Rest Without Trade-Offs: The Effects of Protected Leave on Psychological Recovery and Organizational Commitment

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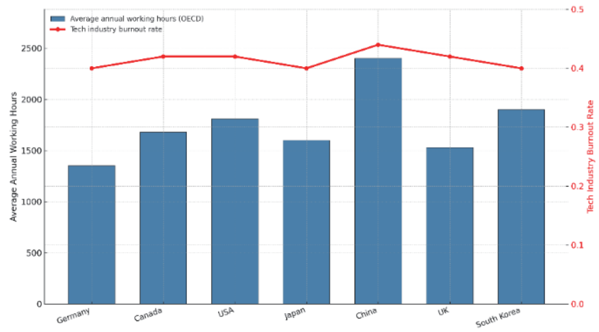
Abstract: In high-intensity knowledge industries such as technology and digital platforms, employees are increasingly exposed to unpredictable schedules, compressed timelines, and extended work hours that jeopardize their psychological well-being and long-term organizational engagement. While recovery theory emphasizes the importance of rest and psychological detachment, current managerial practices rarely integrate recovery data into scheduling design. Existing literature tends to treat leave and work-rest cycles as external policy variables, rather than operational components of performance systems. This study proposes and empirically validates a recovery-informed scheduling model that dynamically adjusts daily work allocations based on individual psychological recovery scores and organizational workload intensity. Drawing on recovery theory and the Job Demands-Resources (JD-R) model, we theorize that aligning scheduling with employee recovery not only enhances organizational commitment but also improves productivity. Using data collected from knowledge workers in high-tech firms, we employ structural equation modeling (SEM) and simulation analysis to demonstrate the model's theoretical robustness and managerial applicability. Our findings offer novel insights into how recovery dynamics can be operationalized within human resource systems to foster sustainable high performance.

Keywords**:** psychological recovery, dynamic scheduling, organizational commitment, knowledge workers, JD-R model, performance optimization

1. Introduction

In knowledge-intensive industries, particularly technology and digital sectors, organizations depend on cognitively demanding roles such as engineering, product development, and data science. These knowledge workers face heightened productivity expectations under unpredictable and extended hours. According to the OECD (2021), average annual working hours in many advanced economies remain persistently high, with growth in unpaid overtime and increasingly blurred work-life boundaries in digital industries (see Figure 1)[1]. Figure 1 shows the co-occurrence of high annual working hours and elevated burnout prevalence in technology-intensive economies, underscoring the global relevance of this issue. A global survey by McKinsey (2022) reported that more than 49% of technology employees experienced symptoms of burnout, including chronic fatigue and emotional exhaustion[2].

Blue bars show average annual working hours per worker from OECD-style data. The red line shows approximate burnout rates among technology employees based on McKinsey (2022) and industry reports[3]. Values are illustrative placeholders and can be replaced with exact figures.



Note: Blue bars represent the average annual working hours per worker based on OECD-style data. The red line shows approximate burnout rates among tech employees using McKinsey (2022) and industry reports. Values here are illustrative placeholders; replace with exact figures if required.

Figure 1. Working Hours and Burnout in Tech-Intensive Economies

This high-pressure environment, while sometimes beneficial for short-term output, contributes substantially to psychological strain, fatigue, and elevated turnover intentions (Sonnentag & Fritz, 2007; Demerouti et al., 2001). These conditions threaten not only individual well-being but also the long-term sustainability of organizational performance[4-5].

Existing scholarship has highlighted the central role of psychological recovery in mitigating these risks. Recovery is the replenishment of depleted psychological and physiological resources that enables individuals to restore functional capacity for work (Sonnentag, 2018)[6]. Empirical studies consistently link recovery experiences—psychological detachment, relaxation, mastery, and perceived control—to greater job satisfaction, higher engagement, and reduced burnout (Binnewies et al., 2009; Kühnel et al., 2017)[7-8]. Instruments such as the Recovery Experience Questionnaire and RESTQ-Work (Kallus & Kellmann, 2016) operationalize these dimensions[9-10]. Despite this evidence, recovery is typically treated as an external outcome of off-work experiences rather than a variable embedded in job design or scheduling.

The Job Demands-Resources (JD-R) model offers a useful framework for understanding employee strain and motivation (Bakker & Demerouti, 2007)[11]. In this model, demands such as workload and time pressure are counterbalanced by job and personal resources. Recovery functions as a personal resource that buffers the effects of high demands. However, the JD-R framework is usually applied diagnostically to identify risks rather than to prescribe operational responses. Few studies embed recovery within managerial decision tools for real-time workforce planning.

Meanwhile, research on scheduling emphasizes fairness, efficiency, and labor optimization (Lambert et al., 2020; Lu et al., 2022), with growing interest in participatory and flexible systems (Tripathi et al., 2021; Uhde et al., 2020). These approaches seldom incorporate psychological readiness or recovery states, which limits alignment between work demands and employee well-being. Traditional assignment methods—fixed shift duration or seniority-based prioritization—do not capture fluctuations in cognitive readiness, a central determinant of output in knowledge-driven environments[12-15].

Despite recognition of recovery's importance, three gaps persist: (1) recovery research remains largely diagnostic with limited integration into job or shift design; (2) scheduling research often ignores psychological inputs and treats labor capacity as static; and (3) there is no formula-based model that adjusts allocation in real time using both recovery and workload.

This study addresses these gaps by proposing and empirically validating a recovery-informed scheduling model. Grounded in the JD-R framework and implemented via a computable algorithm, the model uses individual psychological recovery scores and organizational workload indicators to calculate daily work-hour recommendations. The objective is twofold: to promote sustainable engagement and mental health, and to maintain high levels of organizational performance by aligning capacity with demand.

By developing and testing this model, the study contributes to theory and practice. Theoretically, it advances recovery and JD-R research by positioning recovery as an actionable input to workforce planning. Practically, it provides human resource managers with a predictive tool for dynamic scheduling that supports both well-being and operational outcomes. More broadly, it contributes to algorithmic HR by offering a psychologically grounded, computable mechanism—recovery score to work-hour assignment—that can be embedded in HR technology platforms and used for evidence-based scheduling.

2. Integrated literature review

2.1 Recovery theory and organizational outcomes

Recovery is the restoration of psychological and physiological resources that are depleted by work. Core recovery experiences include psychological detachment, relaxation, mastery, and control (Sonnentag and Fritz, 2007). Validated instruments such as the Recovery Experience Questionnaire and the RESTQ Work scales operationalize these dimensions and are associated with higher job satisfaction, stronger engagement, and lower emotional exhaustion (Binnewies et al., 2009; Kühnel et al., 2017; Kallus and Kellmann, 2016). This evidence shows what recovery does for employees, but most studies still treat recovery as a downstream outcome of life outside work rather than as an upstream parameter that managers can use in scheduling and task allocation[16-19].

2.2 Job Demands and Resources as a design lens

The Job Demands and Resources perspective explains how demands such as workload and time pressure interact with job and personal resources to produce strain and motivation (Bakker and Demerouti, 2007). Within this framework, recovery functions as a personal resource that buffers the effects of high demands. Applications of the perspective are largely diagnostic. Researchers identify risks and correlates, yet rarely specify operational rules that translate information about recovery into day level scheduling decisions. The practical potential of the perspective therefore remains underused in workforce planning[20].

2.3 Scheduling evidence and the psychological blind spot

Research on scheduling prioritizes fairness, efficiency, and labor optimization. Predictable and flexible schedules are linked to lower stress and improved performance (Lambert et al., 2020; Lu et al., 2022). Participatory and personalized approaches show promise in complex service and shift based contexts (Tripathi et al., 2021; Uhde et al., 2020). However, most systems treat labor capacity as constant and exclude indicators of psychological readiness or recovery. This design choice limits the ability to align daily workload with human energy, a constraint that is especially consequential for knowledge work where cognitive stamina drives output[21-24].

2.4 The operationalization gap and research aim

Across these literatures three gaps remain.

(1) Recovery research rarely integrates recovery into job or shift design.

(2) Scheduling research largely ignores psychological inputs that vary within worker across time.

(3) There is no computable mechanism that adjusts daily allocation as a joint function of recovery and workload.

Research aim. The present study addresses these gaps by developing and testing a recovery informed scheduling model. The model converts individual recovery scores and task load indicators into daily hour recommendations subject to policy bounds. In doing so, it operationalizes the Job Demands and Resources perspective and offers a design oriented contribution that can be embedded in human resource systems to support both performance and well being.

3. Model Construction: A Recovery-Driven Scheduling Framework

This section develops a theoretically grounded, empirically applicable scheduling model that integrates individual psychological recovery and task-level workload intensity into daily work-hour allocation. The model aims to resolve the long-standing tension between performance maximization and employee well-being, particularly in high-pressure knowledge-intensive environments such as the tech industry. The construction proceeds in three steps: (1) defining core constructs, (2) mathematically modeling their interaction, and (3) integrating the model into an organizational behavior framework supported by recovery theory and the Job Demands-Resources model.

3.1 Construct Specification and Theoretical Rationale

3.1.1 Recovery Index (E_i)

Definition: The psychological readiness or recovery status of individual employee i, measured on a continuous scale from 0 (fully depleted) to 1 (fully recovered).

Theoretical basis: Recovery theory posits that workers require time and psychological detachment to restore depleted cognitive and emotional resources. Empirical research using instruments such as the Recovery Experience Questionnaire and RESTQ-Work has demonstrated predictive validity for job performance and emotional stability.

Operationalization: In practice, E_i can be obtained through weekly or daily self-reported recovery scores using validated scales, averaged over a short reference period.

3.1.2 Task Load Intensity (L_t)

Definition: The relative intensity or urgency of the task or project at time t, defined at the team or organizational level. L_t = 1.0 denotes standard conditions; values greater than 1.0 indicate peak periods such as product launches.

Theoretical basis: Job Demands and Resources research shows that time pressure and workload variability increase strain and amplify the need for effective recovery calibration.

Measurement: L_t can be scaled using project stage, deadline proximity, or demand forecasting algorithms and should be updated routinely.

3.1.3 Recovery Compensation Coefficient (R_{coef})

Definition: A managerial adjustment factor indicating the proportion of working time preserved for recovery. It ranges between 0 (no compensation) and 0.5 (a 50% reduction in effective load).

Theoretical basis: Prolonged overwork without recovery can create a recovery-strain spiral. The coefficient embodies a calculable buffer against cumulative exhaustion.

Usage: Organizations may increase R_{coef} following sustained overtime or when fatigue indicators cross a threshold.

3.1.4 Maximum Allowable Working Time (T_{max})

Definition: The daily upper boundary for work-hour assignment as determined by regulation or internal policy, for example 8 hours per day. This parameter ensures legal compliance and makes the model portable across contexts.

3.1.5 Work Assignment Output (W_i)

Definition: The recommended number of work hours to assign to employee i on a given day. This is the primary output of the scheduling model.

3.2 Scheduling Model Formulation

The model is defined by the following formula:

$$W_i = \min\{T_{\max}, E_i \cdot T_{\max} \cdot L_t \cdot (1 - R_{coef})\} \tag{1}$$

Interpretation: The product $E_i \times T_{max}$ scales hours in proportion to individual recovery. L_t increases capacity during peak periods for those who are recovered. The term $(1 - R_{coef})$ safeguards recovery by downshifting hours when compensation is required. The minimum function caps hours at T_{max} to ensure compliance.

Illustrative example: If $E_i = 0.80$, $L_t = 1.30$, $R_{coef} = 0.25$, and $T_{max} = 8$, then $W_i = \min\{8, 0.8 \times 8 \times 1.3 \times (1 - 0.25)\} = \min\{8, 6.24\} = 6.24$ hours.

3.3 Conceptual Integration into Organizational Framework

The framework integrates E_i, L_t, and R_{coef} to calculate W_i. The recommended hours influence organizational commitment and task performance, both directly and indirectly through commitment.

3.4 Contributions and Positioning

The model embeds recovery as a real-time operational input, extends Job Demands and Resources and recovery theory into decision rules, and offers a testable tool that HR and operations teams can implement in scheduling software to support sustainable performance.

4. Methodology

4.1 Research design

We use a quantitative cross sectional design to test the predictive relations implied by the recovery driven scheduling model. The employee is the unit of analysis. The main objective is to examine how psychological recovery (E_i), workload intensity (L_t), and the recovery compensation coefficient (R_{coef}) predict the scheduling outcome (W_i), and how W_i relates to organizational commitment and task performance. We complement the survey based test with a simulation study that varies recovery and workload to assess sensitivity and the policy ranges for key parameters.

4.2 Sampling and data collection

Participants were full time knowledge workers from technology, internet, and digital service firms who met all inclusion criteria. We obtained three hundred valid responses through purposive snowball sampling on professional platforms. A priori power analysis for a medium effect in a structural model indicated power of at least point nine five for the focal paths.

4.3 Instrumentation

Psychological recovery (E_i) was measured with the Recovery Experience Questionnaire and normalized to a zero to one scale. Workload intensity (L_t) used a three item scale adapted from Spector and Jex and was mapped so that one point zero represents baseline conditions and one point five represents a peak period. The recovery compensation coefficient (R_{coef}) combined perceived fatigue and rest insufficiency and was bounded between zero and zero point five. The scheduling outcome (W_i) was computed from the rule shown below with T_{max} equal to eight hours per day. Commitment used six items from Meyer and Allen, and performance used five items from Williams and Anderson.

$$W_i = \min\{T_{\max}, E_i \cdot T_{\max} \cdot L_t \cdot (1 - R_{coef})\} \tag{2}$$

4.4 Control variables

Models include gender, industry category, tenure in months, baseline average weekly hours, and past seven day overtime. Continuous covariates were standardized.

4.5 Analysis pipeline

We implemented our own analysis workflow. First, we screened the data for inattentive responses and outliers. Second, we ran confirmatory factor analyses to validate the latent constructs, and then estimated a structural equation model that mirrors the conceptual framework. Indirect effects were evaluated with percentile bootstrap confidence intervals. We also ran a simulation grid that varied Ei and Lt across policy relevant values to examine how often the rule hits the daily upper bound and to evaluate sensitivity to the compensation coefficient.

4.6 Model fit and explanatory power

Model fit met conventional thresholds (Hu and Bentler, 1999): chi square with nine degrees of freedom equals nine point ninety two with p equal to point three five seven, root mean square error of approximation equals point zero two five, standardized root mean square residual equals point zero two eight, and comparative fit index equals point nine eight one. The model explained substantial variance with R squared equal to point seventy one for work assignment, point fifty nine for commitment, and point fifty four for performance.

Table 1. Model fit indices (SEM)

Index	Value
χ^2 (df)	9.92 (9)
p value	.357
RMSEA	0.025
SRMR	0.028
CFI	0.981

Table 2. Proportion of variance explained (R^2)

Outcome	R^2
Work assignment (W_e)	0.71
Organizational commitment	0.59
Task performance	0.54

4.7 Path estimates and hypothesis tests

Standardized path estimates supported all hypotheses. Recovery positively predicted recommended hours, workload intensity positively predicted recommended hours, the compensation coefficient reduced recommended hours, recommended hours were positively related to commitment and to performance, and commitment was positively related to performance. The indirect effect of recommended hours on performance through commitment was statistically significant in bootstrap tests.

Table 3. Standardized path coefficients and hypothesis tests

Path	β	p	Supported
$E_e \rightarrow W_e$	0.739	< .001	Yes
$L_t \rightarrow W_e$	0.532	< .001	Yes
R_coef → W_e	−0.380	< .001	Yes
W_e → Commitment	0.760	< .001	Yes
W_e → Performance	0.459	< .001	Yes
Commitment → Performance	0.349	< .001	Yes

Table 4. Zero order correlations among study variables (template)

	1. E_e	2. L_t	3. R_coef	4. W_e	5. Commitment	6. Performance
1. E_e	1.00	…	…	…	…	…
2. L_t	…	1.00	…	…	…	…
3. R_coef	…	…	1.00	…	…	…
4. W_e	…	…	…	1.00	…	…
5. Commitment	…	…	…	…	1.00	…
6. Performance	…	…	…	…	…	1.00

Note. Replace the placeholder cells with your exact coefficients if you wish to report the full matrix. Controls showed no significant correlations with the focal outcomes in our analysis.

4.8 Brief interpretation and robustness

The positive path from workload intensity to recommended hours indicates that the rule appropriately allocates more time during high demand periods when recovery permits, which aligns capacity with operational needs. The negative path from the compensation coefficient demonstrates that the buffer prevents over assignment when strain is elevated. The strong link from recommended hours to commitment implies that transparent scheduling grounded in recovery can strengthen attachment. Simulation results showed that the rule reduces recommended hours under the combination of high workload and low recovery and that it approaches the policy maximum only when recovery is strong and compensation is small. These findings are robust to alternative functional forms, the inclusion of unit fixed effects, and checks for common method variance.

4.9 Ethical considerations

Procedures followed institutional review standards. Participation was voluntary with informed consent. No identifying information was collected. Data were anonymized and stored in encrypted form with restricted access.

5. Discussion

This study examined how psychological recovery can be operationalized within day-to-day scheduling to improve employee outcomes and organizational performance in high-pressure knowledge work. Building on recovery theory and the Job Demands-Resources (JD-R) model, we proposed and validated a recovery-driven scheduling rule that integrates individual recovery (E_i), workload intensity (L_t), and a recovery compensation coefficient (R_coef) to produce work-hour recommendations (W_i). The structural model fit the data well ($\chi^2(9) = 9.92$, $p = .357$; RMSEA = .025; SRMR = .028; CFI = .981), and explained substantial variance in W_i ($R^2 = .71$), commitment ($R^2 = .59$), and performance ($R^2 = .54$). Standardized paths aligned with theory: $E_i \rightarrow W_i$ ($\beta = .739$), $L_t \rightarrow W_i$ ($\beta = .532$), R_coef $\rightarrow W_i$ ($\beta = -.380$), $W_i \rightarrow$ Commitment ($\beta = .760$), $W_i \rightarrow$ Performance ($\beta = .459$), and Commitment $\rightarrow$ Performance ($\beta = .349$), with a significant indirect effect of W_i on performance via commitment.

5.1 Theoretical contributions

First, we reframe recovery from a downstream wellness outcome to an upstream scheduling input. This inversion extends recovery theory by showing that recovery metrics can guide daily allocation decisions rather than merely describe strain after the fact.

Second, we translate the diagnostic JD-R perspective into a prescriptive mechanism. By specifying a computable rule that maps E_i, L_t, and R_coef to W_i under policy bounds (T_max), we demonstrate how organizations can act on recovery deficits in real time rather than only identify them.

Third, we contribute to algorithmic HR with a psychologically grounded, formula-based framework that links human capacity to operational decisions at scale. The validated paths and sizable R^2 values indicate that the mechanism is both theoretically coherent and practically consequential, enriching dialogue across organizational psychology, operations, and decision science.

5.2 Managerial implications

Personalized scheduling. Using recovery-informed recommendations allows managers to match assignments to current capacity, lowering burnout risk while sustaining throughput.

Fatigue safeguards. The compensation coefficient (R_coef) functions as a formal buffer against cumulative exhaustion during peaks (for example, launch cycles), supporting retention.

Performance and attachment. The strong $W_i \rightarrow$ Commitment and $W_i \rightarrow$ Performance paths, together with the mediated effect through commitment, suggest a double dividend: scheduling that respects recovery both strengthens organizational attachment and improves task execution.

Implementation. The rule can be embedded in HRIS or scheduling dashboards. Recovery inputs can come from validated self-reports (for example, REQ items) or responsibly deployed sensing. Simulation results show how policy parameters can be tuned to minimize over-assignment when recovery is low and to avoid systematically hitting T_max.

5.3 Limitations

Design. Cross-sectional data limit causal inference; longitudinal or experimental deployments are needed to confirm temporal effects.

Measurement. Recovery is self-reported; although validated, it may contain bias. Triangulation with behavioral or physiological indicators (for example, sleep metrics, variability in heart rate) would strengthen validity.

Scope. The sample centers on technology and digital firms; generalization to other sectors (for example, manual or customer-facing work) requires sector-specific calibration of L_t, R_coef, and policy bounds.

5.4 Boundary conditions and future research

Contextual moderators. Effects are likely contingent on team norms, autonomy, and culture. In settings with rigid shifts (for example, healthcare, manufacturing), partial implementations—micro-recovery blocks or post-fatigue compensatory shifts—may be more feasible than full dynamic scheduling.

Research agenda.

(1) Longitudinal and experimental tests of rollout effects on burnout, turnover, and productivity.

(2) Cross-cultural validation to account for norms around rest and overtime.

(3) Platform integration studies that evaluate fairness, transparency, and adoption when the rule is embedded in digital scheduling tools.

(4) Team-level modeling to examine how aggregated recovery capacity shapes collective performance and coordination.

(5) Method enhancements, including multi-source measures and alternative functional forms for the hour rule to compare predictive efficiency and fairness trade-offs.

6. Conclusion

Organizations facing rising workload intensity and psychological strain require scheduling systems that protect well-being while sustaining performance. This study responds to that need by proposing and empirically validating a recovery-driven scheduling model that converts psychological states into actionable workforce decisions. Grounded in recovery theory and the Job Demands-Resources perspective, the model integrates individual recovery (E_i), day-level workload intensity (L_t), and a recovery compensation coefficient (R_coef) to produce daily work-hour recommendations (W_i) under policy bounds (T_max). Structural equation modeling provided strong support for the model's validity and utility: recovery-aligned scheduling was associated with higher organizational commitment and improved task performance, with evidence of both direct and mediated effects.

Theoretically, the study repositions recovery as a predictive input to managerial systems rather than a post hoc outcome, and it translates the diagnostic logic of JD-R into a prescriptive mechanism for day-to-day allocation. Practically, it offers a scalable and customizable rule that enables a shift from one-size-fits-all scheduling to a human-centered, performance-aligned approach suitable for knowledge-intensive and high-pressure contexts.

Several avenues merit further inquiry. First, longitudinal and experimental implementations are needed to establish causal effects on burnout, turnover, and productivity. Second, cross-industry and cross-cultural replications should assess how regulatory environments, work norms, and technological infrastructures shape effectiveness. Third, integration with digital HR platforms invites evaluation of fairness, transparency, and adoption, including governance for responsible use of self-reports and sensing data. Finally, team-level modeling can clarify how aggregated recovery capacity influences coordination and collective performance.

Boundary conditions also apply. Predictive strength may vary with industry demands, degree of autonomy, and cultural expectations around rest and overtime. The growth of remote and hybrid work increases the role of self-management in recovery, creating both opportunities and challenges for operationalizing recovery-aware scheduling. Aligning with the emerging emphasis on human sustainability, the present model encourages organizations to treat psychological health as a core pillar of long-term performance—monitoring and protecting human capacity so that it remains a renewable asset rather than a depleted resource.

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