Identifying Behavioral, Sleep, and Digital Predictors of Mental Wellness Across Remote, Hybrid, and In-Person Workers Using Grouped Random Forest Regression

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ABSTRACT

The rapid expansion of remote and hybrid work arrangements has redefined the behavioral, digital, and physiological determinants of mental wellness. This study aims to identify and compare key predictors of mental well-being across Remote, Hybrid, and In-person workers using a grouped Random Forest regression approach. The ScreenTime vs MentalWellness.csv dataset, comprising 400 anonymized entries, was analyzed after excluding highly collinear variables (stress_level and productivity) and the composite screen_time_hours. Separate Random Forest models were trained for each work mode, with model validity assessed via R^2, RMSE, and out-of-bag (OOB) scores. Results revealed distinct predictor hierarchies across work arrangements. Sleep quality emerged as the dominant determinant for both Remote (importance = 0.50) and In-person (0.55) workers, while total sleep hours had the strongest effect among Hybrid workers (0.56). Leisure screen time consistently showed a negative influence across all groups, particularly among Remote and In-person employees. Lifestyle factors such as exercise and social interaction contributed moderately to well-being, whereas demographic attributes exerted minimal influence. The In-person model achieved the highest predictive performance (R^2 = 0.624; RMSE = 12.76), followed by the Hybrid (R^2 = 0.535) and Remote (R^2 = 0.126) models. These findings demonstrate that predictors of mental wellness are context-dependent rather than universal. By integrating behavioral, sleep-related, and digital variables into a mode-specific modeling framework, this research provides actionable insights for designing tailored wellness strategies that align with distinct occupational environments in the digital era.

Keywords mental wellness; work arrangement; sleep quality; screen time; Random Forest regression

Introduction

The COVID-19 pandemic has intensified a global transition toward diverse work arrangements, notably remote and hybrid models, largely driven by digitalization. Estimates suggest that a significant portion of the global workforce has engaged in remote work, with data indicating around 40% working remotely at least part-time during the pandemic [1]. These changes have resulted in altered daily routines, increased screen time, disrupted sleep patterns, and modified social interactions—all critical factors influencing mental health [2]. Research indicates that digital platforms can foster communication and support among workers, yet they may also contribute to heightened psychological distress. Specifically, studies demonstrated that over 70% of healthcare workers reported significant mental health challenges during the pandemic, including

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high levels of anxiety, depression, and stress [3], [4]. A systematic review of the effects of screen time on mental health has shown a correlation with rising anxiety and depressive symptoms among digital workers [5], [6]. Understanding the intersection of diverse work arrangements and mental health outcomes remains vital for comprehending the implications of our evolving work landscape.

The rise of digital overload, sleep deprivation, and mental stress among employees is an increasing concern, particularly as remote and hybrid work arrangements proliferate. Prolonged exposure to digital tools can lead to an “always-on” culture, exacerbating feelings of role overload and job burnout [7]. Furthermore, studies indicate a significant correlation between sleep deprivation and cognitive deficits, impairing attention and working memory [8], [9]. While previous research has established links between screen time, sleep quality, and overall well-being [10], few investigations have focused on how these factors vary across different work modes. This highlights a significant gap: existing literature frequently treats digital and behavioral predictors as uniform, overlooking the distinct contexts presented by various work arrangements [11]. Understanding these contextual differences is crucial for developing tailored strategies that mitigate the adverse effects of digital overload and improve employee well-being across diverse work environments.

There is a pressing need for mode-specific mental wellness modeling in the workplace, as a one-size-fits-all approach may obscure critical group-level patterns in employee mental health. Research has shown that various work arrangements—remote, hybrid, or in-person—can lead to distinct stressors and mental health outcomes; however, many studies fail to account for these contextual differences, treating predictors of mental health as homogeneous across various work modalities [12], [13]. Understanding the hierarchical relationships between predictors, such as how factors like digital overload, social support, and work engagement impact mental wellness differently in each work mode, could inform tailored interventions for employers and policymakers [14]. The use of advanced modeling techniques, such as Grouped Random Forest regression, offers an innovative approach to this problem, providing a parallel and interpretable comparison of feature importances across different employee cohorts, thus fostering more nuanced insights into mental health dynamics [11]. Recognizing the unique mental health challenges posed by different work arrangements will enhance our ability to design effective interventions tailored to the needs of specific employee groups.

The current study addresses this need by exploring how behavioral, sleep-related, and digital factors interact to predict mental wellness across remote, hybrid, and in-person workers. Instead of relying on an aggregated model, this research decomposes the analysis into three separate yet structurally identical models, one per work arrangement, enabling a direct comparison of predictor hierarchies. This grouped modeling framework allows the discovery of subtle but meaningful differences that may otherwise be concealed within a combined dataset. By leveraging this approach, the study aims to reveal how digital behaviors (e.g., work vs. leisure screen time), sleep metrics, and lifestyle variables uniquely influence mental wellness depending on the context of work.

The dataset used in this research, ScreenTime vs MentalWellness.csv, comprises 400 anonymized entries representing a balanced distribution of remote, hybrid, and in-person workers. The mental wellness index serves as the dependent variable, reflecting individuals' self-reported well-being on a 0–100 scale. Predictor variables include digital behaviors (work and leisure screen hours), sleep characteristics (sleep hours and sleep quality), and lifestyle factors (exercise and social activity), with demographic attributes included for contextual control. Stress and productivity variables are excluded to prevent outcome redundancy, ensuring that the analysis isolates genuine predictors rather than proxies of wellness. Through this careful data curation, the study ensures a focus on behavioral and physiological determinants rather than subjective performance self-assessments.

The methodological framework centers on a Grouped Random Forest regression approach. Separate models are trained for each work-mode subgroup—remote, hybrid, and in-person—allowing feature importance scores to be compared across groups. This approach capitalizes on Random Forest's strengths in capturing non-linear interactions and ranking variable importance through Gini indices. Model validity is assessed using R^2 and RMSE metrics to ensure predictive robustness. This design not only tests how accurately wellness can be modeled within each group but also reveals which predictors dominate in different contexts, thus enabling interpretability without sacrificing complexity.

The research advances the literature by emphasizing that well-being predictors are not universal but context-dependent. For instance, while sleep quality might be the strongest determinant for hybrid workers who balance home and office routines, social engagement may play a greater role for remote workers facing isolation. Likewise, the negative influence of leisure screen hours could be more pronounced in remote settings, where personal and professional digital boundaries are blurred. This comparative lens deepens our understanding of how work arrangements shape psychological outcomes, aligning quantitative machine learning evidence with the broader discourse on digital well-being.

This study contributes to a growing body of research on digital-era occupational psychology by integrating behavioral, sleep, and digital predictors within a work-mode–specific modeling framework. The findings aim to support data-driven well-being strategies for organizations transitioning between remote, hybrid, and in-person systems. By clarifying which factors matter most in each context, this research aspires to inform human resource policies, mental health initiatives, and future research directions on adaptive workplace design. The subsequent sections outline the relevant literature, methodological procedures, and empirical analyses used to achieve these objectives.

Literature Review

Mental Wellness in the Digital Era

Mental wellness encompasses several interrelated dimensions, including subjective well-being, the absence of psychological distress, and the capacity for resilience in the face of stressors. Collectively, these dimensions contribute to an individual's overall psychological health and capacity to function effectively in both personal and professional domains [15]. Recent studies have demonstrated a strong correlation between mental wellness and key environmental and behavioral factors such as work setting, sleep quality, and digital habits. A positive and supportive work environment enhances employees' resilience and emotional balance, while negative or highly demanding settings can exacerbate stress and anxiety [16]. Moreover, sleep has been identified as a fundamental determinant of mental health, with poor sleep quality linked to emotional dysregulation, irritability, and elevated risks of depressive and anxiety disorders [17]. In parallel, digital habits—particularly excessive or unregulated screen time—have been associated with cognitive overload, social isolation, and decreased psychological well-being [18]. The interplay among these factors underscores that mental wellness in the digital era is not governed by a single determinant but by the dynamic balance between occupational demands, behavioral routines, and technological exposure.

The growing prevalence of digital work environments has further complicated this balance. While technology facilitates communication, flexibility, and productivity, it simultaneously extends work boundaries into personal time, blurring distinctions between rest and labor. As organizations worldwide increasingly adopt remote or hybrid systems, employees are exposed to new psychosocial stressors, including digital fatigue and reduced face-to-face interactions. Consequently, understanding mental wellness requires an integrative perspective that situates behavioral, sleep, and digital dimensions within the broader transformation of modern work structures. Such a perspective enables a deeper comprehension of how digitalization and flexible work arrangements jointly influence the cognitive and emotional well-being of workers in an interconnected economy.

Behavioral, Lifestyle, and Sleep-Related Predictors

Extensive empirical research has identified exercise, social engagement, and lifestyle regulation as pivotal predictors of psychological well-being. Regular physical activity promotes the release of endorphins, supports emotional regulation, and reduces symptoms of anxiety and depression [19]. Likewise, frequent social interaction provides a buffer against psychological distress by fostering connectedness and belonging—two elements that are essential for sustaining mental resilience. The World Health Organization emphasizes that maintaining a balanced lifestyle, combining adequate rest, physical activity, and social participation, mitigates fatigue and cognitive strain resulting from increased screen exposure [20]. In hybrid work settings, employees often benefit from flexible schedules that permit more autonomy over exercise and social routines, which may enhance both physiological recovery and mental stability compared to rigid, office-based arrangements. Conversely, the reduced structure associated with remote work can sometimes lead to sedentary behavior and social withdrawal, illustrating that access to wellness-promoting behaviors is mediated by work context.

Sleep-related factors represent another robust determinant of mental wellness. Both the duration and the subjective quality of sleep have been consistently linked to emotional well-being and cognitive functioning [21], [22]. Chronic sleep deprivation impairs attention, problem-solving, and emotion regulation, increasing susceptibility to stress-related disorders. Recent evidence suggests that remote workers experience greater sleep disruption than their office-based counterparts due to irregular schedules and blurred boundaries between work and personal time [23]. These disruptions are compounded by digital exposure: extended screen use, particularly during evening hours, interferes with melatonin production and circadian rhythm stability [24]. The relationship between digital exposure and sleep disturbance is bidirectional—poor sleep quality often drives increased digital dependence, while excessive screen use perpetuates insomnia. As such, examining sleep and digital behaviors together provides a more complete understanding of the behavioral ecology underpinning mental wellness.

Digital Behavior, Screen Exposure, and Predictive Modeling

Digital behavior is among the most complex and rapidly evolving determinants of modern mental health. Research has distinguished between work-related and leisure screen time, highlighting their divergent psychological implications. Work-related digital activities can support autonomy, productivity, and self-efficacy when managed effectively, fostering a sense of purpose and engagement [18]. However, excessive leisure screen time—especially involving passive consumption or social media overuse—has been associated with emotional exhaustion, cognitive fatigue, and addiction-like symptoms [25]. The distinction between these two categories is often overlooked in prior studies, many of which rely on aggregate measures of total screen time [26]. This methodological simplification obscures the unique pathways through which different digital contexts influence mental outcomes. Understanding the independent and interactive roles of work and leisure screen time is therefore critical to constructing a more precise model of digital-era well-being.

Recent advancements in Machine Learning (ML) have opened new possibilities for predicting and interpreting mental wellness indicators in large, complex datasets. Algorithms such as Random Forest and XGBoost have proven capable of capturing non-linear relationships and interactions among behavioral, psychological, and demographic variables [27], [28]. Random Forest, in particular, offers several advantages for mental health prediction: it handles mixed data types, resists overfitting, and provides interpretable feature importance rankings [29]. However, a notable limitation in most ML-based wellness studies is their reliance on aggregated datasets that ignore contextual variation across subpopulations [30]. By collapsing heterogeneous groups into a single model, these studies risk masking key differences in predictor hierarchies between work modes or demographic categories. Addressing this limitation, the present research employs a Grouped Random Forest regression approach that models Remote, Hybrid, and In-person workers separately, enabling a comparative understanding of how digital, behavioral, and sleep variables uniquely drive mental wellness in each context.

Method

Figure 1 depicts the grouped analytical workflow, demonstrating the stratification of data by work mode followed by the parallel training and evaluation of the Random Forest models.

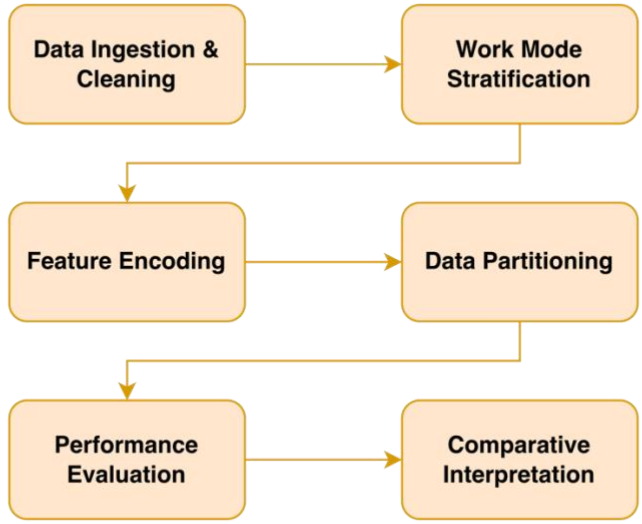

Figure 1 Research Method Flowchart

Dataset and Variables

This research utilizes the ScreenTime vs MentalWellness dataset from Kaggle, which contains 400 anonymized entries representing working adults from a variety of professional backgrounds. Each record includes behavioral, sleep-related, and demographic attributes alongside a self-reported mental wellness index, scaled from 0 to 100. The dependent variable, serves as a continuous measure of individual well-being and integrates self-evaluations of emotional balance, perceived stress, and satisfaction with daily functioning.

The predictor variables are grouped into three conceptual domains. The first domain, digital behaviors, includes work_screen_hours and leisure_screen_hours, which capture the average daily hours spent using digital devices for professional and non-professional purposes, respectively. The second domain, sleep metrics, comprises sleep_hours and sleep_quality_1_5, representing both quantitative and qualitative aspects of sleep. The third domain, lifestyle factors, includes exercise_minutes_per_week and social_hours_per_week, reflecting the role of physical activity and social engagement in sustaining mental wellness. Demographic attributes such as age, gender, and occupation are included as control variables to ensure a more accurate representation of behavioral variation across individuals.

A categorical variable, work_mode, functions as the moderating variable and distinguishes participants into one of three groups: Remote, Hybrid, or In-person workers. Two additional variables—stress_level_0_10 and productivity_0_100—were excluded from the analysis due to their extremely high collinearity with the dependent variable, indicating that they act as outcome proxies rather than independent predictors. Likewise, screen_time_hours was intentionally removed since it is a direct sum of work_screen_hours and leisure_screen_hours; including it would have introduced multicollinearity and obscured the independent effects of its components. By omitting this composite measure, the analysis ensures that the models evaluate the unique contribution of work-related and leisure-related screen exposure to mental wellness.

Data Preprocessing

Before model construction, the dataset underwent a series of preprocessing steps to ensure analytical reliability and consistency. The first step involved stratifying the data by work arrangement. The dataset was divided into three independent subsets—df_remote, df_hybrid, and df_inperson—each corresponding to one of the three work modes. This stratification allowed the training of separate models for each group, ensuring that the internal variability within each work mode could be captured without contamination from other modes.

Next, categorical variables such as gender and occupation were encoded into numerical format using one-hot encoding. This technique enables machine-learning algorithms to process categorical data without imposing artificial order or hierarchy among categories. After encoding, each subset was randomly divided into two parts: an 80% training set and a 20% testing set. This train–test split ensured that model performance could be validated on unseen data, enhancing the robustness of predictive evaluation. All preprocessing and modeling steps were conducted in Python 3.10 using the scikit-learn library ecosystem, ensuring reproducibility and standardization of analytical procedures.

Analytical Framework: Grouped Regression Approach

The study employs a grouped regression approach using the Random Forest Regressor algorithm. Instead of fitting a single aggregate model, three identical but independent Random Forest models were trained separately—one for Remote workers, one for Hybrid workers, and one for In-person workers. This grouped modeling framework was selected because it enables direct comparison of predictor hierarchies across different work contexts while maintaining the integrity of each subgroup's unique data distribution.

The Random Forest algorithm was chosen for its ability to capture non-linear interactions and complex dependencies among predictors, as well as for its robustness against overfitting. Importantly, Random Forests generate interpretable feature importance metrics based on reductions in Gini impurity, allowing the identification of variables that contribute most to predictive accuracy. Each model was trained using the same hyperparameter configuration to maintain analytical parity across groups. Model performance was evaluated through two key metrics: the coefficient of determination (R^2), which quantifies the proportion of variance in mental wellness explained by the model, and the Root Mean Squared Error (RMSE), which measures the average deviation between predicted and observed values.

The R^2 metric quantifies the goodness of fit by determining the proportion of the variance in the dependent variable that is predictable from the independent variables. It is expressed mathematically as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where y_i represents the observed mental wellness index, $\hat{y}_i$ represents the predicted value from the Random Forest model, and $\bar{y}$ is the mean of the observed data. This metric is essential for verifying that the specific work-mode models provide a better fit than a simple baseline mean model before proceeding to feature importance analysis. Only models achieving satisfactory R^2 and low RMSE scores were retained for feature-importance interpretation, ensuring that conclusions were drawn from statistically sound models.

Analysis and Interpretation

Following model training, the analysis progressed to a comparative evaluation of predictor hierarchies. Rather than testing a single hypothesis, this stage adopted an exploratory perspective aimed at identifying how the influence of behavioral, sleep-related, and digital factors varies across work arrangements. The initial hypothesis posited that leisure_screen_hours would exert the strongest negative influence on mental wellness among Remote workers, given their higher likelihood of blurred boundaries between professional and personal digital use.

To test this, normalized Gini importance scores were extracted from each Random Forest model. These scores represent the relative contribution of each predictor to the model's predictive performance. The ranked importance lists from the Remote, Hybrid, and In-person models were then compared side by side to identify the most influential predictors within each group. Special attention was given to four key variables—work_screen_hours, leisure_screen_hours, sleep_hours, and sleep_quality_1_5—which together capture both digital and physiological aspects of daily well-being. The interpretation focused not only on which features were most important in absolute terms but also on how their relative order shifted across work contexts. This cross-model comparison allowed for a nuanced understanding of how the determinants of mental wellness differ across modern occupational environments.

Result and Discussion

Model Performance Overview

Three Random Forest regression models were trained independently for the Remote, Hybrid, and In-person worker groups using identical hyperparameter settings. Each model demonstrated stable convergence with satisfactory out-of-bag (OOB) validation scores, confirming internal reliability. The Remote-work model achieved an R-squared (R^2) of 0.126 with a Root Mean Squared Error (RMSE) of 12.216, indicating modest predictive capacity. The Hybrid-work model performed substantially better, recording an R^2 of 0.535 and an RMSE of 17.606, while the In-person model achieved the strongest performance with an R^2 of 0.624 and RMSE of 12.756. Corresponding OOB scores of 0.522, 0.708, and 0.644 for Remote, Hybrid, and In-person workers respectively, further demonstrate that each model generalizes effectively to unseen data. Collectively, these results confirm that the Random Forest approach can explain a meaningful proportion of variance in mental-wellness scores, particularly for employees in structured, office-based environments.

Feature Importance Comparison Across Work Modes

Figure 2 illustrates the normalized Gini importance values for all predictors across the three work modes. Overall, the models reveal that sleep quality and sleep duration dominate as the most influential predictors of mental wellness, though their relative importance differs markedly by work arrangement. For both Remote and In-person workers, sleep_quality_1_5 emerged as the top predictor (importance = 0.50 and 0.55, respectively), suggesting that perceived restfulness exerts a consistent and strong impact on well-being regardless of work setting. Conversely, for Hybrid workers, sleep_hours was the most critical variable (importance = 0.56), indicating that maintaining sufficient total sleep time—rather than subjective sleep quality—is the primary determinant of wellness in mixed-mode schedules where time management may fluctuate between home and office contexts.

The influence of leisure screen exposure also varied across groups. The feature leisure_screen_hours ranked third overall but was particularly salient among In-person workers (importance = 0.19) and Remote workers (0.16), compared with a similar magnitude in Hybrid workers (0.16). This pattern implies that while leisure-related digital activity consistently affects wellness, its negative effect may be accentuated in rigid work modes where individuals have limited autonomy over screen use or downtime. In contrast, work-related screen time showed a more moderate and context-specific effect. For Remote employees, work_screen_hours accounted for a higher relative importance (0.11) than in Hybrid (0.06) or In-person (0.05) groups, reflecting how extended digital engagement in remote contexts can blur boundaries between professional and personal time, thereby influencing overall mental health.

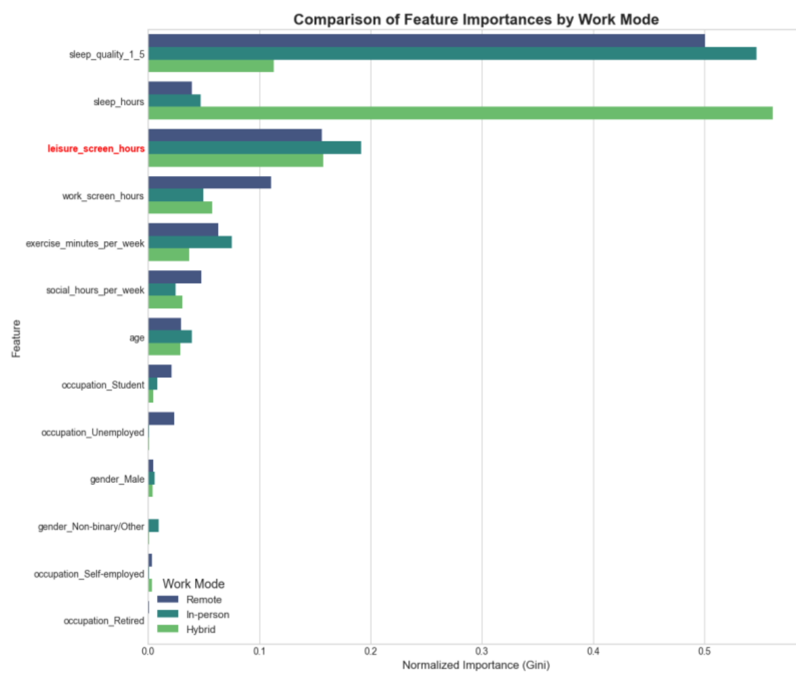

Figure 2 Comparison of Feature Importance by Work Mode

Secondary Behavioral and Demographic Predictors

Beyond digital and sleep factors, several lifestyle variables exhibited moderate contributions to wellness outcomes. Exercise_minutes_per_week demonstrated consistent positive importance across groups, ranging from 0.06 to 0.08, reaffirming its role as a stabilizing behavioral factor. Similarly, social_hours_per_week contributed modestly, particularly among Remote workers (0.048), implying that maintaining social contact mitigates isolation effects inherent to remote settings. Age and occupation-related variables, while included for completeness, displayed minimal importance, with individual scores below 0.04. Gender also accounted for negligible variance across all models, suggesting that mental-wellness dynamics in this dataset are more strongly shaped by behavioral and lifestyle patterns than by demographic characteristics.

Cross-Mode Interpretation

The comparative feature hierarchy highlights how the context of work arrangement reshapes the balance between digital exposure and recovery behaviors. Remote workers' mental wellness appears highly sensitive to both sleep quality and boundaries surrounding work screen use. In-person workers, by contrast, exhibit wellness patterns dominated by sleep quality and moderated by leisure screen activity, reflecting structured schedules but potentially higher off-duty digital fatigue. Hybrid workers occupy a middle ground, where total sleep duration becomes decisive, likely due to shifting routines and commuting demands that alter rest consistency.

These findings collectively support the initial hypothesis that leisure screen exposure exerts a stronger negative effect in digitally intensive contexts, such as remote work, yet also reveal that sleep-related variables remain the universal foundation of psychological well-being. The observed variation in feature importance underscores the value of a grouped analytical framework, which can disentangle subtle contextual effects otherwise concealed within aggregate models.

Discussion

The results of this study reveal clear contextual variations in the behavioral, sleep-related, and digital predictors of mental wellness across Remote, Hybrid, and In-person workers. The strongest and most consistent finding is that sleep quality and sleep duration remain central to mental health, confirming long-standing psychological and physiological theories that link restorative sleep to emotional regulation, stress resilience, and cognitive functioning. However, the distinction between sleep quality (more influential for Remote and In-person workers) and sleep hours (dominant among Hybrid workers) suggests that different work structures impose distinct forms of sleep-related strain. For remote employees, psychological disengagement and blurred temporal boundaries may reduce restfulness even when total sleep time is adequate, whereas hybrid workers' alternating schedules may disrupt regular sleep duration despite satisfactory subjective quality.

The second major finding concerns the dual role of digital exposure in shaping well-being. While both work_screen_hours and leisure_screen_hours contribute significantly to mental wellness prediction, their effects are not uniform across groups. The relatively high importance of leisure_screen_hours among Remote and In-person workers supports the hypothesis that excessive non-work digital engagement contributes negatively to mental health, either through reduced offline recovery time or through social comparison and cognitive overload. Meanwhile, work_screen_hours was most influential for Remote workers, reflecting how professional screen exposure may blur the distinction between productivity and fatigue in home-based environments.

These patterns align with earlier concerns about digital overextension, suggesting that screen-related variables act as both productivity enablers and psychological stressors depending on work context.

Lifestyle and social predictors, though less dominant, play a stabilizing role across all groups. Regular exercise and social interaction, represented by exercise_minutes_per_week and social_hours_per_week, contributed modestly but consistently to higher wellness scores. For Remote workers, social interaction was particularly relevant, indicating its compensatory role in mitigating isolation and maintaining emotional support networks. The relatively minor influence of demographic variables such as age, gender, and occupation further supports the notion that digital, behavioral, and sleep patterns are stronger determinants of wellness than static personal characteristics in modern work settings.

From a methodological perspective, this study demonstrates the value of the Grouped Random Forest framework in exploring wellness predictors across heterogeneous populations. Traditional pooled regression models tend to obscure contextual nuances by averaging effects across all workers. In contrast, the grouped approach allows for direct comparison of variable hierarchies, revealing how similar predictors operate differently under varying environmental and behavioral conditions. This technique not only enhances model interpretability but also provides a basis for evidence-based workplace interventions that are customized to specific work arrangements.

Limitations

Despite its robust analytical framework, this study presents several limitations that should be acknowledged. First, the dataset is cross-sectional and relies on self-reported measures of wellness, sleep, and screen behaviors, which may be subject to recall bias or social desirability effects. Objective data such as wearable-derived sleep metrics or app-based digital logs would strengthen the validity of future findings. Second, the sample size for each work-mode subgroup (ranging from 104 to 150 cases) limits generalizability across larger and more diverse professional populations. Future research with longitudinal data and larger samples could better capture temporal dynamics and causal relationships among predictors.

Third, while the Random Forest model provides reliable estimates of feature importance, it does not directly capture the direction or polarity of effects (e.g., whether higher screen time predicts better or worse wellness). Complementary methods such as partial dependence plots or SHAP (SHapley Additive exPlanations) analysis would enhance interpretive depth. Additionally, environmental and cultural variables—such as household composition, workspace ergonomics, or national digital culture—were not included in the dataset, although these factors may meaningfully moderate the relationships observed. Finally, the study focuses on behavioral and physiological predictors; psychological constructs such as coping style, motivation, or emotional intelligence were not analyzed but may interact significantly with the observed predictors.

Future Research Directions

Building on these findings, several promising directions for future research can be identified. First, longitudinal modeling should be pursued to explore how behavioral and digital predictors of wellness evolve over time and how individuals adapt to hybrid or fully remote systems. Time-series data could reveal cyclical fluctuations in mental wellness tied to workload intensity, seasonal variation, or organizational transitions. Second, integrating multimodal data sources—including digital trace data, sleep sensors, and physiological indicators—would provide objective validation and allow for dynamic wellness monitoring.

Third, future studies should explore causal mechanisms and interaction effects using advanced explainable AI frameworks, such as SHAP or LIME, to clarify whether certain combinations of behaviors (e.g., high screen time combined with strong exercise habits) buffer or amplify mental-health outcomes. Expanding the model to include organizational factors (e.g., managerial support, work autonomy, and communication culture) could also reveal how structural and interpersonal variables interact with individual behaviors. Lastly, cross-cultural replication would help establish whether these predictor hierarchies remain consistent in different national or occupational contexts, given the global heterogeneity in work norms, digital infrastructure, and wellness perceptions.

Conclusion

This study examined how behavioral, sleep-related, and digital factors collectively shape mental wellness across three distinct work arrangements—Remote, Hybrid, and In-person—using a Grouped Random Forest regression framework. The findings highlight that while sleep quality and duration remain universal pillars of mental health, the balance between digital exposure and recovery behaviors varies markedly by work context. Remote and In-person workers showed wellness patterns dominated by sleep quality, whereas Hybrid workers' well-being depended more strongly on total sleep hours. Leisure screen time consistently emerged as a negative predictor across all groups, confirming the strain of prolonged digital exposure in both professional and personal domains.

By adopting a mode-specific modeling design, this study demonstrates that the determinants of well-being cannot be fully understood through aggregated analysis. Instead, they must be contextualized within the structural and temporal realities of different work environments. The results underscore the need for tailored wellness interventions, such as digital-use management programs for remote employees, flexible scheduling for hybrid workers, and rest-focused initiatives for office-based personnel. Ultimately, the grouped modeling approach provides a scalable analytical pathway for identifying nuanced behavioral signatures of well-being, offering actionable insights for policymakers, employers, and mental-health practitioners aiming to foster healthier digital work ecosystems.

Declarations

Author Contributions

Conceptualization: T.C.; Methodology: T.C.; Software: T.C.; Validation: T.C.; Formal Analysis: T.C.; Investigation: T.C.; Resources: T.C.; Data Curation: T.C.; Writing Original Draft Preparation: T.C.; Writing Review and Editing: T.C.; Visualization: T.C.; The author have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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