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Impact of Educational Mismatch on Graduates Employment Prospects in Indonesia: Education and Employment Context

Sri Maryanti[A], Nasri Bachtiar[B], Sri Maryati[C], Dodi Novianto[D]

Abstract

The research analyzes the mismatch between education and job prospects for graduates in the context of education and employment policies in Indonesia, which is caused by the high level of mismatch between university graduates and labor market needs. Data shows that vertical mismatch reached 53.33% and horizontal mismatch 60.52% in 2019, increasing to 55.2% in 2020, then dropping to 40% in 2021, and 33.50% in 2022 experienced horizontal mismatch, and 40% in 2023 experienced mismatch. This phenomenon indicates the low level of graduate integration with the formal labor market and impacts labor productivity, unemployment, job opportunities, wages, job satisfaction, graduate career mobility, and work motivation. The novelty of this research lies in the analysis of both economic and non-economic aspects of educational mismatch, aiming to provide a comprehensive and relevant perspective on education and employment issues. The methods used are applied logistic regression and OLS with samples aged 18-65 years from the National Labor Force Survey. Independent variables: vertical/horizontal mismatch, education, work experience, age, and gender. Dependent variables: employment status, income, and job satisfaction. The results show that education, gender, and age significantly affect vertical mismatch; education, gender, and work experience affect horizontal mismatch. Education and work experience affect income. Vertical and horizontal mismatches affect job satisfaction. This study assists policymakers in aligning labor market needs with the graduates produced, addressing the gap between graduate expectations and reality.

Keywords: *Mismatch Education, College Graduates, Job Satisfaction, Employment Status, Income.*

INTRODUCTION

Education is an important element in improving human resources for sustainable development (Blasques et al., 2021). Easy access to education can improve skills, abilities, productivity, and economic welfare in society (Mitra, 2019; CGD, 2002). As times change, there is a

[A]*Department of Economics, Faculty of Economics and Business, Universitas Lancang Kuning, Pekanbaru, Indonesia, Email: sri_maryanti@unilak.ac.id*
[B]*Department of Economics Faculty of Economics and Business, Andalas University, Padang, Indonesia, Email: nasri@eb.unand.ac.id*
[C]*Department of Economics Faculty of Economics and Business, Andalas University, Padang, Indonesia, Email: srie_jayamahe@yahoo.co.id*
[D]*Department of Mathematics and Data Science, Andalas University, Padang, Indonesia, Email: ddevianto@sci.unand.ac.id*

mismatch between education and employment, or educational mismatch, both vertical and horizontal, which has a significant impact on employment prospects, worker welfare, and economic productivity (Hwang, 2017;Cassidy et al., 2020). Vertical mismatch occurs because the level of education does not match the requirements needed by companies, while horizontal mismatch occurs because the field of study is not relevant to the job obtained (Salas-Velasco, 2021). This phenomenon is increasing in line with rapid industrial and technological changes (Rikala et al., 2024). This condition can be seen from the number of graduates produced that does not match the needs of the job market.

Data from the OECD shows that 30% of OECD member countries face educational issues. Education plays a role in human resource development and is one of the sustainable development goals (Blasques et al., 2021). Easy access to education can facilitate improvements in skills, capabilities, productivity, and the economic prosperity of society (Mitra, 2019; CGD, 2002). In this regard, a new challenge has emerged in Indonesia, namely the mismatch between education and the job market. This mismatch, both vertical and horizontal, has a significant impact on employment opportunities, workers' welfare, and overall economic productivit (Hwang, 2017;Cassidy et al., 2020). The experience of vertical mismatch reaches 40%, and horizontal mismatch also reaches 40%. Fields of study that have difficulty in finding employment in Indonesia include science, technology, engineering, and mathematics (Rachel, 2024). In Spain, a higher rate of mismatch is experienced by graduates in social humanities, while medical and engineering graduates do not experience mismatch (Cortadas-Guasch, 2024). According to Morejón Cabrera & Mariel, (2024)), a master's degree can reduce vertical mismatch. Furthermore, an increase in the number of master's degrees in certain fields, such as health, can reduce horizontal mismatch.

The phenomenon occurring in Indonesia, according to a report from the Demographic Institute of the University of Indonesia (LD-UI), is that in 2019, there was a vertical mismatch of 53.33% and a horizontal mismatch of 60.52%. This research shows that 44.8% work in accordance with their competencies, while 35.48% work below their competencies. This problem is exacerbated by the high levels of informality and an increasing number of graduates not matched by job growth (Prayudhani, 2020). According to the World Bank in 2021, 40% of university graduates in Indonesia work in positions that do not match their qualifications. In 2022, around 33.50% of the Indonesian workforce experienced a horizontal mismatch, while 66.50% worked in fields related to their studies (Yonanda & Usman, 2023). Indonesia's Central Statistics Agency (BPS) stated that in 2023, around 40% of university graduates worked in fields unrelated to their degrees. This percentage increased from 2019, when 25.79% of Indonesian workers were considered overeducated and 17.98% were undereducated. The Ministry of Education and Culture of the Republic of Indonesia mentioned that 80% of university graduates work in fields unrelated to their educational background. This means there is a gap between graduates' expectations and the realities of the labor market, reflecting the low level of integration between graduates and the formal workforce. To address this issue, the Indonesian government has implemented curriculum improvements, vocational training, and the Merdeka Belajar Kampus Merdeka (MBKM) program. However, this mismatch remains a major challenge that causes inefficiency among the educated workforce.

The mismatch between education and employment is caused by difficulties in adjusting admission quotas in higher education institutions, as well as a lack of labor market information at the higher education level (Joseph, 2020). The underutilization of skilled labor has resulted in higher rates of skilled unemployment. This has an impact on the long-term mismatch between the workforce and the job market (Ghaffarzadegan et al., 2017). The mismatch between education and the job market affects future employment prospects because it is closely related to the duration of unemployment (Cassidy et al., 2020). This topic is very important because it has a negative effect on wages and is positively correlated with wage inequality (Di Pietro & Urwin, 2006; Tang & Wang, 2021). Horizontal mismatch (skills not matching jobs) has a negative impact on wages, while vertical mismatch (education not matching jobs) has a positive impact on wages for workers with insufficient or excessive education (Wincenciak, 2023). Mismatch has a significant positive (negative) impact of overeducation on labor productivity (Mahy et al., 2015). This creates income differences between college graduates with specialized skills and those without (Nordin et al., 2010). Previous empirical studies have been widely discussed in the international literature. Most focus on the impact of educational mismatch on unemployment, income/wages, job satisfaction, and career mobility. According to Béduwé & Giret, (2011) vertical mismatch has a strong negative impact on wages, while horizontal mismatch can increase job dissatisfaction and the desire to seek other jobs. According to Sukanti & Sulistyaningrum, (2022b) ; Sitorus & Wicaksono, (2020)) wages have a negative impact on overeducated workers and a positive impact on undereducated workers. Wage mismatch is higher when workers' education is more specific (Schweri et al., 2020).

Mismatches in the labor market have a significant impact on the economy. Mahuteau et al., (2014). stated that vertical mismatches tend to reduce hourly wages, while horizontal mismatches have the potential to erode aggregate income. The alignment of education and employment is positively correlated with wage increases (Allen & Van Der Velden, 2001; Huertas & Raymond, 2024a). However, wage disparities arise due to mismatch which is exacerbated by weak government governance (Tran et al., 2019). A very dominant phenomenon can be seen from the comparison of migrant and local workers Sitorus & Wicaksono, (2022) found that local workers earn lower wages than migrant workers because they are overeducated.

Based on labor absorption, unemployment traps and employment affects can occur if there is persistent educational incompatibility (Esposito & Scicchitano, 2019;2022; Pompei, 2019). This condition is caused by the irrelevance of skills to the needs of the industry (Adely et al., 2021), so job seekers postpone working until they get a position that is considered better than before (Banerjee & Sequeira, 2023). Rogers, (1997) and (Rose & Ordine, 2010) added that universities have a role in determining the length of the waiting period to get a job, therefore universities should ideally have access to information related to the world of work.

The suitability of education can guarantee job seekers to obtain optimal income (Bol et al., (2019). The fluctuations in income earned by overeducated workers are twice as large as those of undereducated workers (Yunisvita, 2020). Indicating a vulnerability in income due to this inconsistency (Chaudhry et al., 2022; X. Li & Lu, 2023). This condition not only has an impact on individual workers but can also hinder the economic development of developing countries (Didier, 2024).

From a financial aspect, it is evident that educational incompatibility, both vertically and horizontally, can reduce job satisfaction if it takes place consistently (Varshavskaya & Podverbnykh, 2023). The impact of ineffectiveness in the use of skills in the workplace can reduce job satisfaction Béduwé & Giret, (2011b).

One of the obstacles to workers' career mobility is that it is difficult for workers to rotate in work due to educational incompatibilities (Albert et al., 2023). On the contrary, the economic condition of workers has improved because their career mobility has increased due to the suitability of the education of the workers (Wen & Maani, 2019). However, there are still many college graduates who have to accept jobs below their qualifications with lower wages than unemployed (Roller et al., 2019).

The lack of research that highlights the perspective of education and employment policies in developing countries, especially in Indonesia, makes it an opportunity for this study to analyze it, because previously the research that was conducted was only limited to non-conformity that had an impact on micro variables such as wages, satisfaction, and motivation (Huertas & Raymond, 2024a; Montt, 2017; Prayudhani, 2020; Sukanti & Sulistyaningrum, 2022a: Rudakov et al., 2019; Veselinović et al., 2020). On average, research related to this inconsistency focuses on developed countries, while the role of labor market institutions and policies in developing countries such as Indonesia has not been explored in depth. In fact, policy interventions such as apprenticeships are considered potential to address this problem (Verhaest et al., 2017; Albert & Davia, 2022; Flisi et al., 2017) Therefore, this study aims to explore the relationship between educational incompatibility and job prospects within the framework of national policies.

The urgency of this study is that the increasing number of job seekers in Indonesia is not The urgency of this study is that the increasing number of job seekers in Indonesia is not proportional to the available jobs, so this is a very complex problem for education in Indonesia. Because what needs to be worried is the diminishing interest of the younger generation to continue education to a higher level because of the long-term implications that are caused, such as educated unemployment, low career mobility, to wage inequality and a decrease in national productivity (Sun et al., 2023; Ordine & Rose, 2015; Mcgowan & Andrews, 2015). Through this study, which uses a logistics management approach using employment data (Sakernas), it can unravel the mismatch between education and employment that occurs in Indonesia by using variables of employment status, income, gender, and work experience.

This research was conducted to fill the gap between academia and the job market by offering a comprehensive analysis that goes beyond the economic aspect, namely by integrating the dimensions of education and employment policies. The novelty of the research lies in the effort to predict the future policy direction of the Indonesian government based on the measurement of the chances of inconsistency that occurs. Through this approach, it is hoped that strategic and practical policy recommendations will be born to minimize mismatches and increase the integration of university graduates into the competitive labor market.

LITERATURE REVIEW

Human Capital

The development of individual skills can be obtained from investment in education, because this is the basis for the development of a country (Hanushek, 2013; Becker, 1993; L. Li, 2014). However, the rate of return on investment in education cannot be directly felt for individuals because higher education investment is volatile (Blagg & Blom, 2018). High education inequality results in a decrease in the rate of return on investment, which means that there is an inefficiency in resource allocation (Mugijayani, 2020; Murillo et al., 2012), in the long term will have an impact on a decrease in income (Takeuchi, 2023a).

Educational Mismatch Theory

Educational mismatches are caused by disparities in individuals' perceptions of the value of education (Cervantes & Cooper, 2022a) as well as misalignment between worker competencies and job requirements (Jacobs & Rycx, 2021; L. P. Shi & Wang, 2022). These mismatches are divided into two: vertical mismatches (skill levels) that can affect income variables to health disparities (Somers et al., 2019b; Zheng et al., 2024), and horizontal discrepancies (relevance of field of study) that impact wages, worker productivity, increasing educated unemployment (Montt, 2017a; L., & W. X. Shi, 2022; Robst, 2007). This discrepancy does not only show the existence of a surplus of graduates but also shows the condition of overeducation and undereducation in the labor market (Ordine & Rose, 2017).

Labor Market Outcomes and Educational Mismatch

The mismatch in education leads to low wages received by workers, as well as decreased job satisfaction and job stability due to inappropriate assignments and training provided as a result of inequality in skill demand, as has happened massively in China (Chen et al., 2024; Jiang

& Guo, 2022; Cervantes & Cooper, 2022b). In developing countries, highly educated graduates are vulnerable to unemployment and the pitfalls of the informal sector, where improving the quality of education has not been able to effectively prevent wage downward trends (Banerjee & Sequeira, 2023; Homs & Marcos, 2018; Esposito & Scicchitano, 2022). Nonetheless, the prestige of an educational institution can serve as a buffer that protects graduates from wage depreciation during economic shocks (Lee, 2024).

The Role of Government Policy in Reducing Educational Mismatch

The synergy between government policies with industry and universities on global dynamics is a solution for the effectiveness of handling educational inconsistencies (Cuesta et al., 2024; Ma & Yang, 2024; Lesjak, 2024). An education system that transforms in a way that balances between theoretical and practical is a way out to overcome market uncertainty, this effort can be made with the integration of the integration of specific technical training and real work experience during the study period (Alqahtani et al., 2024; Anas et al., 2023; Wu, 2011; Peng et al., 2024; Smith & Weiler, 2023)). If the domestic ecosystem is not yet able to absorb these competencies, international labor migration becomes a logical alternative for overeducated graduates to actualize their skills (Ghosh & Grassi, 2020).

METHODS

The analysis used quantitative methods with analytical tools, namely logistic regression and OLS regression. The data source is from the August 2022 Indonesian National Labor Force Survey (Sakernas), which covers the demographic characteristics of each individual, education level, field of study, employment status, and other demographic characteristics. The sample consists of college graduates or those who have completed higher education (diploma, bachelor's, or postgraduate) aged 18–65 years. The aim is to analyze vertical and horizontal inconsistencies and their impact on work outcomes. Separate analyses are conducted for diploma, bachelor's, and postgraduate levels of education, with the aim of determining the impact of inconsistencies between these levels of education.

The dependent variables are (employment status, income, job satisfaction). The employment status variable uses binary data, where 1 means employed and 0 means unemployed. The income variable is the income received each month (in rupiah). The job satisfaction variable is used as a proxy with Principal Component Analysis (PCA) using the job mobility proxy variable, with category 1 meaning not looking for another job and 0 meaning looking for another job. Independent variables: vertical mismatch, horizontal mismatch, education level, work experience, age, and gender. The vertical mismatch variable is analyzed by comparing education levels with the educational requirements needed in the job market. The vertical mismatch variable is binary data categorized as matching = 1 and not matching = 0. The horizontal mismatch variable is detected by comparing the field of study after completing education with their field of work. The horizontal mismatch variable uses binary data with the categories match = 1 and mismatch = 0. The level of education is categorical data consisting of diploma, bachelor's degree, and postgraduate degree. Work experience is measured based on the number of years of work experience. Age is measured based on the individual's age in years. Gender is binary data with the category's male = 1 and female = 0.

To see the impact of each independent variable on the dependent variable, a mapping of mismatches was conducted based on study program, type of work, level of education completed, educational surplus, and educational deficit. The aim is to identify mismatches in Indonesia under several conditions so that government policies can be carefully prepared. This was done using Stata, which grouped vertical and horizontal mismatches based on the above categories.

To analyze the impact of educational mismatches on job prospects for higher education graduates in Indonesia. An analysis was carried out for each variable of mismatch on income, job status, and job satisfaction. Here are some equations to analyze the mismatch of education with job prospects in the context of education and employment policies.

1. Income analysis of vertical mismatch, education level, gender, age and experience

$$\text{Income} = \beta_0 + \beta_1 \text{Mismatch Vertical}_i + \beta_2 \mathit{Education}_i + \beta_3 \text{Sex}_i + \beta_4 \text{Age}_i + \beta_5 \text{Experince}_i + \epsilon_i$$

2. Income analysis of vertical mismatch, education level, gender, age and experience

$$\text{Income} = \beta_0 + \beta_1 \text{Mismatch Horizontal}_i + \beta_2 \mathit{Education}_i + \beta_3 \text{Sex}_i + \beta_4 \text{Age}_i + \beta_5 \text{Experince}_i + \epsilon_i$$

3. Analysis of income based on field of study, occupation, level of education, experience, age and gender

$$\text{Income} = \beta_0 + \beta_1 \text{Field of Study}_i + \beta_2 \mathit{Occupation}_i + \beta_3 \text{Education}_i + \beta_4 \text{Experince}_i + \beta_5 \text{Age}_i + \beta_6 \text{Sex}_i + \epsilon_i$$

4. Analysis of employment status regarding vertical mismatch, level of education, experience, age and gender

$$\text{Employment Status} = \beta_0 + \beta_1 \text{Mismatch Vertical}_i + \beta_2 \mathit{Education}_i + \beta_3 \text{Experience}_i + \beta_4 \text{Age}_i + \beta_5 \text{Sex}_i + \epsilon_i$$

5. Analysis of employment status regarding field of study, occupation, education level, experience, age and gender

$$\text{Employment Status} = \beta_0 + \beta_1 \text{Field of Study}_i + \beta_2 \mathit{Occupation}_i + \beta_3 \text{Education}_i + \beta_4 \text{Experience}_i + \beta_5 \text{Age}_i + \beta_6 \text{Sex}_i + \epsilon_i$$

6. Analysis of job satisfaction regarding overeducation, undereducation, level of education, experience, age and gender.

$$\text{Job satisfaction} = \beta_0 + \beta_1 \mathit{Overeducation}_i + \beta_2 \mathit{Undereducation}_i + \beta_3 \mathit{Education}_i + \beta_4 \text{Experience}_i + \beta_5 \text{Age}_i + \beta_6 \text{Sex}_i + \epsilon_i$$

7. Analysis of job satisfaction regarding field of study, job, education level, experience, age and gender

$$\text{Job Satisfaction} = \beta_0 + \beta_1 \mathit{Field\ of\ Study}_i + \beta_2 \text{Occupation} + \beta_3 \mathit{Education}_i + \beta_4 \text{Experience}_i + \beta_5 \text{Age}_i + \beta_6 \text{Sex}_i + \epsilon_i$$

RESULTS AND DISCUSSION

Income Analysis on Vertical Mismatch, Education Level, Gender, Age And Experience

Figure 1 shows the odds ratio (95% confidence interval) of the revenue logistics model. Once the control variable is entered, the vertical mismatch is not noticeably significant. In contrast, the pattern suggests that experience and education are positively correlated with high-income opportunities, while age groups are negatively correlated. The results table shows the details of the coefficient.

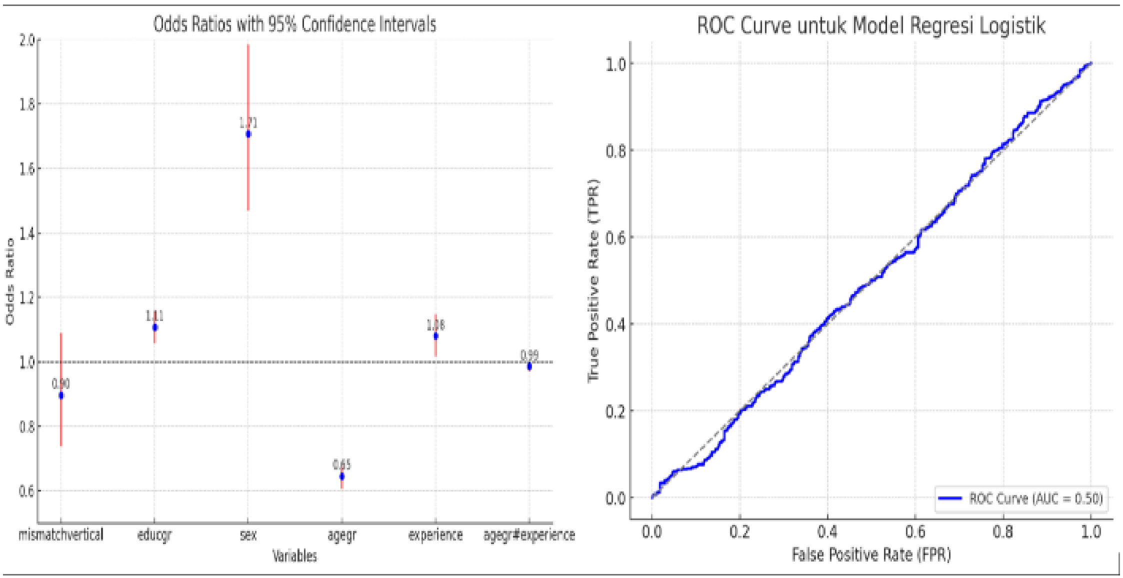

Figure 1. Revenue Visualization Graph Analysis of Vertical Mismatch, Education Level, Experience, and Age

Source: Processed Data

In this study, a total of 48,844 observations were used. LR chi2(5) = 574.43, Prob > chi2 = 0.0000: The model as a whole is significant, showing that there is an influence of at least one of the independent variables on income. Pseudo R2 = 0.0651: This shows that this model explains about 6.51% variation in revenue. Vertical Mismatch: An odds ratio of 0.902, insignificant (p = 0.300), indicating that there is no significant effect of vertical mismatch on revenue. Education (educgr): An odds ratio of 1.110, significant (p < 0.001), indicates that higher education increases income opportunities. Sex: The odds ratio was 1.706, significant (p < 0.001), indicating that gender had a significant effect on income. Age Group (agegr): Odds ratio of 0.627, significant (p < 0.001), indicating that older people tend to have lower income opportunities. Experience: An odds ratio of 1,026, significant (p = 0.010), indicates that more work experience is positively correlated with income. Constant (_cons): An odds ratio of 73.056, significant (p < 0.001), indicates the baseline odds when all independent variables are zero.

The Model Fit Test (Hosmer-Lemeshow Test) can be seen from the value of Chi2(8) = 10.78, Prob > chi2 = 0.2147: A p-value above 0.05 indicates that your logistic regression model matches the existing data. This means that there is not enough evidence to reject the null hypothesis that the model is appropriate. R-squared = 0.2440: Approximately 24.4% of the variation in the dependent variable (vertical mismatch) can be explained by this model. This shows that there is room for improvement in the model. Coef. (Coefficient) where educgr: Negative coefficient (-0.05799) indicates that improved education is associated with a decrease in vertical mismatch, which is statistically significant (p < 0.001). sex: A positive coefficient (0.02646) indicates that gender has a positive significant effect (p < 0.001).agegr: A positive coefficient (0.04519) indicates that increasing age is also positively associated with vertical mismatch (p < 0.001). experience: A negative coefficient (-0.0002825) indicates that work experience is negatively associated with vertical mismatch, but not significant ($p = 0.072$). Multicollinearity Test (VIF) with Mean VIF = 1.07: All VIF values below 10 indicate no serious problems with multicollinearity among independent variables. This shows that the variables in the model are not excessively correlated with each other. The conclusion of this analysis is that this logistic regression model shows that education, gender, and age have a significant effect on vertical mismatch, while work experience does not show a significant effect. The model also fits into existing data, without significant multicollinearity issues.

Similar research was also produced by Adjei & Boateng (2023) mentioned that gender, marital status, education, skills, occupation, and time were significant determinants of education-employment mismatch in urban Ghana. According to Addison et al., (2020) who researches on middle-aged workers, especially those with higher education, while Shin & Bills, (2021) Examining the workforce in the United States with different time periods, both studies concluded that education, gender, and age significantly affected vertical mismatch. (Toscano & Meroni, 2020) Researching across generations and countries that education, gender and age have an effect on vertical mismatch. Previous research that obtained the same results was also conducted by (Esposito, 2020; Hartato Hartato, 2022; Leandro & Hernán, 2016; María del Mar Salinas Jiménez, 2013; Pholphirul, 2017; Takeuchi, 2023b; Bingqiang Li et al., 2024).

In this study, work experience did not have a significant effect on vertical mismatch. This is reinforced by research conducted by Catherine Béduwé & Jean-François Giret, (2011) mention Work experience does not significantly affect vertical mismatch among graduates. Pala, (2015) Work experience may not significantly affect this type of vertical mismatch. Robert, (2014) The work experience accumulated during the study did not significantly affect the vertical mismatch. Rofiq, (2020) This study shows that the experience of industry practices shows a lack of impact on vertical mismatches. Salas-Velasco, (2021) lack of work experience among recent graduates contributes to vertical mismatch but does not apply to graduates who have completed their studies in college. Sana Sellami, (2017) The analysis showed that work experience did not significantly affect vertical mismatch, as the outcome for the interaction effect between mismatch and work experience was not statistically significant. Suwarsito Suwarsito, (2023) Work experience was found to have a lack of influence on vertical mismatch, especially for teacher performance.

Income Analysis of Horizontal Mismatch, Education Level, Experience and Age

Figure 2 shows the robustness check, with a horizontal non-conformance indicator. While the horizontal mismatch did not show a convincing influence, the direction of the main effect (education/positive experience, negative age) remained consistent. These findings are mainly associative, as the ability to explain the model is still limited, as shown by the distribution and residue panels.

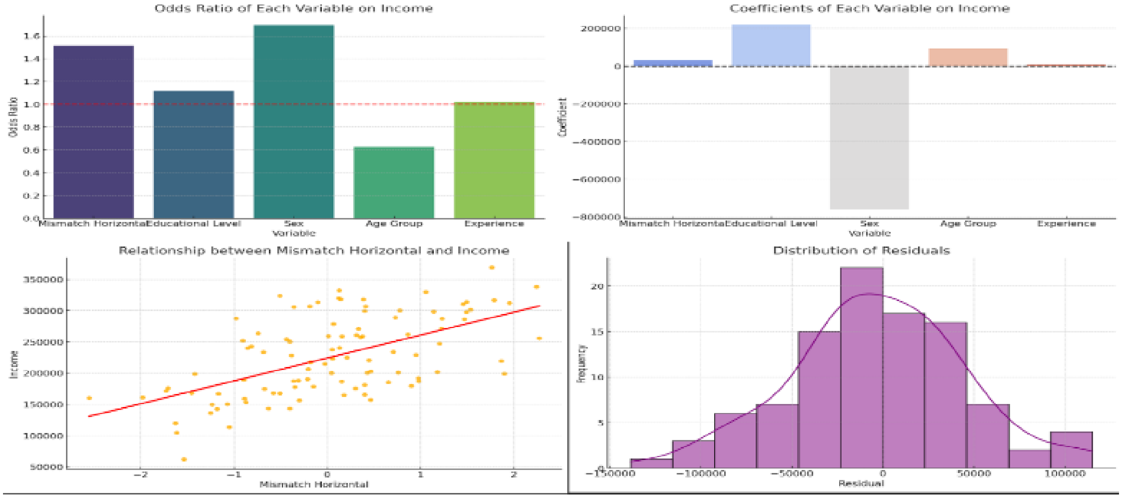

Figure 2. Graph Visualization Revenue Analysis Against Horizontal Mismatch, Education Level,Experience, and Age
Source: Processed Data

Number of obs: This model uses 48,844 observations. LR chi2(5) = 575.58, Prob > chi2 = 0.0000: The model as a whole is significant, showing that at least one independent variable has an effect on income. Pseudo R2 = 0.0652: This model explains about 6.52% variation in revenue. Horizontal Mismatch: Odds ratio of 1.516, insignificant (p = 0.162), indicating that there is no significant effect of horizontal mismatch on revenue. Education (educgr): Odds ratio 1.118, significant (p < 0.001), indicating higher education increases income opportunities. Sex: Odds ratio of 1.695, significant (p < 0.001), indicates that gender has a significant effect on income. Age Group (agegr): Odds ratio 0.627, significant (p < 0.001), indicating that older age is negatively correlated with income. Experience: Odds ratio of 1.026, significant (p = 0.010), indicates that work experience is positively correlated with income. Constant (_cons): Odds ratio 69.905, significant (p < 0.001), indicates the baseline odds when all independent variables are zero.

Model Fit Test (Hosmer-Lemeshow Test) with a value of Chi2(8) = 13.40, Prob > chi2 = 0.0987: A p-value above 0.05 indicates that the model matches the data. Where Model F(5, 48838) = 646.43, Prob > F = 0.0000: The model is significant, showing that independent variables have an effect on revenue. R-squared = 0.0621: This model accounts for about 6.21% variation in revenue. Regression Coefficient: Horizontal Mismatch: The coefficient is 30,900.57, insignificant (p = 0.509), indicating that the type of mismatch has no significant effect on revenue. Education (educgr): The coefficient of 220,547.90, significant (p < 0.001), shows that education has a significant positive effect on income. Sex: Coefficient -758,485.60, significant (p < 0.001), indicating that gender has a negative effect on income. Age Group (agegr): A coefficient of 92,402.30, significant (p < 0.001), indicating that age is positively related to income. Experience: Coefficient 8,602.37, significant (p < 0.001), indicating positive experience related to income. The Multicollinearity

Test (VIF) shows a Mean VIF value = 1.08: All VIF values below 10 indicate there are no serious problems with multicollinearity among the independent variables. In conclusion, the logistic regression model shows that education, gender, age, and experience have a significant influence on income, while the horizontal mismatch does not show a significant influence. The linear regression model also confirms that education and experience affect income, with results varying for education majors and job types.

This finding is in line with the results of research conducted by Takeuchi, (2023b) that horizontal mismatch is more common among female employees. Research conducted by Tran et al., (2023) Generating a horizontal mismatch has an impact on graduates resulting in the alignment between education and job type is critical for optimal income. According to Alzubaidi, (2022) that the horizontal mismatch among graduates in Saudi is significantly influenced by education level, field of study, type of contract, and work experience, but gender and age. Education, gender, age, and experience significantly affected income, while subjective and objective horizontal mismatches showed little or insignificant wage effects, especially in fixed-effect estimates (Schweri et al., 2020). According to Tang & Wang, (2021); Jacobs & Rycx, (2021) that education, gender, age, and experience significantly affected income, whereas horizontal mismatch did not show a significant impact on income levels. Research conducted by Lu & Li, (2021) mentioned that the horizontal mismatch did not show a significant effect on income among highly educated workers. (K. Park & Arce, 2020) Horizontal mismatches do not significantly affect revenue. Other research such as those conducted by Hoffmann, (2019); Jacobs & Rycx, (2021); MNF Waseema, (2022); Quang & Nam, (2019) also obtained the same results as this study.

Number of obs: This model uses 48,844 observations. LR chi2(5) = 575.58, Prob > chi2 = 0.0000: The model as a whole is significant, showing that at least one independent variable has an effect on income. Pseudo R2 = 0.0652: This model explains about 6.52% variation in revenue. Horizontal Mismatch: Odds ratio of 1.516, insignificant (p = 0.162), indicating that there is no significant effect of horizontal mismatch on revenue. Education (educgr): Odds ratio 1.118, significant (p < 0.001), indicating higher education increases income opportunities. Sex: Odds ratio of 1.695, significant (p < 0.001), indicates that gender has a significant effect on income. Age Group (agegr): Odds ratio 0.627, significant (p < 0.001), indicating that older age is negatively correlated with income. Experience: Odds ratio of 1.026, significant (p = 0.010), indicates that work experience is positively correlated with income. Constant (_cons): Odds ratio 69.905, significant (p < 0.001), indicates the baseline odds when all independent variables are zero.

Model Fit Test (Hosmer-Lemeshow Test) with a value of Chi2(8) = 13.40, Prob > chi2 = 0.0987: A p-value above 0.05 indicates that the model matches the data. Where Model F(5, 48838) = 646.43, Prob > F = 0.0000: The model is significant, showing that independent variables have an effect on revenue. R-squared = 0.0621: This model accounts for about 6.21% variation in revenue. Regression Coefficient: Horizontal Mismatch: The coefficient is 30,900.57, insignificant ($p = 0.509$), indicating that the type of mismatch has no significant effect on revenue. Education (educgr): The coefficient of 220,547.90, significant ($p < 0.001$), shows that education has a significant positive effect on income. Sex: Coefficient -758,485.60, significant ($p < 0.001$), indicating that gender has a negative effect on income. Age Group (agegr): A coefficient of 92,402.30, significant ($p < 0.001$), indicating that age is positively related to income. Experience: Coefficient 8,602.37, significant ($p < 0.001$), indicating positive experience related to income. The Multicollinearity Test (VIF) shows a Mean VIF value = 1.08: All VIF values below 10 indicate there are no serious problems with multicollinearity among the independent variables. In conclusion, the logistic regression model shows that education, gender, age, and experience have a significant influence on income, while the horizontal mismatch does not show a significant influence. The linear regression model also confirms that education and experience affect income, with results varying for education majors and job types.

This finding is in line with the results of research conducted by Takeuchi, (2023b) that horizontal mismatch is more common among female employees. Research conducted by Tran et al., (2023) Generating a horizontal mismatch has an impact on graduates resulting in the alignment between education and job type is critical for optimal income. According to Alzubaidi, (2022) that the horizontal mismatch among graduates in Saudi is significantly influenced by education level, field of study, type of contract, and work experience, but gender and age. Education, gender, age, and experience significantly affected income, while subjective and objective horizontal mismatches showed little or insignificant wage effects, especially in fixed-effect estimates (Schweri et al., 2020). According to Tang & Wang, (2021); Jacobs & Rycx, (2021) that education, gender, age, and experience significantly affected income, whereas horizontal mismatch did not show a significant impact on income levels. Research conducted by Lu & Li, (2021) mentioned that the horizontal mismatch did not show a significant effect on income among highly educated workers. (K. Park & Arce, 2020) Horizontal mismatches do not significantly affect revenue. Other research such as those conducted by Hoffmann, (2019); Jacobs & Rycx, (2021); MNF Waseema, (2022); Quang & Nam, (2019) also obtained the same results as this study.

Income Analysis Based on Field of Study, Occupation, Education Level, Experience, Age and Gender

Figure 3 shows the requirements that add to the field of study and work. Education and experience, age, and gender remained positive, but contributions to fields of study and employment were relatively limited after controls were included. The table shows a similar pattern for logit and OLS estimates.

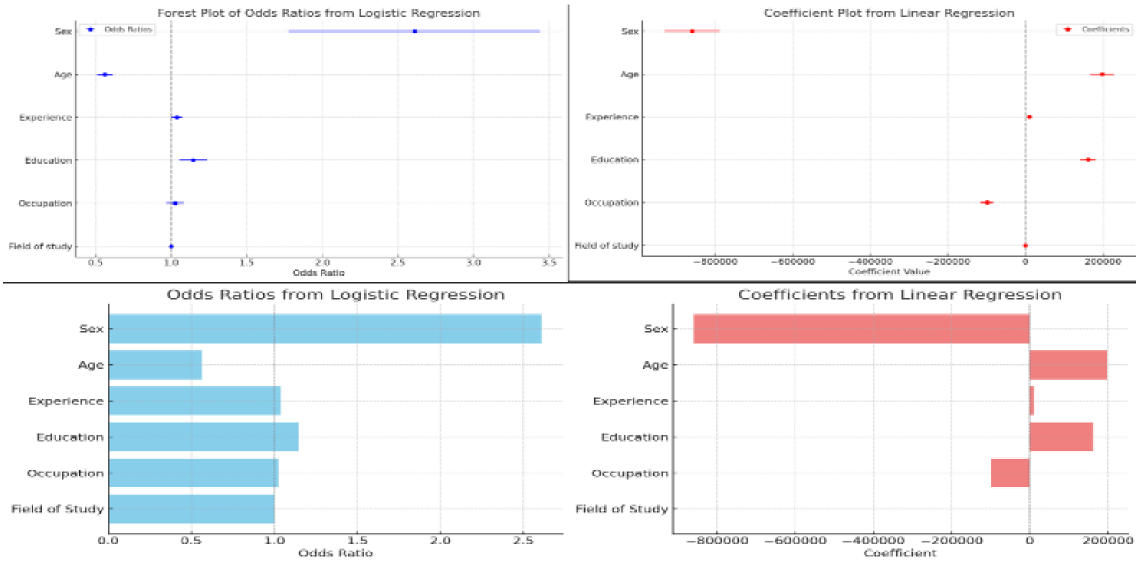

Figure 3. Visualization of Income Graph Analysis Against Field of Study, Occupation, Education Level, Experience, Age and Gender

Source: Processed Data

Number of obs: The model uses 25,425 observations. LR chi2(6) = 242.53, Prob > chi2 = 0.0000: The model is significant overall, showing that at least one independent variable has an effect on income. Pseudo R2 = 0.0803: About 8.03% variation in revenue can be explained by this model. From the value of the Odds Ratio, the Department of Education was obtained: Odds ratio of 0.9997, insignificant (p = 0.251), indicating that the Department of Education did not have a significant effect on income. Occupation: Odds ratio of 1.025, insignificant (p = 0.391), indicates that the type of occupation has no significant effect. Education (educgr): Odds ratio of 1.145, significant (p < 0.001), indicates that higher education is positively related to income. Experience: Odds ratio of 1.038, significant (p = 0.042), indicates that positive work experience is related to income. Age Group (agegr): Odds ratio 0.562, significant (p < 0.001), indicating that older age is negatively correlated with income. Sex: Odds ratio of 2.610, significant (p < 0.001), indicates that gender has a significant effect on income. Constant (_cons): Odds ratio 43.878, significant (p < 0.001), indicates the baseline odds when all independent variables are zero.

For the Model Fit Test (Hosmer-Lemeshow Test), the value of Chi2(8) = 4.16, Prob > chi2 = 0.8427: A p-value above 0.05 indicates that the model matches the data. Linear Regression Value with Model F(6, 25418) = 209.33, Prob > F = 0.0000: The model is significant, showing that independent variables have an effect on income. R-squared = 0.0471: This model accounts for about 4.71% variation in earnings. Regression coefficient obtained by the Department of Education: Coefficient -245.45, significant (p = 0.022), indicating that the type of education major has a negative effect on income. Occupation: Coefficient -99,336.08, significant (p < 0.001), indicating that the type of occupation has a significant negative effect. Education (educgr): The coefficient of 161,303.50, significant (p < 0.001), shows that education has a significant positive effect on income. Experience: Coefficient 10,022.17, significant (p <

0.001), indicating positive experience related to income. Age Group (agegr): A coefficient of 197,608.70, significant ($p < 0.001$), indicating that older age is positively correlated with income. Sex: Coefficient -860,084.70, significant ($p < 0.001$), indicating that gender has a negative effect on income. The Multicollinearity Test (VIF) obtained a Mean value of VIF = 1.15: All VIF values below 10 indicate that there are no serious problems with multicollinearity among the independent variables. The logistic regression model shows that education, gender, age, and experience have a significant influence on income, while education majors and job types are not significant. The linear regression model also confirms that education, experience, and age affect income, with results varying for education majors and job types. The results of the above research are also strengthened by previous research with the same findings, such as those conducted by Bo Cheng, (2023); Polo & Kantola, (2019); Silva Sousa et al., (2019) mentioned that education, gender, age, and experience significantly affected income, while education majors and job types did not show a significant impact.

Analysis of Employment Status for Vertical Mismatch, Level of Education, Experience, Age and Gender

Vertical Mismatch: Odds Ratio: 0.796 indicates that the odds for the job status variable decrease by about 20.4% when a vertical mismatch occurs. The z-value: -6.00 and the p-value 0.000, indicate significant results. This means that vertical mismatches have a significant negative effect on job status (stats). Education Level (educgr): Odds Ratio: 0.947, indicating that increasing education level slightly reduces the chance of employment status (stat). A z-value: -8.53 with a p-value of 0.000 indicates that this result is very significant. This means that the higher the level of education, the lower the chance of employment status (stat). Experience: with an Odds Ratio value: 1.0005, indicating that work experience has no significant influence on employment status (stat). The z-value: 0.34 and the p-value 0.735, indicate that this result is not significant. Gender with an Odds Ratio of 1.37, indicates that gender significantly affects the chances of employment status (stat). This means that certain genders have a higher chance of employment status (stat). A z-value: 14.10 with a p-value of 0.000 indicates that this effect is very significant. Age group (agegr) with an Odds Ratio value: 1,285, shows that with age, the chance of occurrence of employment status (stat) increases. z-value: 28.31 with a p-value of 0.000, indicating a very significant result. The constant (_cons) with the Odds Ratio value: 0.0857, indicates the baseline odds of the model for the job status variable (stat). Significant with a p-value of 0.000.

The Linear Regression analysis obtained an R-squared value of 0.0236 showing that the model was only able to explain about 2.36% of the variation in the dependent variable of occupational status. This shows that the model is not very robust in predicting or explaining job status variables. From this analysis, the value of Vertical Mismatch: Negative coefficient (-0.0313) indicates that the vertical mismatch decreases the value of job status (stat). Education Level (educgr): A negative coefficient (-0.0075) indicates that the higher the education, the lower the employment status value (stat). Experience: Insignificant, coefficient close to zero. Gender: Positive coefficient (0.0448), indicating gender affects significantly. Age (age): A positive coefficient (0.0371) indicates that age contributes positively to the occupational status variable (stat). The Multicollinearity Test (estat vif) where the VIF value ranges from 1.00 to 1.35, shows that there are no serious multicollinearity problems between variables. These values indicate that the independent variables are not very correlated with each other. The conclusion of this analysis is that vertical mismatch and education have a significant negative effect on employment status. Gender and age were significantly positively related to occupational status (stat). Work experience is not significant in affecting job status. The model as a whole showed agreement with the data based on R-squared values and goodness-of-fit test results.

This finding is in line with the results of research conducted by Takeuchi, (2023b); Zheng et al., (2024) with the finding that vertical mismatch occurs when an individual's level of education is not aligned with the requirements of the job, resulting in lower income and psychological distress. Persistent vertical mismatches are associated with poorer mental health outcomes, suggesting that mismatches affect not only financial stability but also overall well-being (Zheng et al., 2024). Gender plays an important role, with research showing that female employees often experience horizontal mismatches more often, which can exacerbate income penalties (Takeuchi, 2023a). Age is positively related to employment status, suggesting that older individuals may have more stable jobs due to accumulated experience and networking. Work experience does not significantly affect job status, suggesting that other factors, such as education and gender, may be more important in determining job placement (Adjei & Boateng, 2023). Research that obtained similar results was also conducted by (Assunção et al., 2020; Huertas & Raymond, 2024b; X. Li & Lu, 2022; Lu & Li, 2021; L. P. Shi & Wang, 2022) that vertical mismatch and education negatively impact employment status, while gender and age positively affect it. Work experience does not significantly affect job status.

Analysis of Employment Status Regarding Field of Study, Occupation, Education Level, Experience, Age and Gender

From Logistic Regression with the number of observations: 29,074 observations, where the value of LR chi2(6) = 1032.47, Prob > chi2 = 0.0000: The model as a whole is significant, indicating that at least one independent variable has an effect on the employment status. Log likelihood = -11854.668: This value is used to calculate the probability of the model. Pseudo R2 = 0.0417: This model describes about 4.17% variation in job status (stat). From the value of the Odds Ratio, the Department of Education was obtained: Odds ratio 0.999998, insignificant (p = 0.983), indicating that the Department of Education did not have a significant effect on the status. Occupation: Odds ratio of 0.986, close to significant ($p = 0.085$), indicates that the type of occupation has a negative effect on status. Education (educgr): Odds ratio 0.890, significant ($p < 0.001$), indicating that higher education is negatively related to employment status. Experience: Odds ratio of 0.995, significant ($p = 0.037$), indicating that work experience has a negative effect on job status (stata). Age Group (agegr): Odds ratio of 1.505, significant ($p < 0.001$), indicates that older age groups have a greater chance of achieving higher employment status (stat). Sex: Odds ratio 1.364, significant ($p < 0.001$), indicating that gender has a positive effect on job status (stat).

The Model Fit Test (Hosmer-Lemeshow Test) obtained a value of Chi2(8) = 199.91, Prob > chi2 = 0.0000: A p-value below 0.05 indicates that the model does not match the data. The Linear Regression value obtained is Model F (6, 29067) = 192.83, Prob > F = 0.0000: The model is significant, showing that the independent variable has an effect on the employment status (stat). R-squared = 0.0383: This model accounts for about 3.83% variation in job status (stat). Regression coefficient of the Department of Education: Coefficient 9.66^{10-07}, insignificant ($p = 0.941$), indicating that the Department of Education has no significant effect. Occupation: Coefficient -0.00187, close to significant ($p = 0.076$), indicating that the type of occupation has a negative effect. Education (educgr): Coefficient -0.01483, significant ($p < 0.001$), indicating that education has a negative effect on employment status. Experience: Coefficient -0.00056, significant ($p = 0.034$), indicating negative experience related to employment status. Age Group (agegr): A coefficient of 0.05936, significant ($p < 0.001$), suggests that older age is positively correlated with employment status. Sex: Coefficient 0.03919, significant ($p < 0.001$), indicating that gender has a positive effect on job status (stat). Multicollinearity Test Value (VIF)Mean VIF = 1.14: All VIF values below 10 indicate no serious problems with multicollinearity among independent variables. In conclusion, the logistic regression model showed that education, gender, and age had a significant influence on employment status (stat), while education majors and job types did not show a strong influence. The results of linear regression confirm the influence of education and age on employment status, with results varying for job types. Research shows that higher levels of education correlate with better job outcomes, and age plays an important role in job stability.

This research is also reinforced by studies that have been conducted, where higher education levels are associated with a lower risk of unemployment and better job security (Zamrik et al., 2021). Individuals with lower educational attainment face a higher risk of work-related health problems, which can affect employment status (Möllestam et al., 2021). Gender differences manifest in work outcomes, with women often facing more barriers in the workplace. Women with lower levels of education are at higher risk of developing problems that can hinder work (Ocaña et al., 2021). According to Case et al., (2021) Age is an important factor, with older individuals often experiencing greater challenges in maintaining a job. Younger workers may have more flexibility in the type of work but face instability in the job compared to older coworkers. Conversely, while education and age significantly affect employment status, the type of occupation and education major may not be as important, suggesting that broader socioeconomic factors play a more substantive role in employment dynamics. The results of the study from Yang, (2018) mentioned that education majors that have the opportunity to cause unemployment can be overcome by continuing education to a higher level.

Analysis of Job Satisfaction on Overeducation, Undereducation, Education Level, Experience, Age and Gender

Number of obs: The model used 57,896 observations. LR chi2(6) = 1364.12, Prob > chi2 = 0.0000: The model as a whole is significant, showing that at least one independent variable has an effect on job satisfaction (stat). Log likelihood = -25999.559: This value is used to calculate the probability of the model. Pseudo R2 = 0.0256: This model accounts for about 2.56% variation in job satisfaction (stat). From the Odds Ratio value: the value of Vertical Mismatch: Odds ratio 0.802, significant ($p < 0.001$), shows that the existence of vertical mismatch is negatively related to job satisfaction (stat). Horizontal Mismatch: Odds ratio 0.755, significant ($p < 0.001$), indicating that the existence of a horizontal mismatch is also negatively related to job satisfaction (stat). Education (educgr): Odds ratio 0.951, significant ($p < 0.001$), indicating that higher education is negatively related to job satisfaction (stat). Experience: Odds ratio of 1,000, insignificant ($p = 0.744$), indicates that work experience has no significant effect on job satisfaction (stat). Age Group (agegr): Odds ratio of 1.280, significant ($p < 0.001$), indicates that older age groups have a greater chance of achieving higher job satisfaction (stat). Sex: Odds ratio 1.371, significant ($p < 0.001$), indicating that gender has a positive effect on status.

The Model Fit Test (Hosmer-Lemeshow Test) obtained a value of hi2(8) = 316.75, Prob > chi2 = 0.0000: A p-value below 0.05 indicates that the model does not match the data. Where the value of Linear Regression with Model F (6, 57889) = 235.76, Prob > F = 0.0000: Significant model, shows that independent variables have an effect on job satisfaction (stat). R-squared = 0.0239: This model accounts for about 2.39% variation in job satisfaction (stat). Vertical Mismatch Regression Coefficient Value: The coefficient -0.0306, significant ($p < 0.001$), indicates that vertical mismatch has a negative effect on job satisfaction (stat). Horizontal Mismatch: The coefficient of -0.0273, significant ($p < 0.001$), indicates that the horizontal mismatch has a negative effect on job satisfaction (stat). Education (educgr): Coefficient -0.0070, significant ($p < 0.001$), indicating that education has a negative effect on job satisfaction (stat). Experience: The coefficient of 0.0000697, insignificant ($p = 0.733$), indicates that work experience has no significant effect. Age Group (agegr): Coefficient 0.0594, significant ($p < 0.001$), indicating that older age is positively correlated with job satisfaction (stat). Sex: Coefficient 0.0392, significant ($p < 0.001$), indicating that gender has a positive effect on job satisfaction (stat). For the Multicollinearity Test (VIF) obtained a Mean value of VIF = 1.14: All VIF values below 10 indicate that there are no serious problems with multicollinearity among the independent variables. In conclusion, the logistic regression model shows that both vertical and horizontal mismatches, education, gender, and age have a significant influence on job satisfaction (stat), while work experience does not show a significant influence.

The influence of vertical and horizontal mismatches, along with demographic factors such as education, gender, and age, significantly impacted job satisfaction, while work experience seemed to have a negligible effect. This conclusion is supported by various studies namely vertical mismatch: Over-education is associated with lower job satisfaction, as seen in Cambodian university graduates, where mismatch leads to counterproductive behaviors such as absenteeism (Sam, 2020). The effect of mismatch on job satisfaction can be seen from vertical and horizontal mismatches, where these two mismatches affect job satisfaction. For example, educational mismatch is linked to lower levels of job satisfaction, especially among young employees in Korea, where lifelong learning can reduce the effects ofi (K. H. Park & Luo, 2023). Gender and age: Studies show that demographic diversity, including gender and age, significantly affects job satisfaction, especially in educational settings (K.Sumithra, 2024; Rokeman et al., 2024; Takeuchi, 2023b). Work experience: In contrast to other factors, work experience did not show a significant correlation with job satisfaction, suggesting that other elements may play a more critical role (K.Sumithra, 2024; Rokeman et al., 2024). While educational mismatches and demographic factors are essential for job satisfaction, it is important to consider that individual preferences and competencies can also shape these outcomes, indicating a more nuanced understanding of the dynamics of job satisfaction. According to Ngigi & Kipkebut, (2014) Education is a significant factor that affects job satisfaction.

Analysis of Job Satisfaction with the Field of Study, Occupation, Education Level, Experience, Age and Gender

From the results of Logistic Regression with the Number of Observations (Number of obs) 29,074 observations. LR chi2(6) = 1032.47, Prob > chi2 = 0.0000: The model as a whole is significant, showing that at least one independent variable has an effect on job satisfaction (stat). Log likelihood = -11854.668: This value indicates how well the model predicted the data. Pseudo R2 = 0.0417: This model accounts for about 4.17% variation in job satisfaction (stat). Odds Ratio for Education Major: Odds ratio 0.999998, insignificant ($p = 0.983$), indicating that education majors do not have a significant effect on job satisfaction (stat). Occupation: Odds ratio of 0.986, close to significant ($p = 0.085$), indicates that occupation has a negative effect on job satisfaction (stat). Education (educgr): Odds ratio 0.890, significant ($p < 0.001$), indicating that higher education is negatively related to job satisfaction (stat). Experience: Odds ratio of 0.995, significant ($p = 0.037$), indicating that work experience has a negative effect on job satisfaction (stat). Age Group (agegr): Odds ratio of 1.280, significant ($p < 0.001$), indicates that older age groups have a greater chance of achieving higher job satisfaction (stat). Sex: Odds ratio 1.364, significant ($p < 0.001$), indicating that gender has a positive effect on job satisfaction (stat).

The Model Fit Test (Hosmer-Lemeshow Test) obtained a value of Chi2(8) = 199.91, Prob > chi2 = 0.0000: A p-value below 0.05 indicates that the model does not match the data. Model Linear Regression Value F(6, 29067) = 192.83, Prob > F = 0.0000: The model is significant, showing that independent variables have an effect on job satisfaction (stat). R-squared = 0.0383: This model accounts for about 3.83% variation in job satisfaction (stat). With the Regression Coefficient for the variable of the Department of Education: Coefficient 9.66e-07, insignificant ($p = 0.941$), indicating that the Department of Education has no significant effect on job satisfaction (stat). Occupation: Coefficient -0.00187, close to significant ($p = 0.076$), indicating that occupation has a negative effect on job satisfaction (stat). Education (educgr): The coefficient of -0.01483, significant ($p < 0.001$), indicates that education has a negative effect on job satisfaction (stat). Experience: Coefficient -0.00056, significant ($p = 0.034$), indicating that experience has a negative effect on job satisfaction (stat). Age Group (agegr): Coefficient 0.05936, significant ($p < 0.001$), indicating that older age is positively correlated with job satisfaction (stat). Sex: Coefficient 0.03919, significant ($p < 0.001$), indicating that gender has a positive effect on job satisfaction (stat). With the Multicolinarity Test (VIF), a Mean VIF value = 1.14 was obtained: All VIF values below 10 indicate that there is no serious problem with multicollinearity among the independent variables. In conclusion, the logistic regression model shows that education, gender, and age have a significant influence on job satisfaction (stat), while education and employment majors do not show a strong influence. Results from linear regression confirm that education and age have an effect on job satisfaction (stat), with results varying for job types.

Job satisfaction was significantly influenced by education, gender, and age, while education majors and job types showed a smaller impact. Research shows that higher education levels generally correlate with increased job satisfaction, although this relationship can vary based on job characteristics and individual perceptions of job suitability. As seen in the study (Furnham & Cheng, 2024) where the education achieved by adults significantly predicted job satisfaction outcomes. Gender differences also play a role, with male employees generally reporting higher satisfaction than women (Watkins, 2024) . Age presents a more complex relationship; While younger employees tend to express higher job satisfaction, older employees may experience a decrease in satisfaction levels (K.Sumithra, 2024; Watkins, 2024). Higher educational attainment is associated with increased job satisfaction, where adult-attained education mediates the effects of childhood intelligence on job satisfaction (Furnham & Cheng, 2024). According to (Polo & Kantola, 2019) Higher education levels often correlate with increased job satisfaction due to better job opportunities and higher earning potential. Educational attainment can improve skills and competencies, leading to greater job fulfillment (Maraldi et al., 2020).

CONCLUSIONS

In this study, we found and analyzed the impact of educational mismatch on the job opportunities of university graduates in Indonesia. This study focuses on educational mismatch (vertical mismatch and horizontal mismatch). These findings show that between income and vertical mismatch, education level, gender, age and experience show that education, gender and age have a significant effect on vertical mismatch, while work experience does not show a significant effect. Meanwhile, income is a horizontal mismatch, level of education, experience, and age. showed that education, gender, age, and experience had a significant influence on income, while the horizontal mismatch did not show a significant influence. In a linear regression model also education and experience affect income, with results varying for education majors and job types.

In the analysis of income against the field of study, occupation, education level, experience, age and gender. showed that education, gender, age, and experience had a significant influence on income, while education majors and job types were not significant. In this linear regression model it is shown that education, experience, and age affect income, with results varying for education majors and job types. For employment status against vertical mismatch, education level, experience, age and gender. It shows that vertical mismatch and education have a significant negative effect on employment status. Gender and age were significantly positively related to occupational status (stat). Work experience is not significant in affecting job status. Meanwhile, the influence of occupational status on the field of study, occupation, level of education, experience, age and gender shows that education, gender, and age have a significant influence on occupational status (stat), while education majors and job types do not show a strong influence. The results of linear regression confirm the influence of education and age on employment status, with results varying for job types. Research shows that higher levels of education correlate with better job outcomes, and age plays an important role in job stability.

The variables of job satisfaction on overeducation, undereducation, education level, experience, age and gender were obtained that both vertical and horizontal mismatch, education, gender, and age had a significant influence on job satisfaction (stat), while work experience did not show a significant influence. Meanwhile, the effect of job satisfaction on the field of study, occupation, level of education, experience, age and gender shows that education, gender, and age have a significant influence on job satisfaction (stat), while the education and employment department does not show a strong influence. The results of linear regression confirm that education and age have an effect on job satisfaction (stat), with results varying for job types.

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