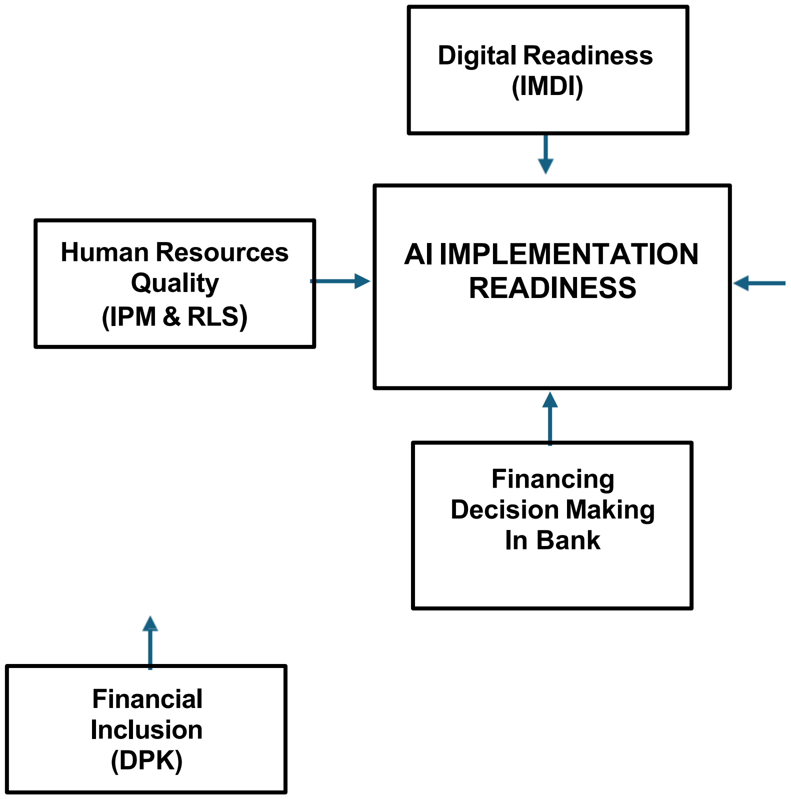

Figure 1. Research Framework

RESEARCH METHODS

This study uses a quantitative approach with a comparative research design between regions to analyze regional readiness for the implementation of *Artificial Intelligence. Intelligence (*AI) as a supporter of banking financing decision-making in Indonesia. The research analysis unit covers 38 provinces in Indonesia using *cross-sectional data* from 2025.

The data used are secondary data obtained from various official sources, namely Third Party Funds (DPK) from the Indonesian Banking Statistics published by the Financial Services Authority (OJK), the Indonesian Digital Society Index (IMDI) from the Ministry of Communication and Digital, the Human Development Index (HDI) and Average Years of Schooling (RLS) from the Central Statistics Agency (BPS), as well as Gross Regional Domestic Product (GRDP) from BPS publications.

The dependent variable in this study is Third Party Funds (TPF), which is proxied as an indicator of formal regional financial activity. Meanwhile, the independent variables consist of the Indonesian Digital Society Index (IMDI) as a proxy for digital readiness, Average Years of Schooling (RLS) and the Human Development Index (HDI) as proxies for human resource quality, and Gross Regional Domestic Product (GRDP) as a proxy for regional economic capacity.
The regression model used in this study is formulated as follows:
$Ln(DPK) = \alpha + \beta_1 \cdot IMDI + \beta_2 \cdot RRLS + \beta_3 \cdot IPM + \beta_4 \cdot Ln(PDRB) + \varepsilon$
Where:

- LNDPK = Logarithm of Third Party Funds;
- IMDI = Indonesian Digital Society Index;
- RRLS = Average Years of Schooling;
- HDI = Human Development Index;

- GRDP = Gross Regional Domestic Product;
- α = constant;
- β = regression coefficient;
- ε = error term.

Data analysis was carried out using the *Ordinary method. Least Squares* (OLS). Before testing the hypothesis, classical assumption tests were conducted, including normality, multicollinearity, heteroscedasticity, and autocorrelation tests to ensure the regression model met the *Best Linear Unbiased criteria. Estimator* (BLUE). Furthermore, testing was conducted using the coefficient of determination (R^2), simultaneous test (F test), and partial test (t test) to identify the influence of each independent variable on formal financial activities as an indicator of regional readiness to support AI implementation in the banking sector.

RESULTS

Descriptive Statistics of Research Variables

Descriptive statistical analysis was conducted to provide an overview of the characteristics of the data used in the study. The variables analyzed included Third Party Funds (DPK Share), the Indonesian Digital Society Index (IMDI), Average Years of Schooling (RLS), the Human Development Index (HDI), and Gross Regional Domestic Product (GRDP). Descriptive statistics included the mean, median, maximum, minimum, standard deviation, and measures of data distribution, including *skewness* and *kurtosis*
.
Table 4.1 shows that all research variables have a total of observations of 38 provinces in Indonesia in 2025.
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DESCRIPTIVE STATISTICS

Date: 02/06/26 Time: 07:35					
Sample: 1 38					
	DPK	IMDI	RLS	IPM	PDRB
Mean	2.632368	44.52658	9.457368	72.38842	5.125263
Median	0.770000	44.76000	9.575000	73.18000	5.250000
Maximum	25.57000	56.97000	11.58000	83.08000	34.17000
Minimum	0.010000	31.11000	4.760000	53.42000	-21.80000
Std. Dev.	5.036364	5.935008	1.189980	5.150227	6.587398
Skewness	3.024362	-0.435819	-1.913872	-1.340730	0.479029
Kurtosis	12.87027	2.806517	8.653619	7.148395	18.24083
Jarque-Bera	212.1813	1.262214	73.80713	38.63240	369.2348
Probability	0.000000	0.532003	0.000000	0.000000	0.000000
Sum	100.0300	1692.010	359.3800	2750.760	194.7600
Sum Sq. Dev.	938.5037	1303.300	52.39394	981.4189	1605.571
Observations	38	38	38	38	38

The analysis results show that the DPK has an average value of 2.63 with a range of 0.01 to 25.57. The high standard deviation of 5.04 indicates a significant gap in banking fundraising activities between provinces. In the digital aspect, the IMDI has an average

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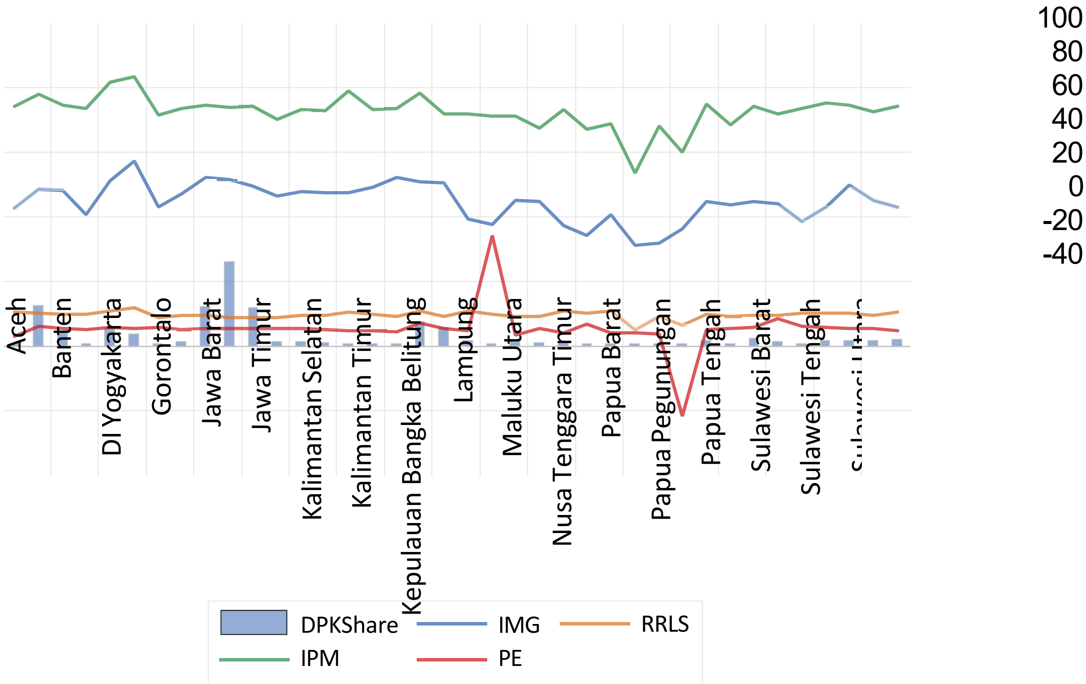
of 44.53 with a minimum value of 31.11 and a maximum of 56.97. This indicates that the level of digitalization in society is relatively diverse, although the differences are not as extreme as those of other variables.

The RRLS variable has an average of 9.46 years, while the HDI has an average of 72.39. Both indicators show that the quality of human resources varies across regions, but the distribution is relatively more even than the economic and financial indicators.

Meanwhile, GRDP has an average of 5.13, with a minimum value of -21.80 and a maximum of 34.17. The standard deviation of 6.59 indicates significant differences in economic capacity between regions in Indonesia.
Based on standard deviation values, the GRDP and DPKS variables exhibit the highest variation, while RRLS has the lowest. This finding indicates that inter-regional disparities are more pronounced in economic and financial aspects than in education. This situation suggests that regional readiness to support the implementation of Artificial Intelligence (AI) in the banking sector still faces challenges of inequality, particularly in terms of economic capacity and regional financial activity.

All variables



This graph presents a complete profile of 38 regions/provinces in Indonesia based on five main indicators:

1. DPKShare : DPK = Third Party Funds
2. IMG : IMDI = Indonesian Digital Human Index
3. RRLS: RLS = Average Years of Schooling
4. HDI: Human Development Index
5. PE : GRDP = Gross Regional Domestic Product

Key Findings by Region:

The analysis of regional groupings shows that there are quite clear differences in the level of readiness to support the implementation of Artificial Intelligence. Intelligence (AI) in financing decision-making. Regions on the island of Java, as well as parts of Sumatra and Sulawesi, are categorized as high-readiness due to their digital infrastructure, technology governance, relatively good quality education and healthcare, supported by stable financing conditions and economic activity. These conditions make these regions most ready for comprehensive AI implementation to improve the accuracy of financing assessments, accelerate the decision-making process, and expand the reach of financial

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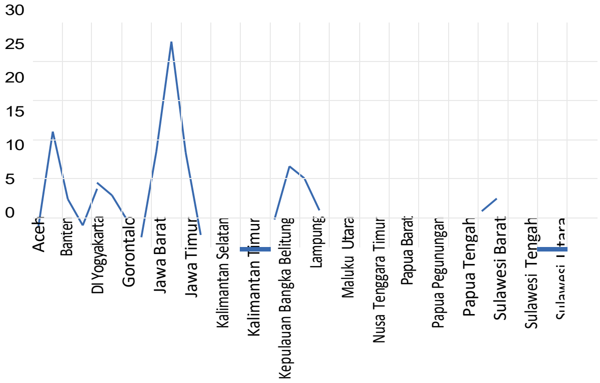
services.

Meanwhile, regions with a medium level of readiness, such as parts of Kalimantan, Lampung, Maluku, and Central Sulawesi, generally have relatively good human development, but still face limitations in digital infrastructure and technological literacy . Furthermore, unequal economic potential and funding indicate that AI implementation needs to be carried out in stages, with a focus on strengthening data infrastructure, improving digital literacy , and developing community capacity for effective implementation.

In contrast, regions in Eastern Indonesia, particularly Papua, the Papua Highlands, East Nusa Tenggara, and several border areas, show a relatively low level of readiness due to limited digital infrastructure, low human resource quality and technological literacy , and limited financial market depth. This situation indicates that the uniform implementation of AI has the potential to widen disparities between regions. Overall, the research results confirm that differences in regional readiness are determined more by gaps in technological infrastructure and human resource quality than by economic factors alone. Regions with higher levels of human development tend to have a better ability to adopt AI technology, so the development of AI-based financing systems needs to be tailored to the characteristics and level of readiness of each region to support equitable access to financing effectively and sustainably.

Graph of Each Variable

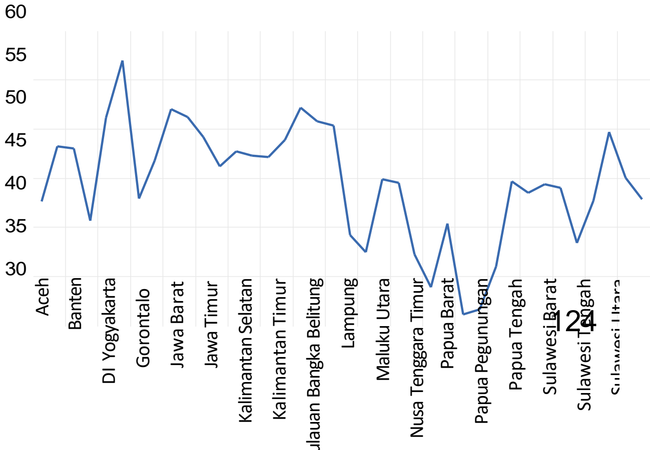
DPKShare



DPK Variable

The distribution of third-party fund (DPK) values shows significant disparities between regions. West Java recorded the highest score, at around 25–26, followed by Aceh and the Bangka Belitung Islands, with scores ranging from 7–12. Most regions, particularly in Eastern Indonesia, such as Papua, East Nusa Tenggara, and Maluku, had scores below 2 or even approaching zero. This situation indicates that financing capacity and customer data availability are not evenly distributed. In the context of AI implementation, regions with high DPK values have a stronger database to improve the accuracy of financing decision-making, while regions with low scores still face data limitations that can reduce them.

IMG



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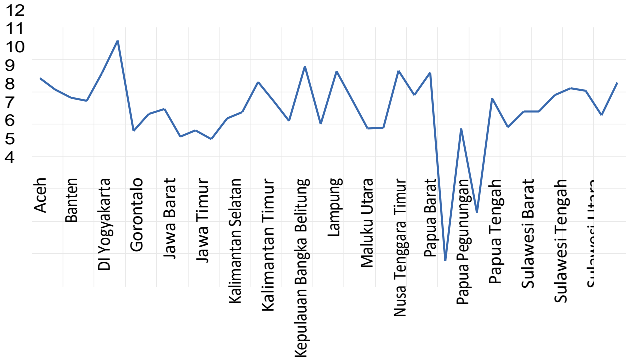
IMDI Variable

The distribution of IMDI scores shows a clear gap between western and eastern Indonesia, with scores ranging from 31 to 57. Yogyakarta Special Region, West Java, and the Bangka Belitung Islands recorded the highest scores (above 50), while Aceh, East Java, and South Sumatra were in the 47-50 range. Conversely, Papua, Highlands Papua, and East Nusa Tenggara had the lowest scores (below 35-40), reflecting limitations in digital infrastructure, data systems, and supporting regulations. These findings suggest that the quality of digital infrastructure and governance are key differentiating factors in regional readiness to support AI implementation.

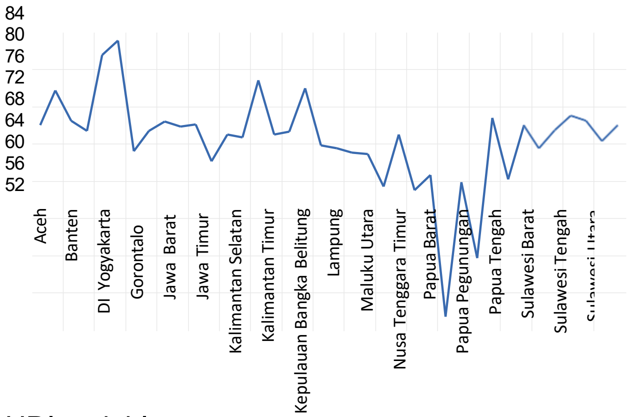
RRLS



RLS Variables

The distribution of RLS values is relatively stable at around 9–11 years, but there are still quite striking disparities between regions. The Special Region of Yogyakarta recorded the highest value (above 11 years), followed by East Kalimantan, the Bangka Belitung Islands, and North Maluku, with a range of 10–11 years. Conversely, Highlands Papua had the lowest value (below 5 years), followed by Central Papua at around 6–7 years. This condition indicates differences in human resource capacity in understanding and managing technology. In the context of AI implementation, human resource quality is a critical factor in supporting system management, data utilization, and understanding the resulting financing decisions.

IPM



HDI variable

The distribution of HDI values is relatively concentrated in the range of 72–80, indicating a fairly even level of human development across most regions. The Special Region of Yogyakarta recorded the highest score (above 80), followed by Aceh, East Kalimantan, and South Kalimantan, with scores ranging from 76–79. Conversely, Highlands Papua had the lowest score (below 55), while Central Papua was around 60. This condition

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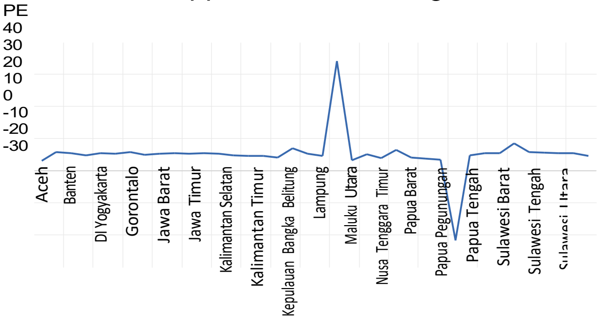
indicates a gap in the quality of education and health between regions. In the context of AI implementation, regions with a high HDI tend to be more ready to adapt to technological innovation, while a low HDI can hinder the use of technology and the quality of data that supports the financing decision-making process.



Analysis of GRDP Variables

The distribution of GRDP values generally ranges from 0 to 8, indicating relatively stable economic conditions in most regions. Lampung recorded the highest value, with a spike above 30, while Central Papua had the lowest value below -20, indicating economic contraction or significant economic change. These findings suggest that the level and stability of economic activity play a role in supporting the availability of economic data needed in the financing process. Regions with stable and positive GRDP tend to have more reliable economic data, while very high or very low values require special attention to avoid bias in AI-based financing decision-making.

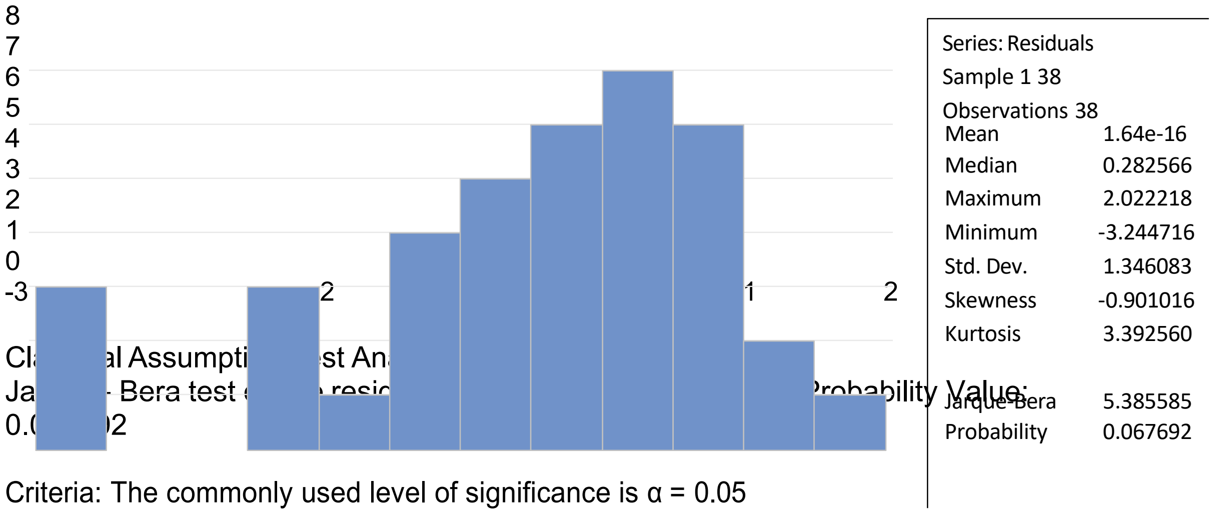
MULTIPLE LINEAR REGRESSION

Dependent Variable : LNDPK Method: Least Squares Date: 02/06/26 Time: 07:22
Sample: 1 38
Included observations: 38

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-11.79240	4.311997	-2.734788	0.0100
IMG	0.150625	0.068457	2.200295	0.0349
RRLS	-0.433670	0.426440	-1.016954	0.3166
IPM	0.226564	0.130486	1.736308	0.0918
PDRB	-6.01E-06	4.02E-06	-1.495239	0.1444
R-squared	0.554536	Mean dependent var		6.675984
Adjusted R-squared	0.500541	S.D. dependent var		2.016813
S.E. of regression	1.425331	Akaike info criterion		3.668764
Sum squared resid	67.04174	Schwarz criterion		3.884236
Log likelihood	-64.70652	Hannan-Quinn criter.		3.745427
F-statistic	10.27003	Durbin-Watson stat		1.541740
Prob (F- statistic)	0.000016			

Source : Output E-reviews 12, data processed by Researchers , 2026
Based on results output on table 4.1 on , so obtained results equality regression as as follows : LNDPK = -11.7923972545 + 0.150625090475*IMG - 0.433669990093*RRLS + 0.22656392742*IPM - 6.01284614994e-06*PDRB

The results of multiple linear regression show that the model used is statistically feasible to explain variations in the depth of regional financing as an indicator of readiness to implement *Artificial Intelligence. Intelligence* (AI), indicated by the F-statistic value of 10.27003 with a probability of 0.000016. The coefficient of determination (R^2) of 0.5545 and Adjusted R^2 of 0.5005 indicate that approximately 50.05-55.45% of the variation in financing depth can be explained by the variables of infrastructure and technological governance (IMDI), human resource quality and financial-technological literacy (RRLS), Human Development Index (HDI), and Gross Regional Domestic Product (GRDP). Partially, the IMDI variable has a positive and significant effect on financing decisions, indicating that improving the quality of digital infrastructure and technological governance can strengthen access and deepen financing, thus becoming a major factor in supporting AI implementation. The HDI variable also shows a positive and significant effect at a 10% confidence level, indicating that the quality of education contributes to increasing the region's ability to adopt a technology-based financing system. In contrast, RRLS and GRDP did not show a statistically significant effect, indicating that formal education levels and regional economic capacity are not directly capable of driving growth without the support of adequate digital infrastructure and human development. This finding confirms that the success of AI implementation in financing decision-making is more determined by technological infrastructure readiness and human development quality than by the size of a region's economic capacity alone.



Cl[illegible]al Assumpti[illegible]st An[illegible]
Ja[illegible] Bera test [illegible] resi[illegible] [illegible]robability Value:
0.[illegible]2

Criteria: The commonly used level of significance is α = 0.05
Because the probability value is > 0.05, then the residual normally distributed , the assumption of normality is met.
residual distribution tends to be centered around zero (mean ≈ 0), with a slight skew to the left (skewness = -0.901) and a peakedness approaching normal (kurtosis = 3.39). The histogram also shows a shape that is close to a bell curve, although there is a slight decrease in frequency in the range -2 to -1.
For research, these results mean that the regression model built meets basic statistical requirements, so that estimates and conclusions regarding the influence of IMDI, RRLS, HDI, and GRDP on regional readiness in implementing AI can be accounted for.

Variance Inflation Factors
Date: 02/06/26 Time : 07:22
Sample: 1 38
Included observations: 38

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	18.59332	347.7837	NA
IMG	0.004686	176.7960	3.006394
RRLS	0.181851	308.9250	4.689927

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IPM	0.017027	1677.079	8.225283
PDRB	1.62E-11	3.667620	1.249060

the multicollinearity test show that all independent variables have Centered VIF values below 10, namely IMG of 3.006, RRLS of 4.690, HDI of 8.225, and GRDP of 1.249. These results indicate that there are no serious multicollinearity problems in the model, so there is no strong linear correlation between the independent variables. Thus, the multicollinearity assumption has been met and the resulting regression coefficients can be interpreted more accurately, stably, and can be used to explain the influence of each indicator on regional readiness in implementing AI statistically.

Heteroskedasticity Test: Breusch-Pagan-Godfrey Null hypothesis: Homoskedasticity

F-statistic	0.610534	Prob. F(4,33)	0.6579
Obs*R-squared	2.618387	Prob. Chi-Square(4)	0.6236
Scaled explained SS	2.362258	Prob. Chi-Square(4)	0.6695

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares Date: 06/06/26 Time: 07:23 Sample: 1 38
Included observations: 38

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.471780	8.548458	-0.523110	0.6044
IMG	0.072392	0.135714	0.533414	0.5973
RRLS	0.089493	0.845410	0.105857	0.9163
IPM	0.042688	0.258686	0.165018	0.8699
PDRB	-1.03E-05	7.97E-06	-1.295891	0.2040

R-squared	0.068905	Mean dependent var	1.764256
Adjusted R-squared	-0.043955	S.D. dependent var	2.765566
S.E. of regression	2.825693	Akaike info criterion	5.037464
Sum squared resid	263.4898	Schwarz criterion	5.252935
Log likelihood	-90.71181	Hannan-Quinn criter.	5.114127
F-statistic	0.610534	Durbin-Watson stat	1.613837
Prob(F-statistic)	0.657949		

the heteroscedasticity test using the Breusch -Pagan- Godfrey method show a probability value of Obs * R- squared of 0.6236 and an F- statistic of 0.6579, all of which are greater than the significance level of 0.05. Thus, the null hypothesis (H_0) is accepted, so it can be concluded that the regression model does not experience heteroscedasticity problems . This condition indicates that the residual variance is constant across all observations, so the homoscedasticity assumption has been met. Therefore, the resulting regression coefficients and standard errors can be considered efficient and reliable, so that the results of the analysis of the influence of IMDI, RRLS, HDI, and GRDP on regional readiness in implementing AI can be interpreted with an adequate level of confidence.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.481681	Prob. F(2,31)	0.6223
Obs*R-squared	1.145303	Prob. Chi-Square(2)	0.5640

the autocorrelation test using the Breusch – Godfrey Serial Correlation LM Test method show a probability value of Obs * R- squared of 0.5640 and an F- statistic of 0.6223, both of which are greater than the 0.05 significance level. Thus, the null hypothesis (H_0) is accepted, so it can be concluded that the regression model does not experience autocorrelation problems up to the 2nd lag . These results indicate that the residuals in each observation are independent and uncorrelated. Therefore, the classical assumption regarding independence The residuals have been fulfilled, so that the resulting regression coefficients and standard errors can be considered reliable to explain the influence of IMG, RRLS, IPM, and GRDP on regional readiness in implementing AI as a supporter of banking financing decision making.

DISCUSSION

This study aims to analyze regional readiness for the implementation *of Artificial Intelligence* (AI) as a supporter of banking financing decision-making in Indonesia. Research results indicate differences in readiness levels across regions, influenced by factors such as digitalization, human resource quality, economic capacity, and formal financial activity. These findings indicate that AI implementation in the banking sector depends not only on the availability of technology but also on the readiness of the regional ecosystem that supports its use.

Regression results show that the Indonesian Digital Society Index (IMDI) has a positive and significant impact on Third Party Funds (DPK). This finding indicates that the level of societal digitalization is a crucial factor in supporting the readiness of AI implementation in the banking sector. The higher the level of digital literacy and utilization in a region, the greater the potential for AI use to support the analysis and financing decision-making process. These results align with research (Solikin et al. 2021) , which confirms that digital infrastructure and capabilities are the main foundations for developing an AI ecosystem. The OECD explains that the success of AI implementation is heavily influenced by digital access, data utilization capabilities, and societal readiness to adopt new technologies. This finding is also supported by a Stanford University report , which shows that regions with higher levels of digitalization tend to have faster AI adoption rates than regions with limited digital infrastructure (Stanford, 2024)

In addition to digital factors, this study found that the Human Development Index (HDI) has a positive and significant effect on third party funds (DPK). This finding indicates that the quality of human resources is a crucial factor in building AI readiness. AI implementation requires a workforce with analytical skills, digital literacy, and the capacity to adapt to technological change. The results of this study support the view that human capital *is one* of the main drivers of digital transformation, as stated in the study (Dewi et al. 2025) . This finding aligns with research conducted by (Rivai et al. 2025), which shows that the quality of human resources has a positive relationship with a region's ability to adopt digital technology and data-driven innovation. Thus, regions with higher levels of human development tend to be better prepared to support AI implementation in the financial sector.

On the other hand, the average years of schooling (RRLS) did not show a significant effect on the DPK. This result indicates that the length of formal education does not necessarily reflect a community's ability to utilize digital technology and AI. In the context of digital transformation, the competencies required include not only formal education but also digital skills, data analysis capabilities, and an understanding of ever-evolving technologies. This finding suggests that increasing AI readiness is not solely achieved through increasing access to formal education but also requires strengthening digital literacy programs and more specific technology training. This finding aligns with research (Achmad Nor Hidayah 2025) which states that a community's digital readiness is more influenced by digital and organizational competencies than by the number of years of education.

This study also found that GRDP had no significant effect on DPK. This finding suggests that a region's economic capacity is not necessarily the primary determinant of AI implementation readiness. Although regions with high economic activity have greater resources to invest in technology, successful AI adoption still requires support from other factors such as digital infrastructure and quality human resources. This finding reinforces the argument that digital transformation is determined not only by economic strength but also by a region's ability to build an inclusive innovation ecosystem. This study's findings align with those of Jayanto and Suparwata (2025), who stated that the success of AI implementation is more determined by digital readiness and human capacity than by the region's economic size.

Overall, the research findings indicate that digitalization and human resource quality are the primary determinants of regional readiness for AI implementation in the banking sector. These findings imply that Indonesia's AI development strategy needs to focus on equitable digital infrastructure, increasing public digital literacy, and strengthening human resource quality. For the banking industry, these findings suggest that AI implementation will be more effective in regions with higher levels of digitalization and higher human resource quality. Meanwhile, for the government and regulators, these findings can serve as a basis for formulating more inclusive digital transformation policies to reduce the gap in AI readiness between regions.

This study has several limitations. First, it only uses *cross-sectional data* from 2025, making it unable to accurately depict changes in regional readiness over time. Second, the indicators used are limited to the digital, human resources, economic, and financial dimensions. Other factors such as the quality of information technology infrastructure, regional innovation, and local government policies have not been incorporated into the research model. Therefore, future research is recommended to use panel data and develop more specific indicators related to AI *readiness* to produce a more comprehensive picture of regional readiness for AI implementation in Indonesia.

CONCLUSION

This study aims to analyze regional readiness for the implementation of Artificial Intelligence (AI) to support banking financing decision-making in Indonesia. The results indicate that regional readiness still experiences significant disparities between provinces. Based on the analysis, the Indonesian Digital Society Index (IMDI) and the Human Development Index (HDI) have a positive and significant effect on formal financial activity, as proxied by Third Party Funds (DPK). In contrast, Average Years of Schooling (RRLS) and Gross Regional Domestic Product (GRDP) do not show a significant effect.

The study also identifies three regional readiness groups: high, medium, and limited. Regions with high readiness are generally located on the island of Java and parts of Sumatra and Sulawesi, supported by higher levels of digitalization and quality human resources. Meanwhile, regions with limited readiness are still dominated by several provinces in Eastern Indonesia, which face limitations in digital infrastructure, human resource quality, and formal financial activity. Therefore, readiness for AI implementation in the banking sector is determined more by the level of digital transformation and quality of human resources than by the region's economic capacity.

Suggestion

Based on the research findings, the government and regulators need to accelerate the equitable distribution of digital infrastructure and improve digital literacy and competency among the public, particularly in regions with low levels of readiness. Furthermore, the banking industry needs to implement AI implementation strategies tailored to the characteristics of each region to ensure the technology's benefits are more inclusive.
Further research is recommended to use panel data across multiple observation periods

and include more specific indicators related to AI readiness, such as information technology infrastructure, regional innovation levels, and digital literacy, to provide a more comprehensive picture of regional readiness for AI implementation in Indonesia.

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