

Insights from the Indonesian family life survey, fifth wave: Job demands-resources profiles and their links to depressive symptoms and life satisfaction

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Abstract

The Job Demands-Resources (JD-R) model explains how job demands and job resources shape workers' psychological well-being through a health impairment process and a motivational process. JD-R research in Indonesia has largely relied on variable-centered approaches, which assume additive and uniform effects of demands and resources, overlooking how these factors combine differently across individuals. This study identified latent worker profiles based on five employment-related JD-R indicators (wage adequacy, working hours, employment status, number of jobs, and social security) and examined their links to depressive symptoms and life satisfaction, using data from the fifth wave of the Indonesian Family Life Survey (IFLS-5), with a final sample of 2,023 formal-sector workers. Latent class analysis identified three profiles: Fully Resourced (29.3%), Adequate but Contract-Vulnerable (47.6%), and Under-Resourced (23.1%), consistently distinguished by the job-resource indicators rather than the job-demand indicators. Membership in both the low-resource and high-resource profiles was significantly associated with depressive symptoms, whereas only the most fully resourced profile was associated with higher life satisfaction. These findings indicate that job resources are distinctly and differentially associated with depressive symptoms and life satisfaction, suggesting that labor policy should consider the configuration of job resources holistically.

Keywords: Job Demands-Resources; latent class analysis; depressive symptoms; life satisfaction; Indonesian Family Life Survey

INTRODUCTION

The Job Demands–Resources (JD-R) model provides a widely used framework for explaining how job characteristics influence workers' psychological well-being (Demerouti et al., 2001). It distinguishes between job demands, which require sustained physical or psychological effort and entail associated costs (e.g., workload, time pressure, emotional demands, role conflict, and long working hours), and job resources, which facilitate goal attainment, buffer job demands, and promote motivation and personal growth (e.g., autonomy, social support, feedback,



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development opportunities, pay, and job security) (Demerouti et al., 2001; Bakker & Demerouti, 2007; Schaufeli & Taris, 2014). These characteristics underlie two core processes: a health impairment process, whereby excessive demands deplete energy and increase burnout risk, and a motivational process, whereby resources foster work engagement and well-being (Bakker & Demerouti, 2007; Schaufeli & Bakker, 2004). The model has subsequently evolved to incorporate personal resources, job crafting, and self-undermining (Bakker & Demerouti, 2017; Bakker et al., 2023). Its flexibility in conceptualizing demands and resources across task, interpersonal, organizational, and individual levels also enables its application across diverse work contexts, including Indonesia's heterogeneous formal and informal labor market (Schaufeli & Taris, 2014; Strauss et al., 2016).

In this study, working hours and the number of jobs are conceptualized as job demands because both reflect the amount of time, energy, and attention that workers are required to invest in their work. Long working hours have consistently been associated with an increased risk of depressive symptoms. A systematic review and meta-analysis by Virtanen et al. (2018), based on pooled individual participant data from multiple cohort studies, found that workers with long working hours had a higher risk of depressive symptoms than those working standard hours. This evidence is further supported by joint estimates from the World Health Organization (WHO) and the International Labour Organization (ILO), which identified long working hours as a contributor to the increasing global burden of depression-related illness (Rugulies et al., 2021). The relevance of working hours is particularly evident in Indonesia, where average working hours reached 42 hours per week in February 2023, exceeding the 40-hour weekly maximum stipulated in Job Creation Law Number 11 of 2020, as amended by Law Number 6 of 2023 (Hamsyah et al., 2024).

Holding multiple jobs can similarly be considered a job demand because it requires workers to allocate their time, energy, and attention across different work roles and may increase the potential for role conflict. Bruns and Pilkauskas (2019), for example, found that low-income mothers who held multiple jobs were more likely to experience depressive symptoms than those with a single job. Given that multiple job holding is relatively common in Indonesia, particularly among informal workers and those with irregular incomes, both working hours and the number of jobs are considered relevant indicators of job demands in the IFLS data analyzed in this study (Strauss et al., 2016).

Conversely, income and social security constitute job resources by helping workers meet basic needs, enhance financial security, and mitigate the adverse effects of job demands (Bakker & Demerouti, 2007; Schaufeli & Taris, 2014). Higher income is associated with greater subjective well-being, particularly overall life evaluation, although its benefits for daily emotional well-being diminish beyond a certain threshold (Kahneman & Deaton, 2010). Social security, including health and pension coverage, further protects workers from financial risks associated with illness, workplace accidents, and job loss, whereas its absence increases job insecurity and the risk of mental health problems (Llosa et al., 2018). This resource is particularly relevant in Indonesia, where many workers, especially those in the informal sector, lack employment-

related social security (Strauss et al., 2016).

Beyond income and social security, employment status can also be considered a job resource, as it reflects the degree of job security, or workers' confidence in retaining their employment over time. Permanent employment provides greater certainty and stability, whereas contract or other non-permanent arrangements may increase job insecurity. A review by De Witte (2005) found consistent evidence that job insecurity is associated with poorer psychological well-being. Similarly, a review of three decades of longitudinal research by De Witte, Pienaar, and De Cuyper (2016) showed that job insecurity is related to deteriorating mental health, although the strength of this association varies across studies. Permanent employment status may therefore be viewed as a structural job resource that provides workers with a greater sense of security and stability, consistent with the JD-R model's proposition that job resources can buffer the adverse effects of job demands on employee well-being (Bakker et al., 2005).

In this study, employment status is considered alongside income and social security as a set of job-resource indicators that collectively reflect the financial, protective, and structural resources available to workers.

It should be noted, however, that these five indicators do not capture the psychological job demands and job resources most commonly examined in JD-R research, such as workload, time pressure, emotional demands, autonomy, or social support. Rather, they represent structural, employment-related demands and resources, that is, objective features of the employment arrangement that overlap considerably with the broader concept of job quality (Brummund et al., 2018). The JD-R model is deliberately open with respect to the content of its constructs: any job characteristic may be classified as a demand or a resource depending on whether it primarily requires sustained effort and entails costs, or whether it helps workers achieve work goals, reduces demands, and stimulates growth (Demerouti et al., 2001; Schaufeli & Taris, 2014). Organizational-level characteristics such as salary, career opportunities, and job security are explicitly listed as job resources in the model (Bakker & Demerouti, 2007). Accordingly, this study does not claim to operationalize the full range of psychological JD-R constructs. Instead, it uses the JD-R model as an organizing framework to examine how employment-related demands and resources, which can be measured in large-scale national surveys such as the IFLS, combine into distinct worker profiles. Throughout this article, the terms job demands and job resources therefore refer to these employment-related indicators, and the findings should be interpreted at this structural level rather than generalized to psychological job characteristics.

Theoretically, the relationships among job demands, job resources, and mental health can be understood through the two parallel processes proposed by the Job Demands–Resources (JD-R) model. High job demands and low resources are expected to increase the risk of depression through the health impairment process, as sustained demands continuously deplete individuals' energy, particularly when adequate opportunities for recovery are lacking. Recovery experiences (i.e., psychological detachment, relaxation, mastery, and control over leisure time)

allow individuals to replenish their depleted resources and recover from work-related effort (Demerouti et al., 2001; Hakanen et al., 2008). Supporting this perspective in the Indonesian context, Hamsyah et al. (2024) found that all four dimensions of recovery experiences were consistently associated with better mental health and lower psychological distress among Indonesian workers, highlighting the importance of recovery opportunities in protecting against the adverse effects of job demands. Similarly, a three-year longitudinal study of Finnish dentists by Hakanen, Schaufeli, and Ahola (2008) demonstrated that job demands consistently predicted increases in burnout symptoms, which subsequently contributed to greater depressive symptoms.

In contrast, low job demands and high job resources are expected to enhance life satisfaction through the motivational process, as they help fulfill basic psychological needs, promote positive affect, and contribute to more favorable evaluations of one's life (Schaufeli & Bakker, 2004; Claes et al., 2023). Consistent with this proposition, Claes et al. (2023) found that job demands and job resources independently contributed to overall subjective well-being, with job resources showing a relatively stronger association with evaluative components of well-being, including life satisfaction.

Depressive symptoms and life satisfaction were selected as the two indicators of mental health in this study for both conceptual and theoretical reasons. Conceptually, the dual-continua model holds that mental health is not merely the absence of mental illness but also the presence of positive well-being, and that these two components are related yet distinct dimensions (Keyes, 2005; Westerhof & Keyes, 2010). Depressive symptoms are among the most prevalent and widely used indicators of the mental illness (ill-being) continuum, whereas life satisfaction constitutes the cognitive-evaluative component of subjective well-being and thus represents the positive mental health continuum (Diener et al., 1999). Theoretically, the two outcomes correspond to the two processes of the JD-R model: depressive symptoms are a downstream health outcome of the health impairment process, whereas life satisfaction reflects the positive outcomes expected from the motivational process (Hakanen et al., 2008; Schaufeli & Bakker, 2004; Claes et al., 2023). Examining both outcomes therefore allows this study to test whether job demands–resources profiles are associated with the negative and positive sides of mental health in similar or different ways. Nevertheless, these two indicators do not cover the full spectrum of mental health; accordingly, the specific outcomes are named explicitly in the title, and the term mental health is used in this article to refer collectively to these two indicators.

In Indonesia, studies using IFLS data have similarly shown that negative life experiences and sociodemographic factors are associated with a high prevalence of depressive symptoms among adults (Alfaqeeh et al., 2025; Irmansyah et al., 2026), while individual and contextual factors contribute to variations in happiness and life satisfaction across the population (Sujarwoto et al., 2018). Despite these findings, research examining how job demands and job resources combine to form distinct latent profiles among Indonesian workers remains very limited. This study therefore seeks to address this gap by identifying job demands–resources profiles using nationally representative data from the fifth wave of the Indonesian Family Life

Survey (IFLS-5) (Strauss et al., 2016).

Research Question and Hypotheses

This study adopts a person-centered approach through latent class analysis (LCA) to identify combinations of job demands and job resources that form latent worker profiles, rather than treating job demands and job resources as two uniform, additive composite scores applied to all workers alike. Accordingly, the study proposes one exploratory research question about the latent profiles that emerge, along with two hypotheses concerning how these profiles relate to depressive symptoms and life satisfaction.

Research Question

What latent profiles emerge from the combination of the five job demands-resources indicators (wage adequacy, working hours, employment status, number of jobs, and social security) among formal-sector workers in Indonesia?

Hypothesis 1

Workers with a profile characterized by high job demands (long working hours and/or holding more than one job) and low job resources (income below the minimum wage, non-permanent employment status, and/or lack of social security) will show higher levels of depressive symptoms than workers with other profiles, and this difference will remain significant after controlling for demographic factors (age, sex, marital status, educational attainment, and area of residence).

Hypothesis 2

Workers with a profile characterized by high job demands and low job resources will show lower levels of life satisfaction than workers with other profiles, and this difference will remain significant after controlling for demographic factors.

RESEARCH METHOD

Data Source and Sample Demographic Characteristics

This study uses data from the fifth wave of the Indonesian Family Life Survey (IFLS-5), fielded in 2014–2015. The IFLS sample was originally drawn in 1993 from households in 13 of Indonesia's then 27 provinces and was representative of approximately 83% of the national population (Strauss et al., 2016). The study received ethical approval from the Research Ethics Committee of the Faculty of Psychology, Universitas Gadjah Mada (Approval No. 6779).

Initially, 23,437 respondents reported an employment status. This sample was then narrowed through three stages of exclusion. First, respondents with informal employment or no formal work contract were excluded, because the employment-status indicator within this study's Job Demands-Resources framework requires a verifiable employment relationship. This criterion excluded 21,414 respondents. Second, respondents working part-time, defined operationally as working fewer than 35 hours per week, were excluded so that the working-hours indicator (normal work versus overwork) could be meaningfully compared only among full-time workers. The 35-hour threshold is used here as an operational (statistical) criterion

rather than as a legal definition of full-time employment. It follows the convention long applied by Statistics Indonesia (Badan Pusat Statistik, BPS) in the National Labor Force Survey (Sakernas), including during the period in which IFLS-5 was fielded, whereby persons working at least 35 hours per week are classified as full-time workers and those working fewer than 35 hours per week as part-time or underemployed workers (Badan Pusat Statistik, 2014). Applying this criterion to the 2014–2015 data is therefore consistent with the official labor statistics definitions in use at the time of data collection. Third, respondents in Lampung Province (26 respondents) were excluded because the 2014 district/city minimum wage figures for that province could not be independently verified, making the wage-adequacy indicator unreliable to compute there.

Because of these eligibility criteria, the final analytic sample described below is not representative of the Indonesian workforce as a whole. Rather, it represents a specific segment of the labor market, namely full-time, formal-sector employees with a permanent or contract employment relationship residing in the 13 IFLS provinces. Informal and part-time workers, who make up the majority of Indonesian workers, are not represented, and the findings should be generalized only to the formal-sector population defined above. Sampling weights were not applied in the analyses. The IFLS-5 sampling weights are designed to make the full respondent sample representative of the population of the 13 IFLS provinces; they were not constructed for a subpopulation defined by employment-related eligibility criteria, and applying them would not restore representativeness with respect to the excluded groups. Moreover, the aim of this study was to identify latent profiles and estimate associations within this subpopulation rather than to produce population-level prevalence estimates, and the regression models adjusted for design-related characteristics such as area of residence (Bollen et al., 2016). The class proportions reported below should therefore be interpreted as sample-based estimates rather than national population estimates.

After all exclusion stages, the final analytic sample comprised 2,023 formal-sector workers (8.6% of the initial sample). The sample's demographic characteristics are shown in Table 1. Respondents' average age was 32.8 years ($SD = 9.7$; range 16–74 years), with a majority male (67.4%) and married (70.1%). In terms of education, nearly half of respondents had completed senior high school (49.5%), followed by those with a Diploma degree or higher (32.0%). Most respondents lived in urban areas (78.9%).

Table 1. Demographic Characteristics of the Final Sample (n = 2,023)

Demographic Characteristic	n	%
Age (years), M (SD)	32.80 (9.73)	
Sex		
Male	1,364	67.4
Female	659	32.6

Marital Status^a

Married	1,419	70.1
Never married	542	26.8
Divorced	40	2.0
Widowed	13	0.6
Separated	9	0.4

Education Level^b

Elementary school or below	150	7.4
Junior high school	224	11.1
Senior high school	1,000	49.5
Diploma or higher	646	32.0

Area Type

Urban	1,597	78.9
Rural	426	21.1

Note: Age range 16 to 74 years. a = For analysis purposes, marital status was grouped into married (n = 1,419; 70.1%) versus not married (n = 604; 29.9%). b = 3 respondents had missing data; education level was also grouped into basic-to-intermediate (n = 1,374; 68.0%) versus higher education (n = 646; 32.0%) for analysis purposes.

Measurement of Job Demands-Resources Indicators

The five Job Demands-Resources (JD-R) indicators used in this study were not adapted from validated psychological instruments; instead, they were constructed from items in the IFLS-5 employment module (Book IIIA, Section TK), guided by the theoretical JD-R framework (Bakker & Demerouti, 2007; Demerouti et al., 2001). This approach has previously been used to build secondary-data-based job-quality indices in developing-country contexts, assigning a binary code to each dimension based on a specific threshold rather than a Likert scale (Brummund et al., 2018). Each of the five indicators is described below.

Wage Adequacy

This indicator was constructed from the monthly income item, compared against the applicable Provincial Minimum Wage (UMP) or District/City Minimum Wage (UMK) for 2014. In Indonesia, the minimum wage is set annually by provincial governors based on the Decent Living Needs standard set out in Manpower Law Number 13 of 2003, Article 88(4), and Regulation of the Minister of Manpower and Transmigration Number 7 of 2013. Governors may also set a UMK based on district/city government proposals, provided it is not lower than the UMP. A newly set minimum wage takes effect on January 1 of the following year, so minimum wage levels vary across regions and over time (Del Carpio et al., 2015); respondents' income was therefore

compared against the threshold specific to their region of residence. UMP and UMK figures for 2014 were compiled from official provincial-level statistical tables of the Central Statistics Agency (BPS, 2015) and the Ministry of Manpower's data portal (Kemnaker, 2024).

Respondents were coded "1" if their income was equal to or above their regional minimum wage threshold, and "0" if it fell below that threshold. For the 17 provinces that set only a single provincial UMP, comparisons were made against that provincial UMP. For West Java, Central Java, and DI Yogyakarta, comparisons were made against the district/city-specific UMK for the respondent's place of residence. For East Java, the lowest district/city UMK in the province was used as a conservative proxy, since complete UMK figures for all districts/cities in that province could not be fully verified from official sources; the use of this proxy is noted as a limitation in the Discussion section.

Working Hours

This indicator was constructed from the item on weekly working hours. Respondents were coded "0" (normal working hours) if they worked 48 hours or fewer per week, and "1" (overwork) if they worked more than 48 hours per week. The 48-hour threshold follows the ILO standard on hours of work and the ILO indicator of excessive working time, defined as working more than 48 hours per week (ILO, 2018); it also exceeds the 40-hour normal weekly working time stipulated in Manpower Law Number 13 of 2003. Respondents working fewer than 35 hours per week were excluded from the sample, consistent with the operational full-time threshold used by BPS in national labor force statistics (Badan Pusat Statistik, 2014), as described in the Data Source and Sample section.

Employment Status

This indicator was constructed from the item on employment relationship status. Respondents were coded "1" if they held permanent employee status and "0" if they held contract employee status. Employment status represents a core resource within the JD-R framework's job security dimension, which is consistently associated with workers' psychological well-being (De Witte, 2005; De Witte et al., 2016). Respondents with informal status or without a formal work contract could not be classified on this indicator and were excluded from the sample, as described in the Data Source and Sample section.

Number of Jobs

This indicator was constructed from the item on the number of jobs held by respondents. Respondents were coded "1" if they held a single job and "0" if they held more than one job. Holding multiple jobs is generally a source of supplementary income for individuals facing limited hours or pay in their primary job, and is associated with lower job quality and more precarious working conditions (Pouliakas, 2017; Conen & de Beer, 2021). This indicator is therefore treated as a marker of vulnerability rather than a preference for additional work.

Social Security

This indicator was constructed from the item on the availability of health and pension benefits provided by the employer. Respondents were coded "1" if they received either or both benefits,

and "0" if they received neither. Social security represents a structural resource that buffers job demands, consistent with the JD-R model's proposition that job resources moderate the negative impact of job demands on well-being (Bakker & Demerouti, 2007; Bakker et al., 2005).

Measurement of Outcome Variables

Depressive Symptoms

Depressive symptoms in IFLS-5, as described by Strauss et al. (2016), were measured using the 10-item CES-D (Radloff, 1977; Andresen et al., 1994). Respondents rated the frequency of each symptom over the past week on a 4-point scale (rarely or none of the time, some days, occasionally, most of the time). The internal-structure validity of this measure in the IFLS-5 dataset was examined by Marvianto (2023) using confirmatory factor analysis and item response theory on the same dataset. The results showed that a unidimensional model fit the data well, although two items, MH-05 and MH-08, showed low factor loadings. IRT analysis confirmed that these two items did not adequately capture depressive tendencies in terms of discrimination, location, or item fit. Both items are positively worded (reflecting positive affect), and a similar pattern has been reported in other Asian populations, raising questions about whether positively worded items can reliably detect depressive symptoms (Iwata et al., 1998). These two underperforming items were therefore dropped, and the final score was calculated from the remaining 8 items, ranging from 0 to 24, with higher scores indicating more severe depressive symptoms. Internal consistency in this study's sample met accepted reliability standards (Nunnally & Bernstein, 1994), with a Cronbach's alpha of .789.

Life Satisfaction

Life satisfaction was measured using a single item (SW00) from the IFLS-5 subjective well-being module (Book IIIA, Section SW), which asked respondents to reflect on their life overall and rate their current level of satisfaction on a 5-point scale. Responses were reverse-coded so that higher scores indicate greater life satisfaction. Although a single-item measure does not fully capture the multidimensional nature of subjective well-being, such measures have shown adequate validity relative to multi-item scales. Cheung and Lucas (2014) compared a single-item measure with the Satisfaction with Life Scale across three large samples and concluded that both measures produce nearly identical answers to substantive questions. This approach has also been used in other studies drawing on the same IFLS-5 dataset for different analyses (Fajri et al., 2026).

Covariates

This study used several demographic variables as covariates in the latent profile model. These variables were drawn from the IFLS-5 household and life-history modules. First, age was modeled as a continuous variable in years. Second, sex was coded as male and female, with female as the reference category. Third, marital status originally comprised five categories, never married, married, separated, divorced, and widowed, but was simplified into married and not married, with married as the reference category, to balance the proportions across categories, since the separated, divorced, and widowed categories each made up less than two percent of the sample and were therefore combined into the not-married category. A similar

approach has been applied in other IFLS-5-based studies, such as Marvianto et al. (2026). Fourth, educational attainment was categorized by respondents' highest completed level rather than total years of schooling, and then grouped into basic-to-intermediate education (elementary school or below, junior high school, and senior high school) and higher education (Diploma or above), with basic-to-intermediate education as the reference category. Finally, area of residence was categorized as urban or rural, with rural as the reference category.

Data Analytic Strategy

This study used latent class analysis (LCA), a person-centered approach that identifies distinct subgroups within a population (Liao & Lian, 2020; Zarate-Ortiz et al., 2022). LCA was estimated using a maximum likelihood estimator with robust standard errors (Muthén et al., 2015). Missing data were handled using likelihood-based estimation, the default approach in Mplus (Asparouhov, 2016). A one-class model was estimated first, and classes were added incrementally until the best-fitting model was identified, testing solutions ranging from one to six classes.

Model fit was then evaluated using several statistical criteria. First, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) were considered, with lower values indicating better fit (Weller et al., 2020). Second, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) was used to test whether a given model fit significantly better than a model with one fewer class (Lo, 2001; Vuong, 1989), supplemented by the bootstrap likelihood ratio test (BLRT). Third, entropy values were examined as an indicator of classification accuracy for the latent classes (Wang et al., 2017). Although there is no definitive threshold for acceptable entropy, values below 0.60 are generally discouraged, values approaching 1.0 are considered optimal (Celeux & Soromenho, 1996), and values above 0.70 are regarded as acceptable (Weller et al., 2020). Fourth, the size of each resulting class was considered, given that prior research suggests a class should ideally comprise at least five percent (5%) of the sample (Shanahan et al., 2013). In addition to these statistical criteria, the interpretability of the resulting classes was also taken into account when selecting the final solution. When the statistical indices did not agree, priority was given to solutions that showed acceptable classification accuracy (entropy ≥ 0.70), contained no class smaller than 5% of the sample, and yielded substantively interpretable classes, consistent with recommendations that class enumeration should integrate statistical and substantive considerations (Nylund-Gibson & Choi, 2018). Once the final solution was determined, posterior probabilities were estimated for each respondent, and each respondent was then classified into their most likely latent class. This class membership was subsequently used as a predictor variable in the regression analysis.

This study then examined the association between latent class membership and depressive symptoms and life satisfaction using hierarchical regression. Class membership was entered as dummy variables, with the largest class as the reference category. Two models were estimated: Model 1, containing only class membership, and Model 2, which added the demographic covariates of age, sex, marital status, educational attainment, and area of residence. Missing data on the outcome and covariate variables ranged from 0.1% to 7.0%

(depressive symptoms = 142; life satisfaction = 125; educational attainment = 3). This was addressed using listwise deletion, given that the proportion of missing data was relatively small and most variables were categorical and conceptually specific, such that imputation could potentially introduce bias (Little & Rubin, 2019). After listwise deletion, the final analytic sample for the regression analysis comprised 1,878 workers (92.8% of the 2,023-worker LCA sample).

This study used several software packages for data processing. RStudio and the R programming language (R Core Team, 2025) were used for data screening, data structuring, and hierarchical regression, while LCA was conducted using Mplus (Muthén & Muthén, 2011).

RESULTS AND DISCUSSION

Latent Profiles of Job Demands-Resources

Models with two to six classes were compared (Table 2). The comparison shows that BIC, SABIC, and CAIC increased consistently as the number of classes grew beyond the two-class model, indicating that these three indices favor a more parsimonious solution. AIC showed a different pattern, reaching its lowest value at the three-class model—slightly lower than for both the two-class and four-class models.

Table 2. Model Fit Comparison Across Class Solutions

Classes	AIC	BIC	SABIC	CAIC	Smallest Class Size	Entropy	ALCPP	VLMR-LRT
2	11681.271	11743.007	11708.059	11754.006	47.6%	0.608	0.904	<0.001
3	11678.391	11773.801	11719.792	11790.802	21.8%	0.728	0.859	0.036
4	11682.253	11811.336	11738.263	11834.336	4.6%	0.668	0.836	0.337
5	11689.293	11852.051	11759.917	11881.052	5.4%	0.525	0.618	0.589
6	11700.805	11897.237	11786.040	11932.238	5.7%	0.615	0.673	0.412

Note. $N = 2,023$. AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; SABIC, Sample-size-adjusted BIC; CAIC, Consistent AIC; ALCPP, average latent class posterior probability; VLMR-LRT, Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (p -value reported). SABIC and CAIC were computed using the standard formula based on the log-likelihood and the number of parameters in each model.

However, when the number of classes was increased to four, the VLMR-LRT was no longer significant ($p = 0.337$), following a significant result for the increase from two to three classes ($p = 0.036$). The four-class model also included a class comprising only 4.6% of the sample, below the 5% minimum threshold set in the Method section; this model was therefore rejected.

Between the remaining two- and three-class models, only the three-class model showed an entropy value above 0.70 (0.728 versus 0.608 for the two-class model). ALCPP for both models exceeded 0.80 (0.904 and 0.859), so this criterion did not meaningfully distinguish between them. This study therefore also considered the interpretability of the resulting classes:

the three-class model was able to separate workers with fully resourced jobs from those with adequate income but vulnerable contract status, a distinction not captured by the two-class model.

Because the fit indices did not converge on a single solution, the final decision was based on an explicit weighing of statistical fit, class size, and theoretical interpretability, as recommended when information criteria and likelihood ratio tests disagree (Nylund-Gibson & Choi, 2018; Weller et al., 2020). With respect to statistical fit, the BIC-based indices (BIC, SABIC, and CAIC) favored the two-class model, whereas the AIC and the VLMR-LRT favored the three-class model. We acknowledge that the BIC, which penalizes model complexity more heavily, has been shown to perform well in class enumeration (Nylund et al., 2007); its preference for the two-class model is therefore a consideration against the three-class solution. However, the two-class model showed an entropy value (0.608) barely above the commonly discouraged threshold of 0.60, indicating poor class separation, whereas the three-class model showed acceptable classification accuracy (entropy = 0.728; ALCPP = 0.859). With respect to class size, every class in the three-class model comprised well over 5% of the sample (smallest class = 21.8%), so none of its classes was too small to be estimated reliably or interpreted meaningfully, unlike the four-class model. With respect to theoretical interpretability, the three-class model identified a substantively meaningful group, namely workers with adequate wages but contract employment and incomplete social security, who were combined with fully resourced workers in the two-class model. This distinction is directly relevant to the JD-R conceptualization of job security as a resource and to the policy debate on contract employment in Indonesia (De Witte et al., 2016). Taken together, the three-class model was selected as the most defensible solution, balancing acceptable fit with clearer class separation and greater substantive interpretability. Given the disagreement among the information criteria, however, this solution should be regarded as the best-supported representation of the data rather than a definitive latent structure, a point revisited in the Study Limitations section.

Table 3. Latent Class Characteristics by Job Demands-Resources Indicator

Indicator	Class 1 Fully Resourced	Class 2 Adequate but Contract-Vulnerable	Class 3 Under-Resourced
Job Demands			
Working hours (overwork)	0.253	0.325	0.297
Number of jobs (>1 job)	0.193	0.162	0.186
Job Resources			
Wage adequacy	1.000	1.000	0.000
Employment status (permanent)	1.000	0.129	0.368
Social security	1.000	0.553	0.335

n (participant classification)	592	963	468
% of sample	29.3%	47.6%	23.1%

Note: N = 2,023. All five indicators follow the naming used in the Method section: Working Hours and Number of Jobs are categorized as job demands, while Wage Adequacy, Employment Status, and Social Security are categorized as job resources. Indicator values represent the empirical endorsement proportion per class based on modal classification. Based on average posterior probabilities across the full sample, the proportions for the three classes were 21.8%, 56.0%, and 22.2%, respectively; the small difference from the modal-classification percentages is a normal feature of LCA rather than an indication of model misspecification.

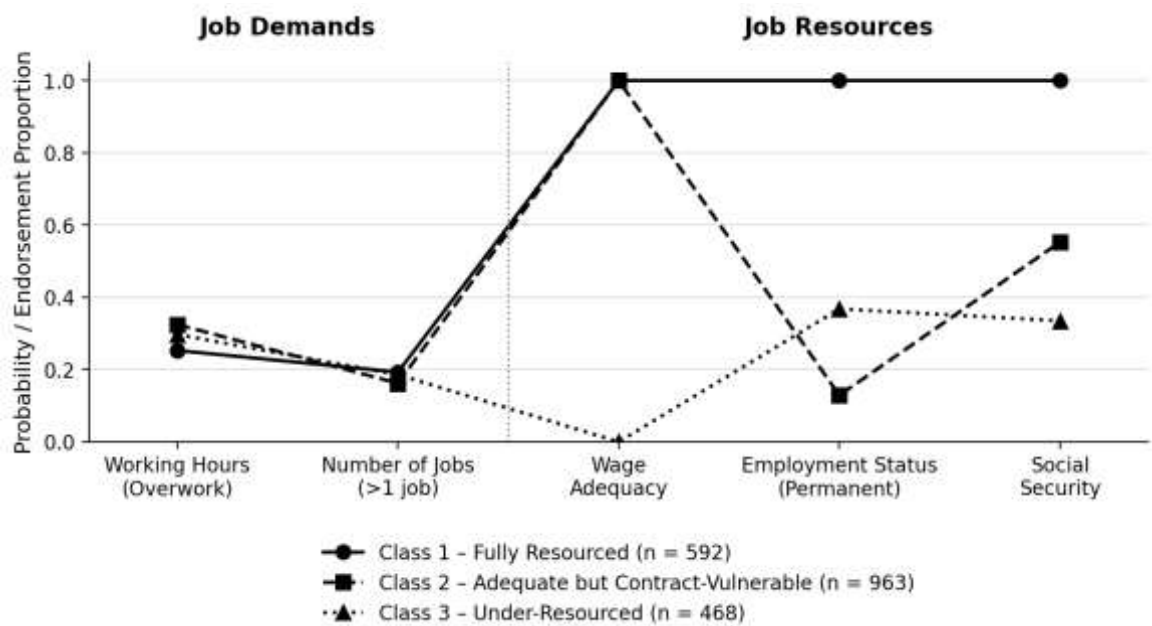


Figure 1. Latent profiles of job demands-resources indicators among Indonesian formal-sector workers. The y-axis shows the probability or endorsement proportion for each indicator. The x-axis presents the five job demands-resources indicators, ordered from the job demands group (Working Hours, Number of Jobs) to the job resources group (Wage Adequacy, Employment Status, Social Security), following the naming used in the Method section. Lines represent the latent classes.

Figure 1 shows that the three latent classes have relatively similar probabilities on the two job demands indicators, working hours and number of jobs, but differ quite clearly on the three job resources indicators: wage adequacy, employment status, and social security. Most workers (47.6%) fall into Class 2, which shows a high probability of wage adequacy (1.000) but a low probability of permanent employment status (0.129) and a moderate probability of social security (0.553). This class is therefore labeled Adequate but Contract-Vulnerable.

A total of 29.3% of workers fall into Class 1, which shows consistently high probabilities

across all three job resources indicators, wage adequacy, permanent employment status, and social security (each 1.000). This class shows the most complete set of job resources among the three, and is therefore labeled Fully Resourced.

The remaining class comprises 23.1% of workers and shows the lowest probability of wage adequacy (0.000) and a similarly low probability of social security (0.335), although its probability of permanent employment status (0.368) is in fact slightly higher than that of Class 2. This class is labeled Under-Resourced.

On both job demands indicators, the three classes show no substantial differences: the proportion reporting overwork ranges from 25.3% to 32.5%, and the proportion holding more than one job ranges from 16.2% to 19.3%. This indicates that the three worker profiles identified in this sample are primarily distinguished by the job resources dimension, while job demands contribute little to differentiating between classes.

These three profiles answer the research question about the combinations of job demands and job resources that form groups of formal-sector workers in Indonesia. It should be noted that the Under-Resourced class, used as the profile that most closely resembles the high-demands/low-resources description in Hypotheses 1 and 2—does not actually show job demands that are clearly higher than those of the other two classes, and is therefore more accurately described as a low-resources profile rather than a combined high-demands/low-resources profile. This caveat is a limitation of interpretation that is revisited in the Discussion section.

Hypothesis 1 Test: Latent Class Membership and Depressive Symptoms

Hypothesis 1 was tested using hierarchical regression with the 8-item CES-D score as the dependent variable. Class membership was entered as two dummy variables, with Class 2 (Adequate but Contract-Vulnerable) as the reference category, since it was the largest class. Model 1 included only these two dummy variables, while Model 2 added five demographic covariates (age, sex, marital status, educational attainment, area of residence). The results of both models are presented in Table 4.

Table 4. Summary of Hierarchical Regression Results Predicting Depressive Symptoms (CES-D)

Variable	B (M1)	SE B (M1)	β (M1)	B (M2)	SE B (M2)	β (M2)
Constant	5.020	0.150	—	7.000	0.420	—
Fully Resourced Class	-1.050	0.240	-.109**	-0.530	0.250	-.054*
Under-Resourced Class	0.720	0.250	.069**	0.830	0.250	.081***
Age				-0.080	0.010	-.169***
Female (ref: Male)				-0.060	0.220	-.007
Urban (ref: Rural)				0.490	0.240	.045*
Married (ref: Not married)				-0.320	0.250	-.033

Higher education (ref: Basic–intermediate)	0.590	0.220	.133**
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Overall Test: Model 1 — $F(2, 1875) = 21.158^{***}$, $p < .001$, $R^2 = .022$. Model 2 — $F(7, 1870) = 16.382^{***}$, $p < .001$, $R^2 = .058$.

Model Comparison: $F(5, 1870) = 14.170^{***}$, $\Delta R^2 = .036$, $p < .001$.

*Note. $N = 1,878$. Reference class category: Class 2 – Adequate but Contract-Vulnerable. * $p < .05$. ** $p < .01$. *** $p < .001$.*

In Model 1, membership in the Fully Resourced class was associated with a lower CES-D score compared with Class 2 ($B = -1.050$, $SE = 0.240$, $\beta = -0.109$, $p < .001$), whereas membership in the Under-Resourced class was associated with a higher CES-D score ($B = 0.720$, $SE = 0.250$, $\beta = .069$, $p = .005$). Model 1 was significant overall, $F(2, 1875) = 21.158$, $p < .001$, $R^2 = .022$. After demographic covariates were added in Model 2, both class associations remained significant, although their coefficients became smaller (Fully Resourced Class: $\beta = -0.054$, $p = .038$; Under-Resourced Class: $\beta = 0.081$, $p < .001$). Age was negatively associated with CES-D score ($\beta = -0.169$, $p < .001$), while living in an urban area ($\beta = 0.045$, $p = .045$) and having higher education ($\beta = 0.133$, $p = .009$) were positively associated. Sex and marital status showed no significant association. Model 2 was significant overall, $F(7, 1870) = 16.382$, $p < .001$, $R^2 = .058$. Adding the five demographic covariates in Model 2 produced a significant improvement in model fit relative to Model 1, $\Delta R^2 = .036$, $F(5, 1870) = 14.170$, $p < .001$.

This pattern is consistent with Hypothesis 1: membership in a class with fewer job resources was associated with higher depressive symptoms, and this association remained significant after controlling for demographic covariates.

Hypothesis 2 Test: Latent Class Membership and Life Satisfaction

Hypothesis 2 was tested using the same procedure, with the life satisfaction score (single item SW00, range 1 to 5) as the dependent variable. The results of both models are presented in Table 5.

Table 5. Summary of Hierarchical Regression Results Predicting Life Satisfaction

Variable	B (M1)	SE B (M1)	β (M1)	B (M2)	SE B (M2)	β (M2)
Constant	3.368	0.026	—	3.321	0.074	—
Fully Resourced Class	0.114	0.041	.069**	0.108	0.044	.065*
Under-Resourced Class	0.001	0.044	.001	0.006	0.044	.003
Age				-0.004	0.002	-.049
Female (ref: Male)				0.116	0.038	.072**
Urban (ref: Rural)				0.036	0.042	.020
Married (ref: Not married)				0.121	0.044	.074**

Higher education (ref: Basic–intermediate)	0.062	0.039	.082
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Overall Test: Model 1 — $F(2, 1875) = 4.427^*$, $p < .05$, $R^2 = .005$. Model 2 — $F(7, 1870) = 4.344^{***}$, $p < .001$, $R^2 = .016$.

Model Comparison: $F(5, 1870) = 4.290^{***}$, $\Delta R^2 = .011$, $p < .001$.

Note. $N = 1,878$. Reference class category: Class 2 – Adequate but Contract-Vulnerable. $*p < .05$. $**p < .01$. $***p < .001$.

In Model 1, membership in the Fully Resourced class was associated with a higher life satisfaction score than Class 2 ($B = 0.114$, $SE = 0.041$, $\beta = .069$, $p = .005$), whereas membership in the Under-Resourced class showed no significant association ($B = 0.001$, $SE = 0.044$, $\beta = .001$, $p = .976$). Model 1 was significant overall, $F(2, 1875) = 4.427$, $p = .012$, $R^2 = .005$. This pattern held in Model 2: the Fully Resourced class remained significant ($\beta = .065$, $p = .015$), while the Under-Resourced class remained non-significant ($\beta = .003$, $p = .898$). Among covariates, being female ($\beta = .072$, $p = .002$) and being married ($\beta = .074$, $p = .006$) were positively associated with life satisfaction, while age, area type, and education showed no significant association. Model 2 was significant overall, $F(7, 1870) = 4.344$, $p < .001$, $R^2 = .016$. Adding the five demographic covariates in Model 2 produced a significant improvement in model fit relative to Model 1, $\Delta R^2 = .011$, $F(5, 1870) = 4.290$, $p < .001$.

These results provide partial support for Hypothesis 2. The class with the most complete job resources (Fully Resourced Class) showed higher life satisfaction than the reference class, consistent with the hypothesized direction. However, the class with the fewest job resources (Under-Resourced Class) did not differ significantly from the reference class on this outcome, unlike the pattern found for depressive symptoms.

This study identified latent profiles of Indonesian formal-sector workers based on five Job Demands–Resources (JD-R) indicators and examined their associations with depressive symptoms and life satisfaction. Latent class analysis of 2,023 workers from the fifth wave of the Indonesian Family Life Survey (IFLS-5) supported a three-class solution, with profiles differentiated primarily by job resources (wage adequacy, employment status, and social security) rather than job demands (working hours and number of jobs). Hierarchical regression analyses further showed that class membership was associated with depressive symptoms in the hypothesized direction, whereas its association with life satisfaction was only partially supported. These findings are discussed in relation to the JD-R framework and the literature on Indonesian workers' mental health.

Latent Profiles of Job Demands-Resources: The Dominance of the Resource Dimension

The identification of three latent profiles, Fully Resourced (29.3%), Adequate but Contract-Vulnerable (47.6%), and Under-Resourced (23.1%), suggests that heterogeneity in job demands and resources among Indonesian formal-sector workers was driven primarily by structural job resources rather than differences in job demands. Although the profiles differed substantially in wage adequacy, employment security, and social security coverage, their levels of overwork and

multiple job holding were relatively similar. This pattern highlights the importance of considering the employment context in which job resources are embedded, particularly employment security and social protection, when applying the JD-R framework to the Indonesian labor market.

However, this resource-dominant pattern should be interpreted with caution, because it may partly reflect how the indicators were operationalized rather than the substantive structure of job demands and resources alone. First, the indicator set was asymmetric, comprising three resource indicators and only two demand indicators, which gives the resource dimension greater weight in the latent class solution. Second, the two demand indicators were coarse binary measures of the quantity of work (overwork and multiple job holding) and did not capture psychological demands such as work intensity, time pressure, or emotional demands, which are central to the JD-R model. Third, the sampling criteria shaped the variability of the indicators: excluding part-time workers truncated variation in working hours, whereas restricting the sample to workers with a formal employment relationship made the permanent-versus-contract distinction a built-in source of heterogeneity. Fourth, the wage-adequacy indicator was perfectly separated across classes (proportions of 1.000 or 0.000), suggesting that the classes were anchored to a considerable extent by this single threshold-based indicator. Consequently, the finding that resources rather than demands differentiated the profiles should be understood as specific to the employment-related indicators available in the IFLS-5, and not as evidence that job demands are generally less important than job resources for Indonesian workers.

This finding also qualifies the assumptions underlying Hypotheses 1 and 2. The Under-Resourced profile did not exhibit distinctly higher job demands, indicating that the expected high-demands/low-resources configuration was not empirically observed. Instead, the latent profiles were primarily differentiated by resource availability, suggesting that job demands and resources may not necessarily cluster in the theoretically expected configurations. One possible explanation is that the exclusion of part-time workers based on the 35-hour operational threshold may have restricted variation in job demands, whereas employment status and social security, shaped more strongly by employer practices and sectoral conditions, remained heterogeneous. Thus, in this context, JD-R research may tentatively benefit from greater attention to the structural and institutional distribution of job resources, rather than assuming that demands and resources necessarily vary together.

The prominence of the Adequate but Contract-Vulnerable profile further underscores this point. Nearly half of the sample occupied a position characterized by adequate income but contractual employment and incomplete social security coverage. This suggests that employment vulnerability can persist despite adequate financial resources, highlighting the multidimensional nature of job resources. From a JD-R perspective, income adequacy alone may therefore be insufficient to capture workers' resource conditions; employment security and social protection may represent distinct and consequential dimensions of the resource environment. This finding is particularly relevant in segmented labor markets such as Indonesia, where access to employment-related resources may vary substantially according to workers'

contractual arrangements (De Witte, 2005; De Witte et al., 2016; Strauss et al., 2016).

Association Between Latent Profiles and Depressive Symptoms

The results of the Hypothesis 1 test support the proposition that latent class membership is associated with depressive symptoms, consistent with the health impairment process described in the JD-R model. Compared with the Adequate but Contract-Vulnerable class as the reference category, workers in the Fully Resourced class reported lower CES-D scores ($\beta = -0.054$, $p = .038$), whereas those in the Under-Resourced class reported higher CES-D scores ($\beta = 0.081$, $p < .001$). Both associations remained significant after controlling for demographic characteristics in Model 2. This gradient, ranging from the class with the most comprehensive resources to the class with the fewest resources, suggests that the accumulation of job resources, particularly permanent employment and social security, may serve as a protective factor against depressive symptoms. This finding is consistent with the extensive literature linking job insecurity to poorer worker mental health (De Witte, 2005; De Witte et al., 2016; Llosa et al., 2018).

Notably, although the two job-demand indicators did not significantly distinguish among the three latent classes, workers in the class with the fewest resources nevertheless reported higher levels of depressive symptoms. This finding suggests that, among Indonesian formal-sector workers, a lack of job resources, particularly adequate wages and social security, may increase the risk of depressive symptoms even in the absence of elevated job demands. This pattern is consistent with the proposition that job resources may be directly associated with workers' psychological well-being, rather than serving solely as moderators of the effects of job demands (Bakker & Demerouti, 2007; Bakker et al., 2005). Because of the cross-sectional design, however, this association cannot be interpreted as a causal effect. However, the contribution of latent class membership to the explained variance in depressive symptoms was relatively modest (R^2 Model 2 = .058), indicating that job resources represent only one of multiple factors underlying depressive symptoms among Indonesian workers. This is consistent with previous research emphasizing the roles of sociodemographic characteristics and other adverse life experiences in shaping depressive symptoms (Alfaqeeh et al., 2025; Irmansyah et al., 2026).

Among the demographic covariates, age was negatively associated with depressive symptoms ($\beta = -0.169$, $p < .001$), indicating that younger formal-sector workers in this sample reported more severe depressive symptoms. This finding may reflect greater psychological pressures during the early stages of a career, including uncertainty about career progression and financial strain. Alternatively, it may reflect a survivorship-type selection process, whereby older workers who remain in the formal sector are more likely to have achieved greater job stability. Living in an urban area was also positively associated with depressive symptoms ($\beta = 0.045$, $p = .045$), potentially reflecting stressors associated with urban living, such as higher living costs and greater competition for employment. Higher educational attainment was likewise positively associated with depressive symptoms ($\beta = 0.133$, $p = .009$), contrary to the common assumption that education generally serves as a protective factor for mental health. One possible explanation is job–education mismatch or relative deprivation, whereby more highly educated workers may hold greater expectations regarding job rewards and consequently experience

greater disappointment when working in contexts characterized by inadequate job resources. However, this interpretation remains speculative and warrants further investigation, for example by examining the interaction between educational attainment and latent class membership. In contrast, sex and marital status were not significantly associated with depressive symptoms, suggesting that, within this sample of formal-sector workers, differences in job resources may be more relevant than these demographic characteristics in explaining variation in depressive symptoms.

Association Between Latent Profiles and Life Satisfaction

Unlike the pattern observed for depressive symptoms, Hypothesis 2 was only partially supported. The Fully Resourced class reported higher life satisfaction than the Adequate but Contract-Vulnerable class in both Model 1 ($\beta = .069$, $p = .005$) and Model 2 ($\beta = .065$, $p = .015$). However, the Under-Resourced class did not differ significantly from the reference class (Model 2: $\beta = .003$, $p = .898$), despite having the lowest levels of wage adequacy and social security.

This asymmetric pattern may reflect the distinction between overall life evaluation and other dimensions of subjective well-being. Kahneman and Deaton (2010) showed that income is consistently associated with life evaluation, although its effects on emotional well-being diminish beyond a certain level. In the present study, the Fully Resourced class may therefore have benefited from the additional resources provided by permanent employment and social security. In contrast, the lack of wage adequacy alone may not have been sufficient to reduce overall life satisfaction, which can also be shaped by adaptation, social comparison, and resources outside the workplace (Sujarwoto et al., 2018). This finding is consistent with Claes et al. (2023), who reported that job resources contribute more strongly to the evaluative component of subjective well-being, although their effects may reflect a threshold rather than a simple linear pattern.

The variance in life satisfaction explained by latent class membership and demographic covariates was small (R^2 Model 2 = .016), substantially lower than that for depressive symptoms. This may partly reflect the limited reliability of the single-item life satisfaction measure, although its validity relative to multi-item measures such as the Satisfaction with Life Scale has been supported (Cheung & Lucas, 2014; Lucas & Donnellan, 2012). The low explanatory power may also reflect the broader, global nature of life satisfaction, which is influenced by diverse life domains beyond work, including family, physical health, and social relationships, whereas depressive symptoms may be more proximal to work-related strain. Among the covariates, being female ($\beta = .072$, $p = .002$) and married ($\beta = .074$, $p = .006$) were associated with higher life satisfaction, whereas age, area type, and educational attainment were not significantly associated.

Theoretical and Practical Implications

Theoretically, these findings highlight the value of a person-centered approach in capturing heterogeneity in job demands–resources configurations that may be obscured by variable-centered approaches assuming additive and uniform effects (Liao & Lian, 2020; Zarate-Ortiz et al., 2022). Rather than treating demands and resources as independent composites, our findings

show that job resources cluster into distinct configurations that differentiate worker profiles and are differentially associated with the health impairment and motivational processes proposed by the JD-R model (Demerouti et al., 2001; Schaufeli & Bakker, 2004). Notably, the employment-related resource indicators, rather than the demand indicators, primarily differentiated the profiles among Indonesian formal-sector workers. This finding tentatively suggests that structural resources such as employment security and social protection may be particularly salient in a non-Western, segmented labor market (Bakker & Demerouti, 2007; Schaufeli & Taris, 2014). However, given the asymmetric and structural nature of the indicators discussed above and the cross-sectional design, this implication should be regarded as a hypothesis to be tested in future research using validated measures of both psychological and structural demands and resources, rather than as a firm extension of the JD-R model.

Practically, the large proportion of workers in the Adequate but Contract-Vulnerable class (47.6%) suggests that employment insecurity is a widespread concern among Indonesian formal-sector workers, extending beyond low income alone. Policies expanding access to permanent employment and employment-related social security for contract workers may therefore have broader reach than those focused solely on raising minimum wages. Meanwhile, the elevated depressive symptoms among workers in the Under-Resourced class underscore the need for integrated interventions addressing both wage adequacy and social security. Despite reporting comparable life satisfaction, these workers showed greater depressive symptoms, highlighting the importance of workplace policies that prioritize mental health prevention alongside broader well-being.

Study Limitations

Several limitations should be considered when interpreting these findings. First, the cross-sectional design using IFLS-5 data does not allow for causal conclusions or rule out the possibility of reverse causality. Second, because the data were collected roughly ten years ago, subsequent changes in labor regulations and the impact of the COVID-19 pandemic may have altered labor market characteristics, so generalizing these findings to the current context should be done with caution. Third, the job demands-resources indicators were constructed from IFLS-5 secondary data using binary coding rather than validated continuous psychometric instruments, which may reduce the granularity of measurement. Moreover, these indicators capture structural, employment-related demands and resources rather than the psychological job characteristics typically measured in JD-R research, and the asymmetric indicator set (three resource and two demand indicators) may have contributed to the resource-dominant profiles. Fourth, restricting the sample to full-time workers with a verifiable employment relationship means the findings cannot be generalized to informal workers. This is an important caveat, given that around 91% of the initial respondents (21,414 of 23,437) were excluded at the first screening stage due to informal status or the absence of a formal work contract. The job demands-resources profile of informal workers therefore remains an important question for future research. Relatedly, sampling weights were not applied, so the class proportions should not be interpreted as estimates for the national formal-sector workforce. Fifth, the information criteria did not unanimously favor the three-class solution, with the BIC-based indices preferring a two-class

model; the three-class solution was selected on the basis of classification accuracy, class size, and interpretability, and its replicability should be examined in independent samples.

Suggestions for Future Research

Future studies could incorporate personal resources and recovery experiences as mediating or moderating variables, given that both constructs are associated with the mental health of Indonesian workers within the health impairment process (Hamsyah et al., 2024). Replication using psychometrically validated job demands-resources instruments, rather than binary indicators derived from secondary data, would enrich understanding of the gradations in job demands and job resources that this study may not have captured. In addition, given that the association between higher education and depressive symptoms ran counter to the general literature, future research could test the interaction between educational attainment and job demands-resources latent class membership to help clarify the underlying mechanism. Extending this line of research to informal-sector workers, who were not covered in this study due to limitations in the employment-status indicator, is also important, given the large share of informal workers within Indonesia's labor market structure (Strauss et al., 2016).

CONCLUSION

Overall, this study shows that a person-centered approach using latent class analysis successfully identified three distinct job demands-resources profiles among Indonesian formal-sector workers, with job resources, particularly employment status and social security, as the primary dimensions distinguishing these profiles. Membership in both the low-resource and high-resource profiles was consistently associated with depressive symptoms, but only the profile with the most complete resources was associated with higher life satisfaction. These findings suggest that employment-related job resources, beyond merely offsetting job demands, show distinct and differentiated associations with depressive symptoms and life satisfaction as two components of mental health, suggesting that labor and workplace mental health policy in Indonesia should consider the configuration of job resources holistically, rather than relying on any single indicator alone. Given the cross-sectional design and the structural nature of the indicators, these associations should not be interpreted causally, and longitudinal research using validated measures is needed to confirm them.

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AI Disclosure

Generative artificial intelligence (AI) and AI-assisted technologies were used solely to improve the readability and organization of the manuscript. All outputs generated through these tools were carefully reviewed, edited, and validated by the author to ensure accuracy, completeness, and alignment with the study's original content. The author assumes full responsibility and accountability for the integrity of the work, including its analysis, interpretation, and conclusions. AI tools were not used for data generation, data analysis, or as a substitute for scholarly judgment, and are not listed as authors or co-authors of this study.

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