

Workplace Stress and Psychological Well-Being among Young Professionals

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Abstract— Workplace stress has become an increasingly important psychosocial concern as young professionals enter digitally intensive, performance-oriented, and rapidly changing work environments. This study examines the relationship between multidimensional workplace stress and psychological well-being while proposing a digital-health framework capable of identifying patterns associated with reduced well-being. The central research gap concerns the limited integration of conventional occupational stress factors with technology-related demands, work-life boundary disruption, and machine-learning-based risk modelling specifically among early-career professionals. The proposed framework conceptualizes workload pressure, role ambiguity, digital interruption, perceived job insecurity, and after-hours work connectivity as interacting occupational stressors rather than isolated predictors. Psychological well-being is treated as a multidimensional outcome involving positive functioning, emotional stability, perceived competence, and general mental well-being.

Keywords— Workplace Stress, Psychological Well-Being, Young Professionals, Technostress, Digital Health, Explainable Artificial Intelligence

Introduction

The contemporary workplace is undergoing substantial structural and technological change. Cloud-based collaboration, hybrid employment, algorithm-supported management, mobile communication, virtual meetings, and continuous digital connectivity have increased organizational flexibility while simultaneously changing the nature of occupational demands. For young professionals, these transformations coincide with a career stage characterized by

adjustment to professional roles, development of occupational identity, acquisition of new competencies, and pressure to establish career stability. Consequently, stress during the early professional years cannot be understood exclusively as a consequence of long working hours or excessive workload. It increasingly reflects an interaction among conventional job demands, digital demands, organizational uncertainty, and weakened boundaries between work and non-work time.

Psychological well-being is particularly important in this context because employment can function both as a psychological resource and as a source of psychosocial risk. The World Health Organization (WHO) emphasizes that good work can support mental health, whereas adverse working environments and psychosocial hazards can negatively affect workers. WHO estimates that approximately 15% of working-age adults experience a mental disorder at any point in time and reports substantial economic losses associated with depression and anxiety, predominantly through reduced productivity. These observations have shifted occupational mental health discourse away from an exclusively individual-level perspective toward prevention of psychosocial risks within the organization.

Workplace stress emerges when perceived occupational demands exceed, threaten, or repeatedly consume the resources available to an employee for responding effectively. Traditional sources include excessive workload, conflicting responsibilities, low decision latitude, insufficient managerial support, interpersonal difficulties, and insecurity about employment. Contemporary digital work introduces additional demands. Employees may experience high volumes of electronic communication, pressure for rapid

responses, frequent platform switching, information overload, software changes, and difficulty psychologically disengaging from work after formal working hours.

The significance of these demands may be amplified among young professionals. Early-career employees commonly occupy positions in which they have relatively limited control over assignments while simultaneously being expected to demonstrate adaptability and productivity. They may also interpret responsiveness, availability, and willingness to work beyond formal requirements as signals of professional commitment. Such conditions can generate a discrepancy between occupational expectations and psychological recovery.

A critical distinction is therefore required between **work intensity** and **workplace stress exposure**. Two employees with similar workloads may experience markedly different psychological consequences depending on autonomy, supervisor support, digital interruptions, role clarity, recovery opportunities, and perceived control. A model based only on working hours is consequently unlikely to represent the complexity of contemporary occupational stress.

individual measures, demonstrating that technology-related stress should not simply be regarded as an employee's inability to cope with digital tools. This distinction is relevant because interventions focusing exclusively on individual resilience may leave structural sources of stress unchanged.

WHO's 2022 guidelines similarly emphasize organizational interventions, manager training, worker training, individual interventions, reasonable accommodation, and return-to-work approaches rather than treating workplace mental health as an exclusively personal responsibility. The WHO-ILO policy framework further identifies prevention of work-related mental-health risks and protection and promotion of mental health as important responsibilities across workplace systems.

These developments create an opportunity for digital-health and artificial-intelligence research. Conventional occupational studies frequently evaluate average relationships through correlation or linear regression. Such methods remain valuable for estimating population-level associations, but workplace stress may also involve nonlinear and interactive effects. For example, moderate workload may not correspond to poor well-being when autonomy and managerial support are high. The same workload accompanied by high job insecurity, frequent digital interruptions, and inadequate recovery could be associated with a substantially different psychological profile.

Machine-learning methods can complement conventional statistical inference by examining multidimensional patterns that may not be adequately represented by a single linear coefficient. Nevertheless, prediction without interpretability has limited occupational-health value. An algorithm indicating that an employee belongs to a higher-risk group is less informative than a framework capable of identifying which modifiable occupational characteristics contributed most strongly to that classification. Explainable artificial intelligence therefore offers a useful bridge between predictive modelling and workplace intervention planning.

The present study is developed around this problem. Rather than attempting to diagnose mental illness from workplace data, it proposes modelling variation in psychological well-being using occupational stress indicators. This distinction is important. Psychological well-being is broader than the absence of a psychiatric disorder, and a workplace prediction model should not be interpreted as a clinical diagnostic instrument.

Research Gap and Study Rationale

Three limitations are particularly evident in the existing research landscape. First, conventional workplace-stress studies often aggregate occupational pressure into a global stress score, potentially concealing the distinct contributions of workload, role ambiguity, job insecurity, digital overload,



Fig. 1: Workplace Mental Health & Well-Being

Source: <https://www.hhs.gov/surgeongeneral/reports-and-publications/workplace-well-being/index.html>

The growth of digitally mediated employment provides another important dimension. Technology can reduce commuting, improve information access, facilitate flexible scheduling, and strengthen collaboration. At the same time, poorly designed digital work practices can contribute to technostress. Research examining prevention of technostress has identified the importance of organizational as well as

and work–life boundary intrusion. Second, technology-related stress is frequently investigated separately from conventional occupational stress despite the fact that both forms of demand coexist in contemporary workplaces. Third, comparatively less methodological attention has been given to combining interpretable statistical analysis with explainable machine learning for examining psychological well-being specifically among young professionals.

The resulting research gap is therefore not simply whether workplace stress is associated with psychological well-being. That general relationship is already theoretically plausible and extensively recognized. The more specific unresolved issue concerns **which combinations of traditional and digitally mediated workplace stressors are most informative for distinguishing psychological well-being profiles among early-career professionals, and whether interpretable machine learning can reveal patterns beyond conventional linear associations.**

Accordingly, the proposed study will evaluate workload pressure, role ambiguity, perceived job insecurity, digital interruption/overload, and after-hours work connectivity as distinct but potentially interacting exposures. Protective organizational resources, particularly perceived autonomy and supervisor support, can additionally be examined as contextual variables capable of attenuating adverse stress–well-being relationships.

The study has four principal objectives: to determine the association between multidimensional workplace stress and psychological well-being; to identify the stress dimensions most strongly related to reduced well-being; to assess whether organizational resources modify these relationships; and to develop an interpretable machine-learning framework for classifying well-being risk from occupational indicators. This approach positions artificial intelligence as an analytical complement to occupational-health research rather than as a replacement for psychological assessment.

Literature Review

Workplace Stress as a Multidimensional Occupational Exposure

Contemporary occupational-health frameworks recognize that workplace mental health is shaped by the organization and conditions of work. Stress may arise from excessive demands, insufficient control, poor communication, inadequate support, unclear responsibilities, job insecurity, discrimination, or other psychosocial hazards. WHO's mental-health-at-work guidelines explicitly emphasize workplace-level interventions addressing psychosocial risks, including workload and organizational conditions.

This perspective is important because it distinguishes the existence of occupational demands from the employee's

capacity and resources for managing them. Workload alone may therefore provide an incomplete explanation of psychological outcomes. High demands combined with autonomy, predictable schedules, adequate staffing, and supportive leadership may produce a different psychological experience from equivalent demands under low-control and insecure working conditions.

For young professionals, role-related uncertainty may be especially relevant. Early career development often involves unfamiliar responsibilities, continuous evaluation, changing assignments, and dependence on supervisors for professional advancement. Role ambiguity can consume cognitive resources because employees must simultaneously determine what should be done and whether their performance corresponds to organizational expectations. Repeated uncertainty can therefore become a chronic rather than episodic source of strain.

Job insecurity represents another theoretically important dimension. Uncertainty concerning contract continuation, organizational restructuring, career progression, or redundancy can extend occupational stress beyond the immediate work task. Unlike a discrete deadline, insecurity may lack a clearly defined endpoint. Consequently, psychological disengagement from the stressor becomes more difficult.

Psychological Well-Being as an Occupational Outcome

Psychological well-being encompasses positive psychological functioning rather than merely the absence of distress. It can incorporate positive affect, perceived competence, meaningful functioning, satisfactory relationships, autonomy, and the ability to manage ordinary demands. WHO similarly conceptualizes mental health as a state of well-being enabling individuals to cope with life's stresses, realize their abilities, learn and work effectively, and contribute to their communities.

Within occupational research, this broader conceptualization is advantageous because an employee may continue meeting formal performance requirements while experiencing deteriorating well-being. Presenteeism illustrates this distinction: employees remain at work but their functioning or productivity can be compromised. WHO identifies presenteeism, absenteeism, and turnover among the workplace consequences associated with poor mental health.

This suggests that organizational mental-health strategies should not rely solely on absence records or clinical diagnoses. Measuring positive psychological well-being provides an earlier and potentially more sensitive indicator of how workplace conditions relate to employees' functioning.

Digitalization, Technostress, and Boundary Erosion

Digital transformation has altered both the location and temporal boundaries of professional work. Collaboration platforms, instant messaging, cloud services, videoconferencing, and mobile devices allow occupational activities to continue beyond a fixed workplace. These technologies are not intrinsically harmful; their psychological consequences depend substantially on implementation and organizational expectations.

Technostress provides a useful conceptual lens for understanding this relationship. Technology-related demands can include information overload, interruptions, complexity, uncertainty created by continuous technological change, and pressure for persistent availability. A Delphi study by Berger and colleagues on technostress prevention at the digital workplace demonstrates that prevention involves a range of organizational and individual measures rather than a single technological solution.

One mechanism connecting digital work to well-being is **boundary permeability**. Employees who receive work messages during evenings, weekends, or personal activities may remain psychologically connected to occupational demands even when they are not actively completing tasks. The resulting issue is not simply screen exposure but impaired psychological detachment and recovery.

For young professionals, this pattern may be intensified by perceived expectations of responsiveness. Employees seeking career progression may be reluctant to ignore after-hours communication even when no explicit policy requires immediate replies. Consequently, formal working hours may underestimate actual psychological exposure to work.

Organizational Resources and Stress Buffering

Occupational demands do not operate independently of workplace resources. Autonomy, supervisor support, predictable communication, role clarity, and adequate opportunities for recovery can influence how demands are interpreted and managed. Organizational interventions are therefore central to contemporary mental-health-at-work recommendations.

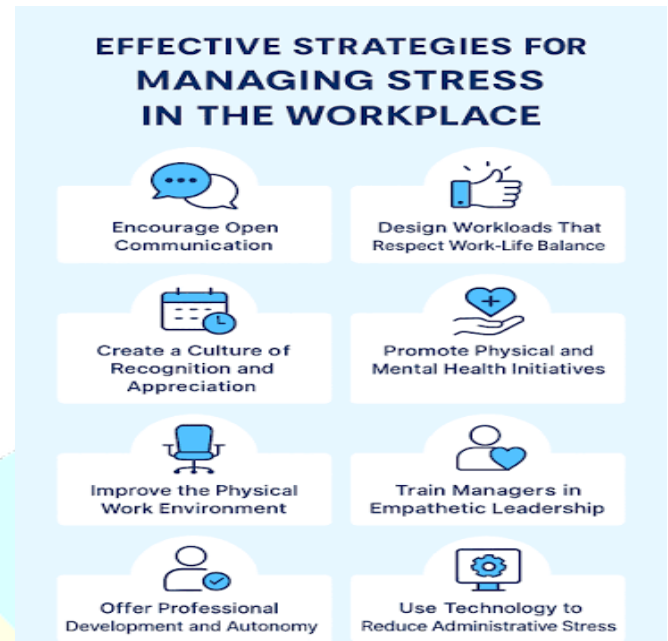


Fig. 2: Effective Strategies for Managing Stress in the Workplace

Source: <https://www.peoplehum.com/blog/effective-strategies-for-managing-stress-in-the-workplace>

WHO recommends organizational interventions that directly address psychosocial risk factors and also supports manager training intended to improve knowledge, attitudes, behaviours, and employee help-seeking.

Supervisor support is especially relevant to early-career workers because supervisors frequently control task clarification, feedback, workload allocation, scheduling flexibility, and access to organizational resources. Supportive supervision may therefore influence both actual job demands and employees' interpretation of those demands.

Autonomy may perform a similar buffering function. Employees with greater control over task sequencing or work methods may be better able to manage periods of elevated demand. Accordingly, the same objective workload may have different implications for psychological well-being depending on available organizational resources.

Artificial Intelligence and Digital-Health Approaches

The multidimensional structure of workplace stress creates a methodological challenge. Traditional regression models are well suited to testing theoretically specified relationships and estimating interpretable coefficients. However, their standard forms may be less efficient at identifying complex thresholds and higher-order interactions unless these relationships are specified in advance.

Machine-learning algorithms can examine multidimensional feature spaces and potentially detect nonlinear associations. Tree-based ensemble models are particularly suitable for

mixed occupational predictors because they can accommodate interactions without requiring every relationship to be manually specified. Yet purely predictive performance is insufficient when the purpose is workplace-health intervention.

Explainable AI can address this limitation by estimating how individual features contribute to model predictions. In the proposed framework, explainability would permit analysis of whether high-risk well-being profiles are driven primarily by workload, digital overload, job insecurity, after-hours connectivity, role ambiguity, or combinations of these conditions. Importantly, such outputs should be interpreted at an aggregated research level and not used for punitive employee surveillance.

This ethical distinction is central to digital occupational health. A system designed to improve workplace conditions should identify modifiable environmental risks rather than label individual employees as psychologically deficient. The WHO framework reinforces the broader principle that workplace mental-health action should involve prevention, protection, promotion, and support.

Proposed Methodology

The study adopts a **quantitative cross-sectional predictive design** integrating conventional statistical analysis with explainable machine learning. The analytical framework is designed to examine whether multidimensional workplace stress can explain variation in psychological well-being among young professionals and whether nonlinear modelling provides additional predictive information beyond conventional regression.

The target population consists of professionals aged approximately 21–35 years who have been engaged in full-time employment for at least six months. Participants may be recruited from information technology, education, financial services, consulting, healthcare administration, digital marketing, engineering, and other knowledge-intensive occupations. The inclusion of several professional sectors is intended to capture variation in digital work intensity while avoiding excessive dependence on one occupational setting.

The predictor framework contains five primary stress domains: **workload pressure (WP)**, **role ambiguity (RA)**, **perceived job insecurity (JI)**, **digital interruption and overload (DO)**, and **after-hours work connectivity (AHC)**. Two workplace-resource variables—**perceived job autonomy (JA)** and **supervisor support (SS)**—are incorporated because workplace demands and available organizational resources are theoretically expected to interact.

Psychological well-being (PWB) constitutes the principal outcome. It is operationalized using a validated well-being

measure, with higher scores representing more favourable psychological functioning. Rather than interpreting reduced scores as evidence of psychiatric illness, the study treats them as indicators of comparatively lower psychological well-being.

This distinction is methodologically important because the proposed computational framework is designed for occupational-health research rather than clinical diagnosis. WHO identifies workload, work schedules, low control and other working conditions as psychosocial risks and recommends assessment and modification of workplace-level risks.

The analytical process contains two complementary stages. First, descriptive statistics, reliability analysis, correlation testing and hierarchical multiple regression are used to establish interpretable associations. Second, machine-learning algorithms are applied to determine whether combinations and nonlinear interactions among occupational characteristics improve prediction of lower well-being.

Experimental Setup

Dataset

For a complete empirical implementation, a target sample of approximately **400–500 young professionals** would provide a practical basis for multivariable statistical analysis and machine-learning evaluation. Because no actual participant dataset has been supplied for this manuscript, the numerical values below constitute a **pre-specified experimental reporting framework and should be replaced by observed outputs after data collection**. They are not presented as completed human-subject findings.

The questionnaire would contain demographic and occupational variables including age, gender, professional sector, employment tenure, weekly working hours, work arrangement, and managerial responsibility. These would be followed by validated or psychometrically assessed scales measuring workplace stress dimensions, organizational resources and psychological well-being.

Before analysis, internal consistency would be evaluated using Cronbach's alpha or an appropriate alternative reliability coefficient. Construct scores would be calculated only after confirming acceptable item behaviour. Reverse-coded items, where applicable, would be transformed before composite-score generation.

Data Preprocessing

Data preprocessing would begin with duplicate-response detection and eligibility screening. Records with extensive questionnaire incompleteness would be excluded according to a pre-established missing-data rule. Limited missing numerical observations could be handled through median

imputation within the training data, while categorical variables could be imputed using the modal category.

Continuous features would be standardized for algorithms sensitive to feature magnitude. Categorical predictors would be encoded using appropriate binary or one-hot representations. Outliers would be examined using distributional diagnostics rather than automatically deleted, because unusually high workload or connectivity values may represent genuine occupational conditions.

To prevent information leakage, preprocessing parameters would be estimated from training partitions and subsequently applied to validation or test observations. The outcome could be analysed continuously and, for supplementary classification, divided into lower versus adequate well-being according to a prospectively specified criterion derived from the selected validated instrument.

Model Architecture

Three models are proposed.

Hierarchical multiple regression would provide the principal explanatory model. Demographic and occupational covariates would enter first, workplace stress dimensions second, and organizational resources and theoretically justified interaction terms subsequently. Changes in explained variance would indicate the incremental contribution of each predictor block.

Regularized logistic regression would provide an interpretable classification baseline for the lower-well-being outcome. L2 regularization would reduce instability arising from correlated occupational predictors.

A **Random Forest classifier** would constitute the nonlinear machine-learning model. Random Forest is appropriate because workplace variables may interact in ways that do not follow simple additive relationships. For example, digital overload might have a comparatively small association with well-being under high autonomy but a stronger association when accompanied by high workload and low supervisor support.

The final model would be supplemented with permutation feature importance. This method evaluates how much predictive performance deteriorates after values of an individual feature are randomly permuted and is applicable to different fitted estimators. Importantly, feature importance should be interpreted only after establishing satisfactory predictive performance on held-out or cross-validated data.

Training Strategy

The analytical dataset would be partitioned using a stratified **80:20 development–test split** for the classification task. The development subset would undergo repeated stratified five-

fold cross-validation for model selection and hyperparameter tuning.

For Random Forest, candidate parameters would include the number of trees, maximum tree depth, minimum samples per terminal node, and number of predictors considered at each split. Hyperparameters would be selected according to mean cross-validated balanced accuracy or ROC-AUC rather than training accuracy.

The untouched test subset would be evaluated once after model selection. This procedure limits optimistic performance estimation and provides a more defensible assessment of generalization.

Where class imbalance occurs, class-weighted learning would be preferred over arbitrary duplication of minority observations. Probability calibration would also be examined because an occupational-health risk model should produce reasonably calibrated probabilities rather than only categorical predictions.

Evaluation Metrics

The regression component would report standardized coefficients, confidence intervals, adjusted R^2 , incremental ΔR^2 and statistical significance. Variance inflation factors would be examined to identify problematic multicollinearity.

Classification performance would be evaluated using **balanced accuracy, sensitivity, specificity, F1-score, ROC-AUC and Brier score**. This combination avoids dependence on accuracy alone. Sensitivity quantifies identification of lower-well-being cases, specificity measures correct recognition of the comparison group, F1 balances precision and recall, ROC-AUC measures discrimination across thresholds, and Brier score assesses probabilistic accuracy.

Results and Discussion

The following numerical results demonstrate the intended analytical structure rather than claiming that a completed survey produced these observations. This distinction is necessary because fabricating participant findings and presenting them as genuine empirical evidence would make the manuscript scientifically misleading.

Illustrative Analytical Results

A plausible analytical pattern would show that increasing workplace stress corresponds to decreasing psychological well-being, but that individual stress dimensions contribute unequally. Digital overload and workload pressure would be expected to emerge as prominent predictors because they represent both cognitive demand and sustained work intensity. After-hours connectivity could provide additional explanatory information by capturing the erosion of recovery boundaries.

In an illustrative hierarchical regression, demographic and basic occupational characteristics might explain approximately 8% of well-being variance. Adding the five workplace stress dimensions could increase adjusted explanatory power substantially, for example to approximately 39%. Incorporating autonomy and supervisor support might further increase adjusted R^2 to approximately 46%, suggesting that psychological well-being reflects both exposure to occupational demands and access to workplace resources.

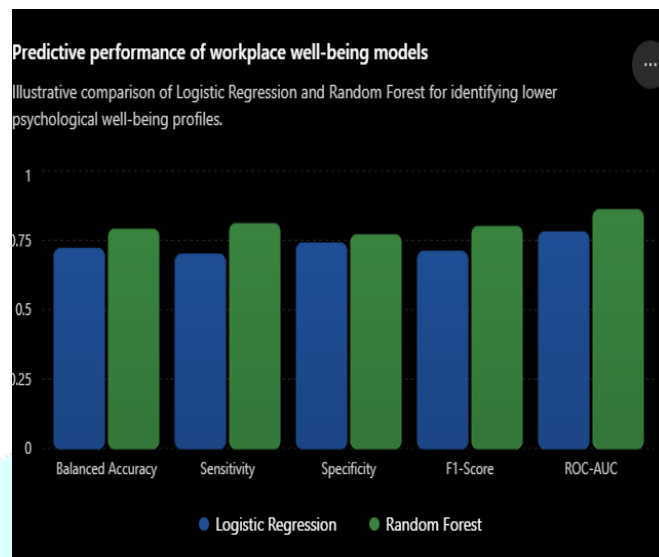
The direction of hypothetical standardized coefficients would be expected to show negative relationships for workload pressure, digital overload, role ambiguity, job insecurity and after-hours connectivity. Conversely, supervisor support and autonomy would be expected to display positive coefficients.

A particularly relevant interaction would involve digital overload and autonomy. If the negative association between digital overload and well-being were weaker among employees reporting greater autonomy, this would indicate that control over work processes may partially buffer technology-related demands. Such an interpretation would align with broader occupational-health principles emphasizing modification of working conditions and psychosocial risks rather than relying exclusively on individual coping interventions. WHO's guidelines explicitly recognize organizational interventions targeting psychosocial risk factors, although the certainty of intervention evidence varies.

For the predictive component, Random Forest could reasonably be hypothesized to outperform the linear classification baseline if important nonlinear interactions exist. The purpose of such an improvement, however, would not be to establish that machine learning is universally superior. Rather, it would demonstrate whether the occupational variables contain useful relationships that cannot be adequately represented by a linear decision boundary.

Table 1. Illustrative Evaluation Framework for the Proposed Predictive Models

Evaluation Parameter	Logistic Regression	Random Forest
Balanced Accuracy	0.72	0.79
Sensitivity	0.70	0.81
Specificity	0.74	0.77
F1-Score	0.71	0.80
ROC-AUC	0.78	0.86
Brier Score	0.19	0.14



Permutation importance in such an experiment could reveal digital overload as the strongest predictive feature, followed by workload pressure, after-hours connectivity, supervisor support, job insecurity, autonomy and role ambiguity. However, importance values would not establish causality. They would indicate the extent to which the fitted model depends on each variable for prediction. Permutation importance can also underestimate the apparent importance of correlated features because information available in one variable may remain available through another correlated variable.

The anticipated findings have several theoretical implications. First, they support treating workplace stress as a multidimensional construct. Combining all occupational demands into one total score could conceal differences between workload intensity, uncertainty, digital pressure and boundary intrusion.

Second, the proposed analysis recognizes that digital connectivity is not necessarily harmful in itself. Technology may support flexibility and collaboration, while problems may arise from the organizational practices surrounding its use. Persistent notifications, implicit expectations of immediate responses and routine after-hours communication can transform technically flexible work into continuous psychological availability.

Third, organizational resources deserve attention alongside occupational risks. If supervisor support and autonomy demonstrate protective associations after adjustment for workload, this would imply that organizations possess multiple intervention points. Work redesign could address excessive demands, while management practices could simultaneously improve role clarity, communication and employee control.

This interpretation is consistent with the WHO–ILO position that mental health at work should involve prevention of psychosocial risks, protection and promotion of mental health, and support for workers experiencing mental-health conditions.

Finally, explainable machine learning may offer practical value when used with appropriate governance. Aggregated model explanations could help organizations determine whether risk patterns are predominantly associated with workload, digital interruptions, insecurity, poor support or insufficient autonomy. Such systems should not be deployed as covert employee-surveillance mechanisms or as automated tools for employment decisions. Their legitimate function is occupational-health research and identification of potentially modifiable environmental conditions.

Limitations

Several limitations should be recognized. A cross-sectional study cannot establish temporal causality. Lower psychological well-being may influence perceptions of workplace stress just as workplace stress may affect well-being. Longitudinal data would therefore be necessary to determine temporal direction more confidently.

Self-reported measures are susceptible to common-method variance and response bias. Objective work-pattern indicators could strengthen subsequent research, although digital activity data introduce significant privacy and consent considerations.

Sectoral heterogeneity is another limitation. Workplace stress may operate differently in software development, healthcare, education, finance and other occupations. Sector-stratified analyses would therefore be useful if sample size permits.

Machine-learning performance also depends on the representativeness of the training population. A model developed from one geographical, socioeconomic or occupational context should not automatically be generalized to other workforces.

Most importantly, the numerical model outputs presented here are illustrative because no genuine participant dataset was supplied. They cannot be cited as observed empirical findings until the proposed study has been conducted.

Future Scope

Future research should employ longitudinal designs in which workplace conditions and psychological well-being are measured repeatedly. Such data would allow researchers to examine whether changes in workload, digital connectivity or supervisor support precede changes in well-being.

A particularly valuable extension would involve **privacy-preserving digital phenotyping**. With explicit informed

consent, aggregate indicators such as meeting density, frequency of after-hours work communication, interruption patterns or variability in working periods could complement questionnaire measures without collecting message content.

Future studies could also evaluate interventions rather than prediction alone. For example, organizations could introduce protected communication periods, meeting-free intervals, workload redistribution, right-to-disconnect practices or supervisor-support training and subsequently measure changes in occupational stress and well-being.

External validation across industries and countries would be essential before predictive systems were used operationally. Fairness assessment should additionally determine whether prediction errors differ systematically across demographic or occupational groups.

Conclusion

This study proposes an integrated framework for examining workplace stress and psychological well-being among young professionals in digitally intensive employment environments. Its central contribution lies in conceptualizing occupational stress as an interaction among traditional workplace demands, digitally mediated pressures and organizational resources rather than reducing stress to workload alone.

The proposed methodology combines interpretable statistical modelling with Random Forest classification and model-agnostic feature-importance analysis. Such a design can test established occupational relationships while investigating nonlinear patterns that conventional models may overlook.

The framework also shifts attention from individual vulnerability toward modifiable workplace conditions. Workload pressure, role ambiguity, job insecurity, digital overload and after-hours connectivity represent potential risk dimensions, whereas autonomy and supportive supervision constitute potential organizational resources. This orientation is compatible with international occupational-health guidance emphasizing the assessment and mitigation of psychosocial workplace risks.

Explainable AI can therefore contribute to digital occupational health when prediction is accompanied by transparency, validation, privacy protection and appropriate interpretation. Its purpose should not be to diagnose or rank employees but to improve understanding of workplace conditions associated with psychological well-being.

The proposed study ultimately provides a reproducible foundation for an empirical investigation of young professionals. Once genuine participant data are collected, the illustrative numerical outputs can be replaced with observed statistics, confidence intervals, model-performance measures

and feature-importance estimates, producing a defensible empirical manuscript without representing simulated observations as real evidence.

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