

A Three-Way Interaction Logistic Regression Analysis of Employment among Recent Vocational Graduates

Fachrizal Fachrizal, Asep Husni Yasin Rosadi, Mia Rahma Romadona, Suryadi Suryadi,
Andi Budiansyah*

National Research and Innovation Agency, Indonesia

Abstract Training certification is commonly interpreted as an observable signal in labor markets characterized by information asymmetry. This study examines employment outcomes among recent vocational education graduates in Indonesia using the National Labour Force Survey (SAKERNAS) from 2018 to 2023. Employment status is modeled as a binary outcome within a logistic regression framework incorporating three-way interaction terms among certification status, gender, and urban–rural location. The results indicate that certification is positively associated with employment outcomes, although its effects vary across demographic and spatial groups. Marginal effects analysis suggests that certification yields larger employment gains among female graduates, while differences across locations are more context-dependent. Additional analysis reveals that the return to certification weakened during the COVID-19 pandemic, highlighting the importance of labor-market conditions in shaping employment outcomes. These findings contribute to the understanding of heterogeneous labor-market transitions among vocational graduates in Indonesia and provide evidence for the development of more targeted workforce policies.

Keywords Training Certificate, Recent Graduate, Job Opportunities, Vocational Higher Education, Indonesia

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1. Introduction

Employment outcomes among newly graduated vocational education students exhibit considerable variation, reflecting differences in individual characteristics as well as labor-market conditions in which graduates seek employment. Although vocational education is designed to improve job readiness through the formation of practice-oriented skills, the availability and credibility of indicators that can be observed and effectively signal employability to employers are still uneven. Drawing on signal theory [1], a specialized training certificate can serve as a credible signal by conveying information regarding the mastery of industry-relevant skills by graduates in the context of information asymmetry. In this role, certification helps reassure employers that applicants meet minimum competency standards [2], thus simplifying the hiring decision-making process [3]. However, the rapid proliferation of certification schemes has also resulted in competing and overlapping standards, which have raised concerns regarding credential inflation and over-certification [4]. The relationship between certification and the employment probability cannot be assumed to be uniform across subgroups of the population. In addition to certification, job opportunities are also influenced by other factors such as geographic location and gender. Evidence from China shows that many new college graduates, including those with vocational qualifications, are increasingly choosing to return to their home areas or rural areas in response to the high cost of urban living, increasingly fierce job competition, and limited family support in cities [5]. In some contexts, rural areas can even

*Correspondence to: Andi Budiansyah (Email: andi.budiansyah@brin.go.id). Research Center Economics for Industry, Services, and Trade, National Research and Innovation Agency, Indonesia.

offer relatively greater access to suitable employment opportunities [6]. Gender also shapes employment outcomes, as male workers still tend to be favored over female workers in most types of jobs [7], including in traditionally female-dominated (pink-collar) jobs [8]. As a result, women remain at a disadvantage in accessing job opportunities [9]. From a statistical point of view, this difference (heterogeneity) shows that employment analysis should not only focus on the average impact. Instead, it is necessary to look at how job opportunities are formed when various factors (demographic characteristics and residential location) interact with each other. Previous studies show that employment outcomes are not randomly dispersed, but are systematically influenced by gender and regional differences. In other words, training certifications does not affect all groups in the same way for all groups, but they can work differently depending on a person's context. If the impact of certification is considered the same for all groups, then important differences between individuals are at risk of being overlooked and the resulting conclusions become incomplete [10]. Therefore, this study emphasizes the importance of intervariable interaction in the employment analysis of vocational graduates. To capture the complexity, this study uses a logistic regression model of three-way interaction to analyze the employment outcome of fresh vocational graduates. Employment status on this study has only two conditions, working or not working, therefore the logistic regression approach is an appropriate option for estimating employment outcome directly [11], [12]. Including the interactions between training certifications, gender, and areas of residence (urban or rural), this study can show how the benefits of certification for each group can differ. This approach helps to provide a more realistic picture of how the labor market works, by capturing invisible relationships under simpler approaches or assumes uniform impacts. The empirical analysis uses survey data from the National Labor Force Survey (SAKERNAS) which is nationally representative from 2018–2023 period. Working status is set as the main variable, justifying the use of a logistic regression estimator. In addition, time variables are also included to analyze the year-to-year variations in labor-market conditions. With this approach, the results of the analysis can show how job opportunities differ by certification, gender, and location of residence in a more contextual way.

Motivation and Main Contributions This study aims to deepen our understanding of the labor market for vocational graduates in Indonesia by simultaneously exploring how vocational certification, gender, and place of residence (urban or rural) mutually influence employment opportunities. While previous study focused on generally examined these factors separately, this study seeks to capture more complex dynamics and reflect the reality of societal diversity. By utilizing the latest SAKERNAS data, this study not only provides an overview of employment conditions across various periods, including during the COVID-19 pandemic, but is also expected to serve as a reference for the formulation of more inclusive and targeted workforce development policies, so that the benefits of vocational certification can be enjoyed more equitably by various segments of society.

2. Data and Method

The data used in this study are obtained from the National Labor Force Survey (SAKERNAS) for the August period conducted by the Central Statistics Agency (BPS). This survey includes a summary of national labor-market conditions for all working-age residents living in sampled households. The main focus of the analysis in this study is data on fresh vocational education graduates, taken from six surveys during the 2018–2023 period. In this study, the term fresh graduate refers to individuals who obtained a diploma (D1–D3) within a period of one year before the date of the survey. **Dependent variable.** According to BPS, a person is considered to be working if they carry out activities to obtain or help earn income, both in the form of money and goods, for at least one continuous hour during the past week. In the National Labor Force Survey (SAKERNAS), respondents were asked whether they worked for at least one hour in the previous week. A response of “yes” is coded as 1, while a response of “no” is coded as 2. **Independent variables.** Vocational training that emphasizes the cultivation of essential job skills, professional expertise, and adaptability leads to skill-level certification, augmenting students' competitiveness and elevating the quality of graduates in the labour market [13], [14]. In the SAKERNAS, respondents were queried regarding acquiring a certificate from an internship or fieldwork experience, with a score of 1 designated for affirmative responses and 2 for negative responses. Job opportunities vary between rural

and urban regions, with rural areas frequently encountering difficulties due to restricted personal networks and a paucity of job opportunities, as large enterprises are infrequent and numerous vacancies remain unadvertised [15]. In SAKERNAS, respondents were asked if they resided in urban or rural areas, with a value of 1 indicating urban residence and 2 indicating rural residence. Gender impacts job opportunities, with males having higher access to positions that align with their college degrees [16]. This indicates that women persistently face challenges, particularly in reconciling professional obligations with familial duties [17], [18]. In SAKERNAS, respondents were asked about their gender, with one assigned to males and two to females. This study also provides an estimated employment probability derived from a three-way interaction between gender, certification, and residence to reveal clear patterns. This study will utilize Logistic Regression with Three-way Interaction Analysis to evaluate the predictive significance of the independent variables on the dependent variables. In Logistic Regression Analysis, only binary coding (0 and 1) is acknowledged; hence, the SAKERNAS coding, which initially utilized values of 1 and 2, will be modified to 0 and 1.

2.1. Logistic Regression Model

The logit scale adapts the original linear regression equation to generate the logit, or natural log of the risks of one outcome category ($\hat{Y}$) compared to the other category ($1 - \hat{Y}$) [20]. This study uses these equations:

$$\ln \left(\frac{\hat{Y}}{1 - \hat{Y}} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon \quad (1)$$

$\hat{Y}$ denotes the probability of belonging to one binary outcome category (employed) instead of the other (unemployed). β_1 represents the model parameter for the independent variable of possessing a training certificate (X_1), β_2 denotes the model parameter for the independent variable of respondents living in urban or rural areas (X_2), β_3 indicates the model parameter for the independent variable of respondents' gender (X_3), β_4 indicates the model parameter for the independent variable interaction between certificate and gender (X_4), β_5 corresponds to the model parameter for the independent variable interaction between certificate and living in an urban area (X_5), β_6 corresponds to the model parameter for the independent variable interaction between gender and living in an urban area (X_6), and β_7 corresponds to the model parameter for the independent interaction variable between certificate, gender, and living in an urban area (X_7). All explanatory variables are specified as binary indicators. Certification status is coded as 1 if the individual possesses a training certificate and 0 otherwise. Gender is coded as 1 for males and 0 for females. Living area is coded as 1 for urban and 0 for rural areas. For example, the coefficient β_1 for certification represents the effect of having a certificate on employment odds, evaluated at the reference group (female, rural individuals). It indicates how the odds of employment change when moving from no certification to certification for this group. Interaction terms are constructed as the product of the corresponding binary variables. The interaction term between certification and gender captures the differential effect of certification across gender groups (β_4). On the three-way interaction term, β_7 captures whether the gender difference in the effect of certification varies between urban and rural areas.

2.2. Logistic Regression Assumptions

Logistic regression is a form of regression analysis employed to forecast the result of a categorical response variable based on one or more predictor variables [19]. Binary logistic regression necessitates a binary dependent variable, while ordinal logistic regression requires an ordinal dependent variable. Fundamental prerequisites for logistic regression encompass the independence of errors, the absence of multicollinearity, and the exclusion of significantly influential outliers [20]. Binary logistic regression necessitates that the dependent variable be binary. The dependent variable in this study is work status, as defined by SAKERNAS, with a binary value of 1 indicating employment and 0 indicating unemployment. **Independence of errors.** This study uses ownership of training certificates, residence locations, and the gender of vocational graduates who completed their studies within one year before the survey as independent factors. The study uses repeated cross-sectional data in which different individuals are surveyed in each wave. To further account for potential within-region dependence arising from the sampling design, cluster-robust standard errors are estimated at the city level. **Lack of multicollinearity.**

Logistic regression needs minimal or no multicollinearity among the independent variables. This indicates that the independent variables should not have excessive correlation between them and should not have analytically significant outliers. The anticipated outcome for a sample member may significantly vary from the actual result. Outliers may affect the model's overall accuracy. Outlier detection analyzes residuals alongside pertinent diagnostic statistics and visual representations.

2.3. Signaling Theory

Signaling Theory provides a robust framework for examining how distinct credentials influence labor market outcomes under conditions of information asymmetry [1]. Within the labor market, this asymmetry arises because job applicants possess precise knowledge of their actual productivity and skill levels, whereas employers do not [21]. When a fresh graduate enters the job market, firms cannot directly observe inherent traits such as work ethic or genuine technical mastery. To bridge this informational gap and mitigate hiring risks, employers must rely on observable, credible signals that reflect a candidate's latent potential [22]. Training certificates or academic credential serve as one such critical signal. Rather than merely reflecting the raw hours invested in their acquisition, these credentials function as a verifiable mechanism that assures employers of an applicant's compliance with specific competency standards. By presenting these observable indicators, graduates effectively communicate their institutional job readiness, thereby streamlining the screening and screening-cost structures for hiring managers. Signaling theory thus illuminates the underlying mechanism of these certificates, framing them as an essential bridge across the informational divide between job seekers and firms [23]. From a statistical standpoint, the empirical application of signaling theory becomes particularly compelling when addressing socio-economic heterogeneity [24]. This study employs a three-way interaction model to demonstrate that signaling strength is rarely uniform, varying significantly based on the characteristics of the sender. In addition to certification as the primary signal, the empirical framework incorporates gender and geographic location as secondary signals. Evaluating these overlapping credentials and their interaction terms offers deeper insights into employment probabilities, revealing whether the institutional credibility of a certificate is systematically amplified or diminished by a graduate's gender and spatial context. Furthermore, the theoretical framework accounts for the phenomenon of signal noise [25]. A rapid proliferation of certification schemes can induce credential inflation, a state where a signal's marginal value degrades due to widespread ownership across the labor force. Specific macroeconomic conditions can similarly erode the efficacy of these credentials. During severe macroeconomic shocks, for instance, even a structurally strong signal may prove insufficient to clear the market or alter firm hiring heuristics amidst widespread contraction.

3. Results and Discussion

3.1. Assumptions Test

Multicollinearity test. There should be no perfect multicollinearity among the predictor variables. A high correlation between predictors can inflate the variance of the parameter estimates and make the model unstable [26]. Correlation among the independent variables in Table 1 is < 0.90 , indicating no multicollinearity among the

Table 1. Multicollinearity test result

	Work	Certificate	Urb_Rural	Gender
Work	1.0000			
Certificate	0.0914	1.0000		
Urb_Rural	-0.0081	0.0233	1.0000	
Gender	0.0442	0.0371	0.0600	1.0000

Source: authors' analysis

independent variables. To assess the fit of a logistic regression model, the Hosmer-Lemeshow test is a widely used

approach. This test ensures agreement between the actual and predicted incidence rates in a given subdivision of the population [27], [28]. The p -value of 0.3189 exceeds the 0.05 significance level, indicating that the model is consistent with the data and that the null hypothesis is accepted. Further evaluation also shows the absence of substantial outliers, although both outliers and influential data points can seriously alter the parameter estimates and the interpretation of the results. Employ robust methodologies or diagnostic evaluations to detect and alleviate the influence of these points [29]. Figure 1 shows that there are no significantly influential outliers in the dataset. This means that the dataset can proportionately affect the parameter estimation.

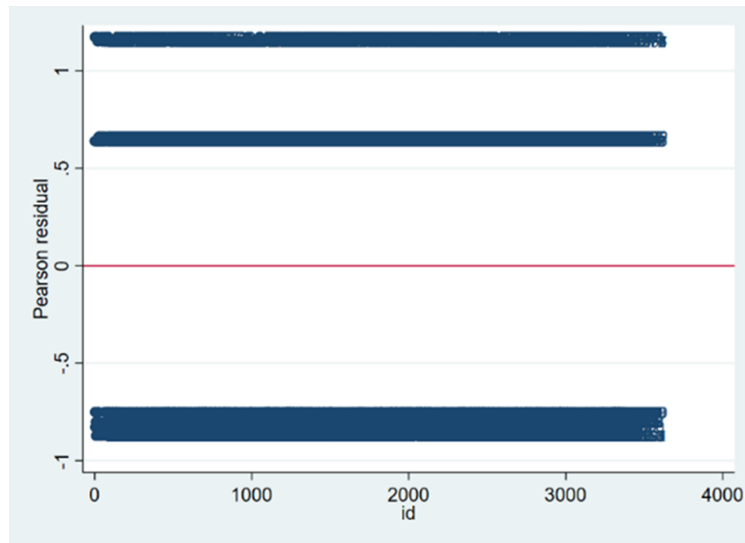


Figure 1. Exclusion of significantly influential outliers.
Source: authors' analysis

Table 2. Variance Inflation Factor (VIF) Diagnostic Results

Variable	VIF	1/VIF
Certificate	3.75	0.266624
Gender	4.51	0.221968
Certificate $\times$ Gender	6.28	0.159132
Urban	2.45	0.407979
Certificate $\times$ Urban	4.97	0.201081
Gender $\times$ Urban	5.60	0.178624
Certificate $\times$ Gender $\times$ Urban	7.01	0.142560
Mean VIF	4.94	

Source: Authors' analysis.

Variance inflation factors (VIFs) were computed to assess multicollinearity among the explanatory variables. All VIF values are below the conventional threshold of 10, indicating that multicollinearity is not a serious concern in the estimated model.

Influence diagnostics based on the DFBETA statistics, computed from a linear probability model approximation, indicate that most observations exert relatively small influence on the estimated coefficients. Although a non-negligible proportion of observations exceed the conventional threshold of $2/\sqrt{N} \approx 0.034$, these exceedances are modest in magnitude and are distributed approximately symmetrically around zero. Overall, the dispersion of the

Table 3. DFBETA Influence Diagnostics

Variable	Std. Dev.	Min	Max	Count > Threshold	% of Sample
<i>_dfbeta_1</i>	~0.017	-0.046	0.038	353	~10.4%
<i>_dfbeta_2</i>	~0.017	-0.063	0.046	241	~7.1%
<i>_dfbeta_3</i>	~0.017	-0.062	0.040	268	~7.9%
<i>_dfbeta_4</i>	~0.017	-0.035	0.029	256	~7.6%
<i>_dfbeta_5</i>	~0.017	-0.029	0.036	159	~4.7%
<i>_dfbeta_6</i>	~0.017	-0.036	0.049	241	~7.1%
<i>_dfbeta_7</i>	~0.017	-0.032	0.049	63	~1.9%

Source: Authors' analysis.

DFBETA values remains limited, suggesting that no individual observation exerts disproportionate influence on the estimated regression coefficients.

3.2. Descriptive statistics

The SAKERNAS 2018–2023 data survey revealed that fresh vocational graduates were predominantly female, lacked a training certificate (except in 2020), and were primarily respondents residing in urban areas (Table 4). The COVID-19 pandemic reduced employment opportunities for respondents, particularly in 2020 and 2021, while simultaneously increasing the prevalence of training certificate ownership among respondents in 2020. The rise in training certificate ownership is ascribed to the implementation of Presidential Regulation Number 36 of 2020 by the Indonesian government, which pertains to Work Competency Development using the Pre-Employment Card Programme (Kartu Prakerja) as a measure to alleviate the effects of the COVID-19 pandemic. Trainees obtain a training certificate upon completing 15 hours of training within a maximum of 15 working days under this programme. This Certificate is expected to enhance the ownership of vocational certificates among fresh graduates in the SAKERNAS survey for this study.

Table 4. Descriptive statistics for vocational fresh graduates

		2018	2019	2020	2021	2022	2023
Gender	Male	36.41%	31.54%	34.16%	35.25%	37.58%	32.29%
	Female	63.59%	68.46%	65.84%	64.75%	62.42%	67.71%
Status	Working	57.30%	56.97%	45.20%	43.09%	51.65%	53.59%
	Not Working	42.70%	43.03%	54.80%	56.91%	48.35%	46.41%
Certification	Have-Certificate	35.12%	36.67%	51.89%	30.18%	42.86%	44.62%
	Non-Certificate	64.88%	63.33%	48.11%	69.82%	57.14%	55.38%
Living Area	Urban	60.63%	58.19%	55.81%	60.14%	67.47%	67.26%
	Rural	39.37%	41.81%	44.19%	39.86%	32.53%	32.74%
N		541	818	688	434	455	446

Source: authors' calculation

The most vocational graduates to be employed in urban locations may be shaped by the Indonesian government's emphasis on vocational education in agriculture, maritime, tourism, and creative industries. These priorities motivate vocational graduates to work in these sectors, frequently more attainable in rural areas [30]. Nonetheless, despite the growth of the services sector, agriculture continues to be a crucial contributor to rural employment, often necessitating vocational skills [31]. The inclusion of temporal dynamics is particularly important in this study given that the observation period (2018–2023) encompasses the unprecedented economic disruption caused by the COVID-19 pandemic. The pandemic represents a structural shock to the labor market, characterized by declines in employment opportunities, sectoral shifts, and the expansion of government intervention programs such as Kartu Prakerja. These changes may alter both the level of employment and the effectiveness of vocational certification as a signaling mechanism. Treating the time variable as a simple control risks obscuring these structural shifts

and potentially attributing pandemic-specific fluctuations to individual characteristics such as certification, gender, or location. Therefore, explicitly analyzing the COVID-19 period is essential to distinguish between temporary shocks and underlying structural relationships, ensuring a more accurate and policy-relevant interpretation of the role of certification in improving employment outcomes. The results reveal significant temporal variation in

Table 5. Year and Certification Interaction on Employment

Year	Coef	p-value
2019	−0.021	0.930
2020	−0.122	0.615
2021	−0.615	0.030**
2022	−0.317	0.235
2023	+0.135	0.618

Source: authors' analysis

both employment outcomes and the returns to certification. Employment probabilities declined sharply during the COVID-19 period, particularly in 2020 and 2021, confirming the presence of a substantial labor market shock. While certification is generally associated with higher employment likelihood, the interaction results indicate that this effect is not stable over time. In particular, the return to certification was significantly reduced in 2021, suggesting that the signaling value of certification weakened during the peak of the pandemic (Table 5). These findings highlight that the impact of certification is context-dependent and may be sensitive to macroeconomic conditions, supporting the reviewer's concern that treating time as a simple control variable may obscure important structural shifts in the labor market.

3.3. Logistics Regression

A binary logistic regression model was employed to establish a relationship between job opportunities and the criteria of fresh vocational graduates. The binary answer variable has two potential outcomes: '1' denotes working, whereas '0' signifies not working. The regression analysis identified significant factors, including certificate ownership, urban or rural residence, and gender. These factors were further examined with two-way and three-way interaction analysis. The results from these selection methods will demonstrate the employment opportunities for fresh vocational graduates in a full 3-way interaction of variables between Gender, Certificate, and Living Area. Table 6 shows the estimated logistic regression results of main variables, two-way interactions, and three-way interactions.

Table 6. Logistic Regression Results for Work Status (Odds Ratios)

Explanatory Variables	Odds Ratio	Robust SE	z	P> z
<i>Baseline: No Certificate, Female, Rural</i>				
Certificate = 1	1.604***	0.181	4.18	0.000
Gender = 1 Male	1.284	0.234	1.37	0.170
Certificate = 1 × Gender = 1	0.920	0.299	−0.26	0.797
Urban = 1	1.206*	0.131	1.72	0.085
Certificate = 1 × Urban = 1	0.884	0.130	−0.84	0.400
Gender = 1 Male × Urban = 1	0.776	0.200	−0.98	0.325
Certificate = 1 × Gender = 1 Male × Urban = 1	1.075	0.435	0.18	0.858
Observations	3382			

Notes: Odds ratios are reported. Cluster-robust standard errors are estimated at the city level. Baseline category is respondents with no certificate, female, and living in rural areas. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculation

3.4. Main Variables

The odds ratio of the main variables, applied to the baseline group (no certificate, female, and rural), that are significant in the estimated results using city-level clustering are *Certificate* and *Living Areas*. The odds of employment for individuals possessing a certificate among female rural respondents are 60.4% higher. Figure 2 demonstrates that the marginal effects results indicate that training certification increases the probability of employment across all demographic and geographic groups. However, the magnitude of this effect is heterogeneous.

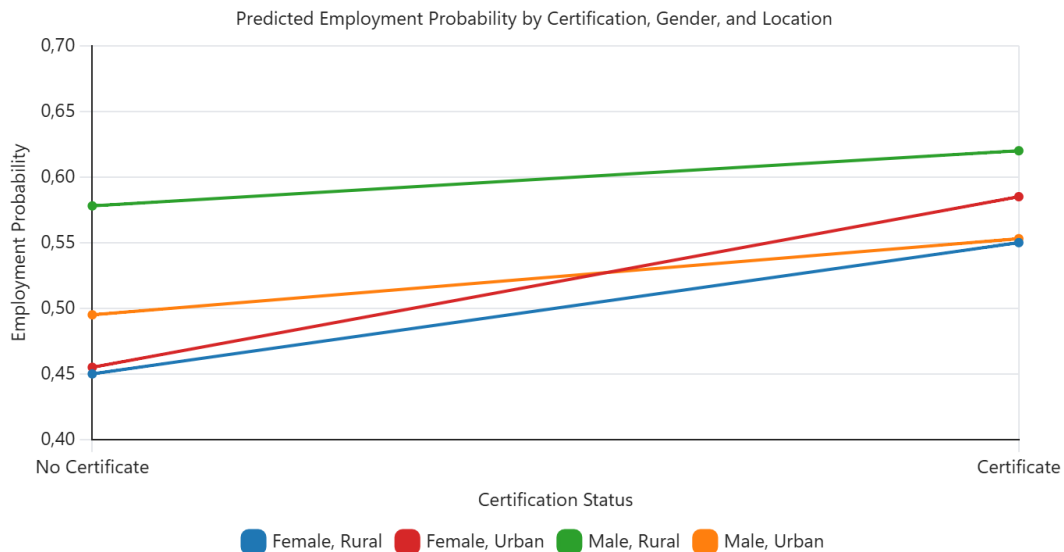


Figure 2. Adjusted Predictions of Certificate $\times$ Gender $\times$ Urb_Rural with 95% CIs

Source: authors' analysis

The increase in employment opportunities is partly driven by the credibility that certificates provide in signaling specific competencies, especially during the hiring process [32]. These certifications enhance the relevance of employees to their job roles [33] and may contribute to greater job security [34]. Many vocational and technical training programmes lead to well-compensated and stable careers, with young workers in technical or industrial fields experiencing income increases of 33% or more [34]. There are observable differences in employment outcomes across gender groups. The male group exhibits approximately 28% higher odds of employment compared to the reference group; however, this effect is not statistically significant at conventional levels. Correspondingly, the predicted probability of employment for the male group is approximately 10–13 percentage points higher than that of their counterparts. Several empirical studies indicate that in urban and suburban areas of Indonesia, employment opportunities for vocational education graduates (vocational workforce) tend to show greater gender equality than in rural areas. In urban and suburban settings, access to a variety of formal job opportunities, better infrastructure, and a more flexible labor market appear to help reduce gender disparities in access to and the quality of jobs for vocational high school graduates [35], [36], [37]. In contrast to rural contexts, which are still influenced by stricter social norms, in urban and suburban areas, the benefits of vocational certification are perceived as more equitable between men and women, both in terms of the speed of entering the labor market and job stability [38], [39]. These findings underscore the potential of vocational education as a more inclusive instrument for equalizing employment opportunities in urban and suburban areas, while also serving as a foundation for human resource development policies that are more sensitive to spatial contexts. The estimated results suggest that individuals residing in urban areas exhibit higher odds of employment compared to those in rural areas (OR = 1.206). However, this effect is only marginally statistically significant at the 10% level. Consistent with this finding, marginal effects indicate that the difference in predicted employment probabilities between urban and rural areas is relatively

small. For example, among non-certified females, the probability of employment increases only slightly from approximately 45.2% in rural areas to 45.9% in urban areas. These results suggest that, while urban residence may provide a modest advantage in employment outcomes, the magnitude of this effect is limited, probably because the job market in Indonesia demands multi-skilled graduates, and the current vocational education system struggles to meet these demands [40]. There is also a significant mismatch between the skills acquired by vocational graduates and the requirements of the job market [41]. This issue is prevalent across both rural and urban areas, leading to similar employment probabilities for vocational graduates regardless of their location. A substantial mismatch is observed between the competencies acquired by vocational graduates and the demands of the labor market [41]. This provides a minor probabilistic ratio for the location variable between a labor market demanding high skills and a vocational education system that lacks the capacity to fulfill the labor market's needs [40].

3.5. Two-way interactions

Although the coefficient on the odds ratio is not statistically significant, marginal effects reveal meaningful differences in magnitude. Certification increases employment probability substantially more for females than males, with gains of approximately 9.7% for females compared to about 4.4% for males. This suggests that certification plays a more prominent role in improving employment outcomes among female graduates, indicating that although males generally have a higher probability of employment, the benefits of certification are particularly pronounced for females. These results suggest that vocational certification plays a significant role in increasing employment opportunities, particularly among females. Participation in job training programs has been shown to increase youth earnings and improve access to stable employment, with females benefiting more than males [42]. Furthermore, females receiving public assistance who participate in such training are significantly more likely to find employment and experience a significant 72% increase in personal income [43].

The interaction between certification and location is not statistically significant in odds ratio terms; however, marginal effects indicate that certification yields slightly larger employment gains in urban areas than in rural areas (3.5%), particularly among females. This suggests modest spatial heterogeneity in the returns to certification. Vocational education in rural areas frequently encompasses specialized training programs that are aligned with the specific industries and needs of the local economy. This targeted approach has the potential to enhance the employability of vocational graduates within the rural job market. Vocational schools in rural areas, for instance, may concentrate on agribusiness or other local industries, equipping graduates with pertinent skills [44].

The interaction between gender and location is statistically significant at the 10% confidence level with a 0.709 odds ratio, especially for males, who are weaker in urban areas. The gender gap in employment probability is substantially larger in rural areas (approximately 12.5%) than in urban areas (around 3.9%) compared to the baseline group. This indicates that gender disparities in employment outcomes vary across geographic areas. Marginal effects show that the gender gap is much larger in rural areas than in urban areas, suggesting that location moderates gender-based differences in employment opportunities. Females from culturally and linguistically diverse backgrounds face significant challenges in obtaining meaningful employment due to a lack of skill development and discrimination [45][46]. Conversely, in urban labor markets, the male employment advantage appears to diminish, possibly due to higher competition [47] and distinct skill requirements [41]. These factors may be the reason why the odds ratio of urban males and females is not significant compared to that of rural females.

3.6. Three-way interactions

The estimated three-way interaction term is not statistically significant, indicating that there is no strong evidence that the joint effect of certification, gender, and location differs systematically beyond the lower-order interaction effects. However, the marginal effects indicate that rural individuals with certification in the males group exhibit the highest predicted probability of employment (62.04%), compared to 45.22% for the baseline category. Certification is positively associated with employment across all groups. For example, among female individuals in rural areas, certification increases the probability of employment by approximately 9.7%. Gender differences are also evident, as male individuals demonstrate higher employment probabilities than their counterparts, particularly in rural areas. Since females in rural areas have difficulty finding regular work even when their educational attainment level is

controlled [48]. The current study also finds that certification is associated with positive employment gains across both urban and rural labour markets. In rural areas, these gains may partly reflect government-targeted vocational programmes designed to improve vocational education quality [44].

3.7. Robustness Check

Given the complexity of the interaction structure in the model, it is important to assess whether the estimated effects are sensitive to model specification. In particular, models that include higher-order interactions may capture heterogeneous patterns but can also introduce instability and overfitting, especially in the presence of limited observations within subgroups. Therefore, comparing a simpler model containing only main effects with the full interaction model provides a useful robustness check. This comparison allows us to evaluate whether the key findings, particularly the role of certification, are consistent and not driven solely by the inclusion of higher-order interaction terms. By examining the stability of coefficients across these specifications, we can ensure that our conclusions reflect underlying structural relationships rather than model-specific artifacts. Robustness checks

Table 7. Model's Robustness Check

	Main Effect		Full Interaction	
	Odds Ratio	P> z	Odds Ratio	P> z
Work				
Certificate=1	1.449*** (0.0955)	0.000	1.604*** (0.181)	0.000
Gender=1	1.051 (0.118)	0.658	1.284 (0.234)	0.170
Urb_Rural=1	1.070 (0.0821)	0.381	1.206* (0.131)	0.085
Observations	3382		3382	

Exponentiated coefficients; Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Source: authors' analysis

comparing a baseline model with only main effects and a full model including interaction terms indicate that the core findings are stable across specifications. In particular, the positive effect of certification on employment remains statistically significant and becomes slightly stronger in the full model (44.9% to 60.4%), suggesting that certification consistently increases employment odds even after accounting for heterogeneity across groups. The effect of gender remains statistically insignificant in both specifications; however, the reduction in the p-value and increase in magnitude in the full model suggest that gender differences may exist but are not sufficiently strong to yield robust statistical evidence. Similarly, the main effect of location is not statistically significant in the baseline model but becomes marginally significant when interaction terms are included. This indicates that spatial differences in employment outcomes are not driven by direct effects alone but are instead shaped by interactions with other characteristics such as certification and gender. While the inclusion of interaction terms slightly modifies the magnitude of some coefficients, most higher-order interaction effects remain statistically insignificant, suggesting limited evidence of strong heterogeneous effects across subgroups. Overall, these results demonstrate that the primary conclusions are not driven by model specification and remain robust to the inclusion of higher-order interactions.

4. Conclusion

This study provides empirical evidence on the relationship between training certification and employment outcomes among recent vocational education graduates in Indonesia using nationally representative repeated cross-sectional

data from 2018 to 2023 and a three-way interaction logistic regression model. The findings indicate that certification is positively associated with employment outcomes, although its effects vary across demographic and spatial groups. The marginal effects analysis suggests that certification generates larger employment gains among female graduates, while differences across locations are more context-dependent and influenced by local labor-market conditions. The results are broadly consistent with signaling theory, indicating that training certificates serve as observable indicators of job readiness in labor markets characterized by information asymmetry. By explicitly modeling the interaction among certification status, gender, and location, this study contributes to the literature on early labor-market transitions by highlighting heterogeneous employment outcomes rather than average effects alone. In addition, the analysis shows that the employment returns to certification were not constant over time and weakened during the peak of the COVID-19 pandemic, underscoring the importance of broader economic conditions in shaping labor-market opportunities. Several limitations should be acknowledged, including constraints associated with survey design, limited occupational detail, and the disruptive effects of the pandemic period. Nevertheless, the findings provide robust evidence to support more targeted workforce development policies and suggest avenues for future research on the longer-term impacts of certification on career trajectories and labor-market mobility.

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