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The Effect of Workload, *Work-Life Balance*, and Burnout on Job Satisfaction with the Mediation of Digital Transformation Readiness Among Generation Z Employees in the Mining Sector in Jakarta

Leoni Angela Fortunata*, Liem Bambang Sugiyanto
Universitas Bunda Mulia, Indonesia
Email: m81250005@student.ubm.ac.id*, L0674@lecturer.ubm.ac.id

ABSTRACT

This study aims to examine the effect of workload, *work-life balance*, and *burnout* on job satisfaction, with digital transformation readiness as a mediating variable, among Generation Z employees in the mining sector in Jakarta. This research employs a quantitative approach using the SEM-PLS method via SmartPLS, with data collected from 155 respondents using a Likert-scale questionnaire. The results indicate that digital transformation readiness has the strongest and most significant positive effect on job satisfaction. Workload, *work-life balance*, and *burnout* do not directly influence job satisfaction. However, digital transformation readiness significantly mediates the relationship between *work-life balance* and *burnout* and job satisfaction, while it does not mediate the relationship between workload and job satisfaction. These findings highlight the strategic role of digital transformation readiness in enhancing job satisfaction among Generation Z employees. Practically, the results provide insights for mining companies in strengthening digital capabilities, supporting employee adaptability to technological change, and sustaining *work-life balance* policies. Nevertheless, this study is limited to Generation Z employees in the mining sector in Jakarta. Future research is recommended to examine similar variables among site-based mining employees in order to obtain a more comprehensive understanding of employee work behaviour.

Keywords: Organizational behaviour, Work Load, Work-life balance, Burnout, Job Satisfaction

INTRODUCTION

Population dynamics are fundamental factors affecting various aspects of development in Indonesia, including the development of the employment sector (Akbar Arjuna et al., 2023). In line with this, Indonesia is also one of the countries in the ASEAN region that makes a significant contribution to long-term digital economic growth, amounting to 41.5 percent (Seah et al., 2024). This condition is concurrent with a national demographic structure dominated by Generation Z, which, based on the 2020 Population Census, is recorded as the largest population group, totalling 75.49 million people or approximately 27.94 percent of the total population. This generation, born between 1997 and 2012, has begun to enter the workforce en masse and is projected to dominate the national labour force in the coming years (Anhar et al., 2024; Bakker & Demerouti, 2017).

Burnout is a response to unresolved long-term occupational stress and manifests as emotional exhaustion, decreased motivation, and reduced productivity, thereby increasing the risk of *turnover intention* (Dudija & Putri, 2024; Hartono & Prapunoto, 2024). The Naluri survey (2024) shows that Generation Z in Asia has the highest *burnout* rate, reaching 62 percent. This finding is consistent with research by Wulandari et al. (2023), which demonstrates that *burnout* has a positive and significant effect on *turnover intention*. One of the primary factors that trigger *burnout* is workload.

Workload refers to the responsibilities that must be completed within a designated timeframe, and employees' perception of this burden can affect the level of job satisfaction they experience (Kharisma & Kurniawati, 2024). Excessive workload can induce emotional stress, reduce work performance, and heighten psychological strain (Weni et al., 2023).

In addition, *work-life balance* is an important need for Generation Z, who hold high expectations regarding work flexibility (Waworuntu et al., 2022). An imbalance between work demands and personal life can cause stress, reduce job satisfaction, and increase *turnover intention* (Nurjanah & Indawati, 2021).

One of the factors that plays a critical role in achieving optimal performance is the level of job satisfaction experienced by employees (Siregar, 2024). Job satisfaction refers to the positive and negative feelings, attitudes, and beliefs that individuals hold regarding their tasks and work environment (Holbert et al., 2021). Job satisfaction reflects employees' comfort with various aspects of their work and influences both organisational commitment and the decision to remain with the company. A decline in job satisfaction increases the tendency to seek other employment opportunities (Wibowo et al., 2024).

Digitalisation has become a transformative force across various industries, including the mining sector, driving companies to modernise work processes and improve operational efficiency (Pavlikhina et al., 2021). The government also emphasises the importance of adopting digital technology to maintain competitiveness and enhance service quality (Bthari Ayeisha & Yudo Anggoro, 2024). In the context of Industry 4.0, digital transformation requires companies to adapt to technology in order to support an integrated, customer-oriented operating model. The post-COVID-19 acceleration of digitalisation has expanded the application of *remote work*, *cloud computing*, data analytics, and artificial intelligence (Wahyudin et al., 2024). Furthermore, the intensification of digital transformation requires companies to adapt rapidly to technology-based work systems while ensuring rigour in the decision-making process (Kludacz-Alessandri et al., 2025).

Digital transformation readiness refers to the degree of preparedness of individuals, institutions, companies, and nations in adopting and utilising digital technology (Nasution et al., 2018). Low digital transformation readiness can increase workload, diminish *work-life balance*, and adversely affect job satisfaction (Wahyudin et al., 2024). This is consistent with the findings of Khuc and Nguyen (2025), which demonstrate that digital transformation exerts a significant influence on work pressure and job satisfaction, particularly through process changes, the adoption of new technologies, and increased demands for workplace adaptation.

This research aims to examine the effect of workload, *work-life balance*, and *burnout* on job satisfaction, with digital transformation readiness as a mediating variable, among Generation Z employees in the mining sector in Jakarta (Bunjak et al., 2021; Chen et al., 2023; da Silva et al., 2022). The specific objectives are to: (1) examine the direct effect of workload on job satisfaction; (2) examine the direct effect of *work-life balance* on job satisfaction; (3) examine the direct effect of *burnout* on job satisfaction; (4) examine the direct effect of digital transformation readiness on job satisfaction; (5) examine the effect of workload on digital transformation readiness; (6) examine the effect of *work-life balance* on digital transformation readiness; (7) examine the effect of *burnout* on digital transformation readiness; (8) assess the mediating role of digital transformation readiness in the workload–job satisfaction relationship; (9) assess the mediating role of digital transformation readiness in the *work-life balance*–job satisfaction relationship; and (10) assess the mediating role of digital transformation readiness in the *burnout*–job satisfaction relationship.

The contributions of this research are both theoretical and practical. Theoretically, it extends the understanding of job satisfaction determinants by demonstrating how digital transformation readiness operates as a mediating mechanism in the relationships between workplace factors and satisfaction outcomes. The findings contribute to the Job Demands–Resources (JD-R) theory by illustrating how digital transformation readiness may function as a personal resource that moderates the impact of job demands on job satisfaction. Practically, the research provides actionable insights for mining companies and human resource practitioners regarding strategies to enhance job satisfaction among Generation Z employees. For organisations undergoing digital transformation, the findings highlight the importance of supporting employee readiness alongside technological implementation. For policymakers, the research informs understanding of workforce dynamics in Indonesia's strategic mining sector. Ultimately, this study contributes to the development of evidence-based human resource strategies that support both organisational effectiveness and employee well-being in Indonesia's digitalising economy.

METHOD

This study employed a quantitative approach with a mediational model research design. This approach was selected because the study seeks to describe and test the relationships and effects among independent variables and a dependent variable through a mediating variable. In the context of this study, the researcher examines how workload, *work-life balance*, and *burnout*, as well as the mediating role of digital transformation readiness, influence job satisfaction among Generation Z employees in the mining sector.

The population in a study refers to the entire group of individuals, events, or phenomena that constitute the focus of investigation (Bougie & Sekaran, 2020). The population in this study comprises employees classified as Generation Z who are currently employed or have previously been employed in mining companies. The sample is the portion of the population selected to represent the overall characteristics of that population, such that the findings may be generalised (Bougie & Sekaran, 2020; Hardani et al., 2020). The sampling technique employed is purposive sampling, defined as the selection of samples based on criteria specified in accordance with the research objectives (Sugiyono, 2019). The sample size was determined in accordance with the guidelines of Hair et al. (2024), which recommend a minimum of 5–10 observations per indicator. With a total of 25 indicators across five variables, the minimum required sample size is 125–250 respondents. To obtain more representative results and to account for invalid or incomplete responses, this study utilised 155 respondents drawn from the Greater Jakarta area.

The data sources in this study comprise both primary and secondary data. Primary data were obtained directly from respondents through the administration of questionnaires, while secondary data were gathered from scientific journals, academic literature, and books relevant to the variables under study. Data collection was conducted using a survey method with a questionnaire instrument compiled as a set of written statements and distributed via Google Form to facilitate completion by respondents. This study involves three independent variables workload (X1), *work-life balance* (X2), and *burnout* (X3) one dependent variable, namely job satisfaction (Y), and one mediating variable, namely digital transformation readiness (Z).

Conceptual and Operational Definitions

Table 1. Conceptual Research Variables

Variable	Reference Source
Workload (X1)	According to Nurhikmah (2022), workload is a set or number of activities that must be completed within a certain period of time.
Work-life Balance (X2)	According to Olanda & Swasti (2023), it is explained that *work-life balance* is a condition where employees can carry out and balance work responsibilities and other roles in their personal lives well, which is supported by the organization with a series of activity designs and organizational culture.
Burnout (X3)	According to Nurhikmah (2022), *burnout* is physical, mental, and emotional fatigue that occurs due to stress suffered over a long period of time, in situations that demand high emotional involvement.
Job Satisfaction (Y)	According to Nabilla et al., (2023), *job satisfaction* is an employee's emotional response to their work's tasks, physical conditions, and social conditions and shows the extent to which their expectations have been met
Digital Transformation Readiness (W)	According to Agostino & Costantini (2022) states that *digital transformation readiness* is defined as the extent to which employees are willing to allocate their energy, attention, and efforts to engage in the technology-based change process, which ultimately affects their work behavior.

Table 2. Operationalization of Research Variables

Variable	Indicator	Reference Source
Workload (X1)	Load Time Sense of Passion Stress Mental	Nurhasanah et al., (2022)
Work-life Balance (X2)	*Time Balance* *Involvement Balance* *Satisfaction Balance*	Rahmawati & Gunawan, (2020)
Burnout (X3)	*Emotional Exhaustion* *Depersonalization* *Decreased Professional Efficacy*	Shah et al., (2021)
Job Satisfaction (Y)	*Employee Salary* *Promotion* *Supervision* *Benefit* *Reward* *Operating Procedure* *Co-worker* *Communication*	Wolor *et al., (*2020)
Digital Transformation	*People*	Hoyng & Lau, (2023)

Readiness (W)	*Technology* *Process* *Customers* *Strategy and Investment*

This study uses an interval scale by referring to the measurement method using *the Likert* scale. A *Likert* scale is a measurement scale used to collect data about respondents' views or attitudes toward a series of statements or items. The *Likert* scale is designed to examine how strongly subjects agree with a statement about a particular subject, object, and event. Respondents were asked to indicate their level of approval or disapproval of the statements. The researcher distributed a questionnaire to the respondents using a Likert scale.

Table 3. Likert Scale

Value	Remarks
1	Strongly Disagree
2	Disagree
3	Disagree
4	Agree
5	Strongly agree

Source: Bougie and Sekaran, 2020

RESULTS AND DISCUSSION

Table 4. Respondent Profiles

Variable	Categories	Quantity	Percentage
Year of Birth	1997–2012 (Generation Z)	155	96.9%
	1981–1996 (Generation Y / Millennial)	5	3.1%
Tenure	< 1 year	26	16.8%
	1-3 years	83	53.5%
	4-6 years	41	26.5%
	> 6 years old	5	3.2%
Gender	Women	87	56.1%
	Male	68	43.9%
Divisions	*Supply Chain / Procurement*	50	32.3%
	Logistics	21	13.5%
	Human Resources (HR)	25	16.1%
	Finance / Accounting	25	16.1%
	Information Technology (IT)	11	7.1%
	General Affairs (GA)	8	5.2%
	Health, Safety, and Environment (HSE)	12	7.7%
	Others	3	1.9%
Departments	Staff	102	65.8%
	Supervisor	28	18.1%
	Assistant Manager	4	2.6%
	Manager	20	12.9%
	Senior Manager / Head	1	0.6%
	Total Respondents	**155**	**100%**

Source: Results of Researcher Data Processing (2026)

From the year of birth, the majority of respondents were included in Generation Z (1997–2012) as many as 155 people (100% of the analyzed sample). Previously, there were 5 respondents from Generation Y/Millennial (1981–1996), but because this study focused on Generation Z, these respondents were eliminated, so that the total number of respondents processed was 155 people.

Based on the length of service, the majority of respondents had 1-3 years of experience as many as 83 people (53.5%), followed by 4-6 years of 41 people (26.5%), less than 1 year of 26 people (16.8%), and more than 6 years of 5 people (3.2%). This data shows that most respondents are in the early to mid-stage stages of their careers, which is relevant for assessing adaptation to organizational policies or innovations.

In terms of gender, the majority of female respondents were 87 people (56.1%), while men amounted to 68 people (43.9%), showing a relatively balanced gender distribution with a slight female dominance.

In terms of division, the most respondents came from Supply Chain/Procurement with 50 people (32.3%), followed by HR and Finance/Accounting with 25 people (16.1%), Logistics with 21 people (13.5%), HSE with 12 people (7.7%), IT with 11 people (7.1%), GA with 8 people (5.2%), and Others with 3 people (1.9%) which included contract operators, receptionists, and engineers. Thus, the research sample covers a variety of additional roles that support the organization's operations.

Based on position, the majority of respondents were 102 staff (65.8%), followed by 28 supervisors (18.1%), managers 20 people (12.9%), assistant managers 4 people (2.6%), and senior managers/heads 1 person (0.6%). These findings show a concentration at the operational and supervisory levels, which has a direct influence on the implementation of daily tasks.

Overall, the demographic and professional characteristics of the respondents show the dominance of young workers of Generation Z, with 1–3 years of work experience, the majority of whom are women, in a position as staff, and come from the Supply Chain/Procurement division. This profile is consistent with research criteria that assess Generation Z's perception, involvement, and adaptation in the work environment (Al Ghifari et al., 2021; Al-Hussami et al., 2017).

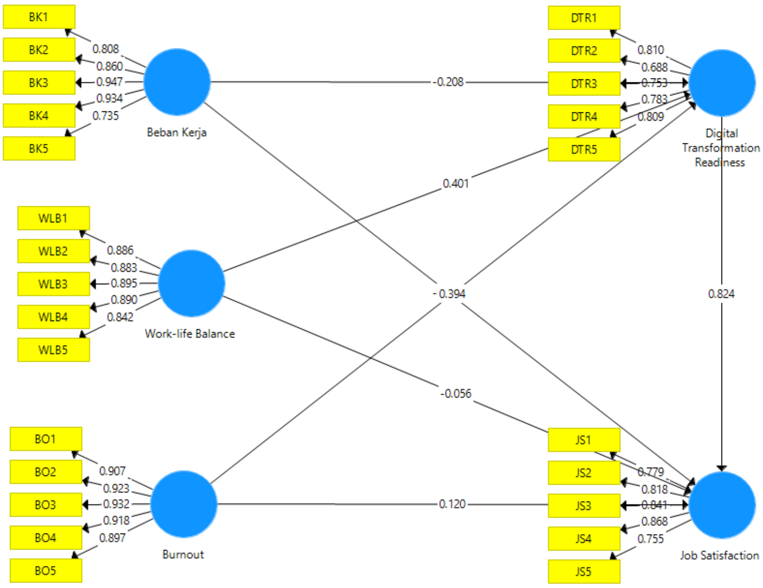
Evaluation *of Measurement Model* (*Outer Model*)

In this model, it is defined how each indicator can relate to its latent variables, or it can be said that the outer model can specify the relationship between latency and its indicators, as follows:

Convergent validity *test*

In the convergent validity test of each of the construct indicators. According to Chin in Ghozali (2015), the reflection of the indicator is assessed based on the correlation between *the item score/component* score and *the construct score* calculated using PLS and an indicator can be said to be valid if *the* loading factor *value is >0.70,* while the *loading factor* of 0.50 to 0.60 can be considered sufficient. So based on this criterion, if there is a *loading factor* below 0.50, it will be eliminated.

Figure 1. Total Overall *Value of Loading Factor* (*Convergent Validity*)



Source: Processed Research Data (2026)

The results of the test on each variable are as follows:

1. Workload Variable (X1): Based on the analysis above, the *loading factor* value of each BK indicator (BK1, BK2, BK3, BK4, BK5) is above 0.7, ranging from 0.735 to 0.9477 so that this proves that all indicators of the Workload variable (X1) used in this study are valid.
2. *Work-life Balance* (X2) Variable: Based on the above analysis, *the loading factor* value of each WLB indicator (WLB1, WLB2, WLB3, WLB4, WLB5) is above 0.70, ranging from 0.842 to 0.895 so that this proves that all *indicators of the Work-life Balance* (X2) variable used in this study are valid.
3. Burnout Variable (X3): Based on the analysis above, the *loading factor* value of each BO indicator (BO1, BO2, BO3, BO4, BO5) is above 0.70, ranging from 0.897 to 0.932 so that this proves that all indicators of *the Burnout* (X3) variable used in this study are valid.
4. *Digital Transformation Readiness* (Z) Variable: Based on the analysis above, *the loading factor* value of each DTR indicator (DTR1, DTR2, DTR3, DTR4, DTR5) is above 0.70, ranging from 0.688 to 0.810 which means that this proves that all indicators of the *Digital Transformation Readiness* (Z) variable used in this study are valid.
5. Job *Satisfaction* (Y) Variable: Based on the analysis above, *the loading factor* value of each JS indicator (JS1, JS2, JS3, JS4, JS5) is above 0.7, ranging from 0.755 to 0.868, this proves that of all the *indicators of the Job Satisfaction* (Y) variable used in this study is valid.

Table 5. Table of Validity Test Results

Indicator	**Loading Factor *Value***	**Remarks**
BK1	0.808	Valid
BK2	0.860	Valid
BK3	0.947	Valid

BK4	0.934	Valid
BK5	0.735	Valid
WLB1	0.886	Valid
WLB2	0.883	Valid
WLB3	0.895	Valid
WLB4	0.890	Valid
WLB5	0.842	Valid
BO1	0.907	Valid
BO2	0.923	Valid
BO3	0.932	Valid
BO4	0.918	Valid
BO5	0.897	Valid
DTR1	0.810	Valid
DTR2	0.688	Valid
DTR3	0.753	Valid
DTR4	0.783	Valid
DTR5	0.809	Valid
JS1	0.779	Valid
JS2	0.818	Valid
JS3	0.841	Valid
JS4	0.868	Valid
JS5	0.755	Valid

Source: Processed Research Data (2026)

According to Ghozali & Latan, in 2015, in addition to using *the loading factor*, *convergent validity* can be determined through AVE (*Average Variance Extracted*) with the condition AVE >0.5. *Convergent validity* is seen from the Average *Variance Extracted* (AVE) examination which in this case explains the magnitude of the variables possessed by the latent construct. So that the more or the greater the number of variables contained by the latent construct, the greater the representation of the variables to the latent construct, the better. Therefore, the AVE (*Average Variance Extracted*) check can be seen the AVE value based on the results of data processing with SmartPLS3 as follows:

Table 6. Average *Variance Extracted* (AVE) Value

Variable	AVE
BK	0.740
BO	0.839
DTR	0.593
JS	0.661
WLB	0.774

Source: Processed Research Data (2026)

It can be seen in Table 4.2 that all variables in this study have an AVE value of > 0.50. The value indicates that each construct has met the criteria for convergent validity. Thus, all variables in this study were declared valid and suitable for use in further analysis.

Construct Reliability *Test*

The construct reliability test was performed to evaluate the internal consistency of the measurement instrument through the assessment *of Composite Reliability* and *Cronbach's Alpha values*. The higher the value of the two indicators, the better the level of consistency of the indicator in representing the latent variable being measured. According to Hair et al. (2014), *the recommended Composite Reliability* and *Cronbach's Alpha* values are greater than 0.70, which indicates that the construct has a good level of reliability. The results can be seen in table 7 below:

Table 7. *Construct Reliability*

Variable	*Cronbach's Alpha*	*Composite Reliability*
BK	0.934	0.934
BO	0.953	0.963
DTR	0.827	0.879
JS	0.871	0.907
WLB	0.927	0.945

Source: Processed Research Data (2026)

Based on Table 4.3, all variables in the reliability test show values that meet the eligibility criteria, either based on *Cronbach's Alpha* or *Composite Reliability*. All the values obtained were above the recommended minimum limit, namely *Cronbach's Alpha* ≥ 0.70 and *Composite Reliability* ≥ 0.70. Thus, it can be concluded that all constructs in this study have a good level of reliability, making them suitable for use in the next stage of structural model testing.

Discriminant Validity *Test*

Discriminant validity is a form of evaluation that aims to ensure that each variable studied conceptually has differences from each other and is empirically proven through statistical testing (Pardede et al. (2025). One of the methods used to assess the validity of the discriminator is to evaluate the *cross loading* value of each indicator. In particular, the loading value of the indicator against the measured construct must be higher than the loading value of the indicator against other constructs (Hair et al., 2014). The results can be seen in table 4.4 below:

Table 8. *Discriminant Validity*

Indicator	Workload	*Work-life Balance*	*Burnout*	*Digital Transformation Readiness*	*Job Satisfaction*
BK1	0,808	0,084	0,615	-0,005	-0,050
BK2	0,860	0,086	0,604	0,056	-0,026
BK3	0,947	0,227	0,577	0,130	0,017
BK4	0,934	0,125	0,622	0,108	0,030
BK5	0,735	0,014	0,593	0,025	-0,028
WLB1	0,589	-0,290	0,907	0,123	0,112
WLB2	0,588	-0,316	0,923	0,142	0,151
WLB3	0,597	-0,269	0,932	0,152	0,160
WLB4	0,636	-0,300	0,918	0,075	0,140
WLB5	0,578	-0,305	0,897	0,058	0,073

BO1	0,067	0,120	0,157	0,810	0,672
BO2	0,025	0,215	-0,024	0,688	0,579
BO3	0,156	0,179	0,187	0,753	0,626
BO4	0,099	0,280	0,040	0,783	0,585
BO5	0,096	0,140	0,120	0,809	0,645
DTR1	-0,095	0,045	0,050	0,601	0,779
DTR2	0,054	0,183	0,107	0,733	0,818
DTR3	-0,008	0,010	0,118	0,667	0,841
DTR4	0,030	-0,016	0,146	0,670	0,868
DTR5	0,074	0,089	0,178	0,605	0,755
JS1	0,137	0,886	-0,295	0,207	0,117
JS2	0,120	0,883	-0,354	0,204	0,065
JS3	0,155	0,895	-0,296	0,239	0,015
JS4	0,156	0,890	-0,255	0,235	0,087
JS5	0,194	0,842	-0,191	0,148	0,052

Source: Processed Research Data (2026)

Based on the results in Table 8, all indicators in each variable show the highest loading value compared to other constructs. In the Workload variable, the BK3 indicator has a *loading factor* value of 0.947 which is higher than the *cross loading* value of Burnout (0.577), *Digital Transformation Readiness* (0.130), *Job Satisfaction* (0.017), and *Work-life Balance* (0.227). The same thing is also shown in the *Burnout* variable, where the BO3 indicator has a loading factor value of 0.932 which is higher than the cross loading value of other constructs. In addition, in the *Digital Transformation Readiness* variable, the DTR1 indicator shows a loading factor value of 0.810 which is higher than the cross loading value of the *Job Satisfaction* construct (0.672) and other constructs. In the *Job Satisfaction* variable, the JS4 indicator has a loading factor value of 0.868 which is also higher than the cross loading value of other constructs. Meanwhile, in the *Work-life Balance* variable, the WLB3 indicator has a loading factor value of 0.895 in the *Work-life Balance* construct, which is higher than the cross loading value of other constructs. Thus, the results of the discriminant validity test through *the cross loading* approach show that all indicators have a stronger correlation to their original construct compared to other constructs. This indicates that each indicator is able to represent the constructed measured appropriately so that the criteria for discriminant validity in this study are declared met. Thus, the variables studied met the *criteria of discriminant validity*.

Evaluation *of Structural Models* (*Inner Model*)

The Inner Model describes the relationships between latent variables based on substantive theory. Where the relationship describes the relationship between independent variables and dependent variables which are then analyzed using path analysis (Riefky & Hamidah., 2019).

a. *R-Square* (R2)

R-Square is used for the measurement of the strength of structural model predictions. In this case, *R-Square* explains the influence of certain exogenous variables on endogenous variables whether the variables have a substantial influence. According to Ghozali and Latan (2015), *the R-Square* values of 0.75, 0.50, and 0.25 indicate a strong, moderate and weak model.

Table 9. Determination Coefficient Test Results

Variable	Coefficient of Determination (R^2)	Remarks
Digital Transformation Readiness	0.123	Weak Relationships
Job Satisfaction	0.678	Moderate Relationship

Source: Processed Research Data (2026)

Based on Table 4.5, it is known that the value of the determination coefficient (R^2) of the *Job Satisfaction* (Y) variable is 0.678. This value shows that the *Job Satisfaction* (Y) variable can be explained by the variables Workload (X1), *Burnout* (X2), *Work-life Balance* (X3), and *Digital Transformation Readiness* (Z) of 67.8%, while the remaining 32.2% is influenced by other variables outside the research model.

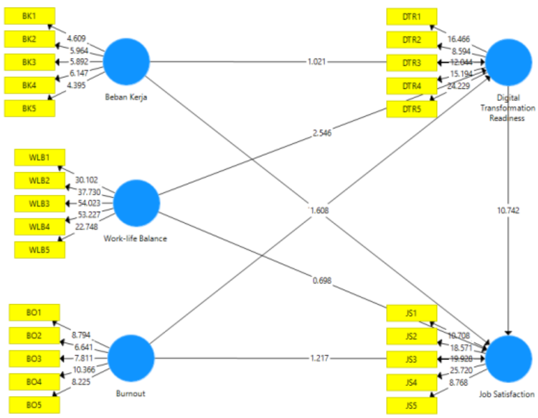
The value of the determination coefficient (R^2) of the *Digital Transformation Readiness* (Z) variable was 0.123 which shows that the ability of the variables Workload (X1), *Burnout* (X2), and *Work-life Balance* (X3) in explaining the *Digital Transformation Readiness* (Z) variable was relatively low, which was 12.3%, while the remaining 87.7% was influenced by other variables outside the research model.

Hypothesis Test

In the hypothesis test, a *structural equation modelling* (SEM) model was used using the SmartPLS 3 program. Hypothesis testing was carried out by comparing the p-Value value with the *level of significance* of 95% (α= 0.05). Hair (2024) reveals the conditions for accepting or rejecting a hypothesis if it meets the following conditions:

- If the P value is ≤0.05 and the T-statistic is ≥1.9677, then Ho is rejected, Ha is accepted.
- If the P value is >0.05 or the T-statistic is <1.9677, then Ho is accepted, Ha is rejected.

Figure 2. Bootstrapping Test Results



Source: Processed Research Data (2026)

Based on the results of data processing using *the bootstrapping* feature in the SmartPLS 3 application as shown in the image above, a *path coefficient* value was obtained which describes the direction and strength of the relationship between variables. The results of the estimated path coefficient in this study are presented in the following table:

Table 10. Results of T-Statistics (*Bootstrapping*) Direct Influence

	***Original Sample* (O)**	***Sample Mean* (M)**	***Standard Deviation* (STDEV)**	***T Statistics* (|O/STDEV|)**	***P_Values***
BK → DTR	-0,208	-0,224	0,213	0,975	0,166
BK → JS	-0,150	-0,133	0.092	1,620	0,054
BO → DTR	0,394	0,404	0,225	1,748	0,041
BO → JS	0,120	0,112	0,110	1,089	0,139
DTR → JS	0,824	0,796	0,080	10,264	0,000
WLB → DTR	0,401	0,399	0,158	2,546	0,006
WLB → JS	-0,056	-0,058	0,080	0,699	0,243

Source: Processed Research Data (2026)

Based on the results of T-Statistics statistical analysis through *bootstrapping* testing on the direct influence presented in the table above, the research findings can be described as follows:

H1: Workload affects *Job Satisfaction*

The test results showed that the path coefficient between Workload and Job Satisfaction was -0.150. This value indicates a negative relationship between Workload and Job Satisfaction, which means that an increase in the workload perceived by employees tends to be followed by a decrease in the level of job satisfaction. However, based on the results of the significance test, a T-statistic value of 1,620 was obtained, which was smaller than 1,967 at a significance level of 5%. These findings show that the effect of Workload on Job Satisfaction is not statistically significant.

The results of this study indicate that workload is not the main factor that affects the level of job satisfaction of respondents in the context of the study. In other words, even though the workload increases, it does not directly decrease employee job satisfaction significantly. This finding is in line with research conducted by Febriyanti and Satrya (2025), which states that workload does not have a significant effect on job satisfaction. Therefore, Hypothesis 1 in this study was rejected.

H2: *Work-life Balance* Affects *Job Satisfaction*

The test results showed that the path coefficient between Work-life Balance and Job Satisfaction was -0.056. This value indicates a negative relationship between Work-life Balance and Job Satisfaction, which suggests that an increase in Work-life Balance tends to be followed by a decrease in the level of job satisfaction. However, based on the results of the significance test, a T-statistic value of 0.699 was obtained, which is smaller than 1.967 at a significance level of 5%. This shows that the effect of Work-life Balance on Job Satisfaction is not statistically significant.

The results of this study indicate that Work-life Balance has not been a factor that directly affects the level of job satisfaction of respondents in the context of the study. Thus, even if there is a change in the level of Work-life Balance, it does not have a significant impact on employee job satisfaction. The results of this study are in line with the findings of Nadhilah, Setiawan, and Susilowati (2024), who stated that work-life balance does not have a significant effect on job satisfaction. Therefore, Hypothesis 2 in this study was rejected.

H3: *Burnout* affects *Job Satisfaction*

The test results showed that the *path coefficient* between *Burnout* and *Job Satisfaction* was 0.120. This value indicates a positive relationship between Burnout and Job Satisfaction, which suggests that an increase in burnout rates tends to be followed by an increase in job satisfaction. However, based on the results of the significance test, a T-statistic value of 1.089 was obtained which was smaller than 1.967 or a P-value of 0.139 which was greater than 0.05. This shows that the effect of burnout on Job Satisfaction is not statistically significant.

The results of this study indicate that burnout is not the main factor that affects the level of job satisfaction of respondents in the context of the study. In other words, the level of burnout experienced by employees does not directly determine the high or low level of job satisfaction. The results of this study are in line with the findings of Amilia and Nugrohoseno (2014), who stated that burnout is not the main predictor of employee job satisfaction. Therefore, Hypothesis 3 in this study was rejected.

H4: *Digital Transformation Readiness* has a significant effect on *Job Satisfaction*.

The test results showed that the path coefficient between Digital Transformation Readiness and Job Satisfaction was 0.824. This value indicates a very strong positive relationship between Digital Transformation Readiness and Job Satisfaction, which means that increased readiness for employees' digital transformation tends to be followed by increased job satisfaction (Djadli & Moussaoui, 2016; Duggan et al., 2020). Based on the results of the significance test, a T-statistic value of 10.264 was obtained which was greater than 1.967 and a P-value of 0.000 which was smaller than 0.05. This shows that the influence of Digital Transformation Readiness on Job Satisfaction is statistically significant.

The results of this study indicate that employees' readiness to face digital transformation, including the ability to adapt to new technologies, changes in work processes, and the use of digital systems, plays an important role in increasing job satisfaction. Digital transformation allows for increased work efficiency, operational flexibility, and employee competency development opportunities that can encourage an increase in positive perceptions of work. The results of this study are in line with the findings of Ngan Kim Khuc and Hieu Nguyen (2025), who stated that digital transformation has an effect on job satisfaction. Therefore, Hypothesis 4 in this study is declared accepted.

H5: Workload affects *Digital Transformation Readiness*

The test results show that the path coefficient between Workload and Digital Transformation Readiness is -0.208. This value indicates a negative relationship between Workload and Digital Transformation Readiness, which means that an increase in workload tends to be followed by a decrease in employee readiness levels in the face of digital transformation. However, based on the results of the significance test, a T-statistic value of 0.975 was obtained, which is smaller than 1.967 at a significance level of 5%. This shows that the influence of Workload on Digital Transformation Readiness is not statistically significant.

The results of this study indicate that the level of workload experienced by respondents has not directly affected employees' readiness to face digital transformation. Although conceptually high workloads have the potential to hinder the ability to adapt to technological changes, in the context of this study this influence was not proven to be significant. The results of this study are in line with the findings of Zhu and Kanjanamekanant (2023), which show that increased workload and task complexity during the digitalization process can increase work pressure and decrease employees' adaptive capacity. This condition encourages employees to focus more on completing routine work rather than developing digital competencies, which ultimately has the potential to reduce Digital Transformation Readiness. Therefore, Hypothesis 5 in this study was rejected.

H6: *Work-life Balance* has a significant impact on *Digital Transformation Readiness*

The test results showed that the path coefficient between Work-life Balance and Digital Transformation Readiness was 0.401. This value indicates a positive relationship between Work-life Balance and Digital Transformation Readiness, which means that an increase in employees' work-life balance tends to be followed by an increase in readiness to face digital transformation. Based on the results of the significance test, a T-statistic value of 2.546 was obtained which was greater than 1.967 and a P-value of 0.006 which was smaller than 0.05. This shows that the influence of Work-life Balance on Digital Transformation Readiness is statistically significant.

The results of this study indicate that the balance between the demands of work and personal life plays an important role in increasing employees' readiness to adapt to technological changes and digital-based work processes. Employees who have a good work-life balance tend to have a more stable psychological state, lower stress levels, and more optimal cognitive capacity to accept and implement organizational changes. The results of this study are in line with the findings of Rini and Syaharani (2025), which show that there is a relationship between work-life balance and readiness for change through increasing employee adaptability. Employees with a good level of work-life balance tend to have openness in evaluating work behavior, and are more willing to accept feedback, criticism, and constructive suggestions in the process of organizational change. Therefore, Hypothesis 6 in this study is declared accepted.

H7: *Burnout* affects *Digital Transformation Readiness*

The test results showed that the path coefficient between Burnout and Digital Transformation Readiness was 0.394. This value indicates a positive relationship between Burnout and Digital Transformation Readiness, which means that an increase in burnout rates tends to be followed by an increase in employee readiness to face digital transformation. Based on the results of the significance test, a P-value of 0.041 was obtained which was smaller than 0.05 but the T-statistic showed 1.748 (below the limit of 1.967), thus showing that the effect of Burnout on Digital Transformation Readiness was not statistically significant.

The results of this study show that although the digital transformation process can increase work demands and potentially cause work burnout, the burnout conditions experienced by employees do not directly determine their level of readiness in facing digital transformation. In the context of an organization, digital transformation readiness is more likely to be influenced by other factors such as organizational support, technology training, and digital competencies rather than by work fatigue alone.

The results of this study are in line with the findings of Galyapina and Kovaleva (2025) which show that digital readiness does not have a significant influence on burnout in educators. The similarity of these results indicates that the relationship between burnout and digital readiness tends to be indirect and not always empirically significant. In other words, the level of individual readiness in facing digital transformation is not always directly related to the conditions of work fatigue experienced, so burnout is not the main factor in explaining the variation in employee digital transformation readiness. Therefore, Hypothesis 7 in this study was rejected.

Table 4.8 Results of T-Statistics (*Bootstrapping*) Indirect Influence

	Original Sample (O)	***Sample Mean* (M)**	***Standard Deviation* (STDEV)**	***T Statistics* (|O/STDEV|)**	***P_Values***
BK → DTR → JS	-0,171	-0,181	0,170	1,008	0,157
BO → DTR → JS	0,325	0,321	0,182	1,786	0,038
WLB → DTR → JS	0,331	0,316	0,124	2,660	0,004

Source: Processed Research Data (2026)

Based on the results of T-Statistics statistical analysis through *bootstrapping* testing on the indirect influences presented in the table above, the findings of the next study can be explained as follows:

H8: *Digital Transformation Readiness* mediates the influence of Workload on *Job Satisfaction*

The test results showed that the indirect influence of Workload on Job Satisfaction through Digital Transformation Readiness had a path coefficient value of -0.171. This value shows a negative relationship, which indicates that increasing Workload tends to decrease Job Satisfaction through Digital Transformation Readiness. However, based on the results of significance testing, a T-statistic value of 1.008 was obtained, which is smaller than 1.967. This shows that these indirect influences are not statistically significant.

The results of this study indicate that Digital Transformation Readiness has not been able to mediate the relationship between Workload and Job Satisfaction. High workloads tend to increase work pressure and reduce employees' capacity to develop readiness for digital transformation. This condition causes digital readiness to be not strong enough to bridge the influence of workload on employee job satisfaction. The results of this study are related to research by Molino et al. (2020) which states that digital technology can function as a job resource that helps employees face high workloads and increase job satisfaction if employees have adequate digital competence and readiness. However, in the context of this study, Digital Transformation Readiness has not shown a significant mediating role. This indicates that employees' digital readiness may not be optimal enough to keep up with the demands of high workloads.

In the perspective of *Job Demands–Resources (JD-R) Theory*, burnout is a condition that arises due to high *job demand* and low *job resources*. Burnout is not only triggered by the high demands of work, but also by the limited work resources that employees have (Yudita, 2024). In the context of this study, digital transformation readiness has not been able to function as an effective *job resource* in helping employees manage workload pressure. This condition causes Digital Transformation Readiness to be unable to bridge the influence of Workload on Job Satisfaction significantly. Therefore, Hypothesis 8 in this study was rejected.

H9: *Digital Transformation Readiness* mediates the effect of *Work-life Balance* on *Job Satisfaction*

The test results showed that the indirect effect of Work-life Balance on Job Satisfaction through Digital Transformation Readiness had a path coefficient of 0.331. This value indicates a positive relationship, which shows that increasing Work-life Balance can increase Job Satisfaction through an increase in Digital Transformation Readiness by 33.1%. Based on the results of the significance test, a T-statistic value of 2.660 was obtained which was greater than 1.967 and a P-value of 0.004 which was smaller than 0.05. This shows that these indirect influences are statistically significant.

The results of this study show that work-life balance not only has a direct effect on job satisfaction, but also plays a role in increasing employee readiness in facing digital transformation, which ultimately has an impact on increasing job satisfaction. Employees who have a good work-life balance tend to have a more stable psychological state, more controlled stress levels, and a higher capacity to adapt to changes in technology and digital work systems. The results of this study are in line with the findings of Wang et al. (2020), who show that the effective use of work technology can improve work-life balance and have a positive impact on job satisfaction, especially when employees are able to manage the boundaries between work demands and personal lives optimally. Therefore, Hypothesis 9 in this study is declared accepted.

H10: *Digital Transformation Readiness* mediates the effect of *Burnout* on *Job Satisfaction*

The test results showed that the indirect effect of Burnout on Job Satisfaction through Digital Transformation Readiness had a path coefficient of 0.325. This value indicates a positive relationship, which shows that an increase in burnout tends to be followed by an increase in Job Satisfaction through an increase in Digital Transformation Readiness by 32.5%. Based on the results of the significance test, a T-statistic value of 1.786 (below the limit of 1.967) and a P-value of 0.038 which is smaller than 0.05, thus showing that the indirect influence is statistically significant.

The results of this study indicate that the experience of burnout does not always have a negative impact on job satisfaction, especially when employees have high readiness to face digital transformation. Digital transformation readiness allows employees to utilize technology to improve work efficiency, simplify operational processes, and reduce excessive work pressure, so that they can maintain a positive perception of work. The results of this study are in line with the findings of Day et al. (2022), which show that digital competence and organizational technology support play a role in reducing burnout rates and increasing job satisfaction. Employees who have a high Digital Transformation Readiness tend to be better able to utilize technology to simplify work, reduce work burnout, and maintain a positive evaluation of their work. Therefore, Hypothesis 10 in this study was rejected.

CONCLUSION

Based on the results of the research analysis, it can be concluded that workload, *work-life balance*, and *burnout* have a role in influencing the *job satisfaction* of Generation Z employees in the mining sector, both directly and indirectly through *digital transformation readiness*. The results of the study show that workload, *work-life balance*, and *burnout* do not have a direct effect on *job satisfaction*. This shows that psychological factors and job demands do not necessarily directly determine the job satisfaction level of Generation Z employees. This study found that digital transformation readiness is the variable that has the strongest influence on job satisfaction. This is shown by the path coefficient value of 0.824 with a T-statistic value of 10.264 and a P-value of 0.000, which shows a positive and statistically significant influence. These findings indicate that employee readiness in facing digital transformation is a major factor in increasing job satisfaction. Employees who have good digital readiness tend to be better able to adapt to changes in technology-based work systems, improve work efficiency, and reduce work pressure that arises due to changes in the digital work environment.

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