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Dependency Ratio, Human Development, and Open Unemployment: Evidence of Urban-Rural Heterogeneity in North Sumatera Province

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ABSTRACT

This study examines links between dependency ratio, human development, and open unemployment across 33 North Sumatran districts and municipalities in Indonesia, from 2017 to 2024, focusing on urban-rural differences. Fixed-effects panel regressions estimate four models: direct effects, dependency ratio–human development interaction, urban-rural moderation, and a three-way interaction. Human development is negatively associated with open unemployment across models. In the baseline model, a higher Human Development Index corresponds to lower unemployment; dependency ratio is also negatively associated, though its significance varies by specification. Urban-rural interaction results suggest both relationships are stronger in urban areas. However, the three-way interaction is insignificant, providing little evidence that the dependency ratio-human development relationship jointly differs by urban-rural context. The findings support labor policies tailored to regional labor-market structures rather than uniform interventions. They also inform targeted interventions by regional policymakers and the Department of Labor, aligning with Sustainable Development Goals 8 (Decent Work and Economic Growth) and 10 (Reduced Inequalities).

ABSTRAK

Penelitian ini menganalisis hubungan rasio ketergantungan dan pembangunan manusia dengan tingkat pengangguran terbuka di 33 kabupaten/kota di Sumatera Utara selama 2017–2024, dengan memperhatikan perbedaan wilayah perkotaan dan perdesaan. Hasilnya menunjukkan pembangunan manusia berhubungan negatif dengan pengangguran terbuka pada berbagai spesifikasi model. Rasio ketergantungan juga berhubungan negatif pada model dasar, tetapi signifikansinya sensitif terhadap perubahan spesifikasi. Model interaksi menunjukkan hubungan kedua variabel dengan pengangguran lebih kuat di perkotaan. Namun, interaksi tiga arah tidak signifikan, sehingga bukti perbedaan simultan hubungan tersebut antara wilayah perkotaan dan perdesaan masih terbatas. Temuan ini menegaskan perlunya kebijakan pengurangan pengangguran yang mempertimbangkan perbedaan struktur pasar kerja, bukan intervensi seragam. Hasil penelitian juga dapat membantu perancang kebijakan regional dan Dinas Tenaga Kerja menyusun intervensi terarah, sekaligus mendukung SDG 8 (Pekerjaan Layak dan Pertumbuhan Ekonomi) dan SDG 10 (Berkurangnya Kesenjangan).

1. INTRODUCTION

Open unemployment remains a persistent structural challenge in regional economic development in Indonesia (Hill, 1998; Sukirno, 2022; Suparman & Muzakir, 2023). Although macroeconomic indicators show relatively stable economic growth in recent years, reductions in unemployment have not occurred evenly across regions. This uneven pattern reflects differences in the capacity of regional economies to generate employment opportunities and absorb labor (Mendez & Siregar, 2023). In North Sumatra Province, substantial disparities in open unemployment are evident across districts and municipalities, suggesting that labor market outcomes are shaped not only by macroeconomic performance but also by regional demographic structures and the quality of human development.

Statistics Indonesia/Badan Pusat Statistik (BPS) District-level data from 2017 to 2024 reveal considerable variation in unemployment dynamics across regions in North Sumatra. Urban municipalities consistently record higher unemployment levels compared to many rural districts. Empirical evidence shows that the unemployment rate in Medan exceeded 10% during the pandemic period in 2020–2021 and remained above 8% in subsequent years. Similarly, Pematangsiantar recorded unemployment levels above 11% in several years, while cities such as Tebing Tinggi and Sibolga also experienced relatively high unemployment rates. In contrast, several rural districts such as Humbang Hasundutan, Pakpak Bharat, and Samosir recorded unemployment rates below 2% for most of the observation period. These disparities highlight the uneven nature of labor market dynamics within the province and indicate that unemployment cannot be explained solely by overall economic performance.

From a demographic perspective, labor market dynamics are closely linked to population structure. The dependency ratio (DR) represents the proportion of non-working-age populations relative to the productive-age population (Johansson & Cheng, 2016; Sriwahyuni et al., 2025). A higher dependency ratio implies a greater economic burden on the working-age population to support dependent groups. This demographic pressure can reduce household economic flexibility and constrain labor market participation. In regions where dependency ratios remain high, local economies may face difficulties in creating sufficient employment opportunities to accommodate the expanding labor force (Groth et al., 2019; Peng & Tsai, 2017). The data from North Sumatra indicate that several districts experienced relatively high dependency ratios during the earlier years of observation, particularly in rural areas where demographic transitions occur more gradually.

In addition to the demographic structure, the quality of human capital plays a crucial role in shaping labor market outcomes. The Human Development Index (HDI) reflects key dimensions of human development, including education, health, and living standards. Improvements in HDI are generally expected to enhance labor productivity and increase employability, thereby contributing to lower unemployment rates (Akinyele, 2024; Elmawazini et al., 2018; Saputro et al., 2023). However, empirical patterns in North Sumatra suggest that higher levels of human development do not always correspond to lower unemployment. Several urban areas with relatively high HDI values continue to experience elevated unemployment rates. For instance, Medan consistently records HDI values above 80, while maintaining unemployment levels significantly above the provincial average. Similarly, cities such as Pematangsiantar and Tebing Tinggi display high human development indicators but still face persistent unemployment challenges.

These patterns illustrate what can be described as a regional unemployment paradox. In principle, improvements in human development and economic modernization should enhance labor market efficiency and reduce unemployment. However, empirical evidence in North Sumatra suggests that regions with higher levels of human development often experience higher unemployment levels than less developed regions. This paradox may occur because improvements in education and human capital increase job expectations and intensify competition in urban labor markets. When job creation fails to expand at a pace comparable to the growth in the skilled labor supply, mismatches between labor supply and labor demand may arise, leading to persistent unemployment, even in economically advanced regions.

The complexity of unemployment dynamics becomes more evident when considering the spatial characteristics of regional labor markets. Labor markets are inherently spatial systems in which employment opportunities, labor mobility, and economic structures vary across geographic locations. Urban areas typically concentrate industrial activities (Deichmann et al., 2008; Scott, 1982), service sectors (He et al., 2025; Parr, 2014), and modern economic institutions (Akhtar et al., 2020) that attract labor from surrounding regions. This concentration of economic activity often increases labor supply in urban areas, intensifying competition for available jobs. Consequently, urban labor markets may experience higher unemployment rates despite stronger economic activity.

Conversely, rural labor markets are often characterized by smaller labor pools (Tacoli, 2003), lower levels of industrialization (D. Chen & Ma, 2022; Crossa & Ovalle, 2026; Duanmu et al., 2025), and a stronger reliance on agricultural or informal economic activities (J. M. Goetz, 2022; Kumar & Pandey, 2021; Lyu et al., 2022). Although these conditions may limit economic diversification, they may also reduce measured open unemployment because individuals are more likely to engage in informal or subsistence activities rather than remain so. Consequently, demographic pressures and improvements in human development may produce different labor market outcomes, depending on regional economic structures. These spatial differences suggest that unemployment dynamics cannot be fully understood without considering regional differences.

Despite the growing body of literature on the determinants of unemployment, several important empirical gaps persist. First, previous studies frequently examine unemployment determinants using national or aggregated provincial data, which may conceal substantial differences across districts and municipalities and limit the identification of localized labor market dynamics (Adu et al., 2018; Anwar, 2026; Hawariyuni & Andrasari, 2022; Zaria & Tuyon, 2023). Second, existing research tends to treat the effects of demographic structure and human development on unemployment as relatively homogeneous across regions, despite substantial differences in economic structure, labor mobility, employment opportunities, and organization of local labor markets. This limitation is particularly relevant when comparing urban and rural areas, where differences in sectoral composition, informality, and labor market opportunities may shape how demographic and human capital conditions are translated into unemployment outcomes. Third, relatively limited attention has been devoted to the interaction between demographic pressure and human development in explaining regional unemployment, particularly when such relationships are considered within different regional labor market contexts (Azolibe et al., 2022; del Olmo-García et al., 2023; Maynou et al., 2022).

Against this background, this study examines the relationship between the dependency ratio (DR), human development index (HDI), and open unemployment (OUE) in North Sumatra Province, while explicitly considering urban-rural regional heterogeneity. The study uses district-level panel data covering 33 districts and municipalities over the period 2017–2024. Rather than assuming that the relationships among the variables are uniform across locations, the empirical analysis progressively evaluates four model specifications: the direct effects of DR and HDI, the interaction between DR and HDI, the moderating role of urban-rural characteristics, and the three-way interaction between DR, HDI, and urban-rural characteristics. The findings of this study are expected to provide important policy insights for regional governments in designing more targeted strategies to reduce unemployment. By identifying how demographic structure and human development interact with regional characteristics, the results can inform the formulation of place-based labor market policies and human capital development programs that respond to the distinct conditions of urban and rural regions. In particular, strengthening investments in education, skills development, and regional economic diversification can enhance workforce productivity and expand employment opportunities across regions. These policy directions are closely aligned with the objectives of the Sustainable Development Goals (SDGs), especially SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities). By promoting inclusive labor market participation and addressing regional disparities in employment outcomes, the study contributes to the broader agenda of fostering sustainable and equitable economic development.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

The Impact of Dependency Ratio on Open Unemployment

The dependency ratio is an important demographic indicator that reflects the proportion of the non-working age population, consisting of children and the elderly, compared to the working-age population. A higher dependency ratio can increase the economic burden on the productive population because more resources must be allocated to support dependents rather than savings, investments, or productive economic activities. This condition may reduce household and regional capacity to create employment opportunities. Pitoňáková (2015) found that the demographic structure influences household economic behavior and is associated with unemployment dynamics in the short run. In Indonesia, Purnomo et al. (2020) also showed that demographic and economic conditions are closely related to unemployment and economic growth. From the aging population perspective, Chen & Tsang (2025) argued that an increasing elderly population may create economic costs that affect firm performance and employment opportunities. Therefore, the dependency ratio can influence open unemployment through labor market participation, household economic pressure, and regional productive capacity.

The negative relationship between the dependency ratio and open unemployment can be logically explained through labor force participation mechanisms. A higher dependency ratio indicates that a larger share of the population consists of children and elderly people who are not classified as part of the active labor force. Consequently, fewer individuals are counted as actively seeking work, which may reduce the recorded open unemployment rate. In this sense, the negative effect does not necessarily indicate stronger labor market performance, but rather reflects a demographic condition in

which many people remain outside the labor market. This is particularly relevant in regions where caregiving responsibilities, informal work, and household-based economic activities limit formal job search behavior. Therefore, a higher dependency ratio may be associated with lower open unemployment because it reduces the number of people officially recorded as unemployed.

The Impact of Human Development on Open Unemployment

Human development plays a crucial role in determining labor market outcomes, particularly open unemployment. The Human Development Index (HDI), which consists of education, health, and standard of living dimensions, reflects the quality of human capital in a region (Sallam et al., 2022). Higher human development is expected to reduce unemployment because better education and health improve labor productivity, employability, and readiness to participate in the labor market. Andini et al (2025) found that human resource development strategies in Indonesia can reduce unemployment, increase welfare, and strengthen work participation. Similarly, Djafar (2019) showed that human development is related to unemployment and labor mobility in Indonesia. However, improvements in human development must be supported by sufficient job creation and appropriate labor market policies. Without adequate employment opportunities, higher education and skills may still result in educated unemployment or skill mismatch. Therefore, human development should be accompanied by vocational training, industrial development, and regional employment strategies to effectively reduce open unemployment.

The negative relationship between human development and open unemployment can also be logically explained through the role of human capital in improving labor market capacity. A higher HDI reflects better education, health, and living standards, which strengthen individuals' skills, productivity, and ability to adapt to labor market needs. As human development improves, workers become more employable and better prepared to access available job opportunities, thereby reducing the probability of being openly unemployed. In this sense, because HDI incorporates a standard-of-living dimension, reverse causality between human development and unemployment cannot be fully excluded. Therefore, regions with higher levels of human development tend to experience lower open unemployment, as their populations possess stronger capabilities to participate productively in the economy.

Hypothesis Development

Based on the theoretical arguments above, the relationship between demographic structure and open unemployment can be understood through the labor force participation mechanisms. A higher dependency ratio indicates a relatively larger proportion of children and older adults outside the working-age population. Because open unemployment only captures individuals who actively participate in the labor force and seek employment, a higher dependency ratio may be associated with a lower measured open unemployment rate. Accordingly, the first hypothesis is as follows:

H1: The dependency ratio is negatively associated with open unemployment.

Human development improves individuals' capabilities through better education, health, and living standards, thereby strengthening productivity, employability, and adaptability to labor market requirements. Regions with higher levels of human development are therefore expected to exhibit stronger workforce capabilities and lower unemployment. Based on this argument, the second hypothesis is proposed as follows:

H2: Human development is negatively associated with open unemployment.

The relationship between the demographic structure and unemployment may also depend on the level of human development. Human development can influence how the working-age population responds to demographic pressure by affecting productivity, skills, labor mobility, and access to employment opportunities. Consequently, similar demographic structures may generate different labor market outcomes across regions with different levels of human development. Therefore:

H3: Human development significantly moderates the relationship between the dependency ratio and open unemployment.

Regional labor markets also differ substantially between urban and rural areas of the country. Urban labor markets generally have more diversified industries, greater labor mobility, stronger formal employment structures, and higher competition among job seekers than rural labor markets. In contrast, rural labor markets tend to rely more heavily on agriculture, informal employment, household-based activities, and subsistence production. These structural differences may influence how demographic conditions are translated into unemployment. Accordingly:

H4: The relationship between the dependency ratio and open unemployment differs significantly between urban and rural regions.

Labor market returns to human development may vary across regional contexts. Improvements in education, health, and workforce capabilities may generate stronger employment effects in urban areas where formal labor markets, industrial activities, and skill-intensive employment opportunities are more developed. In rural areas, the relationship may be weaker because employment remains relatively concentrated in agriculture and informal activities. Therefore:

H5: The relationship between human development and open unemployment differs significantly between urban and rural areas.

The influence of human development on the relationship between demographic structure and unemployment may depend on regional labor market characteristics. The interaction between demographic pressure and human-capital conditions may therefore operate differently across urban and rural economies because of differences in employment structures, labor mobility, informality, and the capacity of local economies to absorb skilled labor. This leads to the final hypothesis:

H6: Urban-rural regional characteristics significantly moderate the interaction between the dependency ratio and human development in explaining the open unemployment.

3. RESEARCH METHOD

This study employs a quantitative research approach using panel data from 33 district and municipal levels in North Sumatra Province. The dataset was categorized into pre-pandemic (2017–2019), pandemic (2020–2021), and recovery (2022–2024) periods to capture structural breaks, isolate the exogenous shock of COVID-19, and evaluate post-crisis resilience across distinct economic regimes. Panel data provide both cross-sectional variations across regions and temporal dynamics. By combining cross-sectional observations of districts and municipalities with time-series information from 2017 to 2024, panel data enable the analysis to capture temporal dynamics and regional heterogeneity in unemployment patterns (Duxbury, 2021; Pindado & Requejo, 2015). By accounting for these time-invariant regional attributes, panel estimation techniques help mitigate the risk of omitted variable bias, thereby strengthening the internal validity of estimated relationships (Zinn & Wolbring, 2023). This approach allows us to track changes in open unemployment within the same regions over time while simultaneously comparing differences across regions.

The dependent variable in this study is open unemployment (OUE), which reflects the proportion of the labor force that is actively seeking employment but has not yet obtained a job. The main independent variables include the dependency ratio (DR) and the human development index (HDI). The dependency ratio represents the demographic structure of the population by measuring the proportion of non-working-age individuals relative to the productive-age population. Meanwhile, the human development index captures the quality of human capital through dimensions of education, health, and living standards.

Urban-rural classification is based on the regional classification reported by Statistics Indonesia (BPS). The variable W takes a value of 1 for urban municipalities/districts and 0 for rural districts according to the official BPS classification used in this study. Because the classification is intended to capture persistent structural differences in regional labor markets rather than annual changes in settlement status, W is treated as time-invariant throughout the observation period. The distribution of the sample between urban and rural units is reported to assess whether the interaction estimates are based on sufficient observations in both regional groups.

For empirical estimation, each variable in this study is defined operationally in accordance with its theoretical meaning in Table 1.

Table 1. **Operational Variables**

Variable Type	Variable	Definition	Measurement	Data Source
Dependent Variable	Open Unemployment (OUE)	The proportion of the labor force that is actively seeking employment but has not yet obtained a job	Percentage (%)	Badan Pusat Statistik (BPS)
Independent Variable	Depedency Ratio (DR)	The ratio of non-working-age population (0–14 and 65+) to the working-age population (15–64)	Percentage (%)	Badan Pusat Statistik (BPS)
Independent Variable	Human Development Index (HDI)	Composite index measuring human development based on education, health, and standard of living	Index Value (0-100)	Badan Pusat Statistik (BPS)
Dummy Variable	Urban-Rural Region (W)	Dummy variable distinguishing regional characteristics	1 = Urban and 0 = Rural	Badan Pusat Statistik (BPS)

To examine the direct and interaction effects and moderating role of urban–rural regional characteristics, the empirical analysis estimates four model specifications.

The first model examines the direct effects of the dependency ratio and human development on open unemployment.

$$OUE_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 HDI_{it} + \varepsilon_{it} \quad (1)$$

The second model introduces an interaction term between the dependency ratio and the human development index to assess whether the quality of human development influences the relationship between demographic structure and unemployment.

$$OUE_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 HDI_{it} + \beta_3 (DRxHDI)_{it} + \varepsilon_{it} \quad (2)$$

The third model incorporates the moderating role of urban–rural regional characteristics in the relationship between the dependency ratio, human development, and unemployment.

$$OUE_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 HDI_{it} + \beta_3 (DRxW)_{it} + \beta_4 (HDIxW)_{it} + \varepsilon_{it} \quad (3)$$

The fourth model estimates a triple interaction specification to examine whether urban–rural regional characteristics moderate the interaction effect between demographic structure and human development.

$$OUE_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 HDI_{it} + \beta_3 (DRxHDI)_{it} + \beta_4 (DRxW)_{it} + \beta_5 (HDIxW)_{it} + \beta_6 (DRxHDIxW)_{it} + \varepsilon_{it} \quad (4)$$

4. DATA ANALYSIS AND DISCUSSION

This section presents the empirical findings of the study. The analysis begins with descriptive statistics to provide an overview of the distribution and variation of the key variables across districts and municipalities in North Sumatra during the observation period. This is followed by the panel model selection process using the Hausman test to determine the appropriate estimation technique.

Subsequently, classical diagnostic tests were conducted to assess potential econometric issues, including multicollinearity and heteroscedasticity. Finally, the results of the four empirical model specifications are presented and discussed to examine the direct effects of the dependency ratio and human development, as well as the interaction and moderating effects of regional characteristics on open unemployment.

Descriptive statistics were employed to provide an overview of the main characteristics of the variables used in the analysis. This preliminary analysis summarizes the central tendency and dispersion of the variables, including the mean, maximum, minimum, and standard deviations. The results are shown in Table 2.

Table 2. **Descriptive Statistics**

Variable	OUE	DR	HDI
Mean	4.701326	55.16212	71.94530
Maximum	12.14000	81.72000	83.23000
Minimum	0.190000	33.12000	59.56000
Standard Deviation	2.682564	8.780111	4.810342

Source: Authors' Calculation (2026)

The average Open Unemployment Rate (OUE) across districts and municipalities during the observation period was 4.70%, indicating a moderate level of unemployment in North Sumatra. The standard deviation of 2.68 suggests noticeable variation in unemployment rates across regions and years, although the dispersion remains relatively moderate compared to the mean. The highest unemployment rate was observed in Pematangsiantar City in 2018, reaching 12.14%, whereas the lowest value occurred in Pakpak Bharat District in 2019, at 0.19%. These figures highlight the substantial disparities in labor market outcomes across districts and municipalities.

The dependency ratio (DR) has an average value of 55.16, implying that every 100 individuals of productive age support approximately 55 dependents. The relatively large standard deviation of 8.78 indicates significant variation in demographic structures across regions. The highest dependency ratio was recorded in the Humbang Hasundutan District in 2017, reaching 81.72%, while the lowest value was observed in Binjai City in 2020, at 33.12%. These differences reflect substantial demographic heterogeneity among districts in North Sumatra.

The mean Human Development Index (HDI) value of 71.95 indicates that the overall level of human development in North Sumatra falls within the high human development category. The standard deviation of 4.81 suggests a relatively limited variation across districts and years. The highest HDI value was recorded in Medan City in 2024 at 83.23, and the lowest was observed in West Nias District in 2017, with a value of 59.56.

Panel Model Selection

To determine the appropriate panel data estimation technique, the Hausman specification test was conducted to compare the fixed effects model (FEM) and the random effects model (REM). The Hausman test produced a probability value of 0.0000, which was lower than the significance level of 0.05 (Algifari, 2021; Wahyudi, 2020; Widarjono, 2023b). Therefore, the null hypothesis that the random effects model is appropriate is rejected, indicating that the fixed effects model provides a more consistent and suitable specification for the panel estimation.

Diagnostic Tests

To determine the appropriate panel data estimation technique, the Hausman specification test was conducted to compare the fixed effects model (FEM) and the random effects model (REM). The Hausman test produces a probability value of 0.0000, which is lower than the significance level of 0.05. Therefore, the null hypothesis that the random effects model is appropriate is rejected, indicating that the fixed effects model provides a more consistent and suitable specification for the panel estimation.

First, multicollinearity was assessed by examining the correlation matrix of the independent variables. Generally, serious multicollinearity problems are suspected when the correlation coefficient between independent variables exceeds 0.80. The results in Table 3 indicate that most independent variables do not exhibit severe multicollinearity.

Table 3. **Correlation Matrix**

Variable	DR	HDI
DR	1	-0.5657401
HDI	-0.5657401	1

Source: Authors' Calculation (2026)

Table 3 shows that all correlation coefficients among the independent variables are below the 0.80 and 0.85 thresholds (Wahyudi, 2020; Widarjono, 2023), indicating the absence of multicollinearity. This means that the independent variables do not exhibit excessively strong linear relationships with one another, allowing their individual associations with open unemployment to be estimated more reliably, without substantial distortion from overlapping explanatory information.

Next, a heteroscedasticity test in Table 4 was performed using the Glejser method by regressing the absolute residual values against the independent variables in the model.

Table 4. **Heterocedasiticity Test**

Variable	Probability
DR	0.3992
HDI	0.6872
DR_HDI	0.3998
DR_W	0.5131
HDI_W	0.4109
DR_HDI_W	0.5096

Source: Authors' Calculation (2026)

Heteroscedasticity was examined using the Glejser test, with all explanatory variables showing probability values greater than 0.05 (Wahyudi et al., 2023). This result indicates that the residual variance is homoscedastic, meaning that the variance of the error terms remains relatively constant across observations. Therefore, the model does not exhibit heteroscedasticity problems, supporting the reliability and efficiency of the estimated coefficients and their associated statistical inference.

Panel Regression Estimation

The first empirical model examines the direct effects of the dependency ratio and human development on open unemployment (Table 5). The dependency ratio has a negative and statistically significant coefficient (-0.059255; $p < 0.01$), suggesting that an increase of one percentage point in the dependency ratio is associated with a 0.059 percentage point decrease in the open unemployment rate, holding other factors constant. The baseline fixed-effects specification indicates that both the dependency ratio and human development are negatively associated with open unemployment. The coefficient of the dependency ratio is −0.059, indicating that a one percentage-point increase in the dependency ratio is associated with an approximately 0.059 percentage-point lower open unemployment rate, conditional on the model specification. The coefficient of HDI is −0.158, implying that a one-point increase in HDI is associated with an approximately 0.158 percentage-point lower unemployment rate. The model

reports an R-squared of 0.907, indicating a high overall model fit. However, this statistic should not be interpreted as evidence that DR and HDI alone explain 90.7 percent of unemployment variation, because the fixed-effects specification also accounts for time-invariant district-specific heterogeneity.

Table 5. **Model 1 Estimation Result**

Variable	Coefficient	Standard Error	Prob.
C	19.32234	3.252888	0.0000
DR	-0.059255	0.012736	0.0000***
HDI	-0.157792	0.037930	0.0000***
R-Squared	0.906909		

Source: Authors' Calculation (2026)
*,**,*** denote significance at 10%, 5%, and 1% levels, respectively

The main strength of Model 1 lies in its strong explanatory power and statistical consistency. The R-squared value of 0.9069 indicates that the model can explain approximately 90.69% of the variation in open unemployment rates across regions. This suggests that the dependency ratio and HDI are highly relevant variables in explaining unemployment dynamics. In addition, both independent variables have negative and statistically significant coefficients at the 1% level, indicating that the estimated relationships are not only theoretically meaningful but also empirically robust. The negative coefficient of HDI confirms that improvements in human development are closely associated with lower unemployment, while the negative coefficient of the dependency ratio reflects the role of demographic structure in influencing labor market participation and recorded unemployment.

The second model in Table 6 introduces an interaction term between the dependency ratio and the HDI.

Table 6. **Model 2 Estimation Result**

Variable	Coefficient	Standard Error	Prob.
C	22.53855	7.468354	0.0028
DR	-0.122084	0.131896	0.3556
HDI	-0.205631	0.106933	0.0557*
DR_HDI	0.000936	0.001955	0.6327
R-Squared	0.907002		

Source: Authors' Calculation (2026)
*,**,*** denote significance at 10%, 5%, and 1% levels, respectively

The results show that neither the dependency ratio nor the interaction term is statistically significant in this specification. The coefficient of the interaction term (0.000936) is statistically insignificant ($p > 0.05$), suggesting that the human development index does not significantly moderate the relationship between the dependency ratio and unemployment. The explanatory power of the model remains high, with an R^2 value of 0.9070, indicating that approximately 90.70% of the variation in unemployment can still be explained by the variables included in the model.

Model 2 examines whether the association between the dependency ratio and open unemployment depends on the level of human development. The interaction coefficient between the DR and HDI is positive but statistically insignificant ($\beta = 0.000936$; $p = 0.633$). Therefore, the results do not provide evidence that human development significantly conditions the association between the dependency ratio and open unemployment. Importantly, the inclusion of the interaction term also

changes the significance of the individual coefficients. The dependency ratio becomes statistically insignificant (p = 0.356), while HDI remains only marginally significant at the 10% level (p = 0.056). This pattern indicates that the baseline relationships are sensitive to the inclusion of the interaction structure. Such changes may arise because interaction models redistribute explanatory variation across the constituent variables and interaction term, and may increase parameter uncertainty.

The third model in Table 7 incorporates regional characteristics through the interaction terms between the explanatory variables and the urban–rural dummy variable.

Table 7. **Model 3 Estimation Result**

Variable	Coefficient	Standard Error	Prob.
C	19.83810	3.195413	0.0000
DR	-0.044721	0.013151	0.0008***
HDI	-0.111143	0.039841	0.0057***
DR_IW	-0.141910	0.052691	0.0076***
HDI_W	-0.312602	0.114613	0.0069***
R-Squared	0.911593		

Source: Authors' Calculation (2026)
*,**,*** denote significance at 10%, 5%, and 1% levels, respectively

The estimation results indicate that both the dependency ratio and HDI exert negative and statistically significant effects on unemployment in rural regions. In rural areas, a 1% increase in the dependency ratio reduces unemployment by 0.044%, while a 1-point increase in HDI decreases unemployment by 0.111%. The interaction terms are also statistically significant, indicating that the effects differ between rural and urban areas. In urban areas, the impact of the dependency ratio becomes stronger, with a combined coefficient of -0.1866, suggesting a larger reduction in unemployment associated with demographic changes. Similarly, the effect of HDI is substantially stronger in urban regions, where a 1-point increase in HDI reduces unemployment by approximately 0.424%. The model remains highly significant, with an R^2 value of 0.9116, indicating that approximately 91.15% of the variation in unemployment is explained by the model.

Model 3 also provides the clearest evidence of urban-rural heterogeneity. Because W = 0 represents rural regions, the coefficient of DR (−0.0447) represents the estimated association between the dependency ratio and open unemployment in rural areas. For urban regions, the marginal association is obtained by adding the DR×W coefficient to the DR coefficient:

DR effect in urban areas = −0.0447 + (−0.1419) = −0.1866.

Thus, the estimated negative association between dependency ratio and open unemployment is approximately four times larger in magnitude in urban areas than in rural areas. Similarly, the HDI coefficient of −0.1111 represents the rural association, while the urban association is:

HDI effect in urban areas = −0.1111 + (−0.3126) = −0.4237.

These results indicate that the association between demographic structure and human development and open unemployment is substantially stronger in urban labor markets. However, these differences should be interpreted as conditional associations rather than causal effects because urban and rural regions may differ systematically in sectoral composition, labor-force participation, informality, migration, and educational structure.

The fourth model in Table 8 estimates a triple interaction specification to examine whether urban–rural characteristics jointly moderate the interaction between demographic structure and human development.

Table 8. **Model 4 Estimation Result**

Variable	Coefficient	Standard Error	Prob.
C	60.06478	24.08713	0.0134
DR	-0.199897	0.137606	0.1477
HDI	-0.229148	0.111483	0.0410**
DR_HDI	0.002325	0.002052	0.2585
DR_IW	-4.666200	3.229550	0.1499
HDI_W	-3.096607	2.006730	0.1242
DR_HDI_W	0.059080	0.042385	0.1647
R-Squared	0.912905		

Source: Authors' Calculation (2026)
*,**,*** denote significance at 10%, 5%, and 1% levels, respectively

The results indicate that HDI maintains a negative and statistically significant relationship with unemployment ($p < 0.05$). However, the dependency ratio and all interaction terms were statistically insignificant. The triple interaction term (DR×HDI×W) was not statistically significant, suggesting that the joint moderating effect of human development and regional characteristics on the relationship between demographic structure and unemployment is not supported by the data. Despite the insignificance of several interaction terms, the explanatory power of the model remains high, with an R^2 value of 0.9129, indicating that approximately 91.29 percent of the variation in unemployment rates is explained by the model.

Model 4 provides a more demanding test of whether the relationship between the dependency ratio and human development is jointly conditioned by urban-rural characteristics. However, the results provide limited empirical support for this three-way conditional relationship. The triple interaction term between DR, HDI, and W is statistically insignificant ($\beta = 0.0591$; $p = 0.165$). The two-way interaction terms are also statistically insignificant, including DR×HDI ($p = 0.259$), DR×W ($p = 0.150$), and HDI×W ($p = 0.124$). The only statistically significant explanatory variable in this specification is HDI, which remains negatively associated with open unemployment ($\beta = -0.229$; $p = 0.041$). This result suggests that the negative association between human development and unemployment remains detectable even after introducing a more complex conditional structure. However, the absence of statistical significance in the interaction terms indicates that the evidence is insufficient to conclude that the DR-HDI relationship varies jointly across urban and rural contexts.

The contrast between Models 3 and 4 is substantively important. Model 3 provides evidence of separate urban-rural differences in the associations of DR and HDI with unemployment, whereas Model 4 does not provide sufficient evidence for a simultaneous three-way conditional relationship. Therefore, the empirical evidence supports a simpler form of urban-rural heterogeneity rather than a more complex three-way interaction structure.

Discussion

Human Development and Unemployment

One of the most consistent findings across the estimated models is the negative and statistically significant effect of the Human Development Index (HDI) on the open unemployment rate. This result suggests that improvements in human development, captured through higher levels of education, improved health conditions, and better living standards, play an important role in enhancing labor productivity and strengthening individuals' capacity to participate effectively in the labor market. Higher levels of human capital increase workforce readiness, improve skill compatibility with labor market demand, and facilitate the matching process between job seekers and employment opportunities. Consequently, regions with stronger human development outcomes tend to experience lower levels of unemployment because individuals possess the competencies and capabilities required by employers.

This empirical finding is consistent with Tatli & Tasci (2021), who found a negative relationship between human development and unemployment in the long run, indicating that improvements in education, health, and income contribute to lower unemployment rates. Similarly, Andini et al (2025) demonstrate that effective human resource development enhances workforce competence, increases labor force participation, and reduces unemployment by improving individuals' preparedness for employment. Evidence from cross-country panel studies also supports this relationship. Karma (2025) shows that broader socio-economic conditions, including human development indicators, significantly influence labor market outcomes, such as youth disengagement from employment and education.

In addition, improvements in education systems and skills development are essential for reducing unemployment in developing and transition economies. Njifen (2024) highlights that strengthening human capital formation can improve employment prospects by enhancing skill acquisition and productivity. Earlier research also emphasizes that regional labor market performance cannot be fully understood without considering the role of human resource development in shaping employment opportunities and workforce capabilities (Napier et al., 1980).

Dependency Ratio and Unemployment Measurement

The empirical findings also reveal that the dependency ratio is negatively and statistically significantly associated with the open unemployment rate. At first glance, this result may appear counterintuitive, as a higher dependency ratio is commonly interpreted as a demographic burden that places additional pressure on the productive age population. In many regional labor markets, particularly in developing economies, a larger share of dependent populations may coincide with lower participation in formal labor markets, thereby reducing the number of individuals actively seeking employment (Lau & Tsui (2020). Consequently, regions with higher dependency ratios may display lower recorded unemployment rates because a substantial portion of the population remains outside the active labor force.

Beyond the statistical relationship, the negative effect of the HDI on open unemployment should be interpreted as evidence that human development functions as a long-term labor market asset. In this context, education, health, and living standards are not merely social indicators but also productive capacities that determine how individuals respond to employment opportunities. Regions with higher HDI are more likely to have workers who are healthier, more educated, and adaptable to changes in labor demand. Therefore, the reduction in unemployment associated with HDI improvement reflects the broader role of human capital in strengthening regional economic resilience.

However, the effect of human development on unemployment may also depend on the ability of the local economy to absorb skilled labor. Improvements in education and health do not automatically reduce unemployment when job creation remains limited or when the structure of employment is dominated by low-productivity sectors. This means that HDI can reduce unemployment more effectively when it is accompanied by industrial growth, investment expansion, vocational training, and stronger labor market institutions. Thus, the findings suggest that human development policies should not be implemented in isolation but should be integrated with employment-oriented regional development strategies.

Moreover, the relationship between dependency ratios and unemployment can also be understood through the lens of household-level labor allocation and caregiving responsibilities. The presence of dependent populations, such as children and elderly individuals, often influences labor supply decisions within households, particularly in contexts where family members must balance income-generating activities with caregiving duties. Ahmed & Floro (2023) suggest that caregiving responsibilities can reduce labor force participation, as individuals may withdraw from or delay entry into the labor market to provide unpaid care. Similarly, Feliberty & Reyes (2015) highlight demographic changes that alter family structures and dependency burdens can influence participation patterns, especially among women and other household members responsible for caregiving roles. In regions where informal economic activities remain prevalent, individuals who are unable to access formal employment frequently engage in subsistence or informal work, which reduces the likelihood of being classified as openly unemployed (Basu, 2011; Marois et al., 2022).

The negative association between the dependency ratio and open unemployment requires particular caution. A higher dependency ratio should not be interpreted as an improvement in labor-market performance. The dependency ratio is a demographic measure based on age composition, whereas the open unemployment rate is calculated among the labor force. Consequently, a region with

a relatively large dependent population may have a smaller proportion of individuals actively participating in the labor market and therefore a lower measured unemployment rate, without necessarily having better employment conditions. This distinction is important because individuals outside the labor force are not classified as openly unemployed. Caregiving responsibilities, household production, informal activities, and subsistence-based work may further reduce the likelihood that individuals are captured by the open unemployment measure. Thus, the negative DR coefficient may partly reflect differences in labor-force participation and the composition of economic activity rather than a direct beneficial effect of demographic dependency on employment.

Urban-Rural Heterogeneity

Another set of results reveals the effects of the dependency ratio and human development on unemployment differ between urban and rural regions, suggesting the presence of spatial heterogeneity in regional labor markets. This difference can be explained by the structural characteristics of urban economies, which generally have more diversified industries, higher labor mobility, and greater competition for formal employment. In contrast, rural labor markets often rely more on agriculture and informal activities, which can absorb surplus labor and reduce recorded unemployment. Zenou (2011) argues that migration also plays an important role in shaping these dynamics, as workers from rural areas frequently move to cities in search of better employment opportunities, increasing labor market competition in urban areas. Furthermore, the economic returns to education and human capital tend to be higher in urban regions, which makes improvements in human development more influential for employment outcomes in cities than in rural areas (Goetz & Rupasingha, 2004). Previous spatial studies also highlight that urbanization and agglomeration contribute to regional differences in unemployment levels (Rusanovskiy & Markov, 2016), while rural employment patterns are influenced by local economic conditions and regional development factors (Fieldsend, 2013).

The spatial heterogeneity found in this study further suggests that the regional labor markets in North Sumatra operate under different structural conditions. Urban areas tend to have more diversified economies, stronger formal labor markets, and higher levels of competition among job seekers. Consequently, changes in the HDI and demographic structure may have a more visible effect on unemployment in urban regions. In contrast, rural areas are more dependent on agriculture, informal activities, and household-based employment, making the relationship between demographic variables, human development, and open unemployment less direct and more complex. Therefore, the findings support the argument that unemployment reduction policies should be spatially sensitive. Urban regions require policies that improve labor market matching, expand formal employment, and strengthen skills-based industries. Rural regions, on the other hand, require policies that improve rural productivity, diversify local economies, and strengthen MSMEs and agro-based industries. Without this spatially differentiated approach, improvements in human development may not be fully translated into employment gains, especially in areas where the economic structure is not yet capable of absorbing an increasingly skilled workforce.

5. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

This study examines the associations between the dependency ratio, human development, and open unemployment across 33 districts and municipalities in North Sumatra during 2017–2024, with particular attention to urban-rural heterogeneity. The findings provide three main insights. First, human development is consistently and negatively associated with open unemployment across the estimated specifications. In the baseline model, a one-point increase in HDI is associated with an approximately 0.158 percentage-point lower unemployment rate. This relationship remains statistically detectable in the more complex specifications, although its magnitude and statistical significance vary with the model structure. Second, the dependency ratio is negatively associated with open unemployment in the baseline specification, but this relationship is not stable across all models. Therefore, the negative association should not be interpreted as evidence that demographic dependency improves labor-market performance. Because open unemployment captures only individuals actively participating in the labor force, the observed relationship may partly reflect differences in labor-force participation, informal employment, caregiving, and other forms of economic activity that are not captured by the unemployment measure. Third, the evidence of urban-rural heterogeneity is strongest in Model 3. The estimated associations of both the dependency ratio and HDI with open unemployment

are stronger in urban regions than in rural regions. However, the three-way interaction estimated in Model 4 is statistically insignificant, indicating that the evidence does not support a joint conditional relationship among the dependency ratio, human development, and urban-rural context.

The results imply that unemployment reduction strategies should prioritize human capital development and spatially differentiated labor market policies. Regional governments should strengthen investments in education quality, vocational training, and workforce skill development to improve labor market readiness. Simultaneously, policies must recognize the structural differences between regions. Urban areas require strategies to expand formal employment, strengthen labor market matching systems, and support innovation-based industries. In contrast, rural areas need policies focused on rural economic diversification, the development of agro-based industries, and strengthening micro, small, and medium enterprises (MSMEs) that can absorb local labor. Without policies that address these spatial differences, improvements in human development alone may not translate into effective unemployment reduction strategies.

The limitation of this study lies in its use of aggregate regional panel data, which may not fully capture individual labor market behavior, informal employment, underemployment, and sectoral differences across regions. In addition, the static panel approach limits the ability to explain the short- and long-run dynamic relationships between demographic structure, human development, and unemployment. Thus, future research should extend the present analysis by employing Panel Autoregressive Distributed Lag (Panel ARDL) models to capture the dynamic adjustment between demographic structure, human development, and unemployment. Unlike static panel estimation, the Panel ARDL enables the identification of both short-run and long-run relationships and allows researchers to estimate the speed at which unemployment responds to changes in demographic and human capital variables. Such an approach would provide deeper insights into the temporal persistence of demographic and developmental effects on regional labor market outcomes.

Future policy strategies should move beyond general employment programs toward the development of integrated regional labor market systems. Governments should strengthen coordination between educational institutions, vocational training centers, and local industries to reduce skill mismatches. In addition, policies that promote regional employment clusters, improve infrastructure connectivity, and support labor mobility across regions are essential for balancing labor supply and demand. These strategies are directly aligned with the objectives of Sustainable Development Goal (SDG) 8 on Decent Work and Economic Growth and SDG 10 on Reduced Inequalities, as they aim to expand inclusive employment opportunities while reducing regional disparities in labor market outcomes.

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