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Original Article

The Role of Digital Entrepreneurship and Cooperatives in Reducing Open Unemployment in Indonesia

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Abstract: Despite positive economic growth trends over the past decade, open unemployment remains one of the main challenges in Indonesia's economic development. The rapid pace of digital transformation presents new opportunities for job creation through digital entrepreneurship. At the same time, cooperatives have long been recognized as grassroots economic institutions with the potential to stimulate the real sector. However, the contributions of both to reducing open unemployment remain debated and have received relatively little attention in empirical studies. This study aims to fill this literature gap by analyzing the influence of digital entrepreneurship and cooperatives on open unemployment in Indonesia during the 2019–2023 period. The study employs panel data regression, with digital entrepreneurship and cooperatives as independent variables and the open unemployment rate as the dependent variable. The results show that digital entrepreneurship has a significantly negative impact on open unemployment, indicating that as digital entrepreneurial activity increases, the unemployment rate decreases. In contrast, cooperatives do not substantially impact unemployment, highlighting the need to revitalize the role of cooperatives in responding to the dynamics of the digital economy. Nevertheless, when considered simultaneously, digital entrepreneurship and cooperatives have a substantial combined effect on open unemployment. These findings underscore the importance of policy support in strengthening digital entrepreneurship through access to financing, training, and infrastructure, while encouraging the modernization of cooperatives to better align with labor market needs. The study recommends that future research incorporate additional macroeconomic variables and extend the observation period to achieve a more comprehensive understanding of the topic.

Keywords: Digital entrepreneurship; Cooperatives; Open unemployment; Panel data approach.

1. Introduction

Unemployment remains one of the major challenges in Indonesia's economic development (Safitri et al., 2023; Tjahjanto et al., 2023). This issue is largely driven by the increasing difficulty of finding employment, particularly in urban areas. Many people aspire to work in the formal sector, but the opportunities are limited (Suhermin & Suryawirawan, 2023). At the same time, the demand for high-quality human resources is rising, as the need for specific qualifications and skills is not easily met. Technological advancements and automation have further narrowed job opportunities across various sectors, intensifying competition among job seekers (Bessen, 2019; Vermeulen et al., 2018). As a result, a portion of the population is forced to work in the informal sector or remain unemployed, worsening the overall unemployment rate (Mutiarasari et al., 2018). Data from the Central Bureau of Statistics (BPS, 2024) indicate that Indonesia's open unemployment rate has generally declined over the past five years. However, the rate of decline has been relatively slow, and a sharp spike occurred in 2020 due to the COVID-19 pandemic. This surge affected nearly all provinces, particularly densely populated areas that are highly dependent on tourism, manufacturing, and daily services. Although economic recovery began in 2021, interprovincial disparities remain, with some regions recovering more slowly than others. This highlights that unemployment remains a serious issue, requiring alternative strategies beyond traditional job creation.

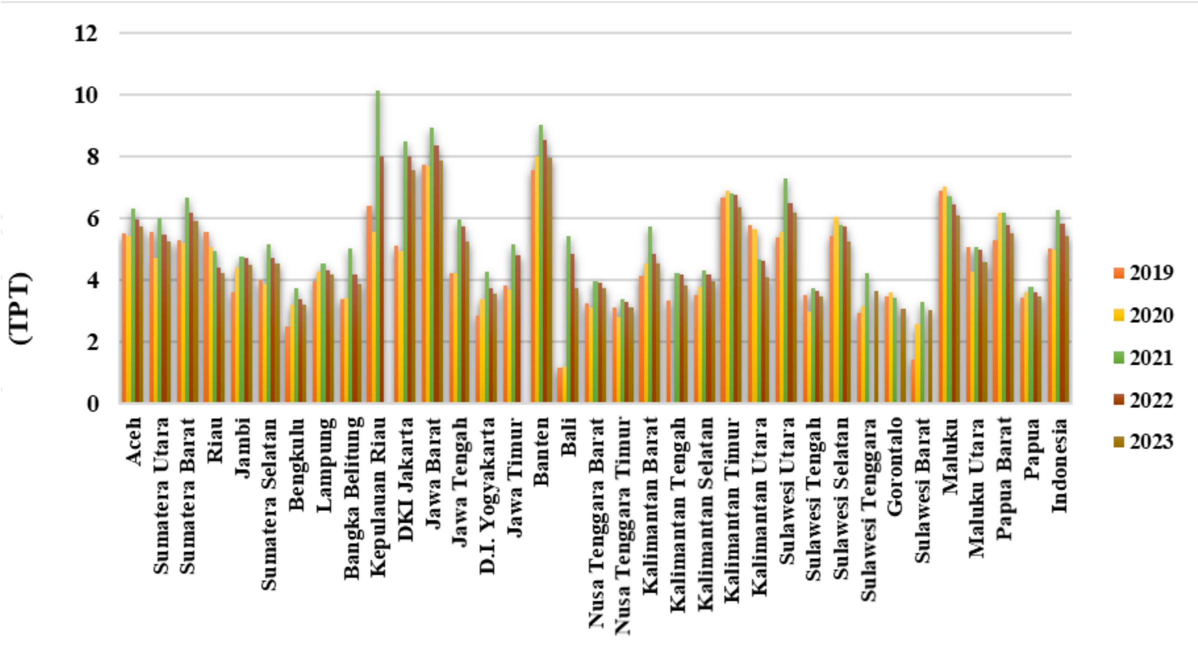

Figure 1. Percentage of Open Unemployment Rate (TPT) in Indonesia, 2019–2023

Source: Central Statistics Agency (2024)

One widely recognized strategy to reduce unemployment is the development of entrepreneurship. Through entrepreneurship, individuals can create their own employment opportunities that align with their interests and skills, while also generating opportunities for others. Entrepreneurship has been shown to foster independence, creativity, and economic competitiveness (Yanti Anggraini et al., 2021). However, entrepreneurial knowledge alone is insufficient. Other factors, such as risk-taking ability, technology utilization, and digital skills, are crucial in determining business success (Noventri et al., 2021; Nursito, 2013). The rise of digital technology has given birth to a new form of entrepreneurship: digital entrepreneurship. This concept emphasizes leveraging information technology across various business activities, including production, promotion, and distribution (Balai Pelatihan dan Pengembangan Teknologi Informasi dan Komunikasi, 2023). E-commerce represents one of the most tangible forms of digital entrepreneurship, enabling entrepreneurs to reach wider markets at relatively low promotional costs (Irawan & Karlinda, 2023). Changing consumer behavior toward more digitally savvy patterns further strengthens the potential of digital entrepreneurship to absorb labor and reduce unemployment.

In addition to digital entrepreneurship, cooperatives also play a significant role in Indonesia's economic development. Historically, cooperatives have been recognized as pillars of the people's economy, strengthening micro, small, and medium enterprises (MSMEs), promoting self-reliance, and creating new jobs (Kadir et al., 2012). BPS data (2024) show that the number of active cooperatives in Indonesia has continued to rise over the past five years. However, growth is more pronounced in larger provinces with better economic infrastructure, such as East Java, Central Java, and West Java. It indicates that cooperatives still hold substantial potential to contribute to job creation and unemployment reduction. Previous studies have highlighted the role of entrepreneurship in reducing unemployment (Misnawati & Yusriadi, 2018; Mutiarasari et al., 2018) , as well as the contribution of cooperatives to the economy (Kadir et al., 2012). However, research integrating digital entrepreneurship with the role of cooperatives in lowering Indonesia's unemployment rate remains relatively limited. In today's digital transformation era, the synergy between digital entrepreneurship and cooperatives could accelerate economic recovery and expand employment opportunities. Based on this context, this study aims to analyze the impact of digital entrepreneurship and cooperatives on Indonesia's unemployment rate. By examining these two factors simultaneously, the study is expected to make theoretical and practical contributions to addressing unemployment in Indonesia, particularly in the digital economy era.

2. Literature Review

2.1. Entrepreneurship and Unemployment

Entrepreneurship, particularly digital entrepreneurship, is widely regarded as an effective strategy for reducing unemployment in Indonesia (Margono, 2022; Nuriyanti & Halilintar, 2025; Rohaetin, 2020). Digital technology enables young people to access markets and start independent businesses easily (Margono, 2022; Nuriyanti & Halilintar, 2025; Reuschke et al., 2022). Research by Ninik Srijani et al. (2022) found that digital entrepreneurship training stimulates students' interest in starting businesses through online marketplaces. It suggests that entrepreneurship education aligned with technological advancements can act as a catalyst for creating new job opportunities. Several studies support this finding. Hazwardy & Gunawan (2020) emphasized that digital entrepreneurship training enhances competitiveness and helps individuals establish their businesses. Similarly, Fariski & Pratiwi (2023) highlighted that entrepreneurship education can overcome psychological barriers, such as the quarter-life crisis, which often impede young people from pursuing entrepreneurial ventures.

At the secondary education level, curriculum-based entrepreneurship training has boosted the entrepreneurial spirit among vocational high school students (Jayanti et al., 2023; Widiyarini, 2018). At the university level, studies by Fitria et al. (2023), Hidayat et al. (2018) and Respati et al. (2023) indicate that entrepreneurship education can reduce graduate unemployment by equipping students with competencies aligned with market needs. However, gaps remain: the open unemployment rate among university graduates remains high, reaching 7.35 percent (Dewi & Manuati Dewi, 2023). It underscores the need for more practical, production-oriented entrepreneurship education approaches (Lestari & Brahma, 2023; Setyoningrum et al., 2023). Thus, the literature confirms that digital entrepreneurship can strengthen competitiveness and promote new job creation. Nevertheless, the challenge of low entrepreneurial interest among higher education graduates remains largely unresolved.

2.2. Cooperatives and Unemployment

Beyond individual entrepreneurship, cooperatives also play a significant role in addressing unemployment. As economic institutions based on familial and democratic principles, cooperatives serve as platforms for joint ventures and as instruments for job creation and community empowerment (Murwadji & Robby, 2017; Rufaidah et al., 2022). Several studies have shown that cooperatives are effective in empowering vulnerable groups. Harini & Septiansyah (2019) emphasize that women's cooperatives can create employment opportunities and improve women's welfare. Yopiana et al. (2023) further note that cooperatives focused on local products can enhance community competitiveness, diversify local economies, and open new job opportunities. In addition, cooperatives support MSMEs by providing access to capital, training, and technical assistance (Hidayat et al., 2018; Rufaidah et al., 2022). Government programs, such as revolving funds, further strengthen cooperatives' role in job creation (Kesumadewi & Aprilyani, 2024). In the Islamic finance context, sharia cooperatives offer a strategic alternative by creating employment while adhering to principles of justice and welfare (Fadli & Yunus, 2023).

However, the literature also highlights several challenges facing cooperatives, including low public trust, limited management capacity, and minimal access to technology (Hariwibowo & Nugrayanti Puteri, 2023; Maftuchah et al., 2022) . Consequently, supportive policy strategies are needed, such as developing school-based cooperatives to instill entrepreneurial values from an early age (Edy et al., 2020; Widati & Herawati, 2020) and conducting ongoing research to assess the success factors of cooperatives in reducing unemployment (Putri & Ash Shidiqie, 2023). Thus, cooperatives hold substantial potential as instruments for labor absorption, particularly through member empowerment, support for MSMEs, and diversification of the local economy. Yet, their effectiveness is constrained by institutional challenges and a lack of innovation, which must be addressed to optimize the contribution of cooperatives to reducing unemployment in Indonesia.

Based on the review literature, we suggest that previous research has primarily examined digital entrepreneurship or cooperatives separately in addressing unemployment. Relatively few studies comprehensively integrate these two approaches within a national strategic framework. Moreover, most studies remain sector-specific (e.g., focusing on students, women, or MSMEs), thereby failing to present a synergistic perspective on how digital entrepreneurship education and cooperatives can create sustainable employment opportunities. Therefore, this study seeks to fill this gap by examining how digital entrepreneurship and cooperatives can complement each other in reducing unemployment in Indonesia. This approach offers an integrative model better suited to the country's socio-economic context.

3. Materials and Methods

This study aims to investigate the impact of digital entrepreneurship and cooperatives on the unemployment rate in Indonesia from 2019 to 2023. The research focuses on 33 provinces in Indonesia, using digital entrepreneurship and the number of cooperative units as independent variables, while the open unemployment rate serves as the dependent variable. The study employs quantitative panel data, which combines cross-sectional and time-series data. The panel dataset includes information on the working-age population engaged in digital businesses, the number of active cooperative units, and the open unemployment rate for each province over the study period. All data were sourced from official secondary sources, primarily the Central Statistics Agency (BPS) and other relevant institutions.

Operational definitions of the research variables were established to clarify the scope of analysis. The dependent variable (Y) is the open unemployment rate (TPT), defined as the proportion of the labor force that is unemployed but actively seeking work, measured as a percentage. The first independent variable (KD) is digital entrepreneurship, defined as the ability of individuals or groups to manage goods or service-based businesses using digital technology. This study is measured by the percentage of the working-age population engaged in online businesses or using digital platforms relative to the total labor force. The second independent variable (KP) is cooperatives, defined as business entities owned and managed collectively by members to improve economic welfare. This variable is measured based on the number of active cooperative units.

Panel data regression analysis is employed to address the research questions. This method is chosen because it combines cross-sectional dimensions (provinces) with time-series dimensions (years), providing more accurate estimates and reducing bias compared to using either data type. The panel regression model applied in this study follows Baltagi (2005), allowing an empirical assessment of the effects of digital entrepreneurship and cooperatives on the unemployment rate in Indonesia over the study period. Based on the specified panel regression equation, the model can be formulated as follows:

$$\mathrm{TPT_{it}} = \alpha + \beta \mathrm{KD_{it}} + \beta \mathrm{Log\_KP_{it}} + \varepsilon_{t} \qquad (1)$$

Whereas: TPT: Open Unemployment Rate; KD: Digital Entrepreneurship; KOP: Cooperatives; α: Constant; β: Coefficient; i: Province in Indonesia; ε: Error Term and t: Year

In panel data analysis, several regression model approaches can be employed, including the Pooled Least Squares (Common Effect Model), Fixed Effects Model (FEM), and Random Effects Model (REM). The Common Effect Model, also known as Pooled Least Squares, is the simplest approach, in which the time and cross-sectional dimensions of the panel data are ignored. This model combines time-series and cross-sectional data into a single dataset and estimates it using the Ordinary Least Squares (OLS) method. For this reason, it is often referred to as the common OLS model.

In contrast, the Fixed Effect Model (FEM) assumes that each cross-sectional unit has a unique intercept, while the slope remains constant over time. This model is also known as the Least Squares Dummy Variable (LSDV) model because it uses dummy variables to differentiate between units. On the other hand, the Random Effect Model (REM) assumes that the variations across units are random and represented as residuals. REM aims to address the limitations of FEM, which relies on dummy variables, provided that the number of cross-sectional units exceeds the number of explanatory variables for valid estimation.

Several diagnostic tests are conducted to determine the most appropriate model: the Chow test, the Hausman test, and the Lagrange Multiplier (LM) test. The Chow test determines whether to use the Common or Fixed Effect Model. If the probability value of the cross-section Chi-square is less than 5 percent, the FEM is selected; otherwise, the CEM is used. If FEM is chosen, the next step is to perform the Hausman test to compare FEM and REM. In the Hausman test, if the probability value is less than 0.05, FEM remains the preferred model; if it is greater than 0.05, REM is deemed more appropriate. Furthermore, if the model selection is between REM and CEM, the Lagrange Multiplier (LM) test using the Breusch-Pagan method is conducted. If the LM test result is less than 5 percent, REM is chosen; if greater than 5 percent, CEM is considered the best model.

Thus, the panel regression model testing process is carried out in stages to ensure that the selected approach aligns with the characteristics of the research data. This stepwise testing determines the model's accuracy and ensures that the estimation results are reliable and statistically robust. In static panel data models, classical assumption tests are important to ensure the regression results are unbiased, consistent, and efficient. For panel data, especially using the Fixed Effect Model (FEM) or Random Effect Model (REM), the key classical assumptions.

4. Results

4.1. Descriptive Statistics

Descriptive statistical analysis is a technique used to summarize and explain the data that has been collected. According to Silvia (2020), this analysis aims to comprehensively understand the observed variables by using statistical measures, including the mean, minimum, maximum values, and standard deviation. This approach aims to present the data more clearly and understandably, while also facilitating a better understanding of the relationships between the independent and dependent variables in the study.

Table 1: Result of Descriptive Statistics

	Open Unemployment Rate (TPT)	**Digital Entrepreneurship (KD)**	**Cooperative (KOP)**
Mean	4.879118	36.82653	206.867
Median	4.58	26.055	3.5955
Maximum	10.12	96.85	3967
Minimum	1.19	4.66	1.012
Std. Dev.	1.596756	27.72554	535.441
Observations	170	170	170

Table 1 shows 170 valid data points for each variable in the TPT sample. The minimum value is 1.190, while the maximum is 10.120, with a mean of 4.879 for 2019–2023. The standard deviation is calculated at 1.597. These statistics indicate that the mean exceeds the standard deviation, suggesting low data deviation and a uniform distribution of values. For the digital entrepreneurship variable, across 170 samples, the minimum value is 4.660, the maximum is 96.850, and the mean for 2019–2023 is 36.827, with a standard deviation of 27.726. It implies that the mean exceeds the standard deviation, indicating minimal data deviation and a relatively even distribution of values. For the cooperative's variable, across 170 samples, the minimum value is 1.012, the maximum is 3,967.000, and the mean for 2019–2023 is 206.867, with a standard deviation of 535.441. This shows that the mean does not exceed the standard deviation, suggesting high variability in the data while maintaining a relatively even distribution of values.

4.2. Panel Regression Model

This study employs panel data regression analysis using three different models: the Common Effect Model (CEM), the Fixed Effects Model (FEM), and the Random Effects Model (REM), each with its own strengths and limitations. The first step is to determine the most appropriate model among the three through a series of diagnostic tests. The Chow and Hausman tests are used to identify the best model specifications.

4.2.1. Chow Test

The Chow test determines the appropriate regression model by evaluating the Chi-squared value. If the probability value is less than 0.05, the FEM is selected; if it is greater than 0.05, the CEM is chosen. The process begins by estimating both the FEM and CEM models, followed by conducting the Chow regression test to determine which model best fits the data.

Table 1. Result of Chow Test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	**Statistic**	**d.f.**	**Prob.**
Cross-section F	21.699304	(33,134)	0.0000
Cross-section Chi-square	314.072820	33	0.0000

Table 2 shows a Chi-squared value of 0.0000, which is less than 0.05, indicating that the FEM is more appropriate than the CEM. Since the Chow test has confirmed FEM as the suitable model, the next step is to perform the Hausman test.

4.2.2. Hausman Test

The Hausman test is used to determine the most appropriate regression model. If the Chi-squared value is less than 0.05, the FEM is selected; if the Chi-squared value is greater than 0.05, the REM is preferred. Before conducting the Hausman test, estimations must be performed using both the FEM and REM models.

Table 2. Result of Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	9.078062	2	0.0107

Table 3 shows a Chi-squared value of 0.0031, which is less than 0.05. It indicates that the FEM is preferred, as it is more appropriate than the REM.

4.3. Fixed Effect Model Regression Estimation

After conducting the Hausman test, the selected model for estimation is the Fixed Effect Model (FEM). The FEM assumes that there are variations in effects across individuals, which are accounted for through differences in intercepts. In this model, everyone is considered an unknown parameter and is estimated using dummy variables. By employing this dummy variable technique, the FEM treats everyone as a unique parameter. When a variable has a scale that differs significantly from other variables, for example, one variable is in the millions while another is in decimal ranges, a log transformation can be applied to reduce the scale difference and improve comparability between variables. This transformation also helps address skewed or non-normal data distributions. However, if other variables are already on a relatively small scale and have an approximately normal distribution, applying a log transformation may not be necessary, as it could alter the data structure without providing significant benefits for the analysis (Gujarati, 2012). The results obtained from the Fixed Effect Model (FEM) regression are as follows:

Table 3. Result of Fixed Effect Model Estimation

Variable(s)	Coefficient	Std. Error	t-Statistic	Prob.
C	5.010109	0.130376	38.42829	0.0000
KD	-0.004541	0.002019	-2.249517	0.0261
LOGKOP	0.015994	0.042211	0.378906	0.7054
Effects Specification				
Cross-section fixed (dummy variables)				
Root MSE	0.628125	R-squared		0.844340
Mean dependent var	4.879118	Adjusted R-squared		0.803682
S.D. dependent var	1.596756	S.E. of regression		0.707486
Akaike info criterion	2.331374	Sum squared resid		67.07195
Schwarz criterion	2.995425	Log likelihood		-162.1668
Hannan-Quinn criter.	2.600838	F-statistic		20.76715
Durbin-Watson stat	1.675879	Prob(F-statistic)		0.000000

Table 4 captures the estimation results using the Fixed Effect Model (FEM). This study indicates that the model is overall significant, as indicated by a Prob(F-statistic) value of 0.0000. It means that the independent variables in the study collectively explain the variation in the dependent variable. An R-squared value of 0.8443 indicates that approximately 84.43% of the variation in the dependent variable can be explained by the independent variables in the model, while factors outside the model explain the remaining 15.57%. The Adjusted R-squared of 0.8037 suggests that the model is fairly robust and remains consistent after accounting for the number of variables used. Partially, the KD variable has a negative and statistically significant effect on the dependent variable, with a coefficient of -0.004541 and a p-value of 0.0261 (less than $\alpha = 0.05$). It indicates that each increase in KD slightly decreases the dependent variable, although the effect is relatively small. In contrast, the LOGKOP variable has an insignificant positive coefficient of 0.015994, as the probability value is 0.7054 (greater than $\alpha = 0.05$). It suggests that LOGKOP does not have a direct impact on the dependent variable. Additionally, the Durbin-Watson statistic of 1.675879 indicates that there is no serious autocorrelation problem in the model. The Root MSE of 0.628125 and the Standard Error of Regression of 0.707486 also indicate the model has a relatively low error rate. Thus, the Fixed Effects Model employed is appropriate, with KD proven to have a significant effect on the dependent variable, while LOGKOP does not show a meaningful influence.

4.4. Classical Assumptions Testing

The classical assumption tests conducted in linear regression using the Ordinary Least Squares (OLS) method include tests for linearity, autocorrelation, heteroscedasticity, multicollinearity, and normality. However, performing all classical assumption tests for every OLS regression model is not always necessary. For example, the autocorrelation test is specifically relevant for time-series data. Applying autocorrelation tests to non-time series data, such as cross-sectional or panel data, would yield results that are either insignificant or irrelevant (Green, 2018).

4.4.1. Normality Test

The normality test aims to determine whether the distribution of data in the regression model, between the dependent and independent variables, follows a normal distribution. A normally distributed dataset indicates that the regression model has good quality. Two methods are commonly used to test data normality: the histogram method and the Jarque-Bera test. The Jarque-Bera statistical test is designed to assess whether the data are normally distributed. The decision rule is as follows: if the Jarque-Bera probability value is greater than 0.05, the residuals are assumed to be normally distributed; conversely, if the probability value is less than 0.05, the residuals are not assumed to be normally distributed.

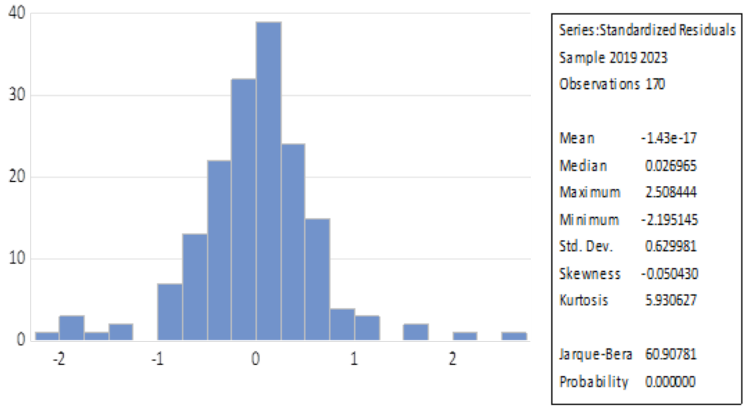

Figure 2. Result of Normality Testing

Figure 2 shows a Jarque-Bera probability value of 0.000000, lower than the 0.05 significance level. Based on this test, it can be concluded that the data in this study are not normally distributed. This condition may occur because the dataset consists of 34 provinces observed over a 7-year period, resulting in a total of 204 observations. Given this reality, the possibility of a non-normal distribution cannot be ruled out. This is supported by Gujarati & Porter (2012), who, based on the Central Limit Theorem, explain that the normality assumption can be disregarded in studies with more than 30 observations.

4.4.2. Multicollinearity Test

The multicollinearity test is conducted to determine whether multicollinearity exists within the data. Multicollinearity is considered present if the correlation coefficient between independent variables exceeds 0.85, whereas it is considered absent if the correlation coefficient between independent variables is below 0.85.

Table 5. Results of the Multicollinearity Test

	KD	LOGKOP
KD	1.0000	0.0103
LOGKOP	0.0103	1.0000

Table 5 displays that the correlation coefficient for each variable is less than 0.85. Therefore, it can be concluded that there is no indication of multicollinearity among the independent variables in the regression model.

4.4.3. Heteroscedasticity Test

The heteroscedasticity test is used to determine whether there is a variance inequality among residuals from one observation to another. When the variance of the residuals across observations remains constant, this condition is referred to as homoscedasticity. Conversely, when the variance changes across observations, it is referred to as heteroscedasticity.

Table 6. Results of the Heteroscedasticity Test

Variable(s)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.424004	0.062680	6.764595	0.0000
KD	-0.000727	0.000970	-0.749484	0.4549
LOGKOP	0.017442	0.020294	0.859508	0.3916

Table 6 captures that the dependent variable shows a Chi-Square Probability value (Obs*R-squared) exceeding the 0.05 significance level (e.g., KD is 0.4549 and LOGKOP is 0.3916). Therefore, we can conclude that there is no heteroscedasticity problem in the regression model.

5. Discussion

5.1. The Effect of Digital Entrepreneurship on the Open Unemployment Rate

The results suggest that digital entrepreneurship has a negative impact on Indonesia's unemployment rate. It suggests that the more people utilize digital platforms to engage in entrepreneurial activities, the greater the contribution toward reducing unemployment. These findings align with Munthe & Nawawi (2023), who emphasized that entrepreneurship, particularly digital entrepreneurship, plays a vital role in economic development and unemployment reduction. Similarly, Hazwardy & Gunawan (2020) found that digital entrepreneurship training enhances workforce competitiveness and encourages individuals to start new businesses. Fariski & Pratiwi (2023) also highlighted that entrepreneurship education helps individuals address personal challenges, such as the quarter-life crisis, increasing their willingness to pursue entrepreneurial activities, and reducing unemployment. Empirically, Adryan et al. (2025) demonstrated that digital transformation has a tangible impact on reducing unemployment across 33 provinces in Indonesia. Noventri et al. (2021) further confirmed that digital literacy opens new business opportunities for the productive-age population, helping curb unemployment. Regionally, Elshaiekh et al. (2023) found that digital integration and expanded broadband access in ASEAN have a positive effect on job creation, although the impact varies across countries. Overall, the present study reinforces the evidence that digital entrepreneurship is an effective and sustainable strategy for addressing unemployment in Indonesia.

5.2. The Effect of Cooperatives on the Open Unemployment Rate

In contrast, the study finds that cooperatives have no significant impact on Indonesia's open unemployment rate. In other words, despite an increase in the number of cooperatives, their contribution to job creation remains limited. Several factors may explain this result. First, most cooperatives are still small in scale, lack professional management, and are unable to accommodate a large number of workers. Second, limitations in capital, weak managerial quality, and low human resource competencies hinder cooperative growth. Third, the primary function of cooperatives, which often focuses on savings and loans, tends to improve member welfare rather than create new employment opportunities. Moreover, the growth in cooperative numbers is often administrative, without corresponding improvements in productivity or technology-based innovation.

These findings are consistent with (Ningsih et al., 2020), who reported that cooperative development in South Sumatra did not affect unemployment due to structural challenges. Azhari (2020) also found that the number of cooperatives, members, capital, and net surplus did not significantly influence unemployment. Similarly, Khan et al. (2024) found that cooperative business volume and MSME turnover had no meaningful impact on the open unemployment rate, as indicated by p-values greater than 0.05. Thus, while cooperatives are theoretically expected to be engines of grassroots economic development, their practical role in reducing unemployment in Indonesia remains limited. Institutional transformation has enhanced managerial quality, and integrating cooperatives with digital technologies is necessary to enable them to play a more significant role in job creation.

6. Conclusion and Recommendations for Future Research

6.1. Conclusion

This study aimed to analyze the effects of digital entrepreneurship and cooperatives on the open unemployment rate in Indonesia during the period from 2019 to 2023, using panel data regression methods. The results indicate that digital entrepreneurship has a negative and significant impact on the open unemployment rate. In other words, the greater the number of individuals engaged in entrepreneurial activities using digital technology, the lower the open unemployment rate in Indonesia. In contrast, cooperatives do not significantly affect the open unemployment rate, suggesting that their role in job creation remains limited or suboptimal. Nevertheless, the simultaneous test results indicate that digital entrepreneurship and cooperatives have a considerable combined impact on open unemployment.

6.2. Recommendations

On the basis of the findings of this study, several recommendations can be proposed:

1. Promote Digital Entrepreneurship: The government, in collaboration with stakeholders, should continue to encourage the development of digital entrepreneurship through policies that support access to capital, provision of digital infrastructure, and technology-based skill training. Collaboration among the private sector, educational institutions, and government is essential to build an innovative and sustainable entrepreneurial ecosystem capable of absorbing more labor.
2. Strengthen Cooperatives: Although cooperatives were found to have no significant effect on unemployment, efforts to strengthen them remain important. The government can encourage cooperative revitalization through the digitalization of management, enhancement of human resource capacities, broader access to capital, and the development of business models that are adaptive to labor market dynamics.
3. Foster Synergy Between Digital Entrepreneurship and Cooperatives: Expanding the synergy between digital entrepreneurship and cooperatives will allow both to complement each other in creating new employment opportunities. Support in training, funding, and integration of digital platforms for micro, small, and cooperative enterprises will strengthen their contribution to reducing open unemployment.
4. Future Research Directions: Subsequent studies should include additional variables such as investment, education, and economic growth, which may also influence the open unemployment rate. Extending the analysis period could provide a deeper understanding of unemployment dynamics in Indonesia and how various factors interact over the long term.

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