Technological Friction: A Comparative Analysis of Work-Life Balance between Information Technology and Administrative Professionals

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Abstrak− Lanskap ekonomi global yang dinamis saat ini menempatkan kesejahteraan sumber daya manusia sebagai prioritas strategis utama organisasi, terutama di tengah tingginya tingkat kelelahan mental pada kelompok pekerja muda. Di ekosistem industri teknologi Indonesia, krisis kesejahteraan tersebut semakin diperparah oleh fenomena paradoks fleksibilitas, di mana tuntutan kerja digital yang konstan sering kali mengaburkan batasan tegas antara kehidupan profesional dan ranah pribadi, sehingga pada akhirnya memicu munculnya stres teknologi (technostress). Penelitian ini bertujuan untuk menguji secara empiris pengaruh langsung Work-Life Balance terhadap kinerja karyawan (Work Performance), mengevaluasi peran moderasi dari stres teknologi terhadap hubungan tersebut, serta menganalisis perbedaan mekanisme moderasi antara karyawan Divisi TI (pekerja teknis) dan Divisi Non-TI (pekerja administratif). Penelitian berpendekatan kuantitatif ini menggunakan metode pemodelan Partial Least Squares Structural Equation Modeling (PLS-SEM). Data primer dikumpulkan melalui kuesioner dari sampel sebanyak 175 pekerja Generasi Z dan Milenial yang aktif bekerja di industri teknologi, terdiri atas 89 pekerja Divisi TI dan 86 pekerja Divisi Non-TI. Evaluasi instrumen dan pengujian hipotesis dilakukan menggunakan algoritma bootstrapping, yang kemudian dilanjutkan dengan Multi-Group Analysis (MGA) untuk menguji signifikansi perbedaan struktural antarkelompok tersebut. Hasil penelitian secara nyata menunjukkan bahwa Work-Life Balance memiliki pengaruh positif dan sangat signifikan secara langsung terhadap pencapaian kinerja karyawan. Pada pengujian efek moderasi dinyatakan tidak didukung karena koefisien interaksi menunjukkan arah positif yang berlawanan dengan prediksi secara teoritis. Stres teknologi terbukti secara meyakinkan memberikan efek penguatan (buffering), di mana tingginya stres justru memperkuat urgensi Work-Life Balance sebagai tameng psikologis esensial bagi para karyawan untuk dapat mempertahankan standar kinerja operasional mereka secara optimal. Selanjutnya, hasil evaluasi MGA mengonfirmasi bahwa efek penguatan ini beroperasi secara signifikan lebih kuat pada pekerja Divisi TI dibandingkan pekerja Divisi Non-TI. Perbedaan ini utamanya diakibatkan oleh tingginya paparan budaya selalu terhubung (always-on) dan ekspektasi beban kerja yang menuntut siaga penuh pada kelompok pekerja teknis. Sebagai solusi praktis, manajemen direkomendasikan menerapkan Protokol Pemutusan Digital, merancang kerangka pemulihan berlapis khusus bagi Divisi TI, serta menerapkan inisiatif kerja asinkron bagi Divisi Non-TI. Kesimpulannya, kesejahteraan psikologis merupakan kebutuhan strategis esensial untuk menjaga produktivitas berkelanjutan.

Kata Kunci: *Work-Life Balance*; Kinerja Karyawan; *Technostress*; Analisis Multi-Grup; Industri Teknologi

Abstract− The current dynamic global economic landscape positions human capital well-being as a primary strategic organizational priority, particularly amidst the high rates of mental exhaustion among young workers. Within the Indonesian technology industry ecosystem, this well-being crisis is further exacerbated by the flexibility paradox, where constant digital work demands frequently blur the strict boundaries between professional and personal life, ultimately triggering technostress. This study aims to empirically examine the direct effect of Work-Life Balance on employee Work Performance, evaluate the moderating role of technostress on this relationship, and analyze the differences in the moderation mechanism between IT Division (technical) and Non-IT Division (administrative) employees. This quantitative study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM). Primary data were collected via questionnaires from a sample of 175 Generation Z and Millennial employees actively working in the technology industry, comprising 89 IT Division and 86 Non-IT Division workers. Instrument evaluation and hypothesis testing were conducted using the bootstrapping algorithm, followed by Multi-Group Analysis (MGA) to assess the significance of structural differences between these groups. The results demonstrate that Work-Life Balance has a positive and highly significant direct impact on employee performance achievement. In the moderation testing, the initial hypothesis was not supported as the interaction coefficient indicated a positive direction, contradicting theoretical predictions. Technostress conclusively demonstrated a buffering (strengthening) effect, wherein high stress levels actually amplify the urgency of Work-Life Balance as an essential psychological shield for employees to optimally maintain their operational performance standards. Furthermore, the MGA evaluation confirmed that this buffering effect operates significantly stronger among IT Division workers compared to Non-IT Division workers. This difference is primarily attributed to intense exposure to the always-on culture and operational workload expectations demanding full standby from the technical group. As a practical solution, management is recommended to implement a Digital Disconnect Protocol, design a tiered recovery framework specifically for the IT Division, and establish asynchronous work initiatives for the Non-IT Division. In conclusion, psychological well-being is an essential strategic necessity for maintaining sustainable productivity.

Keywords: Work-Life Balance, Work Performance, Technostress, Multi-Group Analysis, Technology Industry

1. INTRODUCTION

The global economic landscape, characterized by rapid change and a focus on knowledge, has made human capital the key factor in determining organizational sustainability and competitive edge. The balance between professional and personal life, or Work-Life Balance has evolved from being a supplementary benefit to a key strategic priority. The workplace well-being crisis has become a well-documented global phenomenon, with approximately 77% of workers reporting having experienced mental exhaustion or burnout in their current jobs [1]. The Gallup World Poll indicates that only a third (33%) of all workers worldwide can be categorized as thriving, while a vast majority (58%) fall into the struggling category due to high levels of daily stress [2], [3]. The global response to this well-being crisis is accelerating the adoption of more flexible work models. Employee demand is a significant driving force behind this trend, with surveys revealing that 6 out of 10 employees strongly desire hybrid work arrangements, mainly to enhance Work-Life Balance (76%) and decrease burnout (61%) [4]. Furthermore, the same report highlights that well-being among young workers under the age of 35 has experienced the sharpest decline globally [2].

In Indonesia, the urgency of this imbalance phenomenon is felt much more intensely, particularly in the technology industry which possesses high operational pressures. A total of 73% of workers in Indonesia admit to experiencing mental pressure due to work, with 41% of them showing symptoms of depression or anxiety rooted in the high demands of the work environment [5]. The primary causes of this stress are excessive workloads, a lack of managerial support, and an imbalance between the professional and private spheres [6]. Data from the Central Bureau of Statistics (BPS) also notes that 26.8% of workers in Indonesia are forced to work 49 hours or more per week, a condition that significantly multiplies physical and psychological health risks [7]. Demographic shifts further complicate this situation; the current workforce is dominated by Generation Z (27.94%) and Millennials (25.87%) who possess different value systems [7]. For the younger generation, Work-Life Balance is not merely a complement but a top priority that is often valued higher than financial compensation or career promotions [8]. Failure of organizations to facilitate this need for life balance has been proven to trigger the widespread phenomena of *quiet quitting* and *job hopping*, which can massively harm productivity and talent retention [9], [10], [11], [12].

The core construct in addressing this phenomenon is Work-Life Balance, defined as a condition where individuals are able to optimally manage their time and energy among various work and personal life demands [13], [14]. Effective Work-Life Balance management not only reduces individual stress but also has critical implications for Work Performance, namely, the level of employee effectiveness in carrying out formal *in-role* behaviors and *extra-role* voluntary contributions that support the achievement of organizational goals [15], [16], [17], [18]. Various empirical studies emphasize that organizational policies accommodating Work-Life Balance can positively boost employee commitment, loyalty, and sustainable productivity ,[19] ,[20] ,[21] [22]. The favorable causal relationship between Work-Life Balance and performance has been consistently proven in various empirical tests [23], [24], [25]. This transmission mechanism can be comprehensively explained through Conservation of Resources (COR) Theory, which postulates that individuals are always motivated to protect and retain the resources they value ,[26] ,[27] [28]. Through the lens of COR, the Work-Life Balance acts as a crucial resource to prevent resource loss. When the balance between work and private life is maintained, employees will possess a surplus of cognitive capacity that enables them to make resource investments back into their professional activities, thereby creating a *gain spiral* that culminates in the achievement of superior performance [29], [30], [31].

Nevertheless, the positive transmission from Work-Life Balance to Work Performance in the modern technology industry often does not run smoothly due to the "flexibility paradox." Digital-based work arrangements frequently blur the strict boundaries between personal and professional life (*boundary blurring*), forcing employees to be trapped in an *always-on culture* that constantly drains energy constantly [32], [33], [34]. Technostress is a modern adaptation disease that arises when individuals experience extreme fatigue due to the expectation of using technological instruments that exceed their handling capacity, such as *techno-overload* and constant *techno-invasion* into privacy [35]. Ironically, although Generation Z and Millennials are *digital natives*, studies have found that they are actually the most vulnerable demographic, reporting the highest levels of stress due to technological constraints and the pressure of boundless communication responses [36], [37], [38], [39]. This destructive dynamic can be analyzed through the Job Demands-Resources (JD-R) framework, where technostress is positioned absolutely as a hindrance job demand [40], [41], [42], [43]. High exposure to Technostress triggers a mental health deterioration process that is theoretically predicted to dampen, weaken, or negatively moderate the functional impact of Work-Life Balance facilities on employee performance achievement [44].

The research gap that becomes the primary focus and novelty in this study lies in the unexplored structural condition differences within the technology company ecosystem itself. Until now, research related to work dynamics has often generalized all employees in the technology industry as a single, uniform group. In reality, there is a sharp disparity in workload and demands between employees in the Technology Division (e.g., software developers, IT engineers, and network operation center staff) and employees in the Non-Technology Division (such as human resources, marketing, finance, and administration). Employees in the Technology Division constitute the backbone of the digital infrastructure and are often required to be on standby 24/7 to ensure the reliability of the organizational system, making them far more vulnerable to *techno-overload* and intense *always-on culture* pressures than their peers in support functions or non-Technology Divisions. This difference in work routine characteristics raises the methodological urgency to apply Multi-Group Analysis (MGA) in PLS-SEM statistical modeling. This comparative MGA research aims to comprehensively unravel whether the moderating (weakening) effect of technostress on the relationship between Work-Life Balance and Work Performance occurs at the same magnitude between technical workers in the Technology Division and support workers in the non-Technology Division.

Therefore, this study aims to: (1) empirically examine the direct effect of Work-Life Balance on Work Performance among Generation Z and Millennial employees; (2) examine the moderating role of Technostress in weakening this causal relationship; and (3) analyze the specific differences in the Technostress moderation mechanism between the Technology Division and the non-Technology Division through the MGA. The findings of this study are expected to provide sharp theoretical contributions to the extended validation of COR theory and the JD-R model in the hyper-digital era, while simultaneously presenting practical guidelines for Indonesian technology company management in designing jobs, psychological well-being interventions, and digital communication boundaries that are fairer and more relevant to divisional characteristics.

Drawing on the foundational principles of the COR Theory and the JD-R model, this study constructs a predictive framework to systematically address the outlined empirical gaps. The conceptual model posits that establishing a healthy equilibrium between personal and professional domains is a critical resource that drives optimal employee output. However, the pervasive nature of digital workplace demands introduces technostress as a detrimental boundary condition, theoretically anticipated to erode the psychologic resources gained from this balance. Furthermore, acknowledging the stark disparities in daily operational pressures and always-on expectations, the intensity of this technological friction is projected to differ significantly between technical and administrative personnel. Consequently, the following formal hypotheses are proposed to definitively address the research objectives:

a. H1: Work-Life Balance has a positive and significant direct effect on Work Performance among Generation Z and Millennial employees.
b. H2: Technostress significantly moderates the relationship between Work-Life Balance and Work Performance, such that higher levels of technostress weaken the positive impact of Work-Life Balance on Work Performance.
c. H3: There is a significant difference in the magnitude of technostress's moderating effect on the relationship between Work-Life Balance and Work Performance when comparing employees in the Technology Division and the non-Technology Division.

2. RESEARCH METHODS

2.1 Research Design and Methodology

The selection of this quantitative approach was driven by the objective to empirically test the JD-R model. Within this framework, Work-Life Balance is positioned as a crucial job resource that stimulates Work Performance, while technostress acts as a hindrance job demand that depletes cognitive energy and weakens this positive transmission. Furthermore, a comparative approach through MGA was adopted to examine the specific differences in this moderation mechanism across two distinct job divisions (Technology vs. non-Technology). This MGA is essential to uncover whether differing baseline exposures to 24/7 digital operational pressures significantly alter the destructive impact of technostress on employee performance.

2.2 Population, Sample, and Grouping

The population in this study comprised all employees belonging to the Generation Z (born between 1997 and 2012) and Millennial (born between 1981 and 1996) demographic cohorts employed in technology industry companies in Indonesia. Given that the exact size of the unknown population could not be precisely identified, a purposive sampling approach was used instead of a nonprobability sampling technique. The inclusion criteria for respondents were as follows: (1) Aged between 18 and 43 years; (2) active employee status (not a freelancer or independent contractor) in companies operating within the technology industry ecosystem (e.g., e-commerce, fintech, telecommunications, edutech, or software development); and (3) having worked in their current position for a minimum of 6 months, thus considered to possess sufficient experience to objectively evaluate their Work-Life Balance, Technostress, and Work Performance.

To accommodate the comparative analysis (MGA), the research sample was categorized into two subgroups based on their operational domain and core task characteristics. The first group is the Technology

Division (technical group), which includes employees whose job descriptions directly intersect with digital infrastructure development, maintenance, and 24/7 operation (e.g., software engineers, network operation center staff, data scientists, IT support, and system administrators). The second group is the Non-Technology Division (support group), which encompasses employees in administrative, strategic, and managerial functions (e.g., human resources, digital marketing, finance, public relations, and legal) that do not directly relate to coding or server maintenance. The determination of the minimum sample size adhered to the 10-times rule of thumb [45] while considering the adequacy of statistical power for cross-group comparisons.

2.3 Operational Definitions and Measurement of Variables

This study involved three primary variables measured through a self-report questionnaire. All statement items in the instrument were evaluated using a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

a. Work-Life Balance (WLB) as the independent variable (X): Measured based on the extent to which individuals can proportionally allocate their time and energy between work and personal life. The measurement indicators focused on the Work Interference with Personal Life (WIPL) dimension, which evaluates how work demands and responsibilities drain employees' energy and time, thereby negatively interfering with their personal life routines [46].
b. Work Performance (WP) as the Dependent Variable (Y): Measured based on employees' evaluation of their target achievement effectiveness and behavioral initiatives [15], [16]. This measurement encompasses both *in-role* behaviors, representing the completion of core tasks according to formal job descriptions [18], and *extra-role* behaviors, reflecting additional voluntary dedication and organizational citizenship behavior beyond mandatory duties [17].
c. Technostress (TS) as the moderating variable (M): Measured on the basis of the perception of cognitive load and adaptation issues resulting from technology usage. The indicators encompassed the key dimensions of techno-overload (excessive information load forcing employees to work faster), techno-invasion (invasion of technology into privacy or outside working hours), techno-complexity, techno-insecurity, and techno-uncertainty [35].

2.4 Data Collection Technique

Primary data were collected using a hybrid approach that combined both online and offline questionnaire distributions to maximize the target population's reach and representativeness. The online distribution was executed by disseminating digital questionnaires through professional networking platforms, such as LinkedIn, and various community groups for start-up or technology employees in Indonesia. Concurrently, offline data collection was conducted by administering physical questionnaires to employees at several technology company offices. This combination method was strategically chosen to capture a broader demographic, reaching both tech workers who are highly active in digital forums and those who are more engaged in their physical workplace environments. Throughout the data collection phase, all respondents were provided with clear instructions and were guaranteed full anonymity regarding their identities and responses, ensuring that the acquired data objectively reflect their actual experiences without any external pressure.

2.5 Data Analysis Techniques and Multi-Group Analysis Procedures

The data analysis technique employed was Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software. The selection of PLS-SEM is highly relevant because this method is non-parametric (does not require normally distributed data), highly adaptive to complex models (containing moderation effects), and possesses specialized algorithms to execute cross-group comparative tests [45]. The testing was conducted in two main stages. The first stage was the evaluation of the outer model (Measurement Model) to verify the validity and reliability of the instruments. Convergent validity was tested using loading factor values (> 0.7) and Average Variance Extracted (AVE > 0.5), while discriminant validity was evaluated through the Heterotrait-Monotrait (HTMT) ratio. The construct reliability was assessed using Composite Reliability and Cronbach's Alpha values (> 0.7). The second stage was the evaluation of the inner model (i.e., structural model) to test the hypotheses. This testing focused on path coefficients (β), significance levels (*p-value* < 0.05), the coefficient of determination (R^2), and predictive relevance (Q^2).

Once the overall structural model was confirmed to be valid and fit, the procedure proceeded with the MGA.The MGA in PLS-SEM was conducted to determine whether the differences in specific path coefficient values (particularly on the technostress moderation path) between the Technology Division and non-Technology Division groups were statistically significant. This MGA evaluation used the permutation test and the non-parametric PLS-MGA approach integrated within the SmartPLS system, which are highly robust for assessing multi-group differences without distributional assumptions [45]. If the *p-value* from the intergroup comparison yields a value smaller than 0.05, a significant difference in the intensity of the moderating impact of Technostress on Work Performance between operational IT workers and administrative workers within the technology industry ecosystem can be concluded.

3. RESULTS AND DISCUSSIONS

This section comprehensively outlines the empirical testing results and statistical analysis conducted to address the research hypotheses. The primary data utilized in this study were gathered from a total of 175 young workers (Generation Z and Millennials) employed within the technology industry, specifically consisting of 89 operational IT workers (Technology Division) and 86 administrative or non-IT workers (non-Technology Division). According to the analytical stages of partial least squares structural equation modeling (PLS-SEM) using SmartPLS software, the subsequent presentation of the results is divided into three primary phases. *First*, the measurement model (outer model) was used to verify the convergent validity, discriminant validity, and reliability of the questionnaire. *Second*, the structural model (inner model) was evaluated to assess the model fit and the significance of causal relationships, encompassing the direct effect of Work-Life Balance on Work Performance and the moderating effect of Technostress. *Third*, MGA was used to the intensity of this moderation mechanism between the two divisional groups. Following the presentation of all statistical outputs, this section concludes with an in-depth discussion to contextualize the empirical findings within the JD-R model framework and relevant prior literature.

3.1 Evaluation of the measurement (outer) model

In the PLS-SEM framework, the analytical process begins with the evaluation of the measurement model, commonly referred to as the outer model. This stage primarily aims to verify the psychometric properties of the measurement instruments by assessing the specific relationships between the latent constructs, namely, Work-Life Balance, Technostress, and Work Performance, and their respective observable indicators. Establishing a robust outer model is a mandatory prerequisite because it ensures that before testing any causal relationships, the data obtained from the respondents are highly accurate, consistent, and free from significant measurement errors. The evaluation of the outer model is systematically conducted through two fundamental assessments to guarantee the quality of the measurement instrument: construct validity (encompassing both convergent and discriminant validity) and construct reliability.

3.1.1 Construct Validity

To ensure that the measurement model is psychometrically sound before proceeding to structural hypothesis testing, evaluating construct validity is an essential prerequisite. Construct validity determines the extent to which the operational indicators successfully and accurately capture the underlying latent constructs they are designed to measure [45]. Construct validity is systematically verified in the context of PLS–SEM executed through SmartPLS using two distinct criteria: convergent validity and discriminant validity. Convergent validity focuses on the shared variance among indicators of the same construct to ensure cohesive alignment, whereas discriminant validity establishes the empirical distinctiveness of each construct within the conceptual model. Satisfying both criteria guarantees that the empirical data are highly accurate and free from systematic measurement errors, thereby establishing a robust foundation for the subsequent structural model assessment and MGA.

a. Convergent Validity

Convergent validity is evaluated to ensure that the specific measurement items strongly correlate with and accurately represent their respective latent constructs. The evaluation was conducted using two primary statistical parameters: combined loadings and AVE. The combined loadings matrix assesses an item's validity by examining its factor loading on the intended construct while ensuring that it is adequately distinct from cross-loadings on other constructs. Following the guidelines established by Hair et al. [45] an indicator demonstrates ideal reliability if its loading value exceeds 0.70. Nevertheless, indicators with loading values between 0.40 and 0.70 can be retained in the measurement model, if their inclusion does not cause the AVE of the construct to fall below the requisite threshold. Conversely, any measurement item yielding a factor loading below 0.40 must be strictly eliminated because of its insufficient explanatory contribution.

Furthermore, the AVE is analyzed to measure the proportion of indicator variance that the latent construct successfully captures relative to the variance generated by measurement error. A latent construct must satisfy the absolute requirement for convergent validity by achieving a minimum AVE threshold of 0.50. Attaining this specific value indicates that the construct explains, on average, more than half of the variance of its underlying indicators. The simultaneous fulfillment of acceptable combined loadings and the minimum AVE threshold confirms that the measurement instrument is empirically valid, psychometrically sound, and fully qualified for the subsequent structural model evaluation.

Table 1. Combined loading Results

Indicator	Technostress (TS)	Work-Life Balance (WLB)	Work Performance (WP)	AVE
TS_TC	0.89			
TS_TIS	0.87			
TS_TIV	0.92			0.76
TS_TO	0.93			
TS_TUC	0.76			
WLB1		0.90		
WLB2		0.89		
WLB3		0.89		0.81
WLB4		0.92		
WLB5		0.89		
WP_ERP			0.97	0.93
WP_IRP			0.97	

Source: Data Processed in SmartPLS, 2026

Based on the empirical data processed using SmartPLS, the proposed measurement model successfully fulfills all convergent validity criteria. As presented in Table 1, the combined outer loading values for all measurement items across the three latent constructs Technostress, Work-Life Balance, and Work Performance are highly satisfactory. Specifically, the factor loadings for the five technostress indicators range from 0.76 to 0.93, whereas those for the five Work-Life Balance items yield loadings ranging from 0.89 to 0.92. Furthermore, both Work Performance indicators exhibited exceptionally strong loadings of 0.97. Given that every individual indicator significantly surpasses the ideal threshold of 0.70 recommended by Hair et al., [45], no item elimination was necessary. This confirms that all indicators possess a robust and accurate capability to reflect their respective underlying constructs.

The robustness of the convergent validity is further corroborated by the AVE values detailed in Table 1. The structural analysis yielded AVE scores of 0.76, 0.81, and 0.93 for Technostress, Work-Life Balance, and 0.93 for Work Performance. All recorded values substantially exceed the minimum acceptable threshold of 0.50. These results empirically indicate that each latent construct can explain well over half of the variance in its corresponding indicators, thereby confirming that the variance captured by the constructs is significantly greater than the variance attributed to measurement error. Consequently, the simultaneous achievement of optimal outer loadings and high AVE scores confirms that the measurement instruments used in this study are psychometrically sound, highly valid, and fully qualified for subsequent structural hypothesis testing.

b. Discriminant Validity

Following the establishment of convergent validity, the subsequent step in the evaluation of the outer model is to assess discriminant validity. Discriminant validity ensures that each latent construct in the structural model is empirically distinct and captures phenomena that are not represented by other constructs. Discriminant validity was rigorously evaluated using the HTMT ratio of correlations. The HTMT approach is currently recommended as the primary criterion in PLS-SEM due to its superior sensitivity and specificity in detecting discriminant validity issues compared to traditional metrics, such as the Fornell-Larcker criterion or cross-loadings [47].

The HTMT ratio estimates the true correlation between two distinct constructs if they are perfectly measured. The HTMT values between any pair of latent variables must fall below the conservative threshold of 0.90 to establish discriminant validity definitively [45]. An HTMT ratio strictly below this 0.90 margin provides empirical evidence that the constructs are conceptually separated and do not overlappingly measure the same underlying trait. Satisfying this criterion guarantees the structural integrity of the measurement model, allowing the structural path and multigroup analysis to proceed safely.

Table 2. Heterotrait-Monotrait Ratio (HTMT)

Construct	Technostress (TS)	Work-Life Balance (WLB)
Work-Life Balance (WLB)	0.82	
Work Performance (WP)	0.82	0.86

Source: Data Processed in SmartPLS, 2026

Table 2 presents, the results of the discriminant validity assessment using the HTMT ratio demonstrating that all latent constructs within the research model fulfill the required empirical criteria. The HTMT ratio for the relationship between Work-Life Balance and Technostress is 0.82, while the ratio between Work Performance and Technostress is 0.82. Furthermore, the HTMT value for the interaction between Work Performance and Work-Life Balance was 0.86.

According to the methodological guidelines established by Henseler et al. [47] and Hair et al. [45], discriminant validity is strictly confirmed when the HTMT ratio between any pair of constructs falls below the conservative threshold of 0.90. Given that all values obtained in this matrix consistently remained below the 0.90 margin, no indication of conceptual overlap was found among the investigated latent variables. These findings establish that Technostress, Work-Life Balance, and Work Performance are empirically distinct from one another, thereby ensuring the structural integrity of the measurement model and allowing the structural path evaluation (inner model) to proceed safely.

3.1.2 Construct Reliability

After confirming the validity of the measurement model through convergent and discriminant validity assessments, the final step in evaluating the outer model is to determine construct reliability. Construct reliability measures the internal consistency, stability, and dependability of the measurement instrument, ensuring that the questionnaire items yield consistent results when capturing the targeted latent variables. In the context of PLS-SEM using SmartPLS, this assessment is primarily evaluated using two main parameters: cronbach's alpha and composite reliability. While cronbach's alpha provides a traditional and relatively conservative estimate of internal consistency, composite reliability is generally considered a more precise metric in PLS-SEM because it accounts for the varying outer loadings of the individual indicator variables [45]. To demonstrate adequate internal consistency, both the Cronbach's alpha and composite reliability values for each latent construct must exceed the universally recommended threshold of 0.70. Fulfilling these criteria ensures that the measurement model is highly robust, free from random measurement errors, and qualified for the subsequent structural path evaluation.

Table 3. Construct Reliability Result

Construct	Cronbach's alpha	Composite reliability
Technostress	0.92	0.94
Work-Life Balance	0.94	0.95
Work Performance	0.93	0.97

Source: Data Processed in SmartPLS, 2026

Based on the data analysis results presented in Table 3, all research constructs demonstrate excellent reliability. The Cronbach's alpha value for the technostress construct is recorded at 0.92, with a composite reliability of 0.94. Cronbach's α for the Work-Life Balance construct is 0.94, accompanied by a composite reliability of 0.95. Meanwhile, the Work Performance construct exhibits a highly robust internal consistency, yielding a Cronbach's alpha of 0.93 and a composite reliability of 0.97.

According to the methodological guidelines of Hair et al. [45], a construct is deemed to possess strong internal consistency and dependability if both its Cronbach's alpha and composite reliability values exceed the minimum threshold of 0.70. Given that the reliability coefficients for all three latent variables in this study significantly surpass this threshold, the measurement instruments used are highly stable and accurate. These findings confirm that the questionnaire items consistently measure their intended constructs without being compromised by random measurement error, thereby satisfying the reliability prerequisites and allowing the structural model (inner model) analysis to proceed confidently.

3.2 Structure Model Evaluation (Inner Model)

Once the measurement model (outer model) has been confirmed to fulfill all validity and reliability criteria, the structural model, commonly referred to as the inner model, is evaluated in the subsequent analytical phase in PLS-SEM. This analysis evaluates the hypothesized relationships among the latent constructs to assess the predictive capabilities of the developed research model. Within the SmartPLS software, the structural model evaluation primarily relies on key statistical parameters, specifically focusing on the coefficient of determination (R^2) to measure the model's predictive accuracy and path coefficients to determine the direction and intensity of the relationships between variables.

The R^2 value reflects the proportion of variance in the dependent construct that can be explained by the model's independent constructs. This metric serves as a primary indicator for assessing the model's predictive power, where higher scores indicate a stronger estimation capability toward the criterion variable. Path coefficients are used to evaluate the hypothesized direct effects among latent constructs. The path coefficient values have a standardized range between -1 and +1, where values approaching one (either positive or negative) indicate a strong causal relationship, whereas values closer to zero denote a weak relationship. The empirical validity and statistical significance of these path coefficients are subsequently determined through the bootstrapping algorithm procedure, which generates the requisite T-statistics and *p-values* for hypothesis testing.

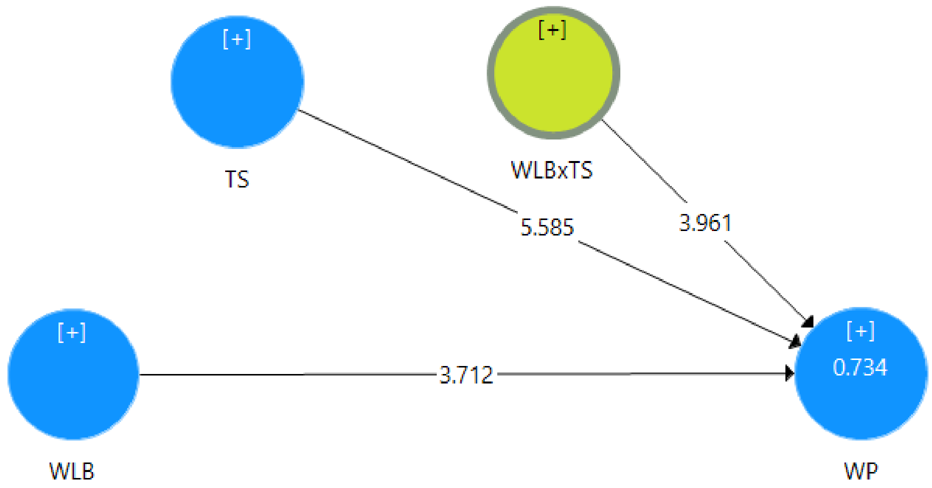

Figure 1. Full model analysis
Note: WLB = Work-Life Balance, TS = Technostress, WP = Work Performance

Table 4. Path coefficient analysis

	Original sample (O)	T Statistics	*p-values*
WLB → WP	0.37	3.96	< 0.01
TS → WP	(0.38)	5.60	< 0.01
WLBxTS → WP	0.21	4.14	< 0.01

Source: Data Processed in SmartPLS, 2026

The evaluation of the structural model (inner model), as depicted in Figure 1 and Table 4, provides empirical insights into the predictive capacity of the model and the significance of the causal relationships among the constructs. The initial assessment of the coefficient of determination (R^2) reveals that the Work Performance variable yields a value of 0.734. This statistically indicates that 73.4% of the total variance in employee work performance can be simultaneously explained by Work-Life Balance, Technostress, and their moderating interaction. According to the PLS-SEM methodological standards, this R^2 value is classified as substantial, demonstrating that the conceptual framework possesses robust predictive accuracy.

Furthermore, the hypothesis testing executed through the bootstrapping procedure confirms the significance of all proposed structural paths. The analysis demonstrates that Work-Life Balance exerts a positive and highly significant direct effect on Work Performance (β = 0.37; T-statistics = 3.96; *p-value* < 0.01), empirically proving that an improved Work-Life Balance directly enhances employee performance. Therefore, hypothesis 1 is statistically confirmed and fully supported.

The evaluation of the moderating interaction effect, yields a positive and statistically significant path coefficient (β = 0.21; T-statistics = 4.14; *p-value* < 0.01). Although the interaction is highly significant, the positive path coefficient value fundamentally contradicts the hypothesized weakening effect. Instead, it indicates a strengthening or buffering mechanism, implying that when technostress levels are high, the positive impact and critical necessity of Work-Life Balance on Work Performance are amplified. Consequently, hypothesis 2 is rejected because the empirical direction of the moderation opposes the theoretical assumption that was initially proposed.

Table 5. f-square result

	Original sample (O)	T Statistics	*p-values*
WLB → WP	0.15	1.57	0.12
TS → WP	0.22	2.68	< 0.01
WLBxTS → WP	0.11	2.08	0.04

Source: Data Processed in SmartPLS, 2026

Following the evaluation of the path coefficients, the structural model assessment proceeds with determining the f-square effect size, which measures the substantive impact and variance contribution of a specific predictor construct on the endogenous construct. According to the established PLS-SEM guidelines [45], f-square values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Table 5 indicates that the relationship between Work-Life Balance and Work Performance categorizing medium effect size and not statistically significant (f-square = 0.15; T-statistic = 1.57; *p-value* = 0.12).

Conversely, the impact of Technostress on Work Performance demonstrates a medium effect size with statistically significant (*ƒ*-square = 0.22; T-statistic = 2.68; *p-value* < 0.01). Furthermore, the moderating interaction term Work-Life Balance and Technostress (WLBxTS) exhibited between the small and medium thresholds, its contribution is statistically significant (*ƒ*-square = 0.11; T-statistic = 2.08; *p-value* = 0.04). These findings confirm that both technostress and its moderating interaction contribute meaningfully and significantly to explaining the variance in Work Performance within the structural model, further validating the moderating mechanism's importance despite its relatively modest effect magnitude.

Following the evaluation of the general structural model, a Multi-Group Analysis (MGA) was performed using SmartPLS to empirically investigate potential heterogeneity within the data set. The primary objective of the MGA procedure is to determine whether the predefined categorical groups, the Technology Division and the non-Technology Division, exhibit statistically significant differences in their respective structural path coefficients. In the context of this research, this comparative analysis is particularly crucial to ascertain whether the moderating effect of Technostress on the relationship between Work-Life Balance and Work Performance varies in magnitude between employees handling core IT operations and those in administrative or non-IT roles. According to the standard PLS-SEM guidelines, a statistically significant difference between the two groups is confirmed when the parametric or non-parametric MGA *p-value* for the path coefficient difference falls strictly below the 0.05 threshold or exceeds the 0.95 margin. Identifying these structural variations is essential for preventing generalized conclusions and to provide targeted managerial implications tailored to each division's unique workload characteristics.

Table 6. Difference in the Moderation Path Coefficient between the IT and non–IT Divisions

	Original sample (O)	T Statistics	*p-values*
WLBxTS → WP (IT Division)	0.35	3.94	< 0.01
WLBxTS → WP (Non-IT Division)	0.12	2.22	0.02

Source: Data Processed in SmartPLS, 2026

Prior to conducting the formal Multi-Group Analysis (MGA) to test for significant structural discrepancies, it is essential to evaluate the specific path coefficients for the moderating interaction independently within the two distinct organizational subgroups. As presented in Table 6, the bootstrapping results reveal that the moderating effect of Technostress on the relationship between Work-Life Balance and Work Performance is statistically significant in both divisions, albeit with vastly different intensities. This interaction yields a substantial positive path coefficient within the IT Division (β = 0.35; *p-value* < 0.01). Conversely, the non-IT Division exhibited a notably weaker positive path coefficient (β = 0.12; *p-value* = 0.02). These group-specific findings indicate that technostress acts as a significant buffering mechanism in both work environments, amplifying the critical necessity of Work-Life Balance to sustain performance. The magnitude of this dynamic is vastly more pronounced for technical workers. The substantially higher beta value in the IT Division suggests that compared to their administrative counterparts, employees directly handling core technological operations rely much more heavily on their work-life equilibrium to maintain productivity under intense technological pressure. This stark observed discrepancy in the magnitude of moderation between the two groups provides a compelling preliminary justification for executing the subsequent MGA procedure to confirm the statistical significance of this variance at the overarching structural level.

Table 7. Results of Multigroup Analysis (MGA)

	Original Path Coefficients-diff (IT Division - Non-IT Division)	*p-value* (IT Division - non-IT Division)
WLB → WP	(0.27)	0.14
TS → WP	(0.24)	0.09
WLBxTS → WP	0.23	0.04

Source: Data Processed in SmartPLS, 2026

The Multi-Group Analysis (MGA) evaluation was conducted to examine the presence of statistically significant differences in the structural path coefficients between the IT Division and the Non-IT Division groups. The analysis focuses on the differences in the path coefficients (β) and their corresponding probability values (*p-value*). Regarding the direct effect of Technostress on Work Performance (β = -0.24; *p-value* = 0.09). Because this *p-value* exceeded the 0.05 significance threshold, no statistically significant difference was found between the IT and non-IT divisions regarding the direct impact of Technostress on Work Performance fluctuations. Similarly, the evaluation of the direct relationship between Work-Life Balance and Work Performance (β = -0.27; *p-value* = 0.14. This probability, being above 0.05, further indicates an absence of empirical divergence, meaning that the direct benefits of Work-Life Balance on Work Performance are distributed similarly across both worker groups.

However, the essential highlight of this comparative analysis is the evaluation of the moderating interaction effect to validate hypothesis 3 (β = 0.23; *p-value* = 0.04). The existence of a substantial structural difference between the two divisions is definitively proven. These empirical findings confirm the acceptance of hypothesis 3, asserting that technostress's magnitude in strengthening (buffering) the positive impact of Work-Life Balance on Work Performance exhibits a significantly different intensity between technical workers in the IT Division compared to supporting administrative workers in the non-IT Division.

3.3 Discussion of Empirical Findings

The preceding evaluation of the structural model and the subsequent MGA have yielded compelling empirical insights into the complex dynamics between Work-Life Balance, Technostress, and Work Performance. While the statistical results solidly confirm the foundational importance of a healthy work-life equilibrium in driving employee output, they also unveil a counterintuitive buffering mechanism. Specifically, the data reveal that heightened technostress amplifies the critical necessity of this balance to sustain performance, fundamentally challenging the initially hypothesized weakening effect. Furthermore, the significant structural divergence observed between the IT and non-IT divisions highlights that specific departmental workloads and the intensity of continuous technological exposure heavily influence these psychologic and operational mechanisms. This subchapter systematically synthesizes these statistical outcomes, contextualizing both the validated hypotheses and the unexpected empirical revelations within the theoretical frameworks of the Conservation of Resources (COR) Theory and the Job Demands-Resources (JD-R) Model. The subsequent discussion elucidates the broader theoretical implications of this integration and provides targeted, practical guidelines for modern, technology-driven organizational ecosystems.

A comprehensive summary of the hypothesis testing results is presented before delving into the findings' detailed theoretical implications to provide a clear overview of the empirical decisions. Table 8 outlines the evaluation of the three developed hypotheses based on the structural model and multigroup analysis outcomes.

Table 8. Summary of Hypothesis Testing Results

Hypothesis	Hypothesized Path/Statement	Empirical Decision
H1	Work-Life Balance → Work Performance (Positive Direct Effect)	Supported
H2	Work-Life Balance x Technostress → Work Performance (Moderating Effect: Weakening)	Not Supported*
H3	Moderation Difference (IT Division vs. non-IT Division)	Supported

The empirical validation of hypothesis 1 confirms that Work-Life Balance exerts a positive and statistically significant direct effect on Work Performance among Generation Z and Millennial employees (β = 0.37; *p-value* < 0.01). The statistical outcome definitively indicates that improvements in managing the equilibrium between professional responsibilities and personal life directly translate into enhanced job performance. This finding provides robust empirical support for COR theory within the context of the modern digital workplace. According to the COR framework, individuals are fundamentally driven to acquire, retain, and protect their valuable cognitive and emotional resources. In an era characterized by a pervasive workplace well-being crisis and high burnout rates, a structured Work-Life Balance serves as a critical resource for achieving a healthy work-life balance. When young professionals are afforded the opportunity to detach from high-pressure work environments and recharge in their personal lives, they successfully prevent the harmful depletion of their psychologic resources. This preservation mechanism fosters a continuous surplus of mental capacity, enabling employees to reinvest these renewed resources back into their professional roles. Consequently, this resource investment initiates a positive gain spiral, where employees not only fulfill their formal in-role duties more but also exhibit higher resilience and voluntary extrarole contributions. Practically, this result directly addresses the urgency highlighted in the preliminary context of this study, proving that for the younger demographic navigating demanding operational pressures, work-life balance is not merely a supplementary corporate perk but a foundational prerequisite for achieving sustainable, high-level organizational productivity.

The evaluation of hypothesis 2 yields a statistically significant yet theoretically counterintuitive finding regarding the moderating role of technostress within the structural model. Although the interaction between Work-Life Balance and Technostress is highly significant (β = 0.21; *p-value* < 0.01), the positive path coefficient fundamentally contradicts the initially hypothesized weakening effect, resulting in to the empirical rejection of hypothesis 2. Instead of dampening the benefits of Work-Life Balance, the data reveal a profound strengthening or buffering mechanism. Interpreted through the lens of the JD-R model, technostress unquestionably represents a severe hindrance demand that drains cognitive energy, as explicitly evidenced by its negative direct impact on employee output. However, because this technological demand is so taxing, the presence of Work-Life Balance becomes exponentially more critical. In digital work environments characterized by high techno-overload, boundary blurring, and the relentless pressure of an always-on culture, employees rely heavily on their work-life equilibrium as a vital compensatory resource. When technostress levels escalate to extreme heights, Work-Life Balance's positive impact on Work Performance is significantly amplified. For Generation Z and Millennial workers facing severe digital friction, establishing strict boundaries to detach from technology is not merely a supplementary benefit; it acts as an indispensable psychologic buffer. Those equipped with a strong work-life balance can successfully shield themselves from the deteriorating effects of technostress, thereby sustaining their performance levels, which comprehensively explains the positive direction of this moderating dynamic.

The testing of hypothesis 3 through MGA procedure provides crucial empirical evidence regarding heterogeneity within the corporate ecosystem, specifically highlighting the differences in the moderation mechanism between the IT Division and the non-IT Division. The evaluation results confirm the existence of significant structural divergence on the interaction path with a difference *p-value* of 0.04 (*p-value* < 0.05). An examination of the coefficients for each group reveals that the buffering (strengthening) effect of Work-Life Balance in sustaining performance under Technostress is stronger for IT Division workers ($\beta = 0.35$) compared to administrative workers in the Non-IT Division ($\beta = 0.12$). This finding explicitly validates the study's conceptual premise and empirically supports hypothesis 3. Workers in the technology division, who act as the backbone of the digital infrastructure, face an inherently more extreme landscape of job demands, including full standby (24/7) and intense exposure to an always-on culture. Referring to the JD-R model framework, the high accumulation of hindrance demands in the form of techno-overload among this technical worker group makes protective resources, namely work-life balance, absolutely vital. For IT Division staff, strict boundaries between professional and personal spaces are not merely a supplementary perk, but a primary psychologic shield that is necessary to prevent drastic performance deterioration. On the other hand, although workers in the Non-IT Division also rely on Work-Life Balance as a stress buffer, the intensity of their reliance is structurally proven to be less critical than that of technical workers. Overall, these comparative findings underscore that the dynamics between technological pressure and psychologic well-being cannot be generalized; rather, they demand managerial interventions that are tailored to each division's workload characteristics.

4. CONCLUSION

This study set out to empirically examine the intricate dynamics between Work-Life Balance, Technostress, and Work Performance among Generation Z and Millennial employees within the modern technology sector. Based on the comprehensive evaluation of the structural model and MGA, several critical conclusions can be drawn that directly answer the developed research problems.

First, addressing the first research problem regarding the direct causal relationship, this study concludes that Work-Life Balance has a positive and highly significant direct impact on Work Performance. Establishing a healthy equilibrium between professional obligations and personal life is proven to be a fundamental driver of productivity, rather than a mere supplementary organizational benefit, in the context of the pervasive global well-being crisis. Aligned with the COR theory, optimal Work-Life Balance acts as a vital psychological resource. When young professionals successfully protect their personal time from work intrusions, they accumulate a surplus of cognitive and emotional energy, which they subsequently reinvest into their roles, culminating in superior in-role and extra-role performance.

Second, addressing the second research problem regarding the moderating role of technological pressure, the study concludes that technostress significantly alters the relationship between Work-Life Balance and Work Performance, albeit in a theoretically counterintuitive direction. Instead of weakening the benefits of work-life balance, high levels of technostress act as a catalyst that amplifies its absolute necessity. The extreme cognitive drain caused by techno-overload and boundary blurring makes work-life balance an indispensable compensatory buffer when viewed through the JD-R Model. Under severe digital friction, employees who maintain strict personal boundaries are able to shield themselves from the deteriorating effects of technostress. This buffering mechanism proves that Work-Life Balance is most critical precisely when technological demands are at their absolute peak.

Third, the MGA confirms that the intensity of this buffering mechanism differs significantly between departments, addressing the final research problem regarding structural disparities within the organization. Reliance on Work-Life Balance to combat technostress is vastly more pronounced among technical workers in the IT Division than among non–IT Division administrative staff. Because IT personnel serve as the backbone of the digital infrastructure and are disproportionately exposed to intense, 24/7, always-on expectations, strict personal boundaries serve as their primary psychological shield against rapid performance degradation and mental exhaustion.

Based on the findings this study, organizations must translate the critical need for Work-Life Balance into tangible, structural interventions. Management is strongly advised to implement a formal "Digital Disconnect Protocol." This specific program would institutionally restrict nonemergency digital communications, such as work-related emails and messaging app notifications, outside of designated working hours and during weekends. By systematically discouraging afterhour server traffic for nonurgent matters, companies can practically dismantle the toxic "always-on" culture. This protocol allows Generation Z and Millennial employees to genuinely detach and replenish their cognitive resources without the lingering anxiety of missing implicit professional obligations, directly addressing the severe hindrance demand caused by technostress.

Furthermore, to address the critical vulnerability of the technical workforce discovered through the MGA, companies should establish a "Tiered Recovery Framework" tailored for the IT Division. Instead of relying on a generalized 24/7 standby expectation that triggers chronic techno-overload, this program introduces a strict, rotating on-call matrix accompanied by mandatory compensatory rest periods. For instance, after an IT employee resolves a late-night server outage or completes a weekend infrastructure maintenance shift, the system must automatically trigger a guaranteed, uninterrupted recovery day. This ensures that the technical staff, who rely most heavily on the Work-Life Balance buffer to sustain their performance, are structurally protected from mental exhaustion. Finally, to address the technological friction experienced by supporting administrative staff, management should introduce an "Asynchronous Work Initiative" within the Non-IT Division, such as implementing a "No-Meeting Wednesday" or designating specific deep-work hours where instant digital replies are not expected. To guarantee the success of these structural changes across all divisions, these initiatives must be paired with a mandatory "Boundary Management Training" program for midlevel and senior leadership. This training will explicitly educate managers to evaluate objective employee output rather than constant digital responsiveness, ensuring that the overarching organizational culture actively supports the psychological boundaries established by younger professionals rather than penalizing them inadvertently.

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