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Human-AI Symbiosis at Work: Psychological, Organizational, and Technological Resources

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ABSTRACT

This study examines the associations among Psychological Factors, External Factors, Technology Factors, and Work-life Balance (WLB), with particular attention to whether Technology Factors statistically mediate the relationships between psychological/organizational resources and WLB. Using a quantitative cross-sectional survey of 190 respondents and Partial Least Squares Structural Equation Modeling (PLS-SEM), the study tested direct and indirect predictive relationships. Psychological Factors showed the strongest positive association with WLB (β=0.415, p<0.001), followed by External Factors (β=0.301, p=0.001) and Technology Factors (β=0.162, p=0.008). External Factors were positively associated with Technology Factors (β=0.288, p=0.011), whereas Psychological Factors were not (β=0.070, p=0.543). Neither the indirect PF → TF → WLB relationship (β=0.011, p=0.575) nor the EF → TF → WLB relationship (β=0.047, p=0.099) was statistically significant. The findings therefore do not support Technology Factors as a significant mediator in either proposed pathway. The results suggest that psychological, organizational, and technological resources may contribute to WLB through differentiated pathways, while stronger conclusions about causal mechanisms require longitudinal or experimental research.

INTRODUCTION

The rapid development of artificial intelligence (AI) and digital technologies has transformed how work is organized and performed. Digital tools can improve efficiency, flexibility, information access, and collaboration, but they can also intensify work demands, blur work–non-work boundaries, and contribute to technostress and digital fatigue. Recent research indicates that the consequences of digital work depend not only on the availability

of technology but also on how employees and organizations experience and support its use (Duan et al., 2023, 2024; Bencsik & Juhasz, 2023; Choi et al., 2024).

Previous empirical research provides evidence that Work-life Balance is associated with both personal and contextual resources. Studies have linked psychological capital, resilience, and related personal resources with better well-being and work–life outcomes, while organizational support, flexible work practices, leadership, and a supportive culture have also been associated with more favorable Work-life Balance outcomes (Abdul Jalil et al., 2023; Borowiec & Drygas, 2023; Lamane-Harim et al., 2023; Ferdous et al., 2023). Research on digital work further suggests that technology may create both resources and demands: technology can increase flexibility and efficiency, yet intensive digital connectivity can extend work into non-work time and create technostress (Duan et al., 2023; Bencsik & Juhasz, 2023; Choi et al., 2024).

The central research gap is that previous studies have largely examined psychological resources, organizational support, and technology-related factors as separate predictors of Work-life Balance, while providing limited empirical evidence on whether Technology Factors function as an intervening mechanism between these resource domains and WLB. Consequently, it remains unclear whether personal psychological resources and organizational resources are associated with WLB through employees' perceptions and use of workplace technology, or whether technology contributes to WLB primarily as a separate resource. This unresolved mechanism is important because technology is embedded in the organizational context: its usefulness and usability may be experienced differently depending on the resources available to employees and the support provided by the organization. The present study therefore addresses this specific theoretical and empirical gap by testing the direct associations of Psychological Factors, External Factors, and Technology Factors with WLB and, more importantly, testing whether Technology Factors statistically mediate the relationships of Psychological Factors and External Factors with WLB.

This study uses Conservation of Resources (COR) Theory as the primary theoretical framework because it provides the overarching logic for examining Work-life Balance as a resource-related outcome. Psychological Factors are conceptualized as personal resources, while External Factors represent contextual resources that can help employees obtain, protect, and mobilize resources. Job Demands–Resources (JD-R) Theory is retained as a complementary mechanism for explaining why organizational support and flexible work arrangements may function as job resources. Technology Acceptance and technology-affordance perspectives are retained only for the technology-specific mechanism: they explain how perceived usefulness, usability, and opportunities created by digital tools may shape employees' experience of technology at work. Thus, the theories are not treated as seven parallel explanations; COR provides the main model logic, JD-R explains organizational resources, and technology perspectives explain the technology-specific pathway.

Cognitive Appraisal Theory reveals that an individual's response to technological developments is determined by the process of cognitive assessment, not by the technology itself. Therefore, an organization must provide support to its employees in understanding and adapting to existing technological developments (Langenbach et al., 2020; Liang et al., 2023;

Muhammad, 2022; Nguyen et al., 2025; Song & Lu, 2024).

This study aims to: (1) test the positive predictive relationship between Psychological Factors and Work-life Balance; (2) test the positive predictive relationship between Technology Factors and Work-life Balance; (3) test the positive predictive relationship between External Factors and Work-life Balance; (4) examine whether Psychological Factors are positively associated with Technology Factors; (5) examine whether External Factors are positively associated with Technology Factors; (6) test whether Technology Factors mediate the relationship between Psychological Factors and Work-life Balance; and (7) test whether Technology Factors mediate the relationship between External Factors and Work-life Balance. The intended findings are to determine whether technology operates as an independent complementary resource and/or as a mediating mechanism linking personal and organizational resources with Work-life Balance.

LITERATURE REVIEW

COR Theory provides the primary framework for the model. It proposes that individuals seek to acquire, preserve, and protect valued resources. In this study, Psychological Factors represent personal resources that may help employees cope with work demands and maintain Work-life Balance. Prior research has associated psychological capital, resilience, and related personal resources with employee well-being and work–life outcomes (Chen et al., 2024; Demerouti, 2025; Borowiec & Drygas, 2023).

Accordingly, Psychological Factors are expected to have a positive predictive relationship with Work-life Balance because employees with stronger psychological resources may be better positioned to regulate demands, protect time and energy, and manage competing work and non-work responsibilities. This proposition focuses on the resource role of psychological capacity rather than introducing an additional overarching theory.

H1: Psychological Factors (PF) are positively associated with Work-life Balance (WLB).

Technology Acceptance and technology-affordance perspectives provide the specific theoretical mechanism for Technology Factors. When digital technologies are perceived as useful, manageable, and capable of creating meaningful opportunities for work, they may support flexibility, efficiency, autonomy, and control. However, technology can also intensify connectivity and work demands. Empirical research on digital work and technostress therefore suggests that the relationship between technology and Work-life Balance is context-dependent (Duan et al., 2023, 2024; Bencsik & Juhasz, 2023; Choi et al., 2024).

On this basis, Technology Factors are expected to show a positive predictive relationship with Work-life Balance when employees experience technology as a useful and supportive work resource. The hypothesis does not assume that technology is universally beneficial; rather, it tests whether the respondents' overall perception of technology is positively associated with their reported Work-life Balance.

The technology pathway is therefore specified as a complementary rather than dominant mechanism. Technology may support work flexibility and efficiency, but these benefits may be limited when organizational conditions or individual resources are insufficient.

H2: Technology Factors (TF) are positively associated with Work-life Balance (WLB).

JD-R Theory provides the complementary explanation for External Factors. Organizational support, flexible work policies, supportive leadership, and a constructive work culture can operate as job resources that help employees manage demands and protect well-being. Prior research links supportive organizational conditions and flexible work practices with Work-life Balance and employee outcomes (Koon, 2022; Lamane-Harim et al., 2023; Ferdous et al., 2023; Filippi et al., 2024).

External Factors are therefore expected to be positively associated with Work-life Balance because organizational resources can reduce the practical and psychological burden of work and provide employees with greater control over when and how work is performed.

H3: External Factors (EF) are positively associated with Work-life Balance (WLB).

The relationship between Psychological Factors and Technology Factors is examined as a test of whether personal resources are associated with employees' perceptions and use of workplace technology. Although resilience and adaptability may help employees respond to change, prior literature also indicates that technology perceptions depend on contextual characteristics such as task fit, usability, training, and organizational support. The present study therefore tests this relationship empirically rather than assuming that psychologically resilient employees will automatically evaluate technology more positively.

If Psychological Factors are positively associated with Technology Factors, this would suggest that personal resources extend into technology-related perceptions. If the relationship is weak or non-significant, it would indicate that psychological resources and technology perceptions operate as relatively distinct domains in the present context.

This distinction is important because technology adoption is not solely a psychological phenomenon. Technology characteristics, task requirements, training, and organizational support may shape technology perceptions independently of individual psychological resources.

The model consequently treats Psychological Factors → Technology Factors as an empirical pathway that requires testing rather than as a theoretical assumption.

H4: Psychological Factors (PF) are positively associated with Technology Factors (TF).

The relationship between External Factors and Technology Factors is grounded in the organizational-resource logic of JD-R and the contextual nature of technology adoption. Organizational support, leadership, training, infrastructure, and a culture that accepts experimentation can provide conditions in which employees are more likely to perceive and use technology positively (Alqudah et al., 2022; Lamane-Harim et al., 2023; Choi et al., 2024).

Thus, External Factors are expected to be positively associated with Technology Factors because organizational conditions can shape the extent to which technology is accessible, supported, relevant, and integrated into everyday work practices.

Flexible work arrangements also illustrate this mechanism: when organizations support digitally enabled work, employees may experience technology as an organizational resource rather than as an additional demand. However, the cross-sectional design means that the study tests association, not whether organizational support causes technology acceptance.

The model therefore specifies External Factors → Technology Factors as a distinct organizational pathway and tests whether this association is stronger than the corresponding pathway from Psychological Factors.

H5: External Factors (EF) are positively associated with Technology Factors (TF).

COR Theory also provides the basis for the proposed mediation relationships. If Psychological Factors are personal resources and Technology Factors are perceived as work resources, technology could theoretically represent one pathway through which personal resources are translated into improved Work-life Balance. However, this mediation should occur only if Psychological Factors are associated with Technology Factors and Technology Factors are associated with WLB.

Accordingly, H6 is a testable indirect relationship rather than an assumption that psychologically resilient employees necessarily benefit more from technology. A non-significant indirect relationship would indicate that the psychological-resource pathway to Work-life Balance is primarily direct or operates through mechanisms not captured by Technology Factors.

The model similarly proposes that External Factors may be associated with Work-life Balance partly through Technology Factors. Organizational resources can create the conditions for effective use of digital tools, which may in turn support flexibility and work control. This pathway is theoretically distinct from the direct organizational-resource pathway because it tests whether technology represents an intermediate mechanism.

H6: Technology Factors (TF) mediate the relationship between Psychological Factors (PF) and Work-life Balance (WLB).

The mediation model is therefore specified as External Factors → Technology Factors → Work-life Balance. Under this logic, a significant indirect relationship would indicate that part of the association between organizational resources and WLB is transmitted through technology perceptions; a non-significant indirect relationship would indicate that technology does not constitute a statistically supported mediation pathway in the present sample.

Taken together, the model integrates three levels without treating them as competing theories: psychological resources at the individual level, organizational resources at the contextual level, and technology as a work-system resource. COR Theory provides the overarching resource logic, JD-R explains organizational resources, and technology perspectives explain the technology-specific pathway.

The resulting framework tests direct associations from Psychological Factors, External Factors, and Technology Factors to Work-life Balance, associations from Psychological and External Factors to Technology Factors, and two specific indirect pathways through Technology Factors. Because the data are cross-sectional, all hypotheses are interpreted as predictive relationships rather than causal effects.

H7: Technology Factors (TF) mediate the relationship between External Factors (EF) and Work-life Balance (WLB).

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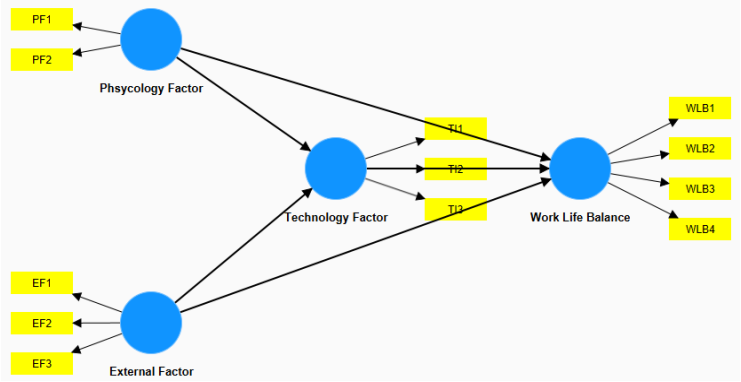

Figure 1. Framework

Based on Figure 1 above, the proposed framework can be explained as a three-level resource model: Psychological Factors and External Factors are exogenous predictors, Technology Factors are both an endogenous outcome and a proposed mediator, and Work-life Balance is the final endogenous outcome. The arrows represent the seven predictive and mediation relationships tested in the study.

Hypotheses

H1: Psychological Factors (PF) are positively associated with Work-life Balance (WLB).
H2: Technology Factors (TF) are positively associated with Work-life Balance (WLB).
H3: External Factors (EF) are positively associated with Work-life Balance (WLB).
H4: Psychological Factors (PF) are positively associated with Technology Factors (TF).
H5: External Factors (EF) are positively associated with Technology Factors (TF).
H6: Technology Factors (TF) mediate the relationship between Psychological Factors (PF) and Work-life Balance (WLB).
H7: Technology Factors (TF) mediate the relationship between External Factors (EF) and Work-life Balance (WLB).

Respondents were recruited using purposive sampling. Eligibility criteria were: (1) currently engaged in paid employment, self-employment, internship, apprenticeship, or other ongoing work-related professional activities; (2) routinely using AI-enabled or other digital technology in those activities; and (3) willing to complete the survey. The final sample consisted of 190 respondents. The term “professionals” is therefore defined by current participation in work-related activities and routine use of workplace/digital technology, rather than by age alone. This criterion explains the inclusion of the 26 respondents aged below 20 years: they met the screening requirements by being actively involved in work-related or professional activities and routinely interacting with AI/digital systems. The screening question required respondents to confirm both current work participation and routine technology use before proceeding to the questionnaire.

The demographic profile in Table 1 should be read directly from the observed sample. Of the 190 respondents, 70 (36.8%) were male and 120 (63.2%) were female. The age distribution was 26 respondents (13.7%) below 20 years, 129 (67.9%) aged 20–25 years, 18 (9.5%) aged 26–30 years, 13 (6.8%) aged 31–35 years, and 4 (2.1%) above 35 years. Regarding tenure at the current workplace, 72 respondents (37.9%) had worked for less than one year,

88 (46.3%) for 1–3 years, 25 (13.2%) for 3–6 years, and 5 (2.6%) for more than six years. Weekly working hours were below 20 hours for 66 respondents (34.7%), 20–40 hours for 67 (35.3%), 41–50 hours for 50 (26.3%), and above 50 hours for 7 (3.7%). These figures are reported consistently with Table 1 and replace the previously inconsistent narrative demographic percentages.

Table 1 Demography

Demographic Variable	Category	Frequency	Percentage
Gender	Male	70	36.8%
Gender	Female	120	63.2%
Age Group	< 20 years	26	13.7%
Age Group	20-25 years	129	67.9%
Age Group	26-30 years	18	9.5%
Age Group	31-35 years	13	6.8%
Age Group	> 35 years	4	2.1%
Tenure at Current Workplace	< 1 year	72	37.9%
Tenure at Current Workplace	1-3 years	88	46.3%
Tenure at Current Workplace	3-6 years	25	13.2%
Tenure at Current Workplace	> 6 years	5	2.6%
Weekly Working Hours	< 20 hours	66	34.7%
Weekly Working Hours	20-40 hours	67	35.3%
Weekly Working Hours	41-50 hours	50	26.3%
Weekly Working Hours	> 50 hours	7	3.7%

Construct Measurement and Operationalization Table 2. Data analysis followed a step-by-step PLS-SEM procedur . First, the measurement model was assessed through Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE) to evaluate internal consistency and convergent validity. Second, discriminant validity was

assessed using the heterotrait–monotrait ratio (HTMT). Third, collinearity was examined using indicator VIF. Fourth, the structural model was evaluated using path coefficients and bootstrapping with 5,000 subsamples, together with p-values and confidence-based significance assessment. Fifth, explanatory and predictive performance was examined using R^2, adjusted R^2, f^2, and Q^2. Finally, mediation was tested using specific indirect effects for the two proposed pathways: PF → TF → WLB and EF → TF → WLB. SRMR and related model-fit indicators were reported as supplementary model diagnostics. Because the design is cross-sectional, the resulting coefficients are interpreted as predictive associations, not causal effects.

Table 2. Construct Measurement and Operationalization

Construct	Operational Definition	Dimensions	Measurement Items	Scale
Psychological Factors (PF)	Personal psychological resources used to cope with work and non-work demands.	Resilience; self-efficacy/self-confidence; self-motivation/emotional regulation	PF1–PF2	5-point Likert (1=Strongly disagree; 5=Strongly agree)
External Factors (EF)	Organizational/contextual resources that support employees in managing work demands and technology use.	Organizational support; flexible work policy; supportive/adaptive leadership	EF1–EF3	5-point Likert (1=Strongly disagree; 5=Strongly agree)
Technology Factors (TF)	Employees' perceived usefulness, usability, and supportive role of workplace technology/AI.	Perceived usefulness; ease of use; reliability/task fit	TI1–TI3	5-point Likert (1=Strongly disagree; 5=Strongly agree)
Work-life Balance (WLB)	Perceived ability to maintain an acceptable balance between work responsibilities and personal/non-work life.	Work–non-work time balance; boundary management; interference/integration	WLB1–WLB4	5-point Likert (1=Strongly disagree; 5=Strongly agree)

All constructs have been validated with participant responses recorded using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Before the main data collection, a pilot test was conducted involving 30 respondents to verify the clarity and reliability of all measurement items.

Data analysis was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 software (Ma et al., 2022; Sarstedt et al., 2022b, 2022a). The analysis carried out in this study included the analysis of Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity using the heterotrait-monotrait ratio (HTMT). Furthermore, the evaluation of the structural model involves

examining the path coefficient, significance level (using bootstrapping with 5000 subsamples), determination coefficient (R^2), effect size (f^2), and predictive relevance (Q^2). Mediation analysis was carried out using a specific indirect effects approach. Model conformity assessment using standardized root mean square residual (SRMR) and other nonconformity measures.

RESULT AND DISCUSSION

Psychological Factors (PF) have a positive and significant influence on Work-life Balance, with a coefficient value of 0.415. This figure shows that internal individual resources, such as mental resilience, emotional level, and strong self-motivation, have a significant influence on life balance compared to technological factors.

Technology Factors show a positive direct predictive association with Work-life Balance of β=0.162 (p=0.008), which is smaller than the corresponding associations for Psychological Factors (β=0.415) and External Factors (β=0.301). This indicates that technology contributes to WLB in the present sample, but its unique predictive contribution is more modest.

Then the results of this study also reveal that there is a complex relationship pattern between technological factors and Psychological Factors. Technological factors have not been able to mediate the relationship between Psychological Factors and Work-life Balance. Even though Psychological Factors, such as high self-motivation, are high, it is not automatically that the individual will always be open to new technological developments.

The model explains 52.6% of the variance in Work-life Balance (R^2=0.526), indicating substantial explanatory relevance for the endogenous WLB construct in this sample. However, this statistic should be interpreted as model explanatory power rather than evidence that the predictors cause WLB.

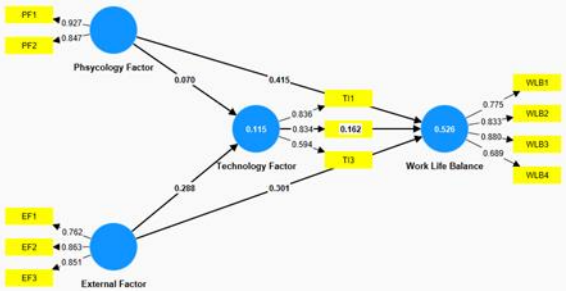

Figure 2. PLS SEM Analysis

This is strengthened by the R-square value for the Technology Factor, which is only 0.115. This indicates that only 11.5% of the variation in technology perception can be explained by this model. Meanwhile, the remaining 88.5% is determined by factors outside this model. Technological advances require positive perceptions from organizations and individual factors.

The model shows strong predictive power for the main construct of Work-life Balance. With an R-square of 0.526, it is explained that 52.6% related to Work-life Balance is influenced by Psychological, Technological, and External Factors. A very consistent adjusted R-square

value (0.519) confirms that this predictive power is stable and substantive in the context of social science research

The R-square results indicate that the proposed model explains a meaningful proportion of the observed variance in Work-life Balance, while explaining a smaller proportion of the variance in Technology Factors (Table 3). These results support continued examination of the structural associations, but they do not establish causal influence among the constructs.

Table 3. R-Square

	R-square	R-square adjusted
Technology Factor	0.115	0.106
Work-life Balance	0.526	0.519

Based on Table 3 above, Technology Factors have an R^2 of 0.115 (adjusted R^2=0.106), while Work-life Balance has an R^2 of 0.526 (adjusted R^2=0.519). Thus, the tested model explains 11.5% of the variance in Technology Factors and 52.6% of the variance in Work-life Balance. These values describe explanatory variance within the sample and should not be interpreted as evidence of causality.

All constructs were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Before the main survey, a pilot test involving 30 respondents was conducted to assess item clarity and preliminary reliability. After the pilot, the final questionnaire was administered to eligible respondents. Responses were screened for completeness before being entered into SmartPLS 4.0.

From the value of f-square (f^2), explaining the fundamental influence of External Factors on endogenous variables shows an interesting pattern. A value of f^2 of 0.050 on the Work-life Balance indicates a small but significant influence. Meanwhile, the influence on the Technology Factor was stronger with a value of 0.097. Thus, organizational policies, management support, and openness to new things have a strategic role in shaping a positive perception of technology.

Technology Factor (f^2 = 0.003), although minimal, still has a substantive influence on Work-life Balance. From this, it is emphasized that the role of Psychological Factors play a very important role in Work-life Balance. Meanwhile, the technology factor has a very small direct influence on the Work-life Balance, with a value of f^2 of only 0.049. This result strengthens the results of the analysis that although technology factors have a significant influence on Work-life Balance, the effect is very limited. Implicitly, the influence of technology factors on Work-life Balance is greatly influenced by Psychological Factors and Organizational Factors. Organizational policy support, leadership, openness, mental resilience, and motivation are catalysts for using technology in every job. If this happens, a Work-life Balance will be created (Table 4).

Table 4. F Square

	External Factor	Psychology Factor	Technology Factor	Work-life Balance
External Factor			0.050	0.097
Psychology Factor			0.003	0.194
Technology Factor				0.049

Based on Table 4 above, the largest f^2 is observed for Psychological Factors → Work-life Balance (0.194), followed by External Factors → Technology Factors (0.097). The remaining effects are small, indicating that psychological resources have the largest unique contribution among the tested predictors.

From the measurement results, it can be seen that all constructs in this study meet acceptable internal reliability standards. Cronbach's alpha value for each construct exceeds the minimum limit of 0.7, except for Technology Factors, with a value of 0.648, which are still in the marginally acceptable category. The Composite Reliability values (rho_a and rho_c) also show good consistency, with all constructs having values above 0.7. This explains that the measurement items are interrelated with each other

Psychological Factors had the highest score with a Cronbach's alpha value of 0.739 and a Composite Reliability of 0.882. Meanwhile, the Work-life Balance also has strong reliability with Cronbach's alpha value of 0.806 and Composite Reliability of 0.874. Validity is convergent; all constructs meet the criteria with an Average Variance Extracted (AVE) value above the minimum threshold of 0.5, where the Psychological Factor has the highest AVE of 0.789 and the Technology Factor has the lowest AVE. Both are still within the normal limit, which is 0.582. Overall, it confirms that the measurement instrument used has sufficient reliability and convergent validity to continue the structural model analysis (Table 5).

Table 5. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
External Factor	0.766	0.770	0.866	0.683
Psychology Factor	0.739	0.801	0.882	0.789
Technology Factor	0.648	0.707	0.803	0.582
Work-life Balance	0.806	0.821	0.874	0.636

Based on Table 5 above, all constructs have composite reliability values above 0.70 and AVE values above 0.50. Technology Factors have a Cronbach's alpha of 0.648, which is lower than the conventional 0.70 criterion but is accompanied by composite reliability of 0.803 and AVE of 0.582; this should therefore be reported transparently as a marginal internal-consistency result rather than described as fully meeting the alpha criterion.

The Heterotrait-Monotrait correlation ratio (HTMT) matrix shows that the entire HTMT value between constructs is below the conservative limit of 0.90. This indicates that each construct in the model has different measurement characteristics and does not overlap with the others. The HTMT value between Psychological Factors and Work-life Balance was 0.829. Then, with the External Factors and the Work-life Balance of 0.805. Both can still explain the relationship between Psychological Factors, external support, and Work-life Balance. Meanwhile, the lower HTMT values between Technology Factors and other constructs (0.440 with External Factors, 0.356 with Psychological Factors, and 0.512 with Work-life Balance) corroborate that perceptions of technology are empirically different and different from psychological and contextual factors.

Although the HTMT value between Psychology Factor and Work-life Balance is close to the threshold of 0.85, this is theoretically acceptable given that they are indeed closely related constructs in the work welfare literature. This strong relationship supports the logic of the model that psychological resources are the main drivers for achieving a life balance, without reducing the validity of the discrimination between the two constructs. On the other hand, the position of Technology Factor with a consistently lower HTMT value reinforces the assumption that technology perception is a unique dimension and not just an extension of Psychological Factors or external conditions.

Overall, the discriminant-validity results are largely acceptable, but the External Factor–Psychological Factor HTMT value of 0.912 exceeds the conservative 0.90 threshold (Table 6). This should be treated as a potential discriminant-validity concern and acknowledged when interpreting the structural results. The concern does not by itself invalidate the model, but it indicates that the distinction between these two constructs should be examined further in future research.

Table 6. Discriminant Validity

	External Factor	**Psychology Factor**	**Technology Factor**	**Work-life Balance**
External Factor				
Psychology Factor	0.912			
Technology Factor	0.440	0.356		
Work-life Balance	0.805	0.829	0.512	

Based on Table 6 above, HTMT values are below 0.90 except for the External Factor–Psychology Factor value of 0.912. This value exceeds the conservative 0.90 threshold and should therefore be acknowledged as a potential discriminant-validity concern rather than stated as evidence that all constructs are clearly distinct.

Based on the results of the Variance Inflation Factor (VIF) test, it can be concluded that this research model is free from critical multicollinearity problems. All indicators in the model have VIF values well below the conservative tolerance limit of 5.0, ranging from 1,207 to 2,345. The highest values were found in the WLB3 indicator of 2,345 and WLB2 of 2,121, which, although relatively higher than other indicators, are still in the safe category and do not threaten the stability of parameter estimation.

A more in-depth analysis revealed that none of the indicators had a VIF value close to or exceeding 3.0, which is a stricter limit often used in social science research. This indicates that each indicator carries unique information and that there is no significant redundancy between predictors in the model. Thus, it can be ensured that the path coefficient and statistical significance generated in the structural analysis are not distorted by the presence of a high correlation between independent variables, so that the research findings are reliable and the interpretation is valid (Table 7).

Table 7 Collinearity Statistics (Model VIF)

	VIF
EF1	1.318
EF2	1.889
EF3	1.939
PF1	1.523
PF2	1.523
TI1	1.313
TI2	1.488
TI3	1.207
WLB1	1.547
WLB2	2.121
WLB3	2.345
WLB4	1.340

Based on Table 7 above, all indicator VIF values range from 1.207 to 2.345, remaining below 3.0 and 5.0. This indicates that critical indicator-level collinearity is not evident in the reported model.

Based on the results of the goodness-of-fit test, this study model shows an acceptable match with a Standardized Root Mean Square Residual (SRMR) value of 0.093 for both models (saturated and estimated). This value is just below the cut-off value of 0.10 recommended for exploratory research in the social sciences, indicating that the difference between the observed correlation matrix and that predicted by the model is relatively low. Although the SRMR value does not reach the strict standard of 0.08, these findings still support the model's global suitability in representing patterns of empirical data relationships.

Other conformity indices, such as the Normed Fit Index (NFI) of 0.671, show that the proposed model provides a substantial improvement compared to the zero model (baseline model). However, the NFI value that has not yet reached 0.90 indicates that there is still room for improvement in model specifications to increase its clarity. Meanwhile, significant Chi-square statistics (335,847) tend to be influenced by sample size and are less used as the primary determinant of fit in PLS-SEM, so the assessment is more focused on SRMR and predictive criteria.

Overall, the combination of fit indicators confirms that the tested structural model has sufficient validity for this study. The acceptable SRMR value, coupled with the predictive power of the model that has been proven in previous R-square analyses, provides a fairly strong basis for interpreting the structural relationships between constructs. These findings support the continuation of the analysis and discussion of theoretical implications, while acknowledging that improvements to the model can be made in future studies to achieve a more optimal level of conformity (Table 8).

Table 8 Model FIT

	Saturated model	**Estimated model**
SRMR	0.093	0.093
d_ULS	0.675	0.675
d_G	0.295	0.295
Chi-square	335.847	335.847
NFI	0.671	0.671

Based on Table 8 above, the SRMR is 0.093 for both the saturated and estimated models, while NFI is 0.671. These indices suggest an exploratory model with acceptable but not strong global fit; therefore, the model should not be characterized as having excellent fit.

Based on the results of path coefficients analysis, this study identified a significant pattern of relationships between external, psychological, technological, and Work-life Balance factors. External Factors showed a positive and significant influence both on Technology Factors (β=0.288, p=0.011β=0.288, p=0.011) and directly on Work-life Balance (β=0.301, p=0.001β=0.301, p=0.001). This indicates that the organizational context and environmental support play an important role in shaping the perception of technology and at the same time, improving the Work-life Balance of employees. On the other hand, Psychological Factors have a very strong and significant direct influence on Work-life Balance (β=0.415, p<0.001β=0.415, p<0.001), but are not significant in influencing Technology Factors β=0.070, p=0.543β=0.070, p=0.543), which confirms that psychological resources play a more important role as a driver of well-being than as a shaping of technological perception.

Technology Factors were positively associated with Work-life Balance (β=0.162, p=0.008), although the associated effect size was small (f^2=0.049). This indicates a statistically supported but relatively modest association. Taken together with the stronger associations of Psychological Factors and External Factors with WLB, the findings suggest that technology

should be considered a complementary factor rather than the sole explanation for WLB. This interpretation is consistent with the observed data and does not imply that technology causes improved WLB.

Table 9 Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
External Factor -> Technology Factor	0.288	0.295	0.114	2.531	0.011
External Factor -> Work-life Balance	0.301	0.299	0.087	3.472	0.001
Psychology Factor -> Technology Factor	0.070	0.074	0.115	0.609	0.543
Psychology Factor -> Work-life Balance	0.415	0.418	0.077	5.361	0.000
Technology Factor -> Work-life Balance	0.162	0.163	0.061	2.661	0.008

Based on Table 9 above, External Factors are positively associated with Technology Factors (β=0.288, p=0.011) and WLB (β=0.301, p=0.001). Psychological Factors are positively associated with WLB (β=0.415, p<0.001) but not significantly with Technology Factors (β=0.070, p=0.543). Technology Factors are positively associated with WLB (β=0.162, p=0.008).

Total Effect Analysis reveals the overall effects between variables, which include direct and indirect effects. External factors showed a strong and significant total effect on Work-life Balance of (β=0.347, p<0.001). This effect is greater than the previous direct effect of (0.301). This increase indicates that in addition to having a direct impact, external factors also contribute indirectly by forming a positive perception of technology. Its influence on the Technology Factor remains significant (β=0.288, p=0.011) while confirming its role as the main driver of a positive technological environment.

Meanwhile, Psychological Factors once again showed dominance as the strongest predictor with a very significant total influence on Work-life Balance (β=0.426, p<0.001). This magnitude is even slightly higher than the direct effect, indicating an additional contribution through other pathways that may not be fully modeled. However, the total effect on the

Technology Factor remained insignificant (β=0.070, p=0.543). This reinforces the findings of this research that individual psychological resources do not significantly shape how they perceive or evaluate technology in the workplace.

Technology Factors were positively associated with Work-life Balance (β=0.162, p=0.008). Because the PF → TF path was not significant, the model does not support an indirect pathway from Psychological Factors to WLB through Technology Factors. The observed technology–WLB association is therefore represented by the direct path in the tested model. This result should be interpreted as a predictive association, not as evidence that technology independently causes better WLB.

Table 10 Total Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
External Factor -> Technology Factor	0.288	0.295	0.114	2.531	0.011
External Factor -> Work-life Balance	0.347	0.349	0.084	4.131	0.000
Psychology Factor -> Technology Factor	0.070	0.074	0.115	0.609	0.543
Psychology Factor -> Work-life Balance	0.426	0.430	0.079	5.424	0.000
Technology Factor -> Work-life Balance	0.162	0.163	0.061	2.661	0.008

Based on Table 10 above, the total association of External Factors with WLB is β=0.347 (p<0.001), while the total association of Psychological Factors with WLB is β=0.426 (p<0.001). These total effects should be interpreted as aggregate predictive associations rather than causal effects.

This study also analyzes Specific Indirect Effects, i.e., testing whether Technology Factors act as mediators in the relationship between external factors and Work-life Balance. The results showed that the indirect path from External Factors to Work-life Balance through Technology Factors had a coefficient of 0.047 with p=0.099, or in other words, did not reach statistical significance at a confidence level of 95% (p<0.05).

Nevertheless, a p-value close to this threshold indicates a weak mediation trend.

However, if the sample size is enlarged or in a certain context, it may be able to play a greater role in the Work-life Balance, especially if there is better external support.

The indirect pathway from Psychological Factors to Work-life Balance through Technology Factors was not significant (β=0.011, p=0.575), while the corresponding External Factors → Technology Factors → WLB pathway was also not significant (β=0.047, p=0.099) (Table 11). These results do not support either proposed mediation hypothesis. The findings therefore indicate that the tested mediation mechanism was not statistically supported in this sample; they do not establish that technology cannot function as a mediator under other conditions or in other populations.

Table 11 Specific Indirect Effects

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
External Factor -> Technology Factor -> Work-life Balance	0.047	0.049	0.028	1.649	0.099
Psychology Factor -> Technology Factor -> Work-life Balance	0.011	0.012	0.020	0.561	0.575

Based on Table 11 above, the indirect relationship PF → TF → WLB is not significant (β=0.011, p=0.575), and the indirect relationship EF → TF → WLB is also not significant (β=0.047, p=0.099). Therefore, neither proposed mediation pathway receives statistical support at $p<0.05$.

H1: Psychological Factors (PF) have a significant positive influence on Work-life Balance (WLB).

Psychological Factors were the strongest predictors of Work-life Balance with a direct coefficient of 0.415 and a total effect of 0.426 ($p<0.001$). These findings are in line with the Resource Conservation Theory (Demerouti, 2025; Li et al., 2024; Su & Li, 2025), where individuals with rich psychological resources, such as mental resilience, self-confidence, strong self-motivation, and controlled emotions, are better able to manage work and non-work demands so as to protect the Work-life Balance (Abdul Jalil et al., 2023; Borowiec & Drygas, 2023; Charoensukmongkol, 2022).

The effect size value (f^2) of 0.194, which is classified as moderate, further confirms the practical significance of this relationship, which suggests that the contribution of Psychological Factors is not only statistically significant but also substantial in an organizational context.

Theoretically, these results reinforce the position of positive psychology in the Work-life Balance literature, which emphasizes that psychological capital serves as internal capital to cope with stress and maintain life integration

From a practical perspective, these findings imply that organizational interventions aimed at improving Work-life Balance need to be carried out in a planned and systematic manner by incorporating elements of self-capacity development, such as mental resilience training and mindfulness programs. This is important so that it can be a foundation that is more important than simply providing technical facilities or flexibility.

H2: Technology Factor (TF) has a significant positive influence on Work-life Balance (WLB).

Technology Factors have a significant influence on Work-life Balance with a lower value of (β=0.162, p=0.008). These findings support the perspective of technology as an enabler, where technology systems that are considered useful, reliable, and easy to use can support employee autonomy, efficiency, and control over work (Bencsik & Juhasz, 2023; Ferdous et al., 2023; Koon, 2022; Pranata et al., 2022).

This will certainly affect the Work-life Balance positively. However, the small effect size (f^2) (0.049) indicates that the unique contribution of technology in explaining Work-life Balance variance is not as large as other factors. An interesting implication of these findings is that technology is not the only solution to overcome the problem of Work-life Balance. Organizations cannot rely solely on the application of advanced technology to overcome the problem of Work-life Balance. The organization must also be able to integrate it with other supporting factors. Good organizational support and individual psychologists will be able to optimally overcome the problem of Work-life Balance. Without all of that support, technology can actually cause new stress problems.

H3: External Factors (EF) have a significant positive influence on Work-life Balance (WLB).

External factors were shown to have a strong and significant influence on Work-life Balance, both directly (β=0.301) and total (β=0.347), with the effect size reaching a moderate level (f^2=0.097). This confirms the Job Demands-Resources (JD-R) Theory, which places organizational support, flexible policies, a healthy work culture, and supportive leadership as key work resources that can prevent burnout and encourage engagement. In this context, a supportive external environment serves as a protector that protects employees from the demands of work (Demerouti, 2025; Hoare & Vandenberghe, 2024; Petrou & Xanthopoulou, 2021; Tomczak & Kulikowski, 2024).

These findings suggest that a systemic approach may be useful when considering Work-life Balance (WLB). This means that Work-life Balance policies will not be effective if they are not supported by an organizational culture that values time constraints, an appropriate reward system, and empathetic leadership. Organizations need to view external factors as social infrastructure that must be built intentionally and sustainably, not just formal policies on paper.

H4: Psychological Factors (PF) have a significant positive influence on Technology Factors (TF).

The results of the analysis rejected the fourth hypothesis, because the relationship between Psychological Factors and Technological Factors was not significant (β=0.070, p=0.543). These findings are interesting because they contradict the common assumption that individuals with high psychological resources tend to be more adaptive and positive in responding to new technologies. This rejection suggests that perceptions of technology are more contextual and technical than psychological; That is, a person's positive or negative assessment of a work system is more determined by factors such as ease of use, relevance of tasks, quality of training, and technical support, all of which are outside the domain of individual psychology.

An important implication of these findings is the need for inclusive and user-centric technology design. Organizations cannot assume that resilient or optimistic employees will automatically be able or willing to adopt new technologies. Therefore, a human-centered design approach is important, that is, one that can inherently adapt to the user's spectrum of competencies and comfort levels. This adaptability must be supported by a robust training program and flexible technical support, regardless of any individual's psychological characteristics.

H5: External Factors (EF) have a significant positive influence on Technology Factors (TF).

Statistically supported finding. External Factors were positively associated with Technology Factors (β=0.288, p=0.011). This result indicates that respondents who reported stronger organizational/contextual support also tended to report more favorable Technology Factors. The finding is consistent with the view that technology perceptions are embedded in the work context, including training, technical support, task fit, and an organizational culture that supports learning and adaptation. The result should be interpreted as an association because the study uses cross-sectional data.

Theoretical interpretation and practical recommendation. The significant EF → TF association is compatible with a resource-based interpretation in which organizational conditions may shape how employees experience workplace technology. However, this finding does not establish that organizational support causes more favorable technology perceptions. Practically, organizations may consider aligning technology implementation with user training, technical support, change management, and opportunities for learning. These are recommendations derived from the pattern of findings, rather than effects demonstrated by the present cross-sectional design.

H6: The Technology Factor (TF) mediates the relationship between Psychological Factors (PF) and Work-life Balance (WLB).

Statistically supported finding. The specific indirect association from Psychological Factors to Work-life Balance through Technology Factors was not significant (β=0.011, p=0.575). This result does not support H6. It is consistent with the non-significant PF → TF association (β=0.070, p=0.543), indicating that the data do not provide statistical support for Technology Factors as a mediating pathway between Psychological Factors and WLB. The direct PF → WLB association remains statistically significant (β=0.415, p<0.001), but because the design is cross-sectional, this pattern should be described as a predictive association

rather than a causal pathway.

Theoretical interpretation. The findings suggest that psychological resources and technology perceptions may represent related but empirically distinguishable domains in this sample. This interpretation is consistent with the proposed framework in which Technology Factors were expected to provide a pathway between personal resources and WLB, but the tested indirect pathway was not supported. Further longitudinal or experimental research is needed before stronger claims can be made about how psychological resources and technology use interact over time.

Statistically supported finding. The specific indirect association from External Factors to Work-life Balance through Technology Factors was also not significant (β=0.047, p=0.099). Therefore, H7 is not supported at the 0.05 significance level. Although EF was positively associated with TF (β=0.288, p=0.011), that association did not translate into a statistically significant indirect association with WLB. The result is important because it directly addresses the proposed mediation mechanism: the data support an EF → TF association, but they do not support TF as a statistically significant mediator of the EF → WLB relationship.

Practical recommendation and future proposition. Because neither mediation pathway was statistically supported, the study should not conclude that technology amplifies or magnifies the positive impact of a supportive work environment. A more defensible practical implication is that organizations may benefit from considering psychological resources, organizational support, and technology implementation as complementary areas when addressing WLB. Future studies could test whether technology characteristics such as digital literacy, task-technology fit, implementation quality, or technology-related demands moderate or mediate these relationships under different organizational conditions. These possibilities are propositions for future research, not findings established by the present data.

Novelty

The main empirical contribution is the identification of a differentiated pattern across the proposed pathways. Psychological Factors were positively associated with WLB but not significantly with Technology Factors, whereas External Factors were positively associated with both Technology Factors and WLB. However, neither the PF → TF → WLB nor the EF → TF → WLB indirect association was statistically significant. Thus, the data do not support the claim that Technology Factors function as a significant mediator in either relationship. The value of the model lies in showing where the proposed mediation mechanism is and is not supported, providing a basis for refinement in future research.

Theoretical Implications

Theoretical implication. The findings provide empirical evidence that the three resource domains should not automatically be assumed to operate through a single mediation mechanism. Within the present cross-sectional sample, Psychological Factors showed a positive association with WLB without a significant association with Technology Factors, while External Factors showed a positive association with Technology Factors. Nevertheless, the indirect paths through Technology Factors were not statistically significant. This pattern

suggests that future theoretical development should examine more specific boundary conditions and alternative mechanisms rather than assuming technology is a universal intermediary.

Theoretical interpretation. The absence of significant mediation should not be interpreted as evidence that technology has no role in WLB. Technology Factors were positively associated with WLB (β=0.162, p=0.008). Rather, the results indicate that the proposed mediation mechanism was not statistically supported in this sample. Longitudinal or experimental designs would be needed to determine whether the relationships among psychological resources, organizational resources, technology, and WLB develop causally over time.

Practical Implications

For organizations, these findings emphasize the importance of an integrated and tiered approach in an effort to improve Work-life Balance. It is necessary to provide training for the development of employees' psychological capacity through structured mental resilience, mindfulness, and emotional intelligence training programs, as these aspects are the strongest foundation for the creation of Work-life Balance.

Organizations need to strengthen external support through empathetic leadership, concrete (not merely symbolic) flexible work policies, and an organizational culture that respects the boundaries between work and personal life. Investment in technology must be balanced with parallel investments in training, ongoing technical support, and feedback mechanisms that allow employees to convey difficulties or system adaptation needs.

CONCLUSION

Based on the statistical analysis, Work-life Balance is associated with three complementary domains examined in this study: Psychological Factors, External Factors, and Technology Factors. Psychological Factors showed the strongest positive association with WLB (β=0.415, p<0.001), while External Factors were also positively associated with WLB (β=0.301, p=0.001). Technology Factors showed a smaller but statistically significant positive association with WLB (β=0.162, p=0.008). External Factors were positively associated with Technology Factors (β=0.288, p=0.011), whereas Psychological Factors were not (β=0.070, p=0.543). Importantly, neither the PF → TF → WLB indirect association (β=0.011, p=0.575) nor the EF → TF → WLB indirect association (β=0.047, p=0.099) was statistically significant.

Accordingly, the evidence supports direct predictive associations among several constructs, but it does not support Technology Factors as a statistically significant mediator of either proposed relationship. The results therefore should not be interpreted as demonstrating that technology transmits psychological resources or amplifies the effect of organizational support on WLB. Instead, technology appears in this model as a complementary factor that is positively associated with WLB and is itself associated with External Factors. The cross-sectional design also limits causal interpretation.

From a practical perspective, organizations may consider a multilevel approach that addresses employees' psychological resources, organizational support, and technology

implementation simultaneously. However, these recommendations are applications of the observed pattern rather than causal prescriptions established by the study. Future research should test whether digital literacy, technology characteristics, task-technology fit, leadership, or job demands condition the relationships observed here.

RESEARCH LIMITATION

This study has limitations because it uses a cross-sectional design, which prevents causal inference, and the samples come from only the region in Indonesia, namely Jakarta. So, this research is not generalizable. The Technology Factor shows marginal reliability, and the model explains only a small part of the variance (R^2 = 0.115), indicating the presence of overlooked variables such as digital literacy or system design quality.

SUGGESTIONS

Based on the findings and acknowledged limitations of this study, future research is encouraged to use observational research methods that observe, measure, and analyze the same individuals or groups repeatedly to establish causal relationships and capture changes over time between Psychological Factors, technology, and Work-life Balance. In addition, expanding the model to incorporate potential moderator variables such as digital literacy, leadership style, or job characteristics that may explain the contingent mechanisms. From a practical standpoint, organizations are encouraged to implement integrated intervention programs that concurrently strengthen employees' psychological well-being through evidence-based training, reinforce organizational support systems through flexible work arrangements, and implement technology using a human-centered design approach supported by sufficient training. Through this alignment, these three pillars can mutually reinforce each other in creating a sustainable work ecosystem that promotes employees' holistic well-being.

REFERENCE

Abdul Jalil, N. I., Tan, S. A., Ibharim, N. S., Musa, A. Z., Ang, S. H., & Mangundjaya, W. L. (2023). The Relationship between Job Insecurity and Psychological Well-Being among Malaysian Precarious Workers: Work–Life Balance as a Mediator. International Journal of Environmental Research and Public Health, 20(3). https://doi.org/10.3390/ijerph20032758

Abu Daqar, M. A. M., Arqawi, S., & Karsh, S. A. (2020). Fintech in the eyes of Millennials and Generation Z (the financial behavior and Fintech perception). Banks and Bank Systems, 15(3). https://doi.org/10.21511/bbs.15(3).2020.03

Adamovic, M. (2022). How does employee cultural background influence the effects of telework on job stress? The roles of power distance, individualism, and beliefs about telework. International Journal of Information Management, 62. https://doi.org/10.1016/j.ijinfomgt.2021.102437

Adams, R. M., Eisenman, D. P., & Glik, D. (2019). Community advantage and individual self-efficacy promote disaster preparedness: A multilevel model among persons with

disabilities. International Journal of Environmental Research and Public Health, 16(15). https://doi.org/10.3390/ijerph16152779

Aksoy, O., Bann, D., Fluharty, M. E., & Nandi, A. (2022). Religiosity and Mental Wellbeing Among Members of Majority and Minority Religions: Findings From Understanding Society: The UK Household Longitudinal Study. American Journal of Epidemiology, 191(1). https://doi.org/10.1093/aje/kwab133

Al Riyami, S., Razzak, M. R., Al-Busaidi, A. S., & Palalic, R. (2023). Impact of work from home on work-life balance: Mediating effects of work-family conflict and work motivation. Heritage and Sustainable Development, 5(1). https://doi.org/10.37868/hsd.v5i1.129

Alqudah, I. H. A., Carballo-Penela, A., & Ruzo-Sanmartín, E. (2022). High-performance human resource management practices and readiness for change: An integrative model including affective commitment, employees' performance, and the moderating role of hierarchy culture. European Research on Management and Business Economics, 28(1). https://doi.org/10.1016/j.iedeen.2021.100177

Azzam, M., Al-Kubaisy, M., Alshrouf, M. A., Al Karmi, J., Alnawaiseh, H., Mehyar, L. M., Ibrahim, S. O., & Abufaraj, M. (2023). Work–Life Balance among Physicians in Jordan. Medicina (Lithuania), 59(5). https://doi.org/10.3390/medicina59050868

Babapour, A. R., Gahassab-Mozaffari, N., & Fathnezhad-Kazemi, A. (2022). Nurses' job stress and its impact on quality of life and caring behaviors: a cross-sectional study. BMC Nursing, 21(1). https://doi.org/10.1186/s12912-022-00852-y

Bak, O., Shaw, S., Colicchia, C., & Kumar, V. (2023). A Systematic Literature Review of Supply Chain Resilience in Small-Medium Enterprises (SMEs): A Call for Further Research. In IEEE Transactions on Engineering Management (Vol. 70, Issue 1). https://doi.org/10.1109/TEM.2020.3016988

Bakker, A. B., & Demerouti, E. (2024). Job Demands–Resources Theory: Frequently Asked Questions. Journal of Occupational Health Psychology, 29(3). https://doi.org/10.1037/ocp0000376

Bansal, S., Garg, N., & Singh, J. (2024). Weight-based teasing and depressive symptoms among Indian college students: exploring the moderating effect of gratitude. Kybernetes, 53(6). https://doi.org/10.1108/K-10-2022-1486

Bauer, G. R., Churchill, S. M., Mahendran, M., Walwyn, C., Lizotte, D., & Villa-Rueda, A. A. (2021). Intersectionality in quantitative research: A systematic review of its emergence and applications of theory and methods. SSM - Population Health, 14. https://doi.org/10.1016/j.ssmph.2021.100798

Bencsik, A., & Juhasz, T. (2023). Impact Of Technostress On Work-Life Balance. Human Technology, 19(1). https://doi.org/10.14254/1795-6889.2023.19-1.4

Bocean, C. G., Popescu, L., Varzaru, A. A., Avram, C. D., & Iancu, A. (2023). Work-Life Balance and Employee Satisfaction during COVID-19 Pandemic. Sustainability (Switzerland), 15(15). https://doi.org/10.3390/su151511631

Bokhari, S. A. A., & Myeong, S. (2022). Use of Artificial Intelligence in Smart Cities for Smart Decision-Making: A Social Innovation Perspective. Sustainability (Switzerland), 14(2). https://doi.org/10.3390/su14020620

Borowiec, A. A., & Drygas, W. (2023). Work–Life Balance and Mental and Physical Health among Warsaw Specialists, Managers and Entrepreneurs. International Journal of Environmental Research and Public Health, 20(1). https://doi.org/10.3390/ijerph20010492

Charoensukmongkol, P. (2022). Supervisor-subordinate guanxi and emotional exhaustion: The moderating effect of supervisor job autonomy and workload levels in organizations. Asia Pacific Management Review, 27(1). https://doi.org/10.1016/j.apmrv.2021.05.001

Chen, G., Wang, J., Huang, Q., Sang, L., Yan, J., Chen, R., Cheng, J., Wang, L., Zhang, D., & Ding, H. (2024). Social support, psychological capital, multidimensional job burnout, and turnover intention of primary medical staff: a path analysis drawing on conservation of resources theory. Human Resources for Health, 22(1). https://doi.org/10.1186/s12960-024-00915-y

Cherian, J., Gaikar, V., Paul, R., & Pech, R. (2021). Corporate culture and its impact on employees' attitude, performance, productivity, and behavior: An investigative analysis from selected organizations of the United Arab Emirates (UAE). Journal of Open Innovation: Technology, Market, and Complexity, 7(1), 1–28. https://doi.org/10.3390/joitmc7010045

Choi, W. S., Kang, S. W., & Choi, S. B. (2024). The dark side of mobile work during non-work hours: moderated mediation model of presenteeism through conservation of resources lens. Frontiers in Public Health, 12. https://doi.org/10.3389/fpubh.2024.1186327

Daraba, D., Wirawan, H., Salam, R., & Faisal, M. (2021). Working from home during the corona pandemic: Investigating the role of authentic leadership, psychological capital, and gender on employee performance. Cogent Business and Management, 8(1). https://doi.org/10.1080/23311975.2021.1885573

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1). https://doi.org/10.1007/s11747-019-00696-0

de Bruijn, E. J., & Antonides, G. (2022). Poverty and economic decision making: a review of scarcity theory. Theory and Decision, 92(1). https://doi.org/10.1007/s11238-021-09802-7

Demerouti, E. (2025). Job demands-resources and conservation of resources theories: How do they help to explain employee well-being and future job design? Journal of Business Research, 192. https://doi.org/10.1016/j.jbusres.2025.115296

Duan, S. X., Deng, H., & Wibowo, S. (2023). Exploring the impact of digital work on work–life balance and job performance: a technology affordance perspective. Information Technology and People, 36(5). https://doi.org/10.1108/ITP-01-2021-0013

Duan, S. X., Deng, H., & Wibowo, S. (2024). Technology Affordances for Enhancing Job Performance in Digital Work. Journal of Computer Information Systems, 64(2). https://doi.org/10.1080/08874417.2023.2188497

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future

of digital and social media marketing research: Perspectives and research propositions. International Journal of Information Management, 59. https://doi.org/10.1016/j.ijinfomgt.2020.102168

Ebrahimi, P., Khajeheian, D., Soleimani, M., Gholampour, A., & Fekete-Farkas, M. (2023). User engagement in social network platforms: what key strategic factors determine online consumer purchase behaviour? Economic Research-Ekonomska Istrazivanja , 36(1). https://doi.org/10.1080/1331677X.2022.2106264

Feng, Z., & Chen, M. (2022). Platformance-Based Cross-Border Import Retail E-Commerce Service Quality Evaluation Using an Artificial Neural Network Analysis. Journal of Global Information Management, 30(11). https://doi.org/10.4018/JGIM.306271

Ferdous, T., Ali, M., & French, E. (2023). Use of flexible work practices and employee outcomes: the role of work-life balance and employee age. Journal of Management and Organization, 29(5). https://doi.org/10.1017/jmo.2020.44

Filippi, S., Yerkes, M., Bal, M., Hummel, B., & de Wit, J. (2024). (Un)deserving of work-life balance? A cross country investigation of people's attitudes towards work-life balance arrangements for parents and childfree employees. Community, Work and Family, 27(1). https://doi.org/10.1080/13668803.2022.2099247

Gabr, H. M., Soliman, S. S., Allam, H. K., & Raouf, S. Y. A. (2021). Effects of remote virtual work environment during COVID-19 pandemic on technostress among Menoufia University Staff, Egypt: a cross-sectional study. Environmental Science and Pollution Research, 28(38). https://doi.org/10.1007/s11356-021-14588-w

Garcia, L. C., Shanafelt, T. D., West, C. P., Sinsky, C. A., Trockel, M. T., Nedelec, L., Maldonado, Y. A., Tutty, M., Dyrbye, L. N., & Fassiotto, M. (2020). Burnout, Depression, Career Satisfaction, and Work-Life Integration by Physician Race/Ethnicity. JAMA Network Open, 3(8). https://doi.org/10.1001/jamanetworkopen.2020.12762

Garg, P., Gupta, B., Chauhan, A. K., Sivarajah, U., Gupta, S., & Modgil, S. (2021). Measuring the perceived benefits of implementing blockchain technology in the banking sector. Technological Forecasting and Social Change, 163. https://doi.org/10.1016/j.techfore.2020.120407

Gülmez, E., Koruca, H. I., Aydin, M. E., & Urganci, K. B. (2024). Heuristic and swarm intelligence algorithms for work-life balance problem. Computers and Industrial Engineering, 187. https://doi.org/10.1016/j.cie.2023.109857

Gupta, S., Schillaci, M., Walker, R., Smith, P. M. C., Watt, M., & Roessner, U. (2021). Alleviation of salinity stress in plants by endophytic plant-fungal symbiosis: Current knowledge, perspectives and future directions. Plant and Soil, 461(1–2). https://doi.org/10.1007/s11104-020-04618-w

Hair, J. F., William, C. B., Barry, J. B., & Anderson, R. E. (2013). Multivariate Data Analysis. Pearson Education Limited.

Harries, A. J., Lee, C., Jones, L., Rodriguez, R. M., Davis, J. A., Boysen-Osborn, M., Kashima, K. J., Krane, N. K., Rae, G., Kman, N., Langsfeld, J. M., & Juarez, M. (2021). Effects of the COVID-19 pandemic on medical students: a multicenter quantitative study. BMC Medical Education, 21(1). https://doi.org/10.1186/s12909-020-02462-1

Herrmann, H. (2023). What's next for responsible artificial intelligence: a way forward through responsible innovation. Heliyon, 9(3). https://doi.org/10.1016/j.heliyon.2023.e14379

Hoare, C., & Vandenberghe, C. (2024). Are They Created Equal? A Relative Weights Analysis of the Contributions of Job Demands and Resources to Well-Being and Turnover Intention. Psychological Reports, 127(1). https://doi.org/10.1177/00332941221103536

Hoque, M. N., Rahman, M. K., Said, J., Begum, F., & Hossain, M. M. (2022). What Factors Influence Customer Attitudes and Mindsets towards the Use of Services and Products of Islamic Banks in Bangladesh? Sustainability (Switzerland), 14(8). https://doi.org/10.3390/su14084703

Huang, R., Yan, P., & Yang, X. (2021). Knowledge map visualization of technology hotspots and development trends in China's textile manufacturing industry. IET Collaborative Intelligent Manufacturing, 3(3). https://doi.org/10.1049/cim2.12024

Jahnke, S. A., Haddock, C. K., Jitnarin, N., Kaipust, C. M., Hollerbach, B. S., Poston, W. S. C., & Leon-Perez, J. M. (2019). The Prevalence and Health Impacts of Frequent Work Discrimination and Harassment among Women Firefighters in the US Fire Service. BioMed Research International, 2019. https://doi.org/10.1155/2019/6740207

Juanda, Riansyah, R. J., Arsadi, & Bethany, L. (2024). Towards Entrepreneurial Campus Sustainability: Integrating Artificial Intelligence for Resource Allocation iBusiness Management. APTISI Transactions on Technopreneurship, 6(3). https://doi.org/10.34306/att.v6i3.410

K S Suryavanshi, A., Bhatt, P., & Singh, S. (2023). Predicting the buying intention of organic food with the association of theory of planned behaviour. Materials Today: Proceedings. https://doi.org/10.1016/j.matpr.2023.03.359

Kadir, K. A., Sahari, N., & Judi, H. M. (2019). Indicators on social media islamic information credibility through an expert agreement. Jurnal Komunikasi: Malaysian Journal of Communication, 35(2). https://doi.org/10.17576/JKMJC-2019-3502-30

Kaur, S. (2024). How does age and gender of the employees influence human resource practices–employee competencies relationship? Evidence-Based HRM, 12(3). https://doi.org/10.1108/EBHRM-05-2023-0119

Kautish, P., Purohit, S., Filieri, R., & Dwivedi, Y. K. (2023). Examining the role of consumer motivations to use voice assistants for fashion shopping: The mediating role of awe experience and eWOM. Technological Forecasting and Social Change, 190. https://doi.org/10.1016/j.techfore.2023.122407

Khan, S., Thomas, G., Kunbhar, B. A., & Mohamed, N. H. M. (2023). Impact of Work–Life Balance on Working Women in the Banking Sector. Administrative Sciences, 13(1). https://doi.org/10.3390/admsci13010007

Kilic, E., & Kitapci, H. (2024). Contextual and Individual Determinants of Sustainable Careers: A Serial Indirect Effect Model through Career Crafting and Person-Career Fit. Sustainability (Switzerland) , 16(7). https://doi.org/10.3390/su16072865

Koon, V. Y. (2022). A multilevel analysis of work–life balance practices. Asia Pacific Journal of Human Resources, 60(2). https://doi.org/10.1111/1744-7941.12268

Kursan Milaković, I., & Ahmad, A. (2023). Online impulse buying and cognitive appraisal

theory: two countries comparison. International Journal of Retail and Distribution Management, 51(12). https://doi.org/10.1108/IJRDM-03-2023-0150

Lamane-Harim, J., Cegarra-Leiva, D., & Sánchez-Vidal, M. E. (2023). Work–life balance supportive culture: a way to retain employees in Spanish SMEs. International Journal of Human Resource Management, 34(10). https://doi.org/10.1080/09585192.2021.1878255

Langenbach, B. P., Berger, S., Baumgartner, T., & Knoch, D. (2020). Cognitive Resources Moderate the Relationship Between Pro-Environmental Attitudes and Green Behavior. Environment and Behavior, 52(9). https://doi.org/10.1177/0013916519843127

Li, X., Hu, A., Song, H., & Wang, Z. (2024). How does workplace support promote postdoctoral career growth? A conservation of resources perspective. Frontiers in Psychology, 15. https://doi.org/10.3389/fpsyg.2024.1294982

Liang, Z., Suntrayuth, S., Sun, X., & Su, J. (2023). Positive Verbal Rewards, Creative Self-Efficacy, and Creative Behavior: A Perspective of Cognitive Appraisal Theory. Behavioral Sciences, 13(3). https://doi.org/10.3390/bs13030229

López Vidales, N., & Rubio, L. G. (2021). Trends in youth behaviour change in the face of the media: Millennials vs Generation Z. Estudios Sobre El Mensaje Periodistico, 27(2). https://doi.org/10.5209/ESMP.70170

Lorentzon, J. I., Fotoh, L. E., & Mugwira, T. (2024). Remote auditing and its impacts on auditors' work and work-life balance: auditors' perceptions and implications. Accounting Research Journal, 37(1). https://doi.org/10.1108/ARJ-06-2023-0158

Lorincová, S., Miklošík, A., & Hitka, M. (2022). The Role Of Corporate Culture In Economic Development Of Small And Medium-Sized Enterprises. Technological and Economic Development of Economy, 28(1), 220–238. https://doi.org/10.3846/tede.2021.15983

Lv, W. (2024). Unveiling the power of teacher credibility and care in learners' motivation through the lens of rhetorical/relational and broaden-and-build theory. Learning and Motivation, 86. https://doi.org/10.1016/j.lmot.2024.101988

Ma, Y., Zhang, L., Song, S., & Yu, S. (2022). Impacts of Energy Price on Agricultural Production, Energy Consumption, and Carbon Emission in China: A Price Endogenous Partial Equilibrium Model Analysis. Sustainability (Switzerland), 14(5). https://doi.org/10.3390/su14053002

Mattarelli, E., Cochis, C., Bertolotti, F., & Ungureanu, P. (2024). How designed work environment and enacted work interactions impact creativity and work–life balance. European Journal of Innovation Management, 27(2). https://doi.org/10.1108/EJIM-01-2022-0028

Mi Alnaser, F., Rahi, S., Alghizzawi, M., & Ngah, A. H. (2023). Does artificial intelligence (AI) boost digital banking user satisfaction? Integration of expectation confirmation model and antecedents of artificial intelligence enabled digital banking. Heliyon, 9(8). https://doi.org/10.1016/j.heliyon.2023.e18930

Mior Shariffuddin, N. S., Azinuddin, M., Yahya, N. E., & Hanafiah, M. H. (2023). Navigating the tourism digital landscape: The interrelationship of online travel sites' affordances, technology readiness, online purchase intentions, trust, and E-loyalty. Heliyon, 9(8).

https://doi.org/10.1016/j.heliyon.2023.e19135

Muhammad, T. (2022). The role of religiosity and religious participation in the relationship between depressive symptoms and cognitive impairment among older Indian adults. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-14744-3

Najib, M., & Fahma, F. (2020). Investigating the adoption of digital payment system through an extended technology acceptance model: An insight from the Indonesian small and medium enterprises. International Journal on Advanced Science, Engineering and Information Technology, 10(4). https://doi.org/10.18517/ijaseit.10.4.11616

Nasution, F. N., & Rafiki, A. (2020). Islamic work ethics, organizational commitment and job satisfaction of Islamic banks in Indonesia. RAUSP Management Journal, 55(2), 195–205. https://doi.org/10.1108/RAUSP-01-2019-0011

Nguyen, L. T., Dang, T. Q., & Duc, D. T. V. (2025). The Dark Sides of AI Advertising: The Integration of Cognitive Appraisal Theory and Information Quality Theory. Social Science Computer Review, 43(2). https://doi.org/10.1177/08944393241258760

Nica, E., Popescu, G. H., Poliak, M., Kliestik, T., & Sabie, O. M. (2023). Digital Twin Simulation Tools, Spatial Cognition Algorithms, and Multi-Sensor Fusion Technology in Sustainable Urban Governance Networks. Mathematics, 11(9). https://doi.org/10.3390/math11091981

Oyewobi, L. O., Oke, A. E., Adeneye, T. D., Jimoh, R. A., & Windapo, A. O. (2022). Impact of work–life policies on organizational commitment of construction professionals: role of work–life balance. International Journal of Construction Management, 22(10). https://doi.org/10.1080/15623599.2020.1742632

Pace, F., & Sciotto, G. (2022). Gender differences in the relationship between work–life balance, career opportunities and general health perception. Sustainability (Switzerland), 14(1). https://doi.org/10.3390/su14010357

Petrie, K., Smallwood, N., Pascoe, A., & Willis, K. (2022). Mental Health Symptoms and Workplace Challenges among Australian Paramedics during the COVID-19 Pandemic. International Journal of Environmental Research and Public Health, 19(2). https://doi.org/10.3390/ijerph19021004

Petrou, P., & Xanthopoulou, D. (2021). Interactive Effects of Approach and Avoidance Job Crafting in Explaining Weekly Variations in Work Performance and Employability. Applied Psychology, 70(3). https://doi.org/10.1111/apps.12277

Pizzutti, C., Gonçalves, R., & Ferreira, M. (2022). Information search behavior at the post-purchase stage of the customer journey. Journal of the Academy of Marketing Science, 50(5). https://doi.org/10.1007/s11747-022-00864-9

Pranata, J. A., Hendrawan, S., Putra Riyanto, M. R., & Gunadi, W. (2022). The Effect of Work-Life Balance and Work Motivation towards Intention to Work from Home in the Future with Job Satisfaction as a Mediator. Revista de Cercetare Si Interventie Sociala, 78. https://doi.org/10.33788/rcis.78.1

Rana, J., Gaur, L., Singh, G., Awan, U., & Rasheed, M. I. (2022). Reinforcing customer journey through artificial intelligence: a review and research agenda. International Journal of Emerging Markets, 17(7). https://doi.org/10.1108/IJOEM-08-2021-1214

Roh, T., Xiao, S., & Park, B. Il. (2024). What makes metaverse users immersed in the flow state in an emerging market? An application of affordance theory and ISSM. Journal of Retailing and Consumer Services, 81. https://doi.org/10.1016/j.jretconser.2024.104012

Roth, L. H. O., Bencker, C., Lorenz, J., & Laireiter, A. R. (2024). Testing the validity of the broaden-and build theory of positive emotions: a network analytic approach. Frontiers in Psychology, 15. https://doi.org/10.3389/fpsyg.2024.1405272

Salehi, V., Moradi, G., Omidi, L., & Rahimi, E. (2023). An MCDM approach to assessing influential factors on healthcare providers' safe performance during the COVID-19 pandemic: Probing into demographic variables. Journal of Safety Science and Resilience, 4(3). https://doi.org/10.1016/j.jnlssr.2023.05.002

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022a). Progress in partial least squares structural equation modeling use in marketing research in the last decade. Psychology and Marketing, 39(5). https://doi.org/10.1002/mar.21640

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022b). Progress in partial least squares structural equation modeling use in marketing research in the last decade. Psychology and Marketing, 39(5), 1035–1064. https://doi.org/10.1002/mar.21640

Scholze, A., & Hecker, A. (2024). The job demands-resources model as a theoretical lens for the bright and dark side of digitization. Computers in Human Behavior, 155. https://doi.org/10.1016/j.chb.2024.108177

Singkheeprapha, P., Jumani, Z. A., & Sukhabot, S. (2022). Is Islamic brand attitudes influence Thai Muslims' buying behavioural intentions: a quantitative analysis using smart-PLS. Journal of Islamic Marketing, 13(11). https://doi.org/10.1108/JIMA-08-2020-0252

Solahudin, D., & Fakhruroji, M. (2020). Internet and islamic learning practices in Indonesia: Social media, religious populism, and religious authority. Religions, 11(1). https://doi.org/10.3390/rel11010019

Song, H., & Lu, S. (2024). The effect of virtual tourism experience on tourist responses: the lens from cognitive appraisal theory. Asia Pacific Journal of Tourism Research, 29(7). https://doi.org/10.1080/10941665.2024.2351126

Song, H., Yang, H., & Sthapit, E. (2025). Robotic service quality, authenticity, and revisit intention to restaurants in China: extending cognitive appraisal theory. International Journal of Contemporary Hospitality Management, 37(5). https://doi.org/10.1108/IJCHM-11-2022-1396

Stankevičiūtė, Ž., & Kunskaja, S. (2022). Strengthening of work-life balance while working remotely in the context of COVID-19 pandemic. Human Systems Management, 41(2). https://doi.org/10.3233/HSM-211511

Stanley, P. J., & Schutte, N. S. (2023). Merging the Self-Determination Theory and the Broaden and Build Theory through the nexus of positive affect: A macro theory of positive functioning. New Ideas in Psychology, 68. https://doi.org/10.1016/j.newideapsych.2022.100979

Su, E., & Li, Z. (2025). The impact of entrepreneurs' military experience on small business exit: A conservation of resources perspective. Journal of Business Research, 186.

https://doi.org/10.1016/j.jbusres.2024.115004

Suhartanto, D., Syarief, M. E., Chandra Nugraha, A., Suhaeni, T., Masthura, A., & Amin, H. (2022). Millennial loyalty towards artificial intelligence-enabled mobile banking: evidence from Indonesian Islamic banks. Journal of Islamic Marketing, 13(9). https://doi.org/10.1108/JIMA-12-2020-0380

Sukhemi, & Sari, M. W. (2023). The Influence of Employee Competence and Use of Information Technology on Financial Accountability with the Success of Information Systems as Moderating Variables. Asian Journal of Business and Accounting, 16(2). https://doi.org/10.22452/ajba.vol16no2.6

Sun, Z., Zhao, L., Mehrotra, A., Salam, M. A., & Yaqub, M. Z. (2025). Digital transformation and corporate green innovation: An affordance theory perspective. Business Strategy and the Environment, 34(1). https://doi.org/10.1002/bse.3991

Tijani, B., Osei-Kyei, R., & Feng, Y. (2022). A review of work-life balance in the construction industry. International Journal of Construction Management, 22(14). https://doi.org/10.1080/15623599.2020.1819582

Tomczak, M. T., & Kulikowski, K. (2024). Toward an understanding of occupational burnout among employees with autism – the Job Demands-Resources theory perspective. Current Psychology, 43(2). https://doi.org/10.1007/s12144-023-04428-0

Tønnessen, Ø., Dhir, A., & Flåten, B. T. (2021). Digital knowledge sharing and creative performance: Work from home during the COVID-19 pandemic. Technological Forecasting and Social Change, 170. https://doi.org/10.1016/j.techfore.2021.120866

Tripodi, F. B., Garcia, L. C., & Marwick, A. E. (2024). 'Do your own research'': affordance activation and disinformation spread.' Information Communication and Society, 27(6). https://doi.org/10.1080/1369118X.2023.2245869

Tsai, H. Y. (2023). Do you feel like being proactive day? How Daily Cyberloafing Influences Creativity and Proactive Behavior: The Moderating Roles of Work Environment. Computers in Human Behavior, 138. https://doi.org/10.1016/j.chb.2022.107470

Ugwu, F. O., Enwereuzor, I. K., & Mazei, J. (2023). Is Working from Home a Blessing or a Burden? Home Demands as a Mediator of the Relationship Between Work Engagement and Work-Life Balance. Applied Research in Quality of Life, 18(1). https://doi.org/10.1007/s11482-022-10084-6

Uzir, M. U. H., Bukari, Z., Al Halbusi, H., Lim, R., Wahab, S. N., Rasul, T., Thurasamy, R., Jerin, I., Chowdhury, M. R. K., Tarofder, A. K., Yaakop, A. Y., Hamid, A. B. A., Haque, A., Rauf, A., & Eneizan, B. (2023). Applied artificial intelligence: Acceptance-intention-purchase and satisfaction on smartwatch usage in a Ghanaian context. Heliyon, 9(8). https://doi.org/10.1016/j.heliyon.2023.e18666

Vanduhe, V. Z., Nat, M., & Hasan, H. F. (2020). Continuance Intentions to Use Gamification for Training in Higher Education: Integrating the Technology Acceptance Model (TAM), Social Motivation, and Task Technology Fit (TTF). IEEE Access, 8, 21473–21484. https://doi.org/10.1109/ACCESS.2020.2966179

Verma, C., Illés, Z., & Stoffová, V. (2020). Identifying technology features impacted attitude of Indian students using regression modeling for real-time system. Materials Today:

Proceedings, 42. https://doi.org/10.1016/j.matpr.2020.08.583

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. International Journal of Information Management Data Insights, 1(1). https://doi.org/10.1016/j.jjimei.2020.100002

Vyas, L. (2022). "New normal" at work in a post-COVID world: work–life balance and labor markets. Policy and Society, 41(1). https://doi.org/10.1093/polsoc/puab011

Wang, S., & Huang, L. (2022). A Study of the Relationship between Corporate Culture and Corporate Sustainable Performance: Evidence from Chinese SMEs. Sustainability (Switzerland), 14(13). https://doi.org/10.3390/su14137527

Wang, Y., Farag, H., & Ahmad, W. (2021). Corporate Culture and Innovation: A Tale from an Emerging Market. British Journal of Management, 32(4), 1121–1140. https://doi.org/10.1111/1467-8551.12478

Xi, N., Chen, J., Gama, F., Riar, M., & Hamari, J. (2023). The challenges of entering the metaverse: An experiment on the effect of extended reality on workload. Information Systems Frontiers, 25(2). https://doi.org/10.1007/s10796-022-10244-x

Xia, G., Henry, P., Chen, Y., Queiroz, F., Westland, S., & Cheng, Q. (2023). The effects of colour attributes on cognitive performance and intellectual abilities in immersive virtual environments. Computers in Human Behavior, 148. https://doi.org/10.1016/j.chb.2023.107853

Yaghmour, A., Alesa, A., Anbarserry, E., Binmerdah, M. A., Alharbi, A., Housawi, A., Almehdar, M., Lytra, H., Alsaywid, B., & Lytras, D. M. (2021). Challenges and obstacles faced by trainee female physicians: An integrative research on gender discrimination, stress, depression and harassment. Healthcare (Switzerland), 9(2). https://doi.org/10.3390/healthcare9020160

Yang, H., Song, H., Xia, L., & Yang, A. (2024). Understanding the consequences of robotic interaction quality and outcome quality: A three-phased affordance theory-based approach. Journal of Hospitality Marketing and Management, 33(6). https://doi.org/10.1080/19368623.2024.2308531

Yoo, J. W., Park, J., & Park, H. (2025). How can I trust you if you're fake? Understanding human-like virtual influencer credibility and the role of textual social cues. Journal of Research in Interactive Marketing, 19(4). https://doi.org/10.1108/JRIM-02-2024-0092

Zhai, X., Zhu, C. J., & Zhang, M. M. (2023). Mapping promoting factors and mechanisms of resilience for performance improvement: The role of strategic human resource management systems and psychological empowerment. Applied Psychology, 72(3). https://doi.org/10.1111/apps.12411

Zhang, H., Zang, Z., Zhu, H., Uddin, M. I., & Amin, M. A. (2022). Big data-assisted social media analytics for business model for business decision making system competitive analysis. Information Processing and Management, 59(1). https://doi.org/10.1016/j.ipm.2021.102762

Zhang, L., Huang, G., Li, Y., & Bao, S. (2021). Quantitative research methods of linguistic niche and cultural sustainability. Sustainability (Switzerland), 13(17). https://doi.org/10.3390/su13179586

Zhong, Y., Liu, W., Lee, T. Y., Zhao, H., & Ji, J. (2021). Risk perception, knowledge, information sources and emotional states among COVID-19 patients in Wuhan, China. Nursing Outlook, 69(1). https://doi.org/10.1016/j.outlook.2020.08.005

Zhu, Y., & Li, N. (2021). Virtual and augmented reality technologies for emergency management in the built environments: A state-of-the-art review. In Journal of Safety Science and Resilience (Vol. 2, Issue 1). https://doi.org/10.1016/j.jnlssr.2020.11.004