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Predicting millennial farmer success by highlighting the role of digitalization and technology in increasing productivity

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This study aims to analyze the main factors that affect the success of millennial farmers in increasing quantity in Indonesia. This study uses a quantitative approach with the K-Nearest Neighbors Regression model to predict the success of millennial farmers based on three main factors, infrastructure, business dynamism, and the adoption of information and communication technology. Secondary data was collected from the conversion index of the number of millennial farmers aged 39+ years who use digital and modern technology, for the three main factors of the regional competitiveness index in 34 provinces with analysis based on Mean Squared Error and Mean Dropout Loss. The results show that infrastructure (0.101) and business dynamism (0.099) have the greatest impact on the success of millennial farmers, while technology adoption (0.025) contributes less. While digitalization is important, its effectiveness depends on the readiness of the infrastructure and supporting business ecosystems. Theoretically, this research enriches the literature on digital transformation in agriculture. In practical terms, these results confirm the need for infrastructure investment and policies that support business innovation so that digitalization has an optimal impact on millennial farmers.

KEYWORDS

millennial farmers, digitalization, agricultural productivity, agricultural technology, machine learning, K-nearest neighbors, infrastructure, business dynamism

1 Introduction

Agricultural transformation toward digitalization is a significant challenge for millennial farmers in increasing productivity and competitiveness. Various studies show that millennial farmers play an important role in supporting this transformation through the use of information and communication technology (Wastutiningsih et al., 2024). Programs such as Millennial Smart Farming have been developed to strengthen the digital ecosystem, open market access, and increase financial inclusion (Wimas Candranegara et al., 2022), while digital marketing through ecommerce and social media helps expand market reach

(Laksamana Khaidir and Nasution, 2024). However, challenges such as low digital literacy, resistance to new technologies, and infrastructure gaps in rural areas still hold back (Usenko et al., 2024). Therefore, a comprehensive strategy is needed to increase digital literacy, provide technology training, and strengthen infrastructure to accelerate digital adoption in the agricultural sector (Hasan et al., 2023). In Indonesia, millennial farmers face structural constraints such as limited infrastructure, complexity of business dynamics, and disparities in the adoption of information and communication technology (ICT), which are challenges in the regeneration of young farmers and agricultural sustainability in the digital era. The younger generation's interest in agriculture has decreased due to negative stigmas, such as low income and the assumption that agriculture is less attractive (Hasta Ningsih et al., 2023). Socio-cultural factors also have in effect, where support from private institutions and the social environment determines their success (Romadi et al., 2024). In addition, low digital literacy and access to technology make it difficult for millennial farmers to adopt Internet of Things (IoT)-based smart farming systems, with anxiety about technology being the main reason for rejection (Harisudin et al., 2023).

Based on data from the Indonesian Central Statistics Agency in 2023 (Sensus, 2024), the number of farmers aged 39 years and older who use digital and modern technology in Indonesia shows significant variation among provinces. The province with the highest number of male farmers is East Java (1,968,087 people), followed by Central Java (1,720,773 people) and West Java (1,152,485 people). These three provinces dominate nationally, reflecting the central role of Java Island as the center of agriculture in Indonesia. On the other hand, provinces in eastern Indonesia such as Maluku (8,198 people), Papua (2,930 people), and North Maluku (7,027 people) have a much lower number of farmers, indicating that access to technology and infrastructure is still limited. From a gender perspective, the number of female farmers utilizing digital technology also shows regional disparities. East Java again became the province with the highest number (296,040 people), followed by Central Java (234,433 people) and South Sumatra (38,364 people). In contrast, provinces such as West Papua (185 people), Jakarta (238 people), and Riau Islands (1,330 people) reported very low numbers, indicating gaps in the empowerment of female farmers in the region. In general, the distribution of this data reflects the inequality among the western and eastern regions of Indonesia, both in the farmer population and the level of adoption of digital technology in the agricultural sector.

This gap shows the need for a more in-depth analysis to understand the interaction among structural factors and technology in supporting the productivity of millennial farmers. Therefore, this study aims to analyze the main factors that contribute to the success of millennial farmers. This study aims to analyze the main factors that affect the success of millennial farmers in increasing quantity through infrastructure integration, business dynamics, and the adoption of digital technology. How does the interaction among infrastructure, business dynamics, and digital technology adoption affect the quantity and success of millennial farmers? The findings of this study are also expected to be the basis for the formulation of more effective policies in supporting the development of the technology-based agricultural sector, so that it can provide long-term benefits for millennial farmers and national food security.

2 Literature review

Digital-based agricultural transformation has a significant impact on millennial farmers by increasing productivity and operational efficiency through innovations such as precision farming and AI, which optimize the use of resources and reduce environmental impact (Ashoka et al., 2023). Empirical studies show that digitalization can increase farmers' income by improving production efficiency and expanding sales channels (Zhang and Fan, 2024). However, the success of technology adoption is influenced by adequate infrastructure, where limited internet access and technological resources in developing countries are a major obstacle for young farmers (Finger, 2023). In addition, government policies play an important role in supporting digital transformation, such as digital literacy programs and financial support, although their effectiveness varies and require integrated solutions to address implementation challenges (Aditi, 2023; Finger, 2023). While digitalization offers many benefits, challenges such as uneven access and limited infrastructure must be overcome for its implementation to be successful, especially for young farmers in various contexts.

The productivity and success of millennial farmers includes their ability to optimize crop yields, use resources efficiently, and adapt to technology and market dynamics. This success is also measured by their resilience to challenges such as access to capital, marketing, and digitalization. Research shows that entrepreneurial characteristics, such as the courage to take risks and innovate, have a significant effect on their business performance (Nur Hidayah et al., 2024). The adoption of ICT has also been proven to increase the productivity of millennial farmers (Novisma and Iskandar, 2023). From a theoretical perspective, the Theory of Planned Behavior (Ajzen, 1991) explains that entrepreneurial intentions are influenced by attitudes, social norms, and behavioral control (Astuti et al., 2023), while the Innovation Diffusion Theory (Miller, 2015) is relevant in understanding the adoption of new technologies to increase productivity. Millennial farmers, who are assumed to be the farming population aged 39 years and below and/or those using digital and modern technologies, are an important focus in the analysis of agricultural transformation in Indonesia. Based on 2023 data published by the Central Statistics Agency (Sensus, 2024), the number of millennial farmers is calculated based on provincial criteria, gender, and technology adoption rate. This data provides an overview of the demographic distribution as well as the pattern of technology use among young farmers, which significantly affects the productivity and competitiveness of the agricultural sector.

Agricultural infrastructure, including roads, irrigation, storage, and digital technology, has a crucial role in improving farmers' productivity, efficiency, and competitiveness in the global market. Investment in infrastructure, especially in underdeveloped areas, has a positive impact on economic growth and agricultural efficiency (Ran, 2021), as well as reducing social inequality and increasing social capital in rural areas (Hesda, 2022). The development of digital infrastructure, such as IoT and agricultural information systems, supports the transformation toward smart and sustainable agriculture (Makarova and Timofeeva, 2022), while access to financial infrastructure allows farmers to adopt modern technologies (Andriushchenko et al., 2020). The Endogenous Growth and Agricultural Transformation theories affirm that infrastructure investment drives long-term economic growth, increases productivity, and strengthens agricultural supply

chains (Kaur, 2023). Infrastructure is one of the main pillars in the formation of the regional competitiveness index (BRIN, 2024), which plays a crucial role in supporting economic growth and the development of the agricultural sector. Based on publications from Indonesian National Research and Innovation Agency, infrastructure is defined through various dimensions that include transportation and utility aspects. The dimensions of transportation infrastructure include road networks, railways, air transportation, and sea transportation, which collectively affect the accessibility of the region as well as the distribution of agricultural products. On the other hand, utility infrastructure includes the availability of electricity and water supply, which is the main support for modern agricultural activities, especially in the implementation of smart irrigation technology and energy-based agricultural product processing systems.

Agricultural business dynamics play an important role in determining the sustainability and competitiveness of the agricultural industry in the era of globalization and digitalization. Factors such as the integration of digital technology, changes in the economic cycle, and diversification strategies are the main drivers of efficiency and productivity. Digitalization, for illustration, improves efficiency through precision agriculture that optimizes resources (Markova, 2021), while the agricultural business cycle is influenced by economic policies, market demand, and external conditions (Jędruchiewicz and Wielechowski, 2024). The dynamic systems approach also helps to analyze the long-term impacts of various business scenarios, including prices, policies, and environmental challenges (Tursun et al., 2022). From the perspective of economic theory, Creative Destruction Theory Schumpeter explains how innovation replaces old business models with more efficient ones, while Value Chain Analysis Porter shows the importance of optimizing supply chains to increase the competitiveness of the agricultural sector (Muflikh et al., 2021). Business dynamics is one of the important pillars in the formation of a regional competitiveness index (BRIN, 2024), which reflects economic activity and the level of development of the business sector in a region. Based on publications from Indonesian National Research and Innovation Agency, business dynamics are measured through several main indicators, including the growth of Business Identification Numbers, the number of banks, and the performance of public services. These three indicators provide an overview of a region's ability to create a conducive business environment, support innovation, and improve operational efficiency of business actors, including in the agricultural sector.

The apply digital technology, especially the IoT and data-based agricultural systems, provides great benefits to farmers by increasing productivity, efficiency, and sustainability. IoT enables real-time monitoring and automation, such as irrigation management and soil conditions, resulting in increased productivity, such as a 98% germination rate in radish plants compared to 50% with traditional methods (Ismail Lafta and Dawood Abdullah, 2024). This technology also optimizes the use of resources through precise measurements of soil nutrients, moisture, and environmental conditions, thereby reducing production costs and minimizing waste (Cihan, 2023; Palarimath et al., 2024). Additionally, customizable IoT platforms for smallholders help them manage agricultural assets effectively, with results such as an 84% success rate in non-cropping season grafting (Lamsal et al., 2023). Nonetheless, challenges such as economic costs and the need for training in the use of technology remain important considerations for farmers (Finger, 2023). These findings show the great potential of digital technology in supporting the transformation of modern agriculture. However, the

implementation of digital technology in the agricultural sector is not spared from challenges. A study by Soesilowati et al. (2020) shows that weak farmer institutions and lack of supporting infrastructure can hinder the effectiveness of the adoption of modern agricultural technology. The adoption of ICT is one of the main pillars in the formation of a regional competitiveness index (BRIN, 2024), which reflects the level of digitalization and technological readiness in a region. Based on a publication from Indonesian National Research and Innovation Agency, ICT adoption is measured through several key indicators, namely the number of mobile phone users, 4G network coverage, fixed-broadband internet subscribers (per 100 residents), and total internet users. These indicators provide an overview of the accessibility and use of digital technology by the public, including millennial farmers, in supporting economic activities and productivity in the agricultural sector.

Although various studies have explored the benefits and challenges of agricultural digitalization, there is still a gap in understanding how factors such as infrastructure, business dynamics, and government policies together affect millennial farmers' success in adopting technology. This study aims to fill this gap by providing a comprehensive analysis of the interaction among these factors and their impact on the quantity of millennial farmers. Research question how does the interaction among infrastructure, business dynamics, and ICT adoption affect the productivity and success of millennial farmers? By answering this research question, the results of this research are expected to provide deeper insights into the factors that contribute to the quantity of millennial farmers, as well as provide practical recommendations for policymakers in supporting digital transformation in the agricultural sector.

3 Method

This study uses a quantitative approach with the K-Nearest Neighbors (KNN) regression method (Chiozza, 2022). The data used in this study consists of two main sources, namely data on the number of millennial farmers in 34 provinces obtained from the Ministry of Agriculture of the Republic of Indonesia and data on infrastructure, business dynamics, and ICT adoption sourced from the regional competitiveness index published by the National Research and Innovation Agency. The research sample consisted of 34 provinces in Indonesia with an analysis unit in the form of the proportion of millennial farmers to the total farmers in each province. The selection of the sample was carried out as a whole (total sampling) because it covered the entire population available in the collected data. Data on the number of millennial farmers is obtained from the annual report of the Indonesian Central Statistics Agency (Sensus, 2024), while other variable data such as infrastructure, business dynamics, and technology adoption in each province are obtained from the 2024 regional competitiveness index (BRIN, 2024). Data collection is carried out through documentation and verification methods by cross-checking among official sources. Each number of millennial farmer proportions from 34 provinces is converted into an index with the formula:

$$I_j = \frac{\sum_{i=1}^n S_{ij}}{n} \quad (1)$$

The results of the total proportion of millennial farmers from 34 provinces in Indonesia as data analyzed with infrastructure, business dynamics, and ICT adoption have been compiled in [Table 1](#).

Furthermore, the analysis was carried out with K-Nearest Neighbors Regression (KNNR) to predict the target value based on the average y -value of the nearest neighbors in the feature space. This model is defined as: $\hat{y}$

$$\hat{y} = \frac{1}{k} \sum_{i \in N_k(x)} y_i \quad (2)$$

with $\hat{y}$ = the predicted value of the success of millennial farmers, k = the number of nearest neighbors used in the prediction, $N_k(x)$ = the set of the nearest neighbor k based on the distance metric, and y_i = the actual value of the third neighbor. Then for the distance among the data points, where x_{im} and x_{jm} are the m -feature values of the i and j samples, measured using Euclidean metrics:

$$d(x_i, x_j) = \sqrt{\sum_{m=1}^M (x_{im} - x_{jm})^2} \quad (3)$$

TABLE 1 Millennial farmer conversion data, pillar index, business dynamics, ICT adoption at provincial level in Indonesia ([Equation 1](#)).

Province	Millennial farmers	Business dynamism	Infrastructure	ICT adoption
Aceh	0.0956	2.9716	2.7755	2.9330
North Sumatra	0.1111	3.6292	3.5886	3.5164
West Sumatra	0.0731	3.7332	2.8671	3.2930
Riau	0.0342	3.1979	2.8229	3.4105
Jambi	0.0218	3.2508	2.3779	3.4525
South Sumatra	0.0706	3.4494	2.7509	3.5800
Bengkulu	0.0175	2.5196	2.6710	4.2558
Lampung	0.0950	3.8114	2.7565	3.6602
Bangka Belitung Islands	0.0062	2.4705	2.9551	4.0934
Riau Islands	0.0024	2.3053	3.0767	4.8580
Jakarta	0.0005	2.1757	4.0917	4.9890
West Java	0.2476	4.2137	4.0508	4.1260
Central Java	0.3616	4.4651	4.1375	3.7993
Yogyakarta	0.0324	3.9985	2.4799	4.4556
East Java	0.4345	4.1506	4.1720	3.9302
Banten	0.0433	3.7690	3.1288	4.1536
Bali	0.0233	3.5239	2.9753	4.7965
West Nusa Tenggara	0.0717	3.3744	2.3981	3.2572
East Nusa Tenggara	0.0285	2.6404	2.2093	3.0007
West Kalimantan	0.0228	2.5272	2.1387	3.1644
Central Kalimantan	0.0107	2.8777	2.5078	3.4273
South Kalimantan	0.0300	3.1448	2.9848	3.8839
East Kalimantan	0.0097	2.8247	2.4125	4.0227
North Kalimantan	0.0021	3.2979	1.9380	3.9785
North Sulawesi	0.0090	3.5544	1.8718	3.7356
Central Sulawesi	0.0164	2.8907	1.9364	2.8759
South Sulawesi	0.0937	4.0204	3.3254	3.4851
Southeast Sulawesi	0.0110	3.0178	2.1647	3.2952
Gorontalo	0.0087	2.9550	1.8058	3.3078
West Sulawesi	0.0098	3.1550	2.2222	3.6331
Maluku	0.0013	2.7663	2.5334	2.8715
North Maluku	0.0013	2.5901	2.0487	2.3357
West Papua	0.0003	3.0602	1.8019	2.8101
Papua	0.0006	3.3155	2.2694	1.4474

Source ([BRIN, 2024](#); [Sensus, 2024](#)).

For model performance evaluation is performed with metrics with Mean Squared Error (MSE):

$$MSE = \frac{1}{2} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (4)$$

next, for the equation notation of the Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE} \quad (5)$$

whereas the equation notation of the Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (6)$$

then the notation of the equation from the Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (7)$$

for the Coefficient of Determination (R^2), where is the average value of the target variable y with equation notation: $\bar{y}$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{(y_i - \bar{y}_i)^2} \quad (8)$$

To understand the key factors that contribute to the success of millennial farmers, Mean Dropout Loss is used, which measures the increase in prediction errors when a feature is omitted from the model. The value of the important feature is defined as:

$$\Delta_j = RMSE_{full} - RMSE_{drop(j)} \quad (9)$$

where Δ_j = feature contribution j , $RMSE_{full}$ = RMSE model with all features, and $RMSE_{drop(j)}$ = RMSE after feature j is removed. Meanwhile, to analyze the individual impact of each variable, where is the contribution of the j feature, the additive explanations approach is used which represents the prediction as the sum of the contribution of the feature to the base value: $\emptyset_j$

$$y = y_{base} + \sum_{j=1}^M \emptyset_j \quad (10)$$

The model is implemented using Python with the Scikit-Learn library. The data was divided into training (70%), validation (15%), and test (15%), with the selection of optimal parameters based on the lowest MSE validation. With this approach, this study ensures accurate

replication and maintains validity and reliability in measuring the success factors of millennial farmers in the digital era.

4 Result

The distribution of millennial farmers shows gender inequality in technology adoption. In almost all provinces, the number of male farmers using digital technology is much higher than that of female farmers. For illustration, in North Sumatra, there are 369,197 male farmers compared to 95,029 female farmers, while in West Kalimantan, the number is 104,787 male and 15,296 female. The gap is widening in provinces with minimal infrastructure, such as West Papua, where only 185 females' farmers are reported to be using modern technology compared to 1,618 male farmers. This shows that the empowerment of female's farmers in utilizing digital technology is still a big challenge, especially in remote areas. From a regional perspective, Java Island shows significant dominance in the number of farmers using digital technology, supported by more advanced infrastructure and a dense population. Meanwhile, provinces outside Java, especially in eastern Indonesia, still lag behind in access to technology and the number of farmers who adopt it. This disparity reflects the development inequality among the western and eastern regions of Indonesia, as well as the need for policy interventions to improve digital technology accessibility for farmers in disadvantaged areas to encourage productivity and competitiveness of the agricultural sector nationally.

The KNN regression model is used to predict the conversion index of millennial farmers in 34 provinces. The model was tested with some nearest neighbors of 1, rectangular weight, and a Euclidean distance metric. The validation results showed a MSE value of 0.008 and MSE in the test data of 0.008. This indicates that the model is optimized against the validation set but has an increase in errors in the test set.

The KNN regression model was used to predict the conversion index of millennial farmers in 34 provinces (Table 2). Based on the results, the KNN model with one nearest neighbor, rectangular weight, and Euclidean distance showed a MSE value of 6.131×10^{-4} on validation and 0.008 on the test data. Although this model is optimized for MSE on validation, higher MSE values on the test data indicate a possible overfitting on the training data. In a study by Mohamed-Amine et al. (2023) showed that KNN regression can provide accurate predictions in agricultural production with an MSE of 0.0057, in line with the finding that this method is effective for small datasets. In addition, research by Srisuradetchai and Suksrikan (2024) proposes a better KNN Random Kernel approach in overcoming overfitting and improving prediction accuracy compared to standard KNN. In the agricultural sector, a study by Sitienei et al. (2023) shows the success of the apply KNN in predicting corn yields, with an MSE of 0.2803 and a fairly high accuracy. Taking this literature into account, the use of KNN for millennial farmer conversion index can be further optimized with approaches such as selecting more suitable kernels to improve accuracy and reduce overfitting.

The KNN regression model used in this study has a MSE value of 0.008 and a RMSE of 0.089, which shows that the average prediction error is still relatively small (Table 2). However, the MAPE value of 65.95% indicates that the error relative to the actual value is still quite

TABLE 2 Summary of model performance, feature importance, and feature contribution to prediction (Equations 2–10).

Model performance summary						
Method	MSE	MSE (scaled)	RMSE	MAE	MAPE	R ²
KNN	0.008	0.139	0.089	0.063	65.95%	0.841
Feature importance						
Feature	Mean dropout loss					
Infrastructure	0.101					
Business dynamics	0.099					
ICT adoption	0.025					
Feature contribution to predictions						
Case	Predictions	Base	Infrastructure	ICT adoption	Business dynamics	
1	0.011	0.061	−0.006	−0.006	−0.038	
2	0.071	0.061	−0.028	0.028	0.01	
3	0.434	0.061	0.072	0.057	0.244	
4	0.023	0.061	−0.032	−0.044	0.039	
5	0.022	0.061	−0.034	0.004	−0.009	

Source: Search results and analysis, 2025.

high, which can indicate a lack of generalization of the model to the new data. With an R^2 value of 0.841, the model has pretty good predictive capabilities, but there is still room for improvement. A study by [Mohamed-Amine et al. \(2023\)](#) shows that KNN regression can provide accurate predictions in agricultural production with a lower MSE value, which is 0.0057, indicating that a model with more optimal parameters can improve prediction accuracy. In addition, research by [Srisuradetchai and Suksrikan \(2024\)](#) proposes a Random Kernel KNN approach that can improve accuracy and reduce prediction errors in regression compared to standard KNN models. Another study by [Sitienei et al. \(2023\)](#) applying KNN regression in corn yield prediction found that this model can achieve an MSE of 0.2803 and an RMSE of 0.4948, which still shows that the KNN technique can be used effectively in agricultural data despite the need for further optimization. Model improvements can be done by exploring more optimal parameters, selecting a more appropriate number of neighbors, to reduce data dimensions to improve prediction accuracy and reduce error rates.

The results of the feature importance analysis in the KNN regression model show that the infrastructure factor (mean dropout loss = 0.101) has the greatest influence on the conversion index of millennial farmers in 34 provinces, followed by business dynamics (0.099) and ICT adoption (0.025). Higher mean dropout losses indicate that the deletion of Infrastructure and Business Dynamics variables has more impact on the increase in prediction errors than ICT adoption, signaling the importance of these two factors in the model. A study by [Mahfouz \(2023\)](#) highlights that a KNN regression approach that considers connectivity among features can improve prediction accuracy. This is in line with the results of the analysis which shows that Infrastructure and Business Dynamics factors are more decisive than ICT adoption, indicating that connectivity in business and infrastructure aspects greatly affects the conversion of millennial farmers. In addition, research by [Lasena et al. \(2023\)](#) emphasizes the importance of feature selection in improving the

performance of KNN models, where more relevant features can reduce overfitting and improve prediction accuracy. The results of this study indicate that policies that focus on strengthening Infrastructure and Business Dynamics can have a greater impact in increasing the conversion index of millennial farmers than simply encouraging the adoption of ICT technology. To improve predictions, the use of ensemble methods or feature selection optimization as proposed in previous studies can be an effective solution.

The results of the additive explanations analysis (Table 2) in the KNN regression model show the contribution of each feature to the prediction of the millennial farmer conversion index. The base value of the prediction remained at 0.061 in all cases, while the contribution of infrastructure, ICT adoption and business dynamics varied. For illustration, in case 3, the contribution of infrastructure (+0.072), ICT adoption (+0.057), and business dynamics (+0.244) significantly increased the prediction to 0.434. In contrast, in case 1, the variables infrastructure (−0.006), ICT adoption (−0.006), and business dynamics (−0.038) reduced the prediction to 0.011, indicating the negative role of these variables in that context. This approach is supported by a study by [Sanagavarapu et al. \(2024\)](#), which suggests that the interpretability of the model can be improved with techniques such as SHAP to understand how each feature affects predictions. Another study by [Mahfouz \(2023\)](#) emphasizes the importance of considering connectivity among variables in the KNN model to improve the accuracy of predictions. These results show that infrastructure, ICT adoption, and business dynamics have different influences in various scenarios.

Figure 1 shows the relationship among the number of nearest neighbors and the MSE for training and validation data in the KNN model, it can be seen that the MSE in the training data increases with the increase in the number of neighbors, while the MSE in the validation data is relatively stable. This indicates that the model is overfitting the number of smaller neighbors and begins to become more generalized as the number of neighbors increases.

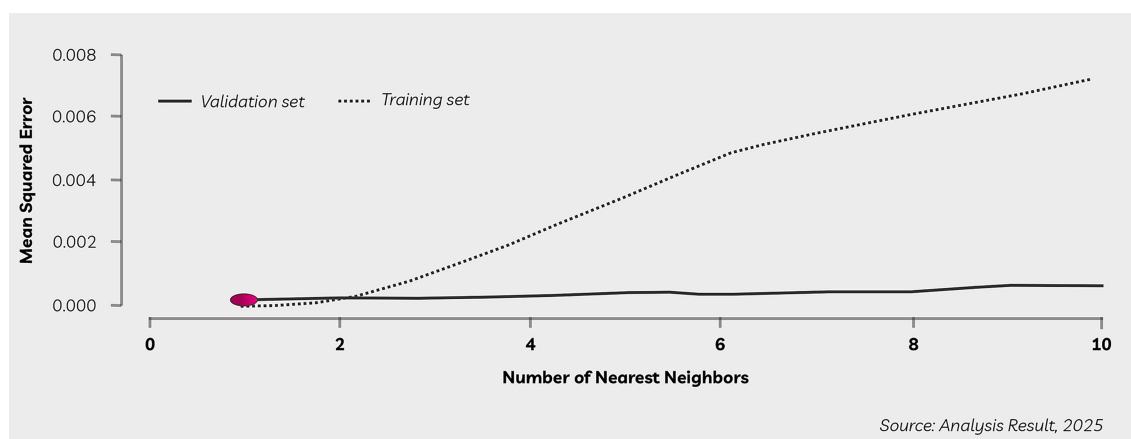


FIGURE 1
Mean squared error plot.

In the context of the conversion of millennial farmers in the agricultural index in 34 provinces of Indonesia, this analysis can be used to understand how certain factors affect the successful transition of young farmers into index-based agricultural systems. For illustration, research by Xie et al. (2022) found that smart agriculture plays a key role in increasing the productivity and attractiveness of the agricultural sector for the younger generation, thereby accelerating the conversion of traditional farmers to millennial farmers. Therefore, the use of predictive models such as KNN in understanding adoption trends and patterns can provide deeper insights into the factors driving the success of this transformation. Predictive model analysis in measuring the conversion of millennial farmers in Indonesia can help in the formulation of more effective policies, especially in improving the sustainability of the agricultural sector in the digital era.

5 Discussion

The results show that the KNN regression model with the parameter of one nearest neighbor and the Euclidean distance metric produces a MSE value of 0.008 and an R^2 of 0.841. This R^2 value shows that the model has a fairly good level of accuracy in predicting the conversion index of millennial farmers, although the MAPE value is quite high, which is 65.95%, indicating that the model still has limitations in generalizing the test data. Feature importance analysis revealed that infrastructure had the largest contribution to the prediction of the millennial farmer conversion index with a mean dropout loss value of 0.101, followed by business dynamics (0.099), while ICT adoption had a lower influence (0.025). This finding is consistent with research by Kawisana et al. (2023) which emphasizes that digitalization of local product marketing can increase farmers' competitiveness through technology-based strategies. In the analysis of the contribution of features to predictions, business dynamics have a significant impact on several cases, especially in increasing the conversion index of millennial farmers, as shown in case 3 with a contribution of 0.244. This is in line with research by Wahyuni and Ndewes (2023) which shows that the apply Good Agriculture Practice based technology can increase agricultural productivity through the

use of innovation in agricultural business practices. However, some cases show that ICT adoption has not contributed significantly to the increase in the conversion index of millennial farmers. These results indicate that while digitalization has great potential in improving agricultural efficiency, challenges in technology accessibility and infrastructure readiness can be major constraints. This is supported by research by Pradana (2021) which shows that access to ICT has a significant influence on economic growth in certain regions. The following are the results of predicting the success of millennial farmers based on the KNN regression model, using the variables infrastructure, ICT adoption, and Dynamism Business as the main factors.

Figure 2 is a visualization of millennial farmer predictions. The highest category, namely 3.5–3.8 (millennial farmers high) which is marked in blue, includes West Java, East Java, and Central Java, with the highest score of 3,856. Category 3.0–3.5 (Quite high millennial farmers), which is marked with dark purple, includes North Sumatra (3,136), Jakarta (3,156), and South Sulawesi (3,136). Furthermore, the category 2.5–3.0 (millennial farmers Moderate) marked in green covers several provinces such as Banten (2,99), Lampung (2,668), and Southeast Sulawesi (2,216). Meanwhile, the 2.0–2.5 category (low millennial farmers) with yellow color covers provinces such as Papua (2,118), Maluku (2,434), and West Nusa Tenggara (2,382). The lowest category, <2.0 (Very Low millennial farmers) which is marked in bright purple, includes the provinces of Gorontalo (1,986), West Papua (1,984), and Central Sulawesi (1,984). From this map, it can be seen that the Java Island region has the highest success rate compared to other regions. In contrast, regions in eastern Indonesia, such as Papua and most of Sulawesi, tend to have lower values. This analysis can provide insight into the factors that affect the difference in success rates in various regions in Indonesia. The success of millennial farmers is uneven throughout Indonesia. Provinces with more developed infrastructure and businesses are better equipped for digital agriculture transformation, while provinces with lower scores need more support in technology access, business training, and agricultural infrastructure.

Each success prediction value obtained from the KNN regression model reflects the relative potential of millennial farmers in each province to succeed in utilizing digitalization and modern technology

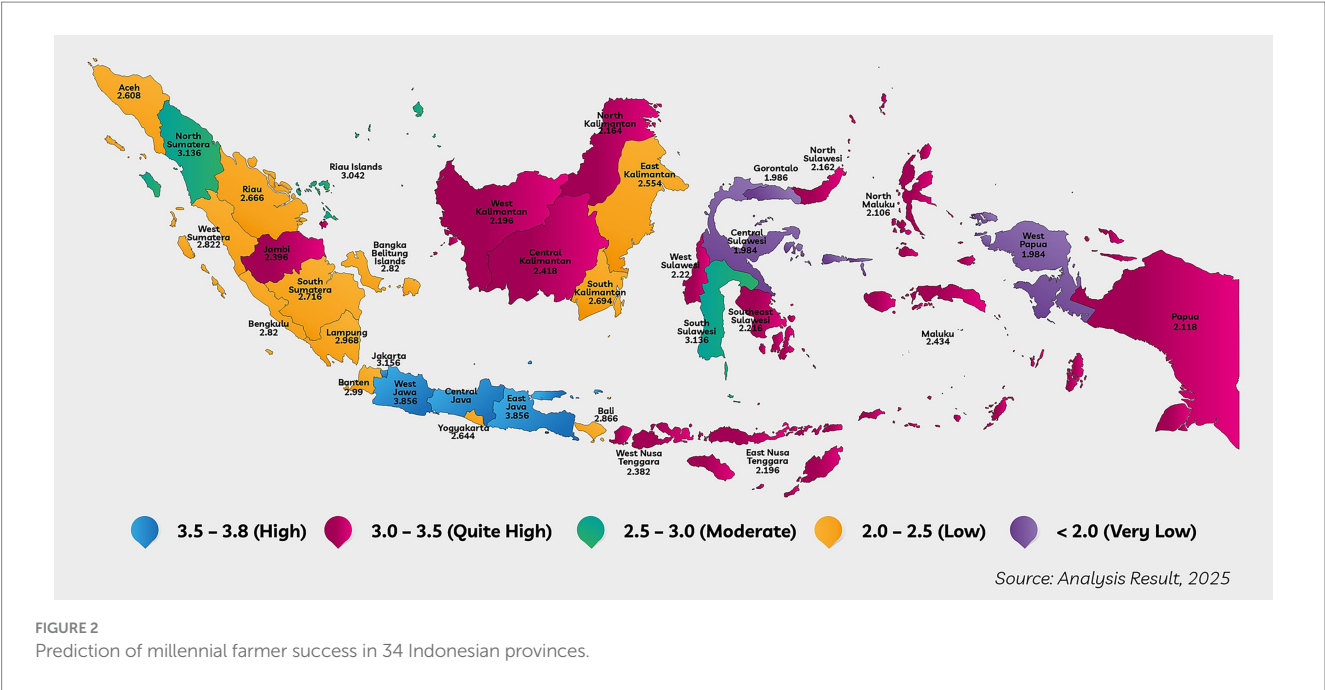


FIGURE 2
 Prediction of millennial farmer success in 34 Indonesian provinces.

TABLE 3 The meaning of each prediction value range.

Value range	Meaning and interpretation	Reference-based solutions
3.5–3.8 (height)	Millennial farmers in this province have a high chance of success. Good infrastructure, high-tech adoption, and a dynamic business ecosystem support agribusiness growth.	Strengthening the Digital Ecosystem (Wimas Candranegara et al., 2022), Business Network Development (Riptanti et al., 2022), Agripreneur Transformation (Wastutiningsih et al., 2024), IoT adoption (Harisudin et al., 2023), Entrepreneurial Character (Riptanti et al., 2024).
3.0–3.5 (quite high)	There is great potential, but there are still aspects that need to be improved, such as access to digital technology or agribusiness business innovation.	Digital transformation in the agricultural sector (Zhevatchenko, 2023), Obstacles and opportunities in the transition to agriculture 4.0 (da Silva et al., 2023), Increasing agribusiness competitiveness through innovation (Gangwar and Jadoun, 2023), The role of digital finance in agricultural innovation (He et al., 2024), Agribusiness digitalization opportunities in developing countries (Goswami et al., 2023).
2.5–3.0 (medium)	Farmers in this region have begun to take advantage of digitalization, but there are still infrastructure constraints or limited business dynamism. Need more support.	The use of digital agricultural management systems (Lazebnyk and Voitenko, 2022). Adoption of digitalization based on a social approach (Abdulai, 2022). Agricultural business digitalization strategy (Marchenko, 2023). Evaluation of the potential for digitalization of the agro-industrial sector (Afanaseva et al., 2021). Agricultural business digitalization model (Leksina, 2021).
2.0–2.5 (low)	Provinces with greater challenges. Infrastructure and technology adoption are still weak, as well as limitations in market access and agribusiness business development. Policy intervention is urgently needed.	Market access and agricultural infrastructure (Narayanamoorthy, 2021), Policy interventions for market access (Villar et al., 2023), The role of technology in reducing post-harvest losses (Talachutla, 2024), Value chain integration and market access in rural areas (Ezeudu and Obimbua, 2024), The impact of digitalization on market access (Xia and Pan, 2024).
< 2.0 (very Low)	A province with major obstacles to the success of millennial farmers. Limited access to technology, capital, and business ecosystems makes it difficult for digital agriculture transformation to develop.	Barriers to technology adoption in precision agriculture (Masi et al., 2023). Obstacles to access capital for young farmers (AR et al., 2024). An undeveloped business ecosystem (Riptanti et al., 2022). Difficulties in digital agricultural transformation (Harisudin et al., 2023). The role of entrepreneurship in the success of millennial farmers (Nur Hidayah et al., 2024).

Source: Search results and analysis, 2025.

in agriculture. The Highest Prediction Value range is 3,856 points while the lowest is 1,984 points so it can be categorized in Table 3.

This finding has implications for the development of digital agricultural policies in Indonesia. To support sustainable agribusiness policymaking and strategies, realistic steps that can be implemented include strengthening digital infrastructure such as internet networks and modern irrigation, skills training for millennial farmers in business management and digital technology, and providing affordable agricultural technology through subsidies or

microfinancing. In addition, pro-innovation policies that provide incentives for agritech actors, encourage green agricultural practices, and build collaboration among the government, the private sector, and farmers to develop innovative solutions are needed. Periodic evaluations of policy impacts are also important to ensure adaptability and relevance to field needs. These measures are expected to effectively increase the productivity of millennial farmers and contribute to the sustainability of the agricultural sector. In addition, a hybrid approach that combines the KNN regression model with other methods such as

Principal Component Analysis (PCA) or ensemble learning can be explored to improve prediction accuracy and reduce the model error rate.

6 Conclusion

This study aims to analyze the main factors that affect the success of millennial farmers in increasing quantity in Indonesia. The results of the study show that infrastructure, business dynamics, and the adoption of ICT have a significant role in the success of millennial farmers. Based on the KNN regression model, infrastructure is the factor with the largest contribution to the conversion index of millennial farmers with a mean dropout loss value of 0.101, followed by business dynamics (0.099) and ICT adoption (0.025). The KNN model used produces a MSE value of 0.008, a RMSE of 0.089, and an R^2 of 0.841, which shows that the model has a fairly good predictive ability although there are still limitations in the generalization of test data, as reflected in the MAPE value of 65.95%.

These findings are relevant to a research question that explores how infrastructure, business dynamics, and ICT adoption affect millennial farmer productivity. Infrastructure and business dynamics have proven to be more dominant than ICT adoption, which shows that structural readiness and business ecosystems are an important foundation for successful digital transformation in the agricultural sector. In practical terms, these results confirm the need for policy interventions to strengthen infrastructure, support business innovation, and improve technology accessibility for millennial farmers, especially in disadvantaged areas.

However, this study has some limitations. First, the KNN model showed signs of overfitting in the training data, which was reflected in the increase in MSE in the test data. Second, the analysis only covers 34 provinces in Indonesia, so the results may not be fully representative for other global or regional contexts. Third, ICT adoption variables have a relatively low influence, which can be caused by data limitations or unequal access to technology in the field.

For future research, it is recommended to use a hybrid approach, such as combining KNN with PCA methods or ensemble learning, to improve prediction accuracy and reduce model error rates. In addition, further research can explore additional factors such as digital literacy, social capital, and the impact of government regulations on the success of millennial farmers. The theoretical implications of this study are to enrich the understanding of the interaction between structural and technological factors in increasing agricultural productivity, while the practical implications are to provide a basis for more effective policy formulation in supporting digital transformation in the agricultural sector.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YH: Project administration, Writing – review & editing, Investigation, Data curation, Writing – original draft, Resources. AP: Writing – original draft, Project administration, Writing – review & editing, Supervision, Investigation, Formal analysis, Funding acquisition, Software, Data curation, Resources, Conceptualization, Validation, Visualization, Methodology. Yardha: Project administration, Conceptualization, Formal analysis, Writing – original draft, Validation. NM: Writing – original draft, Funding acquisition, Conceptualization, Methodology, Data curation. DW: Writing – original draft, Formal analysis, Project administration, Conceptualization. Suharyon: Methodology, Project administration, Writing – original draft, Conceptualization, Resources, Funding acquisition. AT: Project administration, Methodology, Investigation, Writing – original draft, Conceptualization. SW: Methodology, Project administration, Writing – original draft, Funding acquisition. DS: Writing – original draft, Conceptualization, Funding acquisition, Project administration, Supervision. AA: Project administration, Data curation, Writing – original draft, Conceptualization, Funding acquisition.

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