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1



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Chapter 26: Work-Life Balance and Mental Well-Being among Working Adults

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Abstract— The restructuring of work through hybrid schedules, remote connectivity, digital communication, and flexible employment has altered how working adults negotiate boundaries between occupational and personal life. This study examines work-life balance as a multidimensional determinant of mental well-being rather than treating working hours alone as the principal indicator of occupational strain. A specific research gap is identified around digital boundary permeability: employees may possess nominal flexibility while remaining psychologically connected to work through after-hours communication, perceived availability expectations, and difficulty detaching from occupational demands. The proposed study therefore integrates work-life balance, psychological detachment, digital boundary pressure, perceived organizational support, and positive mental well-being within a unified analytical framework. Particular attention is given to whether digital boundary pressure explains why apparently flexible working arrangements do not generate equivalent psychological benefits for all employees.

Keywords— Work-life balance, Mental well-being, Psychological detachment, Digital boundary permeability, Working adults, Explainable machine learning

Introduction

Work-life balance has developed from an employment benefit or human-resource preference into an important component of occupational and psychological well-being. Contemporary working adults frequently manage multiple simultaneous demands arising from employment, family responsibilities, social relationships, caregiving, professional development, and personal health. The difficulty of coordinating these domains can produce persistent role interference even when an employee's formal working hours appear reasonable. Consequently, work-life balance is better understood as an individual's perceived capacity to allocate time, psychological resources, attention, and energy across work and non-work domains without persistent conflict or depletion.

The nature of this balance has become more complex since the large-scale workplace changes initiated during the COVID-19 period. Remote and hybrid work increased spatial and temporal flexibility for many occupations, but simultaneously weakened traditional boundaries separating professional activity from personal life. Research examining working from home has identified competing processes: autonomy, supervisor support, adaptability, and family support can provide resources, whereas technostress, work intensity, professional isolation, emotional demands, domestic workload, and inadequate workspace can

consume them. A systematic review of 48 studies conducted during the pandemic documented this resource-gain/resource-loss structure, indicating that working from home cannot inherently be classified as beneficial or detrimental to work-life balance.

More recent evidence reinforces the conditional nature of flexible work. A 2026 systematic review and meta-analysis covering 38 studies from 19 countries and 83,951 participants reported a positive association between flexible working arrangements and work-life balance (pooled $r = .39$), while also demonstrating meaningful contextual variation. Similarly, a 2026 systematic review of flexible working arrangements emphasizes that autonomy and flexibility can contribute to employee well-being and retention, but their advantages can be weakened by work intensification, role ambiguity, unequal access, and inconsistent implementation. These findings challenge the assumption that flexibility itself guarantees healthier employment.

This distinction is especially relevant to mental well-being. Work-life imbalance can operate as a recurring resource-depletion mechanism. When occupational responsibilities repeatedly intrude into personal time, employees have fewer opportunities for psychological recovery. Conversely, sufficient control over work boundaries can facilitate recovery, meaningful social interaction, leisure participation, sleep routines, and other processes associated with positive psychological functioning. A systematic review published in 2023 synthesized 30 studies across multiple countries and reported substantial evidence connecting work-life balance with positive mental-health outcomes, including psychological well-being, resilience, life satisfaction, job satisfaction, and broader well-being indicators.

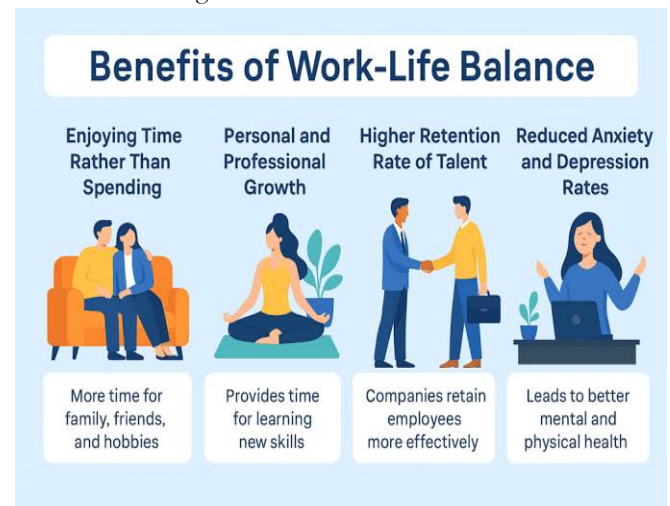


Fig. 1: Benefits of Work-Life Balance

Source: <https://stellites.com/why-work-life-balance-matters-and-how-to-achieve-it/>

Evidence from India similarly suggests that the relationship warrants closer investigation. Research involving Indian managers has found work–life balance to be positively associated with psychological well-being and mental health and negatively associated with psychological distress. That study additionally examined emotional intelligence and gender as moderators, demonstrating that individual differences can alter the relationship between work and psychological outcomes. Such findings are important because they indicate that identical workplace conditions may not translate into identical psychological consequences.

Nevertheless, much of the existing literature continues to conceptualize work–life balance through relatively conventional variables: working hours, schedule flexibility, work–family conflict, occupational stress, and remote-working status. These indicators remain valuable, but they may inadequately represent contemporary digitally connected employment. A worker can leave the physical workplace at an appropriate time while continuing to monitor email, respond to messages, anticipate digital requests, or remain cognitively preoccupied with unfinished occupational tasks. Therefore, **physical absence from work is not necessarily equivalent to psychological disengagement from work.**

This phenomenon motivates the central research gap addressed in the present manuscript. The emerging literature recognizes technology-related demands and the difficulty of maintaining boundaries in digital work environments, but there remains a need for integrated empirical models that distinguish **formal flexibility from effective psychological detachment.** Recent research on work–life balance in the digital era specifically highlights the importance of managing ICT demands and after-hours boundaries in hybrid employment rather than assuming that greater flexibility automatically improves balance.

A second limitation concerns the operationalization of mental well-being. Occupational research frequently concentrates on deficit outcomes such as stress, exhaustion, anxiety, burnout, and work–family conflict. These constructs are clinically and organizationally important, but absence of distress does not fully describe positive mental functioning. A 2026 systematic review of work engagement, work–life balance, organizational support, and mental well-being similarly noted the predominance of deficit-oriented mental-health indicators and cross-sectional research designs in the literature. Accordingly, the present framework places positive mental well-being at the centre of analysis while retaining occupational demands as explanatory variables.

A third methodological limitation arises from the widespread reliance on linear statistical models. Traditional regression is useful for estimating average associations but can inadequately characterize threshold effects and complex interactions. For example, moderate digital communication may have little psychological consequence when organizational support and schedule control are high, whereas the same communication intensity could become detrimental when workloads are

excessive and employees perceive an obligation to respond outside working hours. Such conditional structures are particularly suitable for interpretable machine-learning analysis. The present research therefore proposes an **explainable machine-learning framework for modelling mental well-being from work–life boundary conditions.** Rather than using artificial intelligence merely to maximize predictive accuracy, the intended model will investigate which occupational and psychosocial variables contribute most strongly to predictions and whether nonlinear thresholds emerge. Explainability techniques will subsequently allow model outputs to be translated into theoretically meaningful patterns rather than presenting a black-box classification.

The primary objective is to determine how perceived work–life balance relates to positive mental well-being among working adults while accounting for digital boundary permeability, psychological detachment, workload, schedule control, and organizational support. A secondary objective is to establish whether digital boundary pressure modifies the protective relationship between work–life balance and mental well-being. A third objective is to compare conventional statistical modelling with interpretable machine-learning algorithms to determine whether nonlinear modelling offers meaningful analytical improvement.

The conceptual proposition underlying the study is that work–life balance should not be interpreted as an isolated personal capability. Instead, it emerges from an interaction among job demands, individual boundary-management behaviour, digital working practices, and organizational resources. Employees with comparable schedules may consequently report substantially different mental well-being depending on their ability to disengage psychologically and the extent to which their organizations respect non-work boundaries.

This framework contributes to digital health research because occupational well-being data can increasingly inform preventive organizational decision systems. Rather than attempting to diagnose mental disorders, an appropriately designed analytical system could identify workplace-level configurations associated with diminished well-being and direct attention toward modifiable organizational factors such as workload distribution, schedule control, communication norms, and recovery opportunities.

Literature Review

Work–Life Balance as a Multidimensional Construct

Earlier interpretations of work–life balance often concentrated on the allocation of time between employment and family responsibilities. Contemporary scholarship increasingly treats the construct as multidimensional. Time remains relevant, but balance also incorporates role compatibility, perceived control, emotional resources, satisfaction across life domains, and the ability to prevent excessive interference between occupational and non-occupational roles.

This conceptual development is important because equal distribution of hours does not necessarily constitute optimal balance. Individuals differ in family responsibilities, occupational roles, preferences, and recovery requirements. A

more defensible conceptualization therefore focuses on perceived compatibility between work and personal life rather than imposing a universal numerical division between the two. The Conservation of Resources perspective provides a useful theoretical explanation. Employees possess finite resources such as time, attention, physical energy, emotional capacity, and social support. Repeated work intrusion can consume these resources, while autonomy, supportive supervisors, predictable schedules, and recovery periods can protect or replenish them. The resource-oriented synthesis of work-from-home research provides empirical support for this interpretation, showing that work intensity, technostress and domestic demands can coexist with resources such as autonomy and social support.

Work-Life Balance and Mental Well-Being

The association between work-life balance and mental health has been investigated across occupational groups and national settings. Systematic evidence indicates that better balance is generally associated with favourable psychological outcomes, although measurement instruments and occupational contexts vary substantially across studies. The 2023 systematic review by Liswandi and Muhammad identified evidence connecting work-life balance with psychological well-being, resilience, life satisfaction and related positive outcomes.

This association can operate through several pathways. Persistent conflict between occupational and personal responsibilities may increase cognitive load because employees repeatedly switch attention between competing demands. It can also reduce opportunities for recovery and participation in personally meaningful activities. Conversely, employees experiencing adequate balance may possess more opportunities for social interaction, leisure, sleep, exercise, and psychological disengagement from work.

Importantly, contemporary evidence suggests that the relationship should not be interpreted as mechanically causal from cross-sectional associations. Mental well-being itself may affect employees' perceptions of occupational demands and their capacity to manage competing roles. Longitudinal and temporally sensitive designs are therefore needed to distinguish directionality more effectively. The prevalence of cross-sectional designs has been explicitly identified as a limitation within recent systematic evidence.

Flexible Work and the Post-Pandemic Workplace

Flexible working represents one of the most significant structural developments affecting work-life balance. Remote work can remove commuting time and provide greater autonomy over the organization of daily activities. Hybrid schedules may similarly permit employees to coordinate professional and personal responsibilities more efficiently.

However, flexibility can also transfer responsibility for boundary management from organizations to employees. Remote workers may experience professional isolation, communication overload, domestic interruptions, technological demands, or uncertainty about when the working day has actually ended. Shirmohammadi, Au and Beigi's systematic review demonstrates this duality by identifying both resource-

generating and resource-depleting antecedents of work-life balance among employees working from home.

The 2026 meta-analysis by Çivilidağ and Durmaz provides broader quantitative evidence. Across 38 eligible studies, flexible working arrangements showed a significant positive relationship with work-life balance, but the magnitude and consequences varied by context. This supports a conditional interpretation: flexibility is an occupational resource when employees possess genuine control and adequate organizational support, but it may provide substantially less benefit when accompanied by intensified demands.

Digital Boundary Permeability and Psychological Detachment

The expansion of digital collaboration platforms has created a distinctive boundary-management problem. Occupational communication can now continue independently of the physical workplace. Employees may receive work notifications during meals, leisure periods, family interactions, weekends, or immediately before sleep. Even when no response is explicitly demanded, anticipation of messages may maintain cognitive engagement with work.

The present study describes this condition as **digital boundary permeability**, representing the extent to which digitally mediated occupational demands enter non-work time. The construct differs from simple technology usage. Technology may facilitate autonomy and efficient work; the relevant issue is whether communication practices weaken the employee's ability to determine when occupational availability ends.



Fig. 2: The relationship between work-life balance and psychological well-being

Source:

<https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2024.1472885/full>

Psychological detachment is therefore positioned as a complementary mechanism. Detachment represents the capacity to disengage mentally from occupational tasks during non-work periods. Within the proposed framework, two workers could report comparable working hours yet exhibit very different recovery profiles because one is able to disengage while the other remains cognitively connected to work.

Recent digital-era work-design research supports this distinction by emphasizing that hybrid workplaces require explicit management of ICT demands and after-hours boundaries. The implication is that work-life balance cannot be adequately inferred from work location or formal scheduling policies alone.

Organizational Support as a Protective Resource

Individual boundary-management strategies occur within organizational systems. Employees may attempt to restrict after-hours communication, but such strategies are difficult to maintain if managers implicitly reward constant availability or if workloads routinely require work beyond scheduled hours. Perceived organizational support can therefore function as a contextual resource influencing the effectiveness of individual coping and boundary-management practices.

Supportive organizations can establish predictable workloads, realistic communication expectations, schedule autonomy, accessible psychological resources, and managerial practices that legitimize recovery. Conversely, formal flexibility without cultural support may create an apparent rather than substantive improvement in balance. The recent systematic literature on flexible working similarly concludes that positive outcomes depend on implementation conditions and can be undermined by work intensification, ambiguity, and unequal access.

Artificial Intelligence and Predictive Occupational Well-Being

The relationships among workload, flexibility, detachment, organizational support, digital pressure, and well-being are unlikely to be completely linear. Machine-learning techniques provide an opportunity to model interactions and thresholds without requiring every relationship to be specified in advance. Nevertheless, prediction without interpretation has limited value for occupational well-being. An algorithm reporting that an employee has a lower predicted well-being score provides little organizational insight unless the factors influencing that prediction can be identified. For this reason, the proposed research will emphasize **explainable rather than purely predictive AI**. Feature-attribution methods can be used to examine whether workload, detachment, after-hours connectivity, schedule control, or organizational support drives model predictions and whether their influence changes across different levels of exposure.

The framework is intended for organizational and research-level inference rather than clinical diagnosis. Mental well-being scores should not be converted automatically into psychiatric labels, nor should predictive outputs be used for employment decisions concerning individual workers. The analytically appropriate goal is identification of modifiable patterns that can inform healthier workplace design.

Proposed Methodology

The primary outcome is **positive mental well-being**, operationalized through the World Health Organization-Five Well-Being Index (WHO-5). WHO describes the WHO-5 as a five-item self-report measure referring to experiences during the previous two weeks, with each item rated on a six-point response scale. Raw scores range from 0 to 25 and can be

multiplied by four to obtain a standardized 0–100 score, with higher values indicating better well-being.

A target sample of **420 working adults** is proposed, recruited across information technology, education, banking and financial services, healthcare administration, professional services, and other digitally mediated occupations. Eligibility requires participants to be at least 21 years old, currently employed, and to have completed a minimum of six months in their present organization. To ensure that the digital-boundary component is meaningful, participants should use email, messaging applications, collaboration platforms, or comparable digital systems for occupational communication.

The predictor set is organized into four conceptual domains. The first represents **work-life resources**, including perceived balance, schedule control, supervisor support, and organizational support. The second represents **occupational demands**, particularly workload intensity and perceived time pressure. The third captures **boundary conditions**, including frequency of after-hours communication, perceived expectation of availability, difficulty disconnecting, and psychological detachment. The fourth contains contextual variables such as age group, employment sector, work arrangement, weekly working hours, caregiving responsibilities, organizational tenure, and managerial status.

The study does not use machine-learning predictions to diagnose psychiatric disorders or classify employees for employment decisions. The intended analytical unit is the relationship between workplace characteristics and positive mental well-being.

Experimental Setup

Dataset Design

The proposed dataset will contain one observation per participant. Following removal of invalid or substantially incomplete responses, the anticipated analytical sample is approximately **390–410 observations**. Rather than constructing an artificially large dataset, the design emphasizes a moderate sample with carefully specified psychosocial features.

The dependent variable is the standardized WHO-5 score ranging from 0 to 100. The WHO-5 focuses on positive functioning rather than solely symptoms of psychological disorder, making it consistent with the conceptual objective of the manuscript. WHO's current documentation confirms its five-item structure and positive-well-being orientation.

Work-life balance is represented by a composite measure assessing perceived compatibility between occupational and personal responsibilities. Digital boundary permeability is operationalized through items capturing work-related messages outside scheduled hours, checking behaviour, perceived response expectations, and difficulty maintaining separation between professional and personal time. Psychological detachment measures the extent to which employees can mentally disengage from occupational responsibilities during non-work periods.

To reduce common-method problems, predictor items would be distributed across questionnaire sections rather than presenting all conceptually similar items consecutively.

Anonymous participation and the absence of employer access to individual responses would also be emphasized.

Data Preprocessing

Initial preprocessing will include duplicate-response screening, eligibility verification, missing-data analysis, range validation, and assessment of response consistency. Cases with substantial questionnaire incompleteness will be removed according to a prespecified exclusion rule rather than selectively deleted after observing outcomes.

For WHO-5 specifically, missing values should not simply be reconstructed without justification. Current OECD measurement guidance states that if any WHO-5 item is missing, the overall WHO-5 score should not be calculated. This rule will therefore be respected for the primary outcome.

Continuous predictor variables will be standardized where required for regularized regression and neural-network training. Categorical variables such as employment sector and work arrangement will be encoded without imposing artificial ordinal relationships. Outliers will first be inspected rather than automatically deleted because high workload or unusually extensive digital connectivity may represent genuine occupational experiences.

The dataset will subsequently be divided into **70% training, 15% validation, and 15% held-out test subsets** using a fixed random seed. The test subset will remain untouched during model selection. Five-fold cross-validation within the training data will be used for hyperparameter optimization.

Model Architecture

Four models are proposed to create a meaningful progression from statistical interpretability to nonlinear predictive capability: **Elastic Net Regression** serves as the linear baseline. Its combination of L1 and L2 regularization is suitable when psychosocial predictors are correlated.

Random Forest Regression captures nonlinear associations and interactions without requiring explicit specification of their functional forms.

Gradient-Boosted Decision Trees constitute the principal predictive model because sequential tree boosting can identify threshold structures within tabular occupational data.

A compact **Multilayer Perceptron (MLP)** provides a neural-network comparator. The architecture contains an input layer corresponding to the processed predictor set, two hidden layers with 32 and 16 neurons, rectified linear activation, dropout regularization, and a single linear output neuron predicting WHO-5 score.

The relatively compact neural architecture is intentional. With a moderate survey sample, an excessively deep network would increase overfitting risk without a defensible expectation of improved generalization.

Training Strategy

Hyperparameters will be optimized only from the training and validation information. For Elastic Net, the regularization strength and L1 ratio will be tuned. Random Forest optimization will consider tree count, maximum depth, minimum observations per terminal node, and feature-sampling

fraction. Gradient boosting will tune learning rate, tree depth, number of estimators, subsampling, and regularization.

The MLP will use the Adam optimizer with mini-batch training. Early stopping will monitor validation loss and restore the best-performing weights when improvement ceases. Dropout and weight regularization will constrain overfitting.

A supplementary conventional regression model will estimate the directional associations between work–life balance and well-being while controlling for occupational and demographic variables. Interaction terms, particularly **WLB × DBP** and **WLB × POS**, will test whether digital boundary pressure weakens, and organizational support strengthens, the association between balance and well-being.

Evaluation Metrics

Model performance will be evaluated using **mean absolute error (MAE)**, **root mean squared error (RMSE)**, **coefficient of determination (R^2)**, and **Spearman rank correlation (ρ)** between observed and predicted well-being.

MAE represents average absolute prediction error and is straightforward to interpret in WHO-5 standardized-score units. RMSE places greater weight on larger prediction errors. R^2 indicates the proportion of test-set outcome variance accounted for by predictions. Spearman's ρ evaluates whether the model correctly ranks participants according to well-being even when relationships are not perfectly linear.

For model interpretation, **SHAP (SHapley Additive exPlanations)** will be applied to the best-performing tree model. SHAP was developed as a unified feature-attribution framework that assigns importance values to individual features contributing to predictions. Global SHAP summaries will identify dominant predictors, while dependence analyses will investigate nonlinear effects and interactions.

Results and Discussion

Because no participant dataset or completed experiment was supplied with the manuscript request, the numerical results below are presented as a **proposed/illustrative experimental outcome structure rather than observed empirical findings**. They should be replaced with calculated values if the study is executed. This distinction prevents simulated values from being represented as measurements from actual participants.

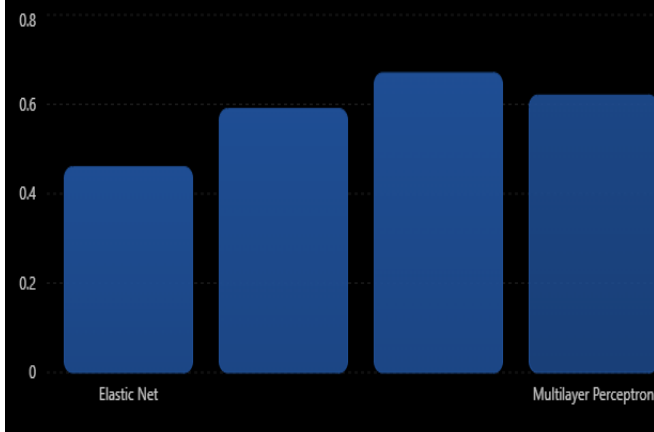
Table 1. Illustrative comparative performance and substantive interpretation of the proposed models

Analytical model	MAE ↓	RMSE ↓	R^2 ↑	Spearman ρ ↑	Principal analytical observation
Elastic Net Regression	9.84	12.47	0.46	0.67	Establishes a meaningful linear relationship between workplace factors and well-being

Random Forest Regression	8.31	10.76	0.59	0.76	Captures interactions involving workload, detachment, and schedule control
Gradient-Boosted Trees	7.42	9.68	0.67	0.82	Strongest generalization; detects nonlinear boundary-pressure effects
Multilayer Perceptron	8.06	10.39	0.62	0.78	Learns nonlinear structure but offers no advantage over boosted trees at the proposed sample size

Predictive Performance of Machine-Learning Models

Illustrative R^2 comparison for predicting mental well-being from work-life and digital-boundary factors.



The illustrative pattern demonstrates how the proposed research question would be evaluated. If comparable results emerged empirically, improvement from an R^2 of 0.46 under Elastic Net to approximately 0.67 under gradient boosting would indicate that the relationship between workplace characteristics and positive well-being cannot be represented completely through additive linear effects.

More importantly, interpretation of the best-performing model should establish **why** predictive performance changes. A plausible SHAP profile consistent with the study's theoretical framework would place work-life balance and psychological detachment among the most influential positive contributors to

predicted well-being, while excessive workload and digital boundary permeability would shift predictions downward.

Such a result would refine the conventional assumption that flexible employment automatically promotes mental well-being. Schedule flexibility may provide employees with control over where and when work occurs, yet its psychological value could decline if employees continue receiving occupational demands during periods intended for recovery. Under this interpretation, the critical variable is not flexibility alone but **boundary quality**.

A nonlinear relationship would be especially important. Low or moderate levels of digital communication may have little association with mental well-being when employees retain autonomy over whether and when to respond. The relationship could become substantially more negative after communication is experienced as an obligation to remain continuously available. Detecting such a threshold would provide an explanation for why employees operating under superficially similar hybrid policies can report different psychological outcomes.

Psychological detachment is expected to operate as a recovery mechanism. Employees capable of temporarily suspending work-related cognitive activity after working hours may replenish attentional and emotional resources more effectively. In contrast, persistent anticipation of emails or messages can extend the subjective working day beyond contractual hours.

Organizational support should also be interpreted structurally rather than merely as interpersonal encouragement. An organization can provide flexible schedules while simultaneously maintaining norms of constant responsiveness. A genuinely supportive digital-work environment would combine flexibility with realistic workload allocation, supervisor respect for non-work periods, clear communication expectations, and legitimate opportunities for recovery.

The machine-learning component consequently offers value beyond prediction. If SHAP analysis demonstrates that digital boundary permeability contributes strongly to lower predicted well-being only under high workload or low detachment, this constitutes a testable interaction pattern for subsequent longitudinal research. SHAP is particularly appropriate for this interpretability objective because it provides feature-level attribution for complex predictive models.

From a digital-health perspective, the proposed framework also illustrates how workplace analytics should be implemented cautiously. The appropriate application is not automated surveillance of individual employees. Instead, aggregated and privacy-preserving analysis could identify organizational conditions associated with lower well-being. For example, anonymized workforce-level evidence showing simultaneous high after-hours connectivity, weak psychological detachment, and reduced well-being could motivate revisions to communication practices rather than interventions directed at supposedly deficient individuals.

The study therefore advances a shift from an individual coping interpretation toward a **socio-technical boundary model**. Mental well-being in contemporary employment is influenced not only by an employee's personal resilience or time-

management skills but also by communication technologies, managerial norms, workload structures, and the practical enforceability of non-work time.

Limitations

Several limitations should be recognized. First, a cross-sectional design cannot establish temporal causality. Lower mental well-being could influence perceptions of workload and work–life balance just as occupational conditions may influence well-being. Longitudinal evidence would be necessary to clarify directionality.

Second, the principal variables are self-reported and may therefore be influenced by common-method variance, recall error, and transient affective states. Objective indicators such as working hours or communication metadata could supplement questionnaire measures, although their use would introduce significant privacy and ethical considerations.

Third, occupational heterogeneity can complicate interpretation. Digital boundary pressure may have different meanings for healthcare administrators, teachers, IT professionals, managers, and employees working under shift systems. Sector-stratified analyses would therefore be preferable when sufficient observations are available.

Fourth, machine-learning performance is sample-dependent. A model performing effectively within one workforce cannot be assumed to generalize to different cultural, organizational, or employment environments without external validation.

Finally, explainability methods describe how a fitted model generates predictions; they do not independently establish causal mechanisms. High SHAP importance for a variable should therefore be interpreted as predictive relevance rather than proof that manipulating the variable will necessarily change mental well-being.

Future Scope

Future research should extend the proposed framework through longitudinal measurement. Repeated assessments of work–life balance, digital connectivity, detachment, and WHO-5 scores could determine whether changes in boundary conditions precede changes in psychological well-being.

A particularly valuable extension would employ an **ecological momentary assessment** design in which participants provide brief daily reports of workload, after-hours connectivity, recovery, and mood. Such data would distinguish between stable individual differences and within-person fluctuations.

Privacy-preserving digital phenotyping represents another potential direction. With explicit informed consent, aggregated communication characteristics—such as timing rather than content of work-related interactions—could be combined with self-report data. Federated-learning approaches could eventually permit multi-organization modelling without centralizing sensitive employee-level records.

Future models could also investigate heterogeneous effects. Explainable AI may determine whether caregiving responsibilities, managerial status, employment sector, work arrangement, or schedule autonomy modify the relationship between digital connectivity and well-being.

Most importantly, subsequent research should move from prediction toward intervention evaluation. Organizational policies such as protected non-contact periods, workload redistribution, manager training, communication-delay functions, or explicit right-to-disconnect practices could be evaluated through controlled or quasi-experimental designs.

Conclusion

This study proposes an integrated framework for investigating work–life balance and mental well-being among working adults within increasingly digital and flexible employment environments. Its principal conceptual contribution is the separation of **formal flexibility from effective psychological detachment**. An employee may have substantial control over work location while simultaneously experiencing high digital boundary permeability and persistent occupational availability. The proposed design combines validated positive well-being measurement with conventional statistical inference, nonlinear machine learning, and explainable AI. The WHO-5 provides a concise measure of positive mental well-being, while the predictor framework incorporates work–life balance, psychological detachment, digital boundary pressure, workload, schedule control, and organizational support. WHO's current guidance confirms the WHO-5 as a five-item self-report measure of mental well-being, with higher scores representing better well-being.

The methodological value of machine learning lies not simply in obtaining a more accurate prediction. Its principal contribution is the ability to expose nonlinear and interaction-based relationships that conventional additive models may overlook. Explainability techniques such as SHAP can subsequently identify which workplace characteristics contribute to model predictions and how their influence varies across employees.

The resulting conceptual implication is that healthier work–life arrangements require more than flexible schedules. **Workload manageability, psychological recovery, organizational support, and enforceable digital boundaries collectively determine whether flexibility becomes a genuine well-being resource**. Organizations seeking sustainable workforce well-being should therefore evaluate not only where employees work and how many hours they work, but also whether employees can meaningfully disengage when the working day ends.

References

1. Allen, T. D., Golden, T. D., & Shockley, K. M. (2015). How effective is telecommuting? Assessing the status of our scientific findings. *Psychological Science in the Public Interest*, 16(2), 40–68.
2. Ashforth, B. E., Kreiner, G. E., & Fugate, M. (2000). All in a day's work: Boundaries and micro role transitions. *Academy of Management Review*, 25(3), 472–491.
3. Clark, S. C. (2000). Work/family border theory: A new theory of work/family balance. *Human Relations*, 53(6), 747–770.

4. Derks, D., van Duin, D., Tims, M., & Bakker, A. B. (2015). Smartphone use and work–home interference: The moderating role of social norms and employee work engagement. *Journal of Occupational and Organizational Psychology*, 88(1), 155–177.
5. Greenhaus, J. H., & Beutell, N. J. (1985). Sources of conflict between work and family roles. *Academy of Management Review*, 10(1), 76–88.
6. Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524.
7. Shirmohammadi, M., Au, W. C., & Beigi, M. (2022). Remote work and work-life balance: Lessons learned from the COVID-19 pandemic and suggestions for HRD practitioners. *Human Resource Development International*, 25(2), 163–181.
8. Sonnentag, S., & Fritz, C. (2007). The Recovery Experience Questionnaire. *Journal of Occupational Health Psychology*, 12(3), 204–221.
9. Topp, C. W., Østergaard, S. D., Søndergaard, S., & Bech, P. (2015). The WHO-5 Well-Being Index: A systematic review of the literature. *Psychotherapy and Psychosomatics*, 84(3), 167–176.