IJEBE INTERNATIONAL JOURNAL OF ECONOMICS, BUSINESS AND ENTREPRENEURSHIP

Vol. 9, No. 2, 2026

The Influence of Industrial Physchology, Workload, and Work Environment on Productivity: A Case Study of Gen Z in Jakarta

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ABSTRACT

As the newest entry into the labor market, Generation Z exhibits distinct professional expectations. However, existing organizational behavior literature focuses heavily on Millennials, leaving an empirical gap regarding Generation Z in emerging urban economies like Jakarta, where studies predominantly analyze organizational factors in isolation. To address this gap, this study proposes a novel, integrated framework examining the partial and simultaneous effects of industrial psychology, workload, and work environment on Generation Z's productivity in Jakarta. Using a quantitative approach, data were collected from 100 Generation Z employees via structured questionnaires and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that industrial psychology and workload significantly increase productivity. Crucially, workload functions as a challenge stressor that stimulates cognitive activation among digital natives. Conversely, the work environment has no significant direct effect, functioning primarily as a baseline hygiene factor in modern urban corporate settings. Simultaneously, the three predictors account for 39.2% productivity variance. Theoretically, this research advances a context-specific productivity model for digital-native talent by redefining traditional stress and environmental theories. Practically, it suggests that managers prioritize role clarity, performance transparency, and structured task engagement over physical office enhancements.

Keywords: Industrial Psychology, Workload, Work Environment, Productivity, Generation Z.

INTRODUCTION

Generation Z (born 1997–2012) is rapidly establishing its presence as a dominant demographic force in today's global workforce. In Jakarta, Indonesia's primary economic hub, data from the DKI Jakarta Civil Registry (Dukcapil) recorded 2,791,205 Generation Z residents in the first semester of 2025, underscoring their critical role in the urban labor market. As true digital natives who grew up alongside the rapid evolution of digital technology, Generation Z brings distinct workplace expectations and behavioral characteristics. They prioritize rapid career progression, transparent performance evaluation, and mental well-being, while actively seeking work-life balance and operational flexibility. Optimizing their operational productivity is

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vital for national economic growth, especially considering that Indonesia's labor productivity reached US$ 28.6 thousand per worker in 2022, ranking fifth within ASEAN (APO Productivity Databook, 2024).

Despite their potential to drive organizational performance, managing Generation Z talent presents unique corporate challenges. Unlike earlier cohorts, Generation Z views employment primarily through the lens of personal fulfillment and competency development, actively avoiding overly rigid or high-friction environments to prevent burnout. Furthermore, their high technological agility fosters a preference for workplace autonomy, making them more inclined to change jobs in pursuit of better self-improvement opportunities (Iorgulescu, 2016; Yacine & Karjaluoto, 2022). When managed with ambiguous roles or substandard environments, turnover intention increases while productivity declines. Conversely, flexible working arrangements and psychological safety have been shown to optimize their performance (SWA, 2025).

Despite the expanding literature on youth workforce management, existing research suffers from critical theoretical and empirical limitations. First, conventional organizational behavior models are historically centered on Millennials (Generation Y) and earlier cohorts, failing to explain how hyper-connected digital natives evaluate cognitive strain, organizational psychology, and environmental factors in high-density corporate settings. Second, existing studies frequently examine predictors, such as physical office environment, task workload, or organizational psychology, in isolation, missing the systemic interplay among these constructs. Third, empirical evidence contextualized within emerging metropolitan centers in Southeast Asia remains scarce, leaving an academic void regarding an integrated behavioral model tailored to young urban professionals.

To address these academic gaps, this study delivers explicit theoretical and contextual novelty by establishing an integrated productivity model for Generation Z employees within the DKI Jakarta region. Specifically, this study contributes to organizational behavior literature by simultaneously evaluating the partial and joint effects of Industrial Psychology (X_1), Workload (X_2), and Work Environment (X_3) on Employee Productivity (Y) within a unified Structural Equation Modeling (PLS-SEM) framework. Furthermore, it re-evaluates whether task demands act as a disruptive hindrance stressor or a stimulating challenge stressor that enhances cognitive efficiency among digital-native talent, while also reassessing physical office expectations in an era where flexible working arrangements are normalized.

Ultimately, this study offers dual contributions. Theoretically, it enriches organizational behavior literature by delivering a validated, context-specific productivity model for digital natives in an emerging Asian megapolitan economy. Practically, it provides HR decision-makers and organizational leaders with actionable insights to prioritize role clarity, appraisal transparency, and structured task engagement over physical office aesthetics

LITERATURE REVIEW

Industrial and Organizational Psychology applies psychological principles to optimize human behavior, well-being, and performance in occupational settings (Munandar, 2011; Muchinsky, 2000). Rather than operating as an abstract framework, industrial psychology

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enhances productivity through specific psychological mechanisms, specifically through goal clarity, task-competency congruence, and intrinsic psychological empowerment.

In the context of Generation Z employees in urban environments, who prioritize career transparency, continuous feedback, and self-actualization over rigid hierarchies (Mahmoud et al., 2021), organizational interventions function as critical psychological drivers. According to Goal Setting Theory (Locke & Latham, 2002) and Self-Determination Theory (Deci & Ryan, 2000), when organizational practices provide structured evaluation criteria and align job demands with individual competencies, they fulfill fundamental needs for competence and self-efficacy.

Mechanistically, clear performance standards eliminate role ambiguity and reduce cognitive load associated with organizational anxiety. By diminishing cognitive friction and uncertainty, young talents are able to reallocate their mental resources, creative focus, and technological capabilities toward goal-directed task execution rather than navigating organizational politics or ambiguity. Consequently, this alignment directly heightens task performance, operational efficiency, and overall output. Based on these theoretical foundations, the study proposes the following hypothesis:

H1: Industrial psychology positively influences productivity.

Workload refers to the volume, complexity, and time pressure associated with assigned tasks (Munandar, 2011; Hancock & Meshkati, 1988). Although excessive workload is widely linked to cognitive fatigue and performance decline in conventional occupational literature, modern stress theories distinguish between distinct stressor types. Grounded in the Challenge Stressor–Hindrance Stressor Framework (Cavanaugh et al., 2000), workload, when structured within optimal cognitive boundaries, functions as a *challenge stressor* that stimulates psychological activation, task engagement, and problem-solving motivation rather than strain.

In the context of Generation Z workers in Jakarta, who exhibit high digital literacy and adapt rapidly to fast-paced environments (Saputra et al., 2021), understimulating roles frequently lead to boredom, diminished focus, and organizational disengagement (*boreout*). Aligning with Activation Theory and the Yerkes-Dodson Law, moderate task demands elevate arousal levels to an optimal threshold necessary for maximum performance. A structured and demanding workload provides the necessary psychological impetus, challenging their capabilities while satisfying their intrinsic drive for achievement and personal development.

When provided with manageable yet rigorous task demands, Gen Z employees utilize digital tools, technological agility, and internal motivation to streamline workflow execution. This heightened cognitive arousal fosters focused concentration and temporal discipline, transforming moderate workload demands into enhanced operational efficiency and higher output volume. Based on these theoretical foundations, the study proposes the following hypothesis:

H2: Workload has a positive influence on productivity.

The work environment encompasses physical facilities, atmospheric conditions, safety protocols, and interpersonal dynamics within an organization (Sunyoto, 2015; Winata, 2022). Grounded in the Job Demands-Resources (JD-R) Model (Bakker & Demerouti, 2007) and Person-Environment (P-E) Fit Theory (Kristof-Brown et al., 2005), a supportive work environment

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serves as an essential organizational resource that directly regulates physiological comfort, cognitive strain, and intrinsic motivation.

By mitigating operational disruptions and environmental strain, a supportive work environment conserves workers' physical and mental energy. Rather than expending cognitive effort on adapting to sub-optimal ambient conditions or navigating interpersonal stress, employees can reallocate their sustained attention, problem-solving capacities, and technical skills directly toward core task execution. This systematic optimization of cognitive and physical resources enhances work continuity, accuracy, and overall output efficiency. Based on these theoretical mechanisms, the study proposes the following hypothesis:

H3: Work environment has a positive influence on productivity.

METHODS

Population-based research generally requires gathering data from every individual within a specified group. For the purposes of this investigation, the designated target population encompasses Generation Z workers residing and actively working in the DKI Jakarta region. Because of the vast scale of this demographic and the absence of an exact total population figure, a non-probability sampling approach utilizing a purposive sampling strategy was employed.
To ensure sample clarity and context validity, specific inclusion criteria were established:

1. Age and Demographic: Born between 1997 and 2012 (aged 14 to 29 years) and residing in DKI Jakarta;
2. Employment Status and Type: Actively employed as either full-time or part-time staff across various business sectors/industries;
3. Tenure: Possessing a minimum work experience of at least 6 months in their current organization to ensure adequate familiarity with workplace environment, workload, and productivity dynamics.

To establish an appropriate sample size, the Cochran Formula (Sujalu et al., 2021) was utilized with a 10% margin of error, establishing a baseline requirement of 96 participants. This number was subsequently adjusted upward to 100 respondents to streamline and optimize the data analysis phase. Through this defined selection method, a final sample of 100 Generation Z participants was successfully gathered. Furthermore, a sample size of 100 respondents is deemed adequate and statistically robust for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, as contemporary guidelines recommend a minimum sample size of 100 to achieve sufficient statistical power in models of moderate complexity (Hair et al., 2022).

Primary data were collected using a structured online questionnaire distributed to Generation Z employees operating within the DKI Jakarta region. To ensure item clarity and eliminate linguistic bias, measurement items originally sourced from English literature underwent a forward-and-backward translation process into Indonesian, accompanied by pre-test adjustments to fit the local organizational context. All research variables were evaluated using a 5-point Likert Scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

The measurement procedures and operationalization for each variable are detailed as follows:

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1. Industrial Psychology (X1) was evaluated through 5 measurement items adapted from the frameworks of Muchinsky (2000), covering dimensions such as selection and placement, training and development, performance management, organizational development, quality of work life, and ergonomics.
2. Workload (X2) was measured using 5 items adapted from the subjective workload dimensions of the NASA-TLX framework (Hancock & Meshkati, 1988), mental demands, physical demand, temporal demand, own performance, effort and frustration.
3. Work Environment (X3) comprised 5 items adapted from Sunyoto (2015), encompassing interpersonal dynamics, workplace atmosphere, physical environmental conditions (lighting and ventilation), facility availability, and safety standards.
4. Productivity (Y) was operationalized using 6 items adapted from performance frameworks by Sutrisno (2019), assessing intrinsic competence, continuous quality and quantity improvement efforts, daily motivation, self-development drive, output standard adherence, and input-output efficiency.

This study applies the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique carried out through the SmartPLS 4 software application to evaluate and explore the systemic correlations and impacts among the variables integrated within the research framework. The analytical procedure follows a systematic two-stage evaluation process adhering to Hair et al. (2022).

In the first stage, the Measurement Model (Outer Model) is evaluated to establish reliability and validity. Indicator reliability and convergent validity are assessed using outer loadings, where values should equal or exceed 0.708, alongside the Average Variance Extracted (AVE), which must be at least 0.50 to ensure that each construct explains more than half of its indicators' variance. Internal consistency reliability is confirmed using Composite Reliability (CR) and Cronbach's Alpha, with both metrics requiring values of 0.70 or higher. Discriminant validity is subsequently established using the Heterotrait-Monotrait ratio of correlations (HTMT), ensuring that values remain below the threshold of 0.85 or 0.90 to prove that the constructs are empirically distinct.

In the second stage, the Structural Model (Inner Model) is evaluated to test the hypothesized relationships. Collinearity among the predictor constructs is first examined using the Variance Inflation Factor (VIF) to rule out lateral multicollinearity, ensuring VIF values remain below 3.0 or at least below 5.0. The explanatory power and effect size of the model are then evaluated through the Coefficient of Determination (R^2), which measures the proportion of variance explained in the dependent variable, as well as the Effect Size (f^2) to evaluate the relative contribution of each predictor. Finally, hypothesis testing and statistical significance are conducted through a non-parametric bootstrapping procedure with 5,000 subsamples, deriving path coefficients (β), t-statistics with a critical threshold of $t > 1.96$ for a two-tailed test at a 5% significance level, and p-values ($p < 0.05$).

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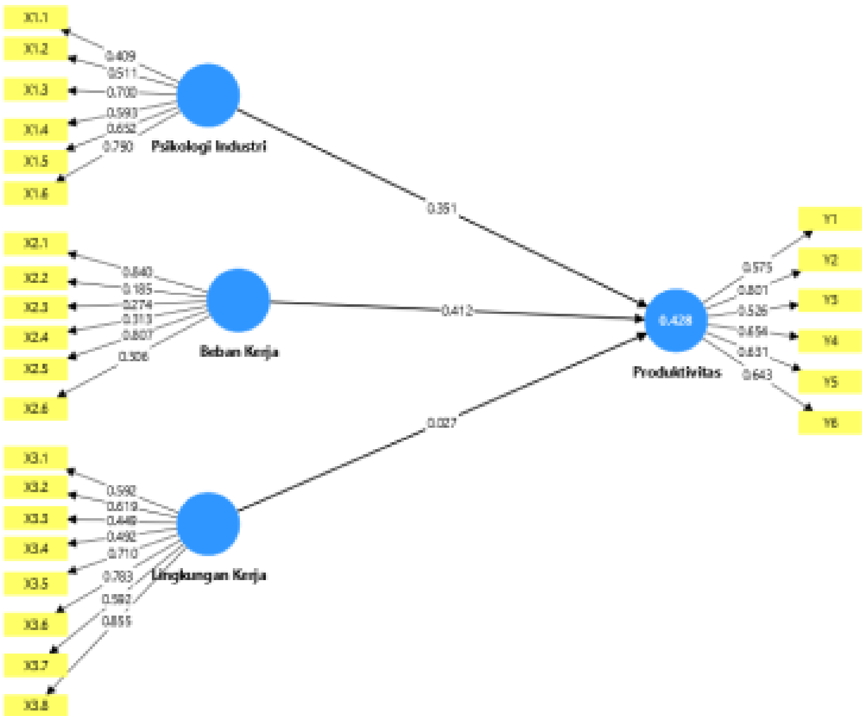
RESULTS

To handle the processing of highly complex structural models, this study employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique via SmartPLS 4. The choice of this analytical software aims to streamline the modeling and testing processes of complex variables.

Convergent validity testing uses loading factors to determine how well indicators capture their latent constructs. While a loading factor above 0.7 is ideal for a strong relationship, indicators scoring between 0.4 and 0.7 can be retained if they help increase the composite reliability above 0.7 or the AVE above 0.5. The initial results from this phase are visualized in the following path diagram:

Figure 1: Research Path Model



Referring to the data presented in the path model above, a number of indicators were found whose validity values have not yet reached the minimum threshold, thus requiring an in-depth evaluation. This stage is conducted by reviewing indicators that have a loading factor score between 0.40 and 0.70. These indicators will only continue to be used in the model if they are able to increase the composite reliability value above 0.70 or boost the ave value to exceed 0.50.

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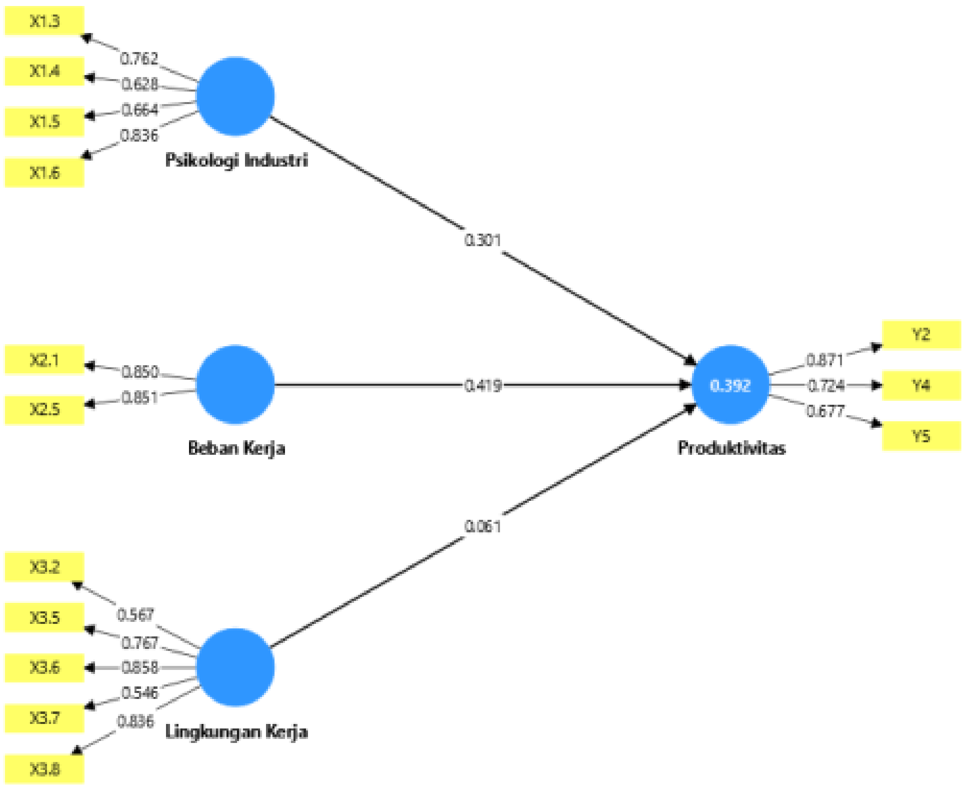
Figure 2: Research path model after elimination



A total of 12 indicators, specifically X1.1, X1.2, X2.2, X2.3, X2.4, X2.6, X3.1, X3.3, X3.4, Y1, Y3, and Y6, were excluded from the measurement model. These items failed to satisfy the convergent validity threshold due to low outer loadings (< 0.70 or acceptable rule-of-thumb limits), which compromised the Average Variance Extracted (AVE) of their respective constructs. Following an iterative elimination process, the retained indicators demonstrated acceptable factor loadings ranging from 0.40 to 0.70, which significantly enhanced overall model quality without compromising the conceptual integrity of the constructs. Consequently, the modified model successfully fulfilled convergent validity criteria, with all constructs achieving the required minimum AVE value of 0.50 and Composite Reliability (CR) exceeding the standard threshold of 0.70.

The empirical distinctiveness and uniqueness of each latent construct within the model are verified through discriminant validity assessment. In PLS-SEM analysis, this procedure utilizes the Heterotrait-Monotrait (HTMT) ratio method. To satisfy the evaluation criteria, the HTMT score must be at most 0.90 for variables with theoretical proximity, whereas a maximum cutoff of 0.85 is enforced for constructs that differ conceptually.

Table 1: Discriminant Validity

Variable	X1	X2	X3	Y
X1				
X2	0.390			
X3	0.720	0.573		
Y	0.556	0.794	0.472	

Source: Data Prepared by the authors

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Based on the findings in the table, all indicator values are below the 0.90 criterion. This indicates that each indicator correlates more strongly with its original latent construct than with other variables. Consequently, the discriminant validity standard has been met, confirming that these indicators precisely represent distinct latent dimensions.

This study applies composite reliability analysis to evaluate the level of internal consistency among the indicators comprising a construct. The reliability standard of the instrument is determined based on the Cronbach's Alpha and composite reliability values. The criteria are met if both parameters show values that exceed the 0.70 threshold.

Table 2: Composite Reliability

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
X1	0.730	0.779	0.816	0.528
X2	0.618	0.618	0.840	0.723
X3	0.780	0.862	0.844	0.529
Y	0.651	0.728	0.804	0.581

Source: Data Prepared by the authors

Evident from the table, the reliability requirements have been successfully met by all latent variables. While some values for Cronbach's Alpha and Composite Reliability dropped below 0.70, they remain justifiable within an exploratory context at a range of 0.60 to 0.70, adhering to the guidelines of Hair et al. (2017) given that other validity criteria hold true. This overall instrument validity and reliability is further solidified by an AVE value surpassing 0.50, which verifies adequate convergent validity.

To determine whether meaningful linear correlations exist among the independent variables of this study, this specific analysis was conducted. The resulting data and evaluation metrics are compiled in the table that follows:

Table 3: Variance Inflation Factor

Inner VIF Value	VIF	Description
Industrial Pyschology → Productivity	1.481	Non Multicollinearity
Workload → Productivity	1.222	Non Multicollinearity
Work Environment → Productivity	1.603	Non Multicollinearity

Source: Data Prepared by the authors

Based on the data in the table, the multicollinearity test results recorded a Variance Inflation Factor (VIF) value of 1.481 for the industrial psychology variable, 1.222 for workload, and 1.603 for work environment. Since all obtained values are well below the conservative criterion of 3.00 as well as the maximum threshold of 5.00, it can be concluded that the model in this study shows no indication of significant multicollinearity issues.

The R-Square test is utilized to evaluate how effectively the exogenous variables can explain or predict the variance found in the endogenous variable. A comprehensive breakdown of this coefficient of determination analysis is provided in the following table:

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Table 4: R-Square

Variable	R-Square
Productivity	0.392

Source: Data Prepared by the authors

The data yields an R-Square value of 0.392, indicating that 39.2% of the variability in productivity can be explained by the collective influence of industrial psychology, workload, and work environment. The rest of the variance, amounting to 60.8% (rounded to 61%), is attributed to alternative determinants that were not examined within the scope of this study.

To evaluate the significance of causal relationships in PLS-SEM, researchers utilize bootstrapping. This procedure produces T-statistics used for validating both indicator outer loadings and path coefficients between constructs. Hypotheses are accepted if they achieve a T-statistic above 1.96 and a P-value under 0.05 (at a 95% confidence interval), confirming that the independent variable significantly affects the dependent variable.

Table 5: Path Coefficient Value

Variable	Original Sample (O)	Sample Mean (M)	Standard Deviation	T-Statistic	P-Values	Decision
Industrial Pyschology → Productivity	0.301	0.313	0.128	2.351	0.019	Significant
Workload → Productivity	0.419	0.374	0.134	3.128	0.002	Significant
Work Environment → Productivity	0.061	0.102	0.165	0.369	0.712	Not Significant

Source: Data Prepared by the authors

According to the results, two primary predictors, workload and industrial psychology, demonstrate a notable capacity to alter the productivity of Generation Z workers in Jakarta. These outcomes highlight that organizational ergonomics, performance management, mental demands, and individual effort serve as core drivers of employee efficiency. Meanwhile, the final variable, work environment, shows a negligible impact on productivity. This lack of significance implies that variables such as office facilities, peer relationships, safety standards, and the organizational climate do not critically modify productivity thresholds.

DISCUSSION

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the partial and simultaneous effects of industrial psychology, workload, and work environment on the operational productivity of Generation Z employees in DKI Jakarta. Based on the structural model evaluation, the empirical findings demonstrate that workload ($\beta = 0.419, p = 0.002$) exerts the strongest positive direct effect on productivity, followed by industrial psychology ($\beta = 0.301, p = 0.019$). Conversely, the work environment exhibits no

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statistically significant effect ($\beta = 0.061, p = 0.712$). Simultaneously, these three exogenous variables account for 39.2% of the variance in employee productivity ($R^2 = 0.392$), while the remaining 60.8% is shaped by unexamined external factors.

The empirical finding that workload serves as the primary driver of productivity offers a key theoretical contribution to stress literature regarding digital natives. Contrary to traditional assumptions viewing workload as an inherently negative driver of fatigue, these results align with the Challenge Stressor–Hindrance Stressor Framework (Cavanaugh et al., 2000) and the Job Demands–Resources (JD-R) Model (Bakker & Demerouti, 2007). For Generation Z employees operating in Jakarta's fast-paced corporate environment, structured task demands, analytical problem-solving, and time pressure operate as challenge stressors that induce eustress (positive stress). Grounded in Activation Theory and the Yerkes-Dodson Law, moderate task demands elevate psychological arousal to an optimal threshold necessary for maximum performance. Given Generation Z's high digital literacy and technical agility, understimulating roles frequently induce boredom and disengagement (*boreout*). Manageable yet demanding tasks stimulate cognitive activation, fostering focus and temporal discipline that translate into heightened operational output. From a managerial perspective, organizations must avoid both task underload and acute overload by deploying structured workload tracking tools, capacity planning dashboards, and sprint management frameworks to calibrate optimal task complexity, thereby leveraging workload as a constructive challenge

Regarding industrial psychology, the statistical results confirm that applying structured organizational psychology principles significantly enhances Generation Z productivity. Viewed through Social Exchange Theory (Blau, 1964), when an organization provides transparent performance appraisal metrics, competency-aligned placement, and clear career development pathways, employees perceive these initiatives as a direct organizational investment in their human capital. Through the norm of reciprocity, Generation Z workers respond with heightened task engagement and operational efficiency. Furthermore, in accordance with Goal Setting Theory (Locke & Latham, 2002) and Self-Determination Theory (Deci & Ryan, 2000), transparent performance standards eliminate role ambiguity and reduce cognitive load associated with organizational anxiety. Fostering psychological safety allows young talents to direct their mental focus and technical capabilities toward primary goals rather than navigating organizational ambiguity. Practically, human resource departments should replace ambiguous evaluation systems with transparent, KPI-based performance tracking and real-time feedback loops, while establishing structured mentoring programs to reduce work-related anxiety and facilitate knowledge transfer

Conversely, the analysis demonstrates that the work environment has no significant direct influence on Generation Z productivity. Neither the quality of physical infrastructure nor office climate acts as a primary determinant of performance fluctuations. Theoretical justification for this non-significant result aligns directly with Herzberg's Two-Factor Theory, which categorizes physical work conditions as hygiene factors. Hygiene factors serve primarily to prevent job dissatisfaction, but they do not function as intrinsic motivators for peak performance. In modern urban centers like Jakarta, basic office facilities are largely established and taken for granted as baseline corporate standards. Coupled with the widespread normalization of flexible working arrangements (hybrid/remote working), Generation Z's operational orientation is no

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longer tethered to physical office spaces, but rather to goal clarity, job autonomy, and cognitive engagement. Consequently, corporate leaders should reallocate operational capital away from superficial, aesthetic office upgrades toward formalizing Flexible Working Arrangements (FWA), hybrid work infrastructure, advanced digital collaboration tools, and outcome-based performance appraisal systems

CONCLUSION

This study confirms that the productivity of Generation Z employees in DKI Jakarta is significantly driven by the application of industrial psychology principles and manageable workload distribution, whereas physical work environment quality yields no significant impact as it is now perceived as a baseline expectation (*hygiene factors*). Theoretically, these findings enrich the Industrial and Organizational Psychology (I/O) literature and extend the *Job Demands-Resources* model within the context of digital natives, demonstrating that structured, cognitively demanding tasks act as productivity catalysts rather than stress triggers. Practically, the results advise HR managers to pivot investment priorities from physical facility upgrades toward strengthening psychological ecosystems, specifically transparent performance evaluations, digital skill development, and equitable workload management. Future research should expand the geographical scope beyond the metropolitan area and incorporate additional predictor variables, such as psychological safety, work-life balance, and leadership styles, to deepen the empirical understanding of Gen Z productivity dynamics.

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