Digital technology and job quality: multidimensional insights from the labor market in East Java

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DOI: 10.22437/ppd.v14i1.45877	Received: 21.06.2025	Revised: 28.04.2026	Accepted: 29.04.2026	Published: 30.04.2026

Abstract

Digital technology transformation has a significant impact on labor market dynamics, both in terms of job quantity and quality. This study aims to analyze the extent to which digital technology influences workers' job quality in East Java Province using a multidimensional approach. The measurement method used in this study is the Job Quality Index (JQI) developed by the World Bank, which assesses four dimensions of job quality: income, security, benefits, and job satisfaction. This study uses 2023 *Sakernas* data, comprising 39,425 observations. The analytical method employed is binary logistic regression. Robustness tests across various model specifications are conducted to ensure the stability of the results. The findings show that using digital technology increases the likelihood of achieving better job quality by up to 2.3 times compared to non-users. Other individual characteristics, such as education, training, gender, and age, also positively influence workers' job quality. Conversely, participation in the Pre-Employment Card (*Prakerja*) Program and living in urban areas are found to have negative effects. This study highlights the importance of digital literacy and inclusion, as well as human capital investment through education and competency-based training aligned with labor market needs.

Keywords: *Digital technology; Human capital; Job quality index; Labor market*

JEL Classification: J24, J28, J81, J83

INTRODUCTION

Digital technology transformation has significantly changed the way human life is conducted. This technological disruption has not only reshaped the structure of economies and labor markets but also transformed work processes and professional relationships. The World Development Report (World Bank, 2019) states that digital technology provides new opportunities, improves productivity, and creates numerous jobs. In Indonesia, internet penetration has continued to rise, indicating growing public acceptance of digital technology. Data from the Indonesian Internet Service Providers Association (Asosiasi Penyelenggara Jasa Internet Indonesia, or APJII) show that in 2023, Indonesia's internet penetration reached 78.19% and has consistently increased over previous years (APJII, 2023). Alongside the growth in internet users, the digital economy in Indonesia has also expanded. In 2019, gig economy workers in Indonesia were estimated to reach 2.3 million, primarily in online transportation and other service sectors (Permana et al., 2023). However, the Central Bureau of Statistics (Badan Pusat Statistik, or BPS) reports that up to 60.12% of the national labor force is employed in the informal sector (BPS, 2023). These conditions indicate that although digital technology offers new opportunities, challenges related to job quality—such as income security, the absence of employment contracts, and inadequate social protection—remain. These phenomena highlight the urgency of assessing how digital technology influences not only the quantity but also the quality of jobs, particularly in regions such as East Java Province, which makes a significant economic contribution, has diverse characteristics, and has a large labor force.

In the context of the labor market, attention is no longer focused solely on how many jobs are available but also on the quality of those jobs. Decent work is not only about the level of wages received but also encompasses broader issues such as social protection and the fulfillment of workers' rights (ILO, 2013). The ILO, through the Decent Work Agenda, emphasizes that everyone should have access to decent work—not only in terms of income but also in a more humane sense, referring to work that respects the dignity and human rights of every individual (BPS, 2024). This perspective aligns with global commitments under the Sustainable Development Goals (SDGs), particularly Goal 8, which promotes inclusive economic growth, the expansion of productive employment opportunities, and the realization of decent work for all without exception.

As the concept of decent work evolves, it is essential to recognize the growing influence of digital technology in shaping both employment opportunities and job quality. In this context, Human Capital Theory becomes increasingly relevant, as digitalization requires workers to continuously improve their skills and adapt to change. The ability to use digital technology can now be considered part of human capital accumulation itself (Becker, 1962; Fleischhauer, 2007). Thus, according to this theory, workers with digital competencies are more likely to earn higher incomes and secure better-quality jobs.

This theory can be enriched through the Capability Approach, developed by Amartya Sen, which views human well-being beyond income or resources by focusing on individuals' real capabilities to pursue valued ways of living. This approach places human development at the core of the analysis and offers a more comprehensive understanding of well-being (Wasito, 2023). From this perspective, decent work should not only provide adequate income but also ensure a sense of security, social participation, and control over time (Brummund et al., 2018). While Human Capital Theory emphasizes the importance of investing in education and skills, including digital skills, as factors that increase productivity and economic opportunity, the Capability Approach goes a step further by questioning whether these resources can truly be converted into real well-being. Within this framework, digital skills are understood not only as tools for increasing productivity but also as factors that open broader opportunities for individuals in the labor market. Drawing on these perspectives, this study examines digitalization not only as a form of human capital investment but also as a factor that expands workers' capabilities to access better jobs.

By measuring job quality through a multidimensional index, this study moves beyond conventional wage-based assessments. It provides a more comprehensive understanding of how digital skills are translated into actual improvements in job conditions. In doing so, this study contributes to the literature by bridging the gap between skill formation and welfare realization and by providing a richer explanation of how digital transformation shapes job quality in developing regions.

Numerous studies have shown that the adoption of digital technology in the business sector has created new jobs, increased labor productivity, and encouraged wage growth (Atasoy & Pavlou, 2012; Cai et al., 2024; Dhyanasaridewi, 2020; Ghodsi et al., 2024; Luptáčik & Nežinský, 2026; Miho et al., 2023; Ningsih, 2024) and has even facilitated the transition to entrepreneurship (Fossen & Sorgner, 2018). Other studies (Berg et al., 2023; Piasna, 2024) show that digital technology can improve job quality by increasing skills, wages, and flexibility, but may also reduce it when not supported by adequate regulation and social protection. Several findings also indicate that the unequal adoption of digital technology has the potential to deepen inequalities in job quality, including income, security, and access to social protection (Cai et al., 2024; You et al., 2024).

Meanwhile, Heeks (2017) explains that platform workers in the gig economy are often classified as independent contractors, depriving them of access to labor rights, including social security and protection through formal employment contracts. In fact, many workers in the platform sector earn incomes below the minimum wage and face health risks due to the lack of social protection (Bajwa et al., 2018). This indicates that without adequate protection systems, the positive impact of digital technology may be uneven, especially in the informal sector. In East Java Province, only 379,364 of 7,130,059 informal sector workers are covered by social protection (Patoppoi, 2022). This suggests that, despite the potential of digital technology to improve job quality, significant inequalities in social protection persist, particularly among informal-sector workers in East Java Province.

Job quality measurement at the regional level, particularly in East Java Province, has yet to be conducted, leaving the impact of digital technology on job quality in this region unexplored. Informal sector workers dominate the labor market in East Java Province, and many lack employment contracts and access to social protection. This contributes not only to social inequality but also poses long-term risks to worker productivity, especially in sectors with low levels of human resources (Erumban, 2024; Royuela & Suriñach, 2013). Therefore, a multidimensional framework for measuring job quality, including indicators such as income, job security, social protection, and job satisfaction, is necessary. This approach is crucial for accurately determining the role of digital technology in accelerating inclusive and sustainable growth in East Java Province.

Despite a growing body of literature examining the relationship between digitalization and labor market outcomes, existing studies remain inconclusive regarding its implications for job quality. On the one hand, studies rooted in Human Capital Theory suggest that digitalization enhances productivity, wages, and access to better jobs through skill upgrading. On the other hand, emerging evidence from the platform economy literature highlights that digitalization may also intensify job insecurity and precarious employment. This divergence indicates that the relationship between digital technology and job quality is not linear but rather contingent on workers' ability to convert digital access and skills into meaningful labor-market outcomes.

Therefore, this study addresses this gap by examining the role of digital technology in shaping job quality using a multidimensional framework that integrates both monetary and non-monetary dimensions. By focusing on East Java Province as a case study, this research not only provides region-specific empirical evidence but also contributes to the broader debate by reconciling the dual perspectives of digitalization as both an opportunity and a potential source of risk for workers in the labor market. This multidimensional perspective is expected to offer the Government of East Java Province a holistic understanding of regional labor conditions and to provide an empirical foundation for formulating more responsive, inclusive, and sustainable labor policies.

METHODS

This study uses secondary data from the August 2023 National Labor Force Survey (*Sakernas*), published by the Central Bureau of Statistics (*Badan Pusat Statistik*, BPS). *Sakernas* is a nationally representative, routine survey that collects individual-level data on demographic characteristics, employment, income, education, and digital access across Indonesia. The survey employs stratified random sampling within census blocks to ensure both geographic and demographic representativeness. This study examines the relationship between independent variables and job quality outcomes using cross-sectional data. In this context, the term *influence* refers to a statistical association observed at a specific point in time. Given this focus, the use of cross-sectional data is considered appropriate and sufficient to address the research objectives, as such designs are well-suited to identifying relationships among variables when properly specified (Maier et al., 2023; Spector, 2019). The unit of analysis in this study is employed individuals in the labor force who have reported income data, with a specific focus on East Java Province. The final sample consists of 39,425 individual observations.

The dependent variable in this study is workers' job quality. Job quality is classified into two categories: good jobs and bad jobs. The measurement of job quality in this study employs the Job Quality Index (JQI) developed by the World Bank, based on the work of Brummund et al. (2018), which adopts the multidimensional poverty measurement framework proposed by Alkire and Foster (2011). In line with this method and considering data availability, this study uses four dimensions to measure the JQI: income, security, benefits, and job satisfaction.

The first dimension represents the monetary aspect and is used to assess whether a job provides adequate income for a decent standard of living. The remaining dimensions are non-monetary and capture aspects of job quality beyond income that contribute to workers' well-being. The second dimension is job security, assessed by the presence of a formal work contract lasting more than one year, reflecting protection against economic shocks. The third dimension is job benefits, which evaluate whether a job provides social protection, such as health insurance or pension benefits. The final dimension is job satisfaction, proxied by whether a worker holds only one main job. Table 1 presents an overview of each dimension and its corresponding indicators as applied in this study's JQI framework.

Table 1. JQI measurement dimensions

Dimension	Indicator
Income (JQI_{income})	The worker earns an income above the district/city minimum wage (UMK) where they are employed.
Security ($JQI_{security}$)	The job includes a formal contract with a duration of more than one year.
Benefit ($JQI_{benefit}$)	The worker receives health insurance or pension benefits.
Satisfaction ($JQI_{satisfaction}$)	The worker has only one main job.

The observational data used in this study include all members of the labor force with reported income information, as income is a prerequisite for JQI assessment.

Therefore, employed workers who do not report income are excluded from the analysis. The district/city minimum wage (UMK) is used as the minimum income threshold in this study, on the assumption that the UMK represents the minimum standard for a decent wage in the area, as set by the government. Each indicator within the JQI framework is treated as a binary outcome. Failure is assigned a score of 0, while success is assigned a score of 1.

The construction of the Job Quality Index (JQI) in this study follows the approach of Brummund et al. (2018) as a reference. That study used the poverty line as the threshold for determining income adequacy. In their approach, earning a wage above a minimum threshold is treated as a necessary condition for a job to be considered of acceptable quality. Specifically, if a worker's income falls below this threshold, the job is automatically classified as low quality, regardless of its non-monetary attributes.

Following this logic, this study adopts a similar approach by incorporating an income threshold as a binding constraint in constructing the Job Quality Index. However, since *Sakernas* does not include expenditure data, this study takes a slightly different approach by using the district/city minimum wage (UMK) as an alternative benchmark. The use of the UMK is consistent with policy-based definitions of a minimum decent living standard and serves as a relevant benchmark within the Indonesian labor market context. This adjustment ensures that the income dimension remains aligned with the conceptual framework of income adequacy used in prior studies, while maintaining empirical applicability given the available data.

Workers earning below the UMK are automatically classified as having poor job quality and assigned a JQI score of 0, based on the assumption that such jobs do not provide a decent standard of living. Thus, the non-monetary dimensions are considered insufficient to compensate for inadequate income in these cases. In other words, earning a decent income is treated as a necessary condition for high-quality jobs in this study. If an individual's income meets or exceeds the UMK threshold, the income dimension is assigned a score of 1, and the JQI is then calculated as the average of all dimensions. The final result of this measurement ranges from 0 to 1. After calculation, the JQI score is dichotomized. A job is considered a good job if the JQI ≥ 1/2, in which case *jqi_cat* is assigned a value of 1. Conversely, if the JQI < 1/2, jqi_cat is assigned a value of 0, indicating a poor-quality job.

The general JQI formula in this study is as follows:

$$JQI_i = \begin{cases} 0, & \text{if } JQI_{\text{income},i} = 0 \\ \frac{JQI_{\text{income},i} + JQI_{\text{security},i} + JQI_{\text{benefit},i} + JQI_{\text{satisfaction},i}}{4}, & \text{if } JQI_{\text{income},i} = 1 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots . (1)$$

$$jqi\_cat_i = \begin{cases} 0, & \text{if } JQI_i < \frac{1}{2} \\ 1, & \text{if } JQI_i \geq \frac{1}{2} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The main independent variable used in this study is digital technology. A potential concern related to this variable is endogeneity, as individuals who adopt digital technology may systematically differ from non-users in both observable and unobservable characteristics. To mitigate this concern and minimize potential bias, several control variables capturing observable individual characteristics are included in the analysis to account for individual-level differences, including educational background, training participation, age, gender, and place of residence. This approach helps reduce omitted variable bias to some extent, although it does not fully eliminate endogeneity arising from unobserved heterogeneity. It also helps reduce the likelihood that the observed relationship merely reflects pre-existing differences among respondents. Future research may address this limitation by employing more advanced identification strategies to better isolate the impact of digital technology on job quality.

Furthermore, robustness checks using alternative model specifications are conducted to assess the consistency of the results. The findings remain stable across models, indicating that the main results are not sensitive to model specification. Table 2 presents a detailed description of the independent and control variables.

The dependent variable in this study is dichotomous; therefore, binary logistic regression is used as the analytical model. Binary logistic regression can estimate the probability of an individual attaining good job quality based on a set of predictor variables. Estimation is performed using the Maximum Likelihood Estimation (MLE) method. Logistic regression is selected because it is well-suited for binary outcomes and produces odds ratios (ORs), which can be interpreted as relative probabilities.

Table 2. The definition of variables

Variable	Definition	Category
digital	Use of the internet and digital technology in job-related activities	0 = Does not use digital technology or the internet; 1 = Uses digital technology and the internet
education	Highest level of completed education	0 = Primary; 1 = Secondary; 2 = Tertiary
training	Participation in any training/course/workshop	0 = Did not participate; 1 = Participated
Prakerja (Pre-Employment Card Program)	Completion of the first training under the Pre-Employment Card Program	0 = Did not complete; 1 = Completed
age	Age of the worker	Continuous variable
gender	Gender of the respondent	0 = Female; 1 = Male
urban	Classification of place of residence	0 = Rural; 1 = Urban

The binary logistic regression model in this study is specified as follows:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 digital_i + \beta_2 education_i + \beta_3 training_i + \beta_4 prakerja_i + \beta_5 age_i + \beta_6 gender_i + \beta_7 urban_i + \varepsilon_i \quad \text{... (3)}$$

In this model, P_i denotes the probability that worker i has a good-quality job, and ε_i represents the error term. The coefficient of primary interest is β_1, which captures the association between digital technology use and the likelihood of attaining good job quality after accounting for individual-level characteristics.

RESULTS AND DISCUSSION

Results

The descriptive results provide an initial picture of job quality among workers in East Java Province. As shown in Table 3, the average JQI score is 0.39, which is below the good-job threshold of 0.5. This indicates that, on average, workers in East Java Province remain concentrated in low-quality jobs. Consistently, only 22.5% of workers are classified as having good jobs. Job satisfaction is the most fulfilled dimension, while job benefits are the least fulfilled, as illustrated in Figure 2. This pattern is consistent with Patoppoi (2022), who reports that only a small proportion of workers in East Java Province are covered by social protection. These findings suggest that although many workers report satisfaction with their jobs, most still lack employment contracts, social protection, and decent income, all of which contribute to the province's low job quality score.

Table 3. Variables descriptive statistics

Variable	Mean	St. Deviasi	Observation
jqi	0.3931769	0.2623335	39,425
jqi_cat	0.2253139	0.4177942	39,425
digital	0.5044769	0.4999863	39,425
education	0.7264172	0.661843	39,425
training	0.2045149	0.4033518	39,425
prakerja	0.020241	0.1408253	39,425
age	45.09451	14.26803	39,425
gender	0.6348763	0.4814709	39,425
urban	0.6745973	0.468531	39,425

The determinants of a good job are presented in Table 4. The use of digital technology, the main independent variable in this study, shows a statistically significant association with job quality. Other independent variables, representing individual characteristics, also show statistically significant associations with workers' likelihood of attaining good job quality.

Table 4. Good job determinants

Variabel	Coef	Odds ratio	P value
digital	0.8330534***	2.300332	0.000
education			
secondary	0.4924918***	1.636389	0.000
tertiary	1.631065***	5.109315	0.000
training	0.2267708***	1.254542	0.000
prakerja	-0.4898388***	0.6127252	0.000
age	0.8385277***	2.312959	0.000
gender	0.0150213***	1.015135	0.000
urban	-0.0743594**	0.928338	0.011
Binary Logistic Regression	Number of obs = 39,425 LR chi2(8) = 4445.42 Prob > chi2 = 0.000 Pseudo R^2 = 0.1057		

*Significance level *** 1%, ** 5%, * 10%*

Figure 2 also illustrates the dominant proportion of digital technology use across each dimension of job quality. In all dimensions, workers who use digital technology in their jobs experience greater benefits than those who do not. Overall, the results indicate that all independent variables in this model significantly affect workers' likelihood of attaining good job quality in East Java Province.

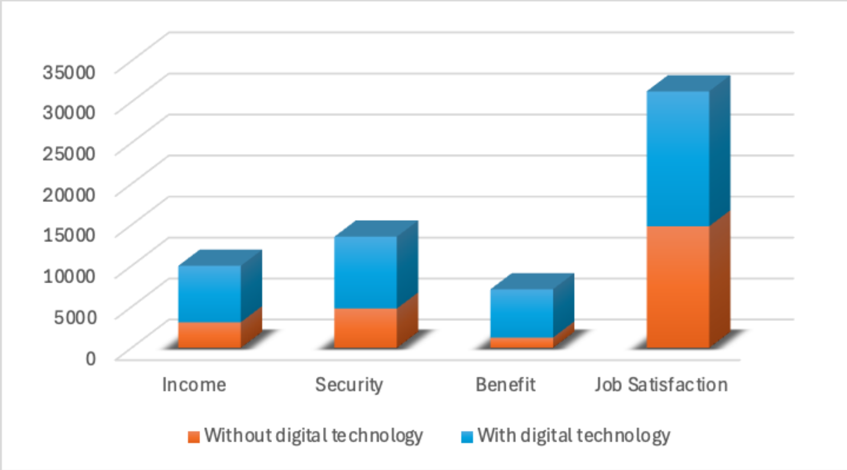

Figure 2. Job quality dimension distribution based on the use of digital technology

Table 5 presents the results of four alternative model specifications. *JQI_cat* represents the main model, a binary logistic regression, with the dependent variable a dichotomous job quality indicator. *JQI_R* uses linear regression with the Job Quality Index (JQI) ratio as the dependent variable, calculated as the proportion of fulfilled job quality dimensions for each individual. Meanwhile, *JQI > 1/2* and *JQI = 1* are binary logistic regression models applying stricter thresholds for good job quality (*JQI > 1/2*) and very good job quality (*JQI = 1*). The results show that the effects of the main explanatory variables remain relatively stable and statistically significant across all model specifications, indicating robust findings.

Table 5. Robustness tests on good job quality determinants

Variable	JQI_cat	JQI_R	JQI > 1/2	JQI = 1
digital	0.8330534***	0.0627764***	0.6620065***	1.028433***
education				
secondary	0.4924918***	0.0714011***	1.302409***	2.344857***
tertiary	1.631065***	0.267824***	2.627218***	3.959726***
training	0.2267708***	0.0467897***	0.5057438***	0.6121516***
prakerja	-0.4898388***	-0.0697752***	-0.6124505***	-0.759404***
age	0.8385277***	0.025261***	0.4777928***	0.4617354***
gender	0.0150213***	-0.0015185***	-0.0186691***	0.0071797***
urban	-0.0743594**	0.0492277***	0.4359581***	0.4740333***
Pseudo R^2	0.1057		0.2096	0.2559
Adj R^2		0.2283		
Observation	39,425	39,425	39,425	39,425

*Significance level *** 1%, ** 5%, * 10%*

The robustness test provides additional evidence on the stability of the relationship between digital technology use and job quality. Across model specifications, digital technology use consistently shows a positive and statistically significant coefficient at the 1% level. The magnitude of the coefficient varies across models. In the main model, the coefficient is 0.833, decreasing to 0.662 at the intermediate job-quality threshold and increasing to 1.028 at the stricter job-quality threshold.

Overall, the results from the binary logistic regression and robustness tests show that digital technology use is consistently positive and statistically significant across all model specifications. The coefficient is larger in the *JQI = 1* model, which represents the highest job-quality standard. Education, training, gender, and age are also positively associated with the likelihood of attaining better job quality. By contrast, completion of the first training in the Pre-Employment Card Program is negatively associated with good job quality across all models. Urban residence shows a negative association in the main model, although its direction varies across alternative specifications.

Discussion

The use of digital technology in the workplace, the main independent variable in this study, significantly increases workers' likelihood of attaining better jobs than those who do not use it. The estimation results show that workers who use digital technology are up to 2.3 times more likely to have better jobs than those who do not. This value should be understood as a relative likelihood between groups rather than a direct increase in probability, allowing baseline probability differences across groups to be properly accounted for. The pseudo R^2 value of around 0.10 cannot be interpreted in the same way as R^2 in linear regression, since the two measures are fundamentally different both conceptually and in terms of scale. As widely acknowledged in the empirical and methodological literature, pseudo R^2 values are generally lower by nature, and a relatively small value does not necessarily indicate that the model is inadequate or poorly specified. In the context of social science research using individual-level cross-sectional data, such a value is quite common and acceptable, given the inherent complexity of human behavior, which cannot be fully captured by the available variables alone. Moreover, the primary goal of this analysis is to identify statistically meaningful relationships rather than to maximize the predictive power of the model (Hu et al., 2006; Mittlböck & Schemper, 1996; Ozili, 2022; Veall & Zimmermann, 1996).

This finding aligns with previous studies showing a positive relationship between digital technology, internet use, and job quality (Cai et al., 2024; Shi, 2023; Xiong & Yu, 2024). Figure 2 also shows that digital workers receive greater benefits across all dimensions, including formal contracts, compared to non-digital workers. This indicates that workers with digital skills have better access to formal and more structured employment. This effect reflects the implication that digitalization in the formal sector provides workers with access to social protection, thereby improving job quality. This is also in line with Brummund et al. (2018), who state that formality is one of the key determinants of attaining better jobs.

From a human capital perspective, digital technology operates through a skill-enhancement mechanism: the use of digital tools facilitates the accumulation of human capital, particularly digital skills, thereby increasing worker productivity and their ability to access higher-quality jobs. Piasna (2024) finds a positive correlation between computer use and earnings, indicating that highly skilled workers are more likely to use technology than low-skilled workers, who tend to work in lower-paying elementary occupations. The use of digital technology also helps reduce gender gaps by providing greater access for women and people with disabilities to increase their income and improve their working conditions toward more decent work (Christensen et al., 2018; Pandey, 2024). These mechanisms are consistent with Human Capital Theory, which emphasizes skill accumulation as a driver of productivity, and are further enriched by the Capability Approach, which highlights the importance of converting workers' digital skills into real opportunities for achieving better job quality.

Control variables in this study represent individual characteristics. The analysis indicates that both education and participation in training increase workers' likelihood of obtaining high-quality jobs. Education has a positive effect on job quality, with higher education associated with greater chances of attaining better jobs. Workers with secondary education are 1.6 times more likely to have good jobs than those with only elementary education, which serves as the reference category for the education variable in this study. The effect is even stronger for workers with tertiary education, who are 5.1 times more likely to have good-quality jobs. A similar result is shown by the training participation variable, which increases workers' likelihood of accessing better job quality by up to 1.2 times. This finding implies that human resource competencies remain dominant factors influencing workers' job quality. Becker, as cited in Crespo et al. (2017), argues that the positive effect of education on worker productivity provides several advantages, such as access to higher income, better social protection, and a more favorable workplace environment. This finding is also consistent with previous studies that reinforce the importance of human capital (Brummund et al., 2018; Crespo et al., 2017; Hovhanniyan et al., 2024).

Other individual characteristics that enhance workers' chances of improving their job quality are gender and age. The analysis indicates that male workers are 2.3 times more likely than female workers to have good job quality. Although previous studies have noted that digital technology widens women's access to opportunities (Christensen et al., 2018; Pandey, 2024), this study's findings provide evidence that gender inequality persists in the labor market. Three main factors explain gender inequalities in access to good jobs: differences in productivity, preferences, and labor-market discrimination (Crespo et al., 2017). Becker, as cited in Crespo et al. (2017), highlights differences stemming from education before entering the labor market or from career interruptions due to motherhood.

Furthermore, Becker explains that lower productivity among women can also be caused by women's greater division of roles in household and domestic responsibilities, as well as prejudice-based discriminatory behavior by employers. In addition, women are less likely to choose competitive environments, thereby affecting their access to strategic positions in employment (Stier & Yaish, 2014). Meanwhile, age remains closely related to human capital, as workers gain more relevant experience and accumulate longer tenure. This has a positive impact on productivity, particularly since age is strongly related to work experience and seniority, both of which are known to be associated with job quality (Crespo et al., 2017).

An interesting finding from the analysis is that completing the first training in the Pre-Employment Card Program and living in urban areas decreases workers' likelihood of attaining good job quality. This result should be understood in the context that Pre-Employment Card Program participants are members of the labor force who are unemployed or vulnerable workers. It indicates that although they may have completed the first training in the program, most of them likely still lack sufficient competencies and skills to enter the formal sector. In addition, the positive impact of the Pre-Employment Card training program may materialize only in the long term, due to lagged effects that this study may not capture. Returns to human capital investment often emerge over a longer period, suggesting a lagged effect that is not fully captured in cross-sectional analysis. However, this also implies that short-term evaluations may underestimate the effectiveness of such programs.

On the other hand, studies by Andina (2022) and Nguyen et al. (2023) also highlight that regional governments have only limited involvement in supporting the implementation of the Pre-Employment Card training program, as well as a misalignment between training materials and labor market demand. The initial training provided in the *Kartu Prakerja* program may be too general or insufficiently aligned with labor market needs, resulting in limited improvements in workers' productivity and employability. This reflects a skill-mismatch problem, in which the competencies acquired do not align with the requirements of formal or higher-quality jobs. Consequently, participants, who are predominantly unemployed or vulnerable workers, may remain trapped in low-quality or informal employment despite having completed training.

Participation in training programs represents access to resources such as skills, knowledge, and certification, but it does not automatically guarantee the expansion of real opportunities. Structural constraints, such as limited access to formal jobs and weak institutional linkages, may hinder participants' ability to convert training into improved job quality. From the perspective of the Capability Approach, this result highlights the critical role of conversion factors in transforming resources into actual outcomes. Therefore, enhancing the effectiveness of the Pre-Employment Card Program depends not only on skill provision but also on the broader ecosystem that supports improvements in workers' job quality. Moreover, stronger synergy between the central and regional governments is needed. In addition, the training curriculum should be aligned with labor market demand so that the program can deliver greater long-term benefits to the workforce and sustain improvements in participants' employability.

The results of this study differ from those of previous studies, which found that living in an urban area increases the likelihood of achieving better job quality compared to living in a rural area (Hovhanniyan et al., 2024). However, urban areas offer a wide range of employment opportunities, from vulnerable informal-sector jobs to high-quality formal jobs. This study argues that the result reflects the dual structure of urban labor markets, where the coexistence of high-quality formal jobs and a large share of precarious informal or platform-based employment creates uneven outcomes across workers. This structure intensifies competition and unequal access to quality jobs, with many urban workers concentrated in low-wage, insecure positions lacking social protection (Ahmed & Nauriyal, 2024; Mehta & Awasthi, 2022). Urban advantages are also unevenly distributed, with vulnerable groups, including women, migrants, and residents of marginalized neighborhoods, more likely to be trapped in precarious work, thereby further reducing their chances of achieving good job quality (Gerber, 2022; Van Doorn & Vijay, 2021).

Another possible reason is the risk of mismatch that occurs in urban areas due to intense job competition (Putranto et al., 2024). This finding also shows that although urban areas offer broader job opportunities, intense competition often forces highly skilled workers to accept jobs that are misaligned with their qualifications, thereby reducing their likelihood of achieving high-quality jobs. This indicates that returns to skills are not solely determined by individual investment but are also shaped by labor market absorption capacity. Conversion constraints, such as competition, segmentation, and unequal access to stable employment, limit workers' ability to transform these opportunities into quality jobs.

However, living in an urban area shows different patterns depending on the model specification. Under stricter thresholds for good and very good job quality, living in an urban area appears to increase the likelihood of attaining good job quality compared to living in a rural area. This indicates that good and very good jobs are concentrated in urban areas, highlighting the dual nature of urban labor markets, which offer greater opportunities but also greater inequality in outcomes, depending on workers' skills and labor-market positioning. Consequently, urban labor markets exhibit a polarization effect, where one segment of workers benefits from high-quality employment while a larger share remains in low-quality or mismatched jobs.

The findings of this study demonstrate that digitalization plays an important role in improving job quality, particularly by increasing access to formal, better-structured employment, which in turn provides greater access to social protection and more stable working conditions. At the same time, the analysis reveals that the impact of digitalization is not uniform. This study shows that access to digital skills must be accompanied by the ability to convert them into real employment outcomes. The presence of skill mismatch, labor market segmentation, and structural constraints limits workers' ability to translate digital skills into better job quality. These findings suggest that the relationship between digitalization and job quality is shaped not only by individual skill accumulation but also by labor markets' and institutions' capacity to absorb and support those skills.

CONCLUSION AND RECOMMENDATIONS

Conclusion

Based on this study's results, digital technology emerges as a key determinant of improving workers' job quality in East Java Province. Workers who use digital technology tend to have better access to formal, more structured employment, which, in turn, increases their chances of attaining higher-quality jobs. In addition to digital technology, individual characteristics such as education and training remain important factors, reinforcing the role of human capital in shaping labor market outcomes. At the same time, the findings indicate that gender inequality persists, with male and older workers having relatively better chances of obtaining good-quality jobs.

This study also reveals that the impact of digitalization is not uniform across workers. Participation in the Pre-Employment Card Program is associated with a lower likelihood of attaining high-quality jobs, suggesting a potential mismatch between training content and labor market demand. Similarly, living in urban areas does not automatically guarantee better job quality, as high competition and labor market segmentation may limit access to quality employment. However, under stricter job quality criteria, high-quality jobs tend to be more concentrated in urban areas, reflecting the dual structure of urban labor markets.

Overall, this study contributes to the literature by providing a multidimensional perspective on job quality that integrates both monetary and non-monetary aspects, while highlighting the role of digital technology not only as a productivity-enhancing factor but also as a mechanism that shapes workers' access to better employment conditions. These findings suggest that improving job quality requires not only expanding digital access but also strengthening the capacity of workers and labor market institutions to translate digitalization into meaningful employment outcomes.

Recommendations

Based on the findings of this study, policies aimed at improving job quality should go beyond increasing access to digital technology and focus on strengthening the broader ecosystem that supports its effective use. The Government of East Java is encouraged to promote digital inclusion through more targeted, practical digital literacy programs, while simultaneously improving the quality of education and training systems to align them with labor market needs. In addition, strengthening the linkage between training programs—such as the Pre-Employment Card Program—and employment opportunities is essential to reduce skill mismatches and improve participants' chances of accessing better-quality jobs. Efforts to address structural inequalities in the labor market, including gender disparities and unequal access to formal employment across regions, should also be prioritized.

This study is limited by its cross-sectional data, which restricts the ability to capture long-term dynamics and causal relationships between digital technology and job quality. In addition, the analysis focuses primarily on observable individual characteristics and does not fully account for institutional and structural factors that may influence labor market outcomes. Therefore, future research is encouraged to use longitudinal data and more advanced identification strategies to better understand the causal mechanisms underlying the relationship between digitalization and job quality. Expanding the analysis to include institutional factors, labor market policies, and regional economic structures would also provide a more comprehensive understanding and support the development of more effective and inclusive labor policies.

ACKNOWLEDGMENT

The author gratefully acknowledges the financial support provided through the cost-sharing scholarship program jointly funded by the Ministry of National Development Planning of the Republic of Indonesia (Bappenas) and the Provincial Government of East Java. This support has been instrumental in completing this study.

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CONFLICT OF INTEREST

The authors declare no conflict of interest

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