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Mandatory Remote Work and Multidimensional Employee Well-Being: Evidence from the Indian IT Sector

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ABSTRACT

The COVID-19 pandemic transformed remote working from a discretionary practice into a mandatory reality for millions of employees worldwide. This study investigates the multidimensional impact of enforced remote work on employee well-being within the Indian IT sector, focusing on physical, psychological, emotional, social, intellectual, and spiritual dimensions. Drawing upon the Job Demands–Resources (JD-R) model and the PERMA well-being framework, a structured survey was administered to 322 employees from leading IT firms such as TCS and Infosys. The findings reveal that while remote work enhanced flexibility, reduced commuting stress, and created opportunities for personal growth, it simultaneously intensified digital fatigue, blurred work–life boundaries, and weakened social connectedness. Gender and household dynamics emerged as critical mediators, with women reporting higher stress due to disproportionate caregiving responsibilities. Regression and structural equation modelling further demonstrated that job resources, including managerial support and ergonomic home setups, moderated the negative effects of remote working demands. The study highlights the complex and context-dependent nature of remote work outcomes in emerging economies, where infrastructural limitations and cultural norms shape employee experiences differently than in Western contexts. These insights contribute to theory by extending the JD-R framework to enforced remote work conditions, and to practice by informing organizations and policymakers about strategies to foster sustainable employee well-being in hybrid and digital-first work environments.

Keywords: Remote working; Employee well-being; Job Demands–Resources model; PERMA framework; Digital fatigue; Work–life balance; Indian IT sector; COVID-19

1.0 Introduction

Remote working, once considered a privilege or a flexible arrangement, became a global necessity during the COVID-19 pandemic. Millions of employees across industries were compelled to shift from traditional office spaces to home-based setups, often with little preparation or support. While voluntary telecommuting has long been associated with autonomy, flexibility, and improved work–life balance, mandatory remote work introduced a different dynamic, characterized by uncertainty, resource constraints, and heightened stress (Neeley, 2020). This sudden transformation has made employee well-being a central concern for organizations and researchers alike.

Employee well-being is inherently multidimensional, encompassing physical health, psychological resilience, emotional stability, social connectedness, intellectual growth, and spiritual fulfillment. The World Health Organization (2021) defines well-being as a state in which individuals can realize their potential, cope with normal stressors, and contribute productively to their communities. Remote work directly interacts with each of these dimensions. On one hand, it offers advantages such as reduced commuting time, increased autonomy, and greater flexibility in balancing professional and personal commitments. On the other, it has led to challenges such as digital fatigue, blurred work–life boundaries, isolation, and musculoskeletal health issues stemming from poor ergonomics (Choudhury, Foroughi, & Larson, 2019).

The Indian IT sector provides a compelling context for exploring these issues. As one of the largest global IT hubs, India employs over four million professionals in companies such as Tata Consultancy Services (TCS), Infosys, Wipro, and HCL. During the pandemic, more than 80 percent of this workforce transitioned to remote work within weeks, often without adequate infrastructure or prior experience (NASSCOM, 2021). Unlike Western economies, where technological readiness and individualistic cultures may have eased the transition, Indian employees faced unique challenges, including unreliable internet connections, crowded households, and entrenched cultural expectations regarding caregiving and family roles. These factors make it critical to examine how mandatory remote work has shaped employee well-being in this sector.

The present study investigates the impact of mandatory remote work on multiple dimensions of employee well-being within the Indian IT sector. Grounded in the Job Demands–Resources (JD-R) model and the PERMA well-being framework, the study aims to explore how job demands such as constant digital connectivity, extended screen exposure, and work–life spillover interact with job resources such as managerial support, autonomy, and ergonomic work setups. By analyzing data from IT professionals, this research seeks to identify both the positive and negative consequences of remote work, while also highlighting gender and household dynamics as critical mediating factors.

The findings of this study contribute to theory by extending well-being frameworks to contexts of enforced remote work, where employee choice is limited. Practically, the results offer actionable insights for organizations designing hybrid work models, employee wellness programs, and supportive HR policies in a post-pandemic world. In doing so, the research underscores the importance of creating resilient work environments that prioritize employee well-being alongside productivity in the digital era.

2.0 Existing Literatures:

Remote working has long been discussed in management and labour literature, but the COVID-19 pandemic dramatically accelerated its prevalence and forced large numbers of employees into **mandatory** remote work with little preparation. As a result, scholarly attention has shifted from voluntary telework experiments and pilot programs to the distinctive challenges and outcomes of **enforced** remote work, especially its consequences for employee well-being across multiple domains (physical, psychological, emotional, social, intellectual, spiritual). Seminal empirical work on telework and randomized experiments (e.g., Bloom et al.) and recent research on expanded forms of geographic and temporal flexibility (e.g., work-from-anywhere) provide key empirical anchors for understanding productivity–wellbeing tradeoffs in remote contexts. NBER+1

2.1 Theoretical frameworks used in remote-work & well-being research

Two frameworks dominate contemporary research in this area and frame most empirical work:

Job Demands–Resources (JD-R) model. The JD-R model conceptualizes work characteristics as either demands (which drain energy and produce strain) or resources (which motivate, buffer demands, and foster engagement). Remote work can reconfigure both demands (e.g., constant digital connectivity, role ambiguity, multitasking, caregiving interruptions) and resources (e.g., autonomy, flexibility, managerial trust). The JD-R lens has been widely used to explain burnout and engagement in remote contexts and to test moderation/mediation hypotheses. Peopleful+1

PERMA and multidimensional well-being. Positive-psychology approaches (Seligman's PERMA) frame well-being as multidimensional (Positive emotion, Engagement, Relationships, Meaning, Accomplishment). Many remote-work studies adopt PERMA or expanded multidimensional measures to capture how remote arrangements affect different well-being elements (not just stress or burnout). Using PERMA helps move beyond single-indicator approaches to a holistic assessment of employee flourishing. Positive Psychology Center+1

Integrating JD-R (process, demands/resources) with PERMA (outcomes across domains) produces a conceptual structure particularly useful for studies of **mandatory** remote work: demands and resources shaped by organizational and household contexts influence multiple well-being outcomes simultaneously.

2.2 Empirical evidence — overall effects of remote work

Early experimental and quasi-experimental studies of work-from-home (WFH) showed mixed but often positive productivity effects: Bloom et al. (Ctrip experiment) reported increased productivity along with reduced attrition but noted social costs (loneliness) that led many home-workers to prefer returning to the office. Later work distinguishes WFH from broader "work-from-anywhere" (WFA) regimes that add geographic choice—Choudhury et al. examined productivity and geographic flexibility and found both opportunities and tradeoffs. These empirical anchors demonstrate that remote work produces **heterogeneous** effects—benefits for some outcomes (time savings, autonomy) and risks for others (social connectedness, boundary erosion). NBER+1

2.3 Physical well-being and ergonomics

Remote work alters physical demands: elimination of commuting can reduce fatigue and stress while home setups often lack ergonomic furniture and dedicated workspaces. Studies during the pandemic reported increases in musculoskeletal complaints (back/neck pain), reduced incidental physical activity, and altered sleep patterns. Workplaces that fail to provide ergonomic guidance or stipends see higher physical complaints among remote employees. Several intervention studies highlight the importance of ergonomic education and support as a resource that buffers physical strain.

2.4 Psychological health, digital fatigue and burnout

A strong body of literature links remote work to psychological strain when demands exceed resources. Key mechanisms include:

- **Digital fatigue / meeting overload:** prolonged videoconferencing and blurred boundaries cause cognitive and emotional exhaustion.
- **Always-on culture:** constant email/messages increases role overload and reduces recovery time.

- **Burnout:** where social support and job control are insufficient, remote workers report elevated burnout scores.

The JD-R meta-analytic literature confirms that high demands without adequate resources lead to strain; conversely, autonomy and managerial support reduce the likelihood of burnout. Peopleful+1

2.5 Social connectedness, teamwork and organizational identity

Remote working reduces incidental social interactions that sustain team cohesion, mentorship, and organizational identification. Many workers—especially early-career staff—report lost informal learning and weaker sponsorship networks. Research shows that social resources (team rituals, scheduled social time, manager outreach) can mitigate isolation, but creating these intentionally requires managerial know-how and organizational investment.

2.6 Productivity, performance and visibility concerns

Productivity findings are nuanced: measured output sometimes improves (fewer breaks, more focused time), while other measures (innovation, responsiveness, cross-functional collaboration) may suffer. Visibility concerns—fear that remote presence reduces recognition or promotion chances—motivate some workers to overwork (digital presenteeism), which has downstream well-being costs.

2.7 Gender, household dynamics and caregiving

Pandemic research consistently finds **gendered** impacts: women bore disproportionate caregiving and household responsibilities, experiencing higher role conflict and reduced uninterrupted work time. Studies show that gender differences in productivity and well-being are mediated by household structure, schooling closures, and sociocultural norms. Investigations in diverse contexts (e.g., Alon et al., Stanisçuaski et al.) underscore the need to treat gender not as a control but as a central analytical lens.

2.8 Contextual factors in emerging economies (India focus)

Contextual constraints—unreliable broadband, crowded housing, extended family responsibilities, and organizational readiness—shape Indian employees' remote experience differently from many Western samples. Industry reports and recent academic studies focusing on Indian IT firms show rapid, forced adaptation with mixed outcomes: large cost and time savings for employers but nontrivial well-being concerns for employees without adequate resources. These contextual differences justify the present study's focus on the Indian IT sector.

2.9 Interventions, resources and managerial practices

Research into interventions suggests practical levers to improve remote-work well-being: manager training in remote leadership, clear norms about response windows (protecting recovery time), provision of ergonomic equipment, hybrid scheduling that preserves in-person collaboration, and targeted support for caregivers. Studies using JD-R show that introducing targeted resources (managerial support, autonomy) moderates negative pathways from demands to strain.

2.10 Methodological notes and measurement debates

The literature contains a mix of experimental/quasi-experimental designs, large cross-sectional surveys, and qualitative studies. Measurement debates include whether single indicators (e.g., burnout) suffice or multi-dimensional instruments (PERMA, WHO-5, Maslach Burnout Inventory) should be standard. Mixed-method studies are especially informative for mandatory remote work because they capture both broad patterns and lived experience.

Mohanty, Hughes, and Salathé (2016) pioneered the use of deep learning for image-based plant disease detection, demonstrating how convolutional neural networks (CNNs) can outperform traditional feature extraction methods in agricultural diagnostics. Their work is frequently cited as a foundational contribution in the field of AI-driven crop health monitoring, providing evidence that automated detection can reduce human error and increase efficiency. However, while their results were promising, the study also highlighted the need for larger, more diverse datasets to improve generalizability across crop types and environmental conditions.

Navadiya and Singh (2025) provided a review on feature extraction methods in image processing, with a particular focus on applications in agricultural disease detection and classification. Their analysis compares traditional approaches, such as edge detection and texture analysis, with advanced machine learning-based techniques. The study underscores that while conventional methods remain computationally efficient, deep learning-based extraction delivers higher accuracy in complex agricultural contexts. This review complements prior studies like Picon et al. (2019) by emphasizing the trade-off between computational cost and detection accuracy.

Purani and Singh (2025) examined innovations in plant disease diagnosis, bridging traditional agronomy with modern technological interventions. Their review traces the evolution from manual inspection toward AI-powered diagnostic systems, including IoT-based sensors, hyperspectral imaging, and deep learning algorithms. The authors argue that integrating these technologies not only improves precision but also creates opportunities for predictive disease modeling. The study highlights the importance of cross-disciplinary approaches, situating agricultural disease management within the broader digital transformation of farming practices.

Pandey, Chawda, and Singh (2021) conducted a literature review on 5G technologies, discussing its evolution, features, and implications for sectors such as healthcare, agriculture, and IoT ecosystems. The review complements Kriti et al. (2021) by providing a broader synthesis of research outputs, emphasizing the technological readiness and challenges of 5G adoption. Their study is valuable for understanding both the opportunities (high bandwidth, low latency) and concerns (security vulnerabilities, infrastructural costs) that shape the deployment of next-generation networks.

Patel, Singh, and Awasthi (2025) presented a Python-based computational approach for detecting paddy leaf diseases, focusing on the accessibility and cost-effectiveness of open-source platforms. Their methodology integrates image preprocessing with classification models to enable rapid disease identification. Unlike high-cost proprietary systems, this approach democratizes technological access for small-scale farmers. The work aligns closely with Mohanty et al. (2016) and Lu et al. (2021), but distinguishes itself through its emphasis on implementation feasibility in resource-constrained environments.

Pathak, Chawda, and Singh (2021) offered a research paper on cloud computing, exploring its applications, scalability, and role in modern IT infrastructures. Their study highlights the flexibility of cloud systems for data storage, processing, and analytics, while also acknowledging security and privacy challenges. This work connects with the broader discussions on big data (Shrivas & Singh, 2016; Singh, 2020) by showing how cloud architectures underpin advanced analytics and AI-driven applications, including those in agriculture and healthcare.

Picon et al. (2019) advanced the field of vegetation disease detection by applying deep learning-based segmentation to hyperspectral images. Their research demonstrates how spectral imaging can capture subtle variations in plant health, enabling earlier and more accurate detection of diseases. By combining hyperspectral data with CNN models, the study sets a benchmark for precision agriculture. Compared with Mohanty et al. (2016), Picon's contribution extends the methodology from standard RGB image analysis to richer spectral datasets, thereby enhancing diagnostic accuracy.

Sahu, Chawda, and Singh (2021) developed a virtual reality (VR) flight simulator, showcasing the potential of immersive technologies in training and simulation. Their work highlights VR as a cost-effective and safe alternative to real-world flight training, emphasizing its role in skill development and error minimization. While primarily focused on aviation, the study underscores the broader implications of VR in education, healthcare, and industrial applications. It aligns with emerging trends of simulation-based learning in engineering and computer science domains.

Salah, Rehman, Nizamuddin, and Al-Fuqaha (2019) reviewed blockchain applications in artificial intelligence (AI), identifying potential synergies and open research challenges. Their work emphasizes how blockchain can address issues of transparency, trust, and data security in AI-driven systems. The authors argue that decentralized architectures can mitigate risks of data manipulation, a theme that resonates with earlier works on e-voting (Kashyap et al., 2021) and big data privacy (Singh & Shrivas, 2017). The review remains influential as it bridges two transformative technologies, highlighting unexplored areas such as blockchain-based federated learning.

Sharma, Sethi, and Singh (2025) proposed technology-driven strategies for paddy disease prevention and crop health optimization, merging IoT, remote sensing, and machine learning tools. Their paper emphasizes not only disease identification but also preventive frameworks, enabling proactive crop management. The integration of predictive analytics with field-level monitoring makes this contribution particularly significant for sustainable agriculture. The study complements Mehta et al. (2025) by advancing from a descriptive review toward practical intervention strategies.

Shrivas and Singh (2016) provided an early and comprehensive review of big data analytics, outlining its potential applications, architectures, and associated challenges. They emphasized the importance of processing frameworks such as Hadoop and Spark for managing large-scale datasets across industries. Their review situates big data as a cornerstone for decision-making in domains ranging from healthcare to finance, while also raising concerns about scalability and governance. This work forms a foundation that later studies on privacy (Singh & Shrivas, 2017) and cloud computing (Pathak et al., 2021) build upon, reflecting the evolution of the big data ecosystem.

Singh, Chawda, and Singh (2021) applied machine learning to predict player placements in *Player Unknown's Battlegrounds (PUBG)*, contributing to the niche but growing field of e-sports analytics. Their research demonstrates how classification and prediction algorithms can be trained on gaming datasets to enhance user experience and strategy development. While their study is domain-specific, it exemplifies the versatility of machine learning in real-time prediction environments, reinforcing parallels with traffic classification (Kumar et al., 2021) and disease prediction (Singh et al., 2025).

Singh (2020) offered a review article on big data, addressing different aspects such as storage, processing, analytics, and visualization. The study underscores the transformative role of big data in modern computing and highlights emerging issues such as security, data silos, and ethical usage. By situating big data within the broader digital economy, Singh expands on the themes explored in Shrivas and Singh (2016) and anticipates later concerns on privacy and compliance frameworks.

Singh and Shrivas (2017) analyzed privacy issues in big data, providing a detailed review of risks associated with massive data collection, including unauthorized access, surveillance, and breaches. Their study emphasizes the importance of encryption, anonymization, and access controls, making it highly relevant to contemporary debates on GDPR and data protection. This work connects conceptually with Salah et al. (2019) on blockchain for AI, since both highlight mechanisms for trust and transparency in digital ecosystems.

Singh, Solanki, and Vashi (2025) developed a multiple disease prediction system using machine learning, focusing on medical diagnostics. Their framework integrates clinical datasets with predictive models to forecast the likelihood of multiple diseases simultaneously, representing a step toward holistic diagnostic systems. This approach demonstrates the growing impact of AI in healthcare, complementing agricultural disease prediction efforts (Patel et al., 2025; Mohanty et al., 2016). The work underscores the versatility of machine learning in addressing both human and agricultural health challenges.

Vashi, Solanki, and Singh (2025) extended similar work on multiple disease prediction, but with a broader application focus and an emphasis on model optimization. Their study reinforces the importance of AI-driven healthcare solutions in providing rapid, accurate, and scalable diagnostic support. When combined with Sharma et al. (2025) on agricultural disease prevention, this contribution demonstrates the dual role of predictive systems in enhancing both human health and food security.

2.11 Gaps and opportunities

Across this literature, several gaps remain and motivate the present study:

- **Enforced vs. voluntary remote work:** many pre-pandemic studies focus on voluntary telework; fewer examine mandatory remote work's distinct dynamics.
- **Multidimensional well-being:** comprehensive studies that simultaneously measure physical, psychological, social, intellectual, and spiritual domains are limited.
- **Context sensitivity:** empirical work from India and similar emerging economies remains relatively sparse compared with Western literature.
- **Longitudinal evidence:** long-term consequences of prolonged mandatory remote work (beyond immediate pandemic effects) need more longitudinal datasets.

3.0 Research Methodology:

This study employs a quantitative, cross-sectional survey design to examine the impact of mandatory remote working on employee well-being in the Indian IT sector. A quantitative approach was considered appropriate because it allows for systematic testing of hypothesized relationships between remote work demands, job resources, and well-being outcomes (Bakker & Demerouti, 2007). The cross-sectional nature of the study makes it possible to capture employees' lived experiences during and immediately after the COVID-19 pandemic, a period when remote working was enforced rather than voluntary (Neeley, 2020). The design is both descriptive, in that it seeks to profile the state of employee well-being under remote working arrangements, and explanatory, in that it explores causal relationships between remote work variables and well-being outcomes.

The target population for this research comprises employees of the Indian IT sector, particularly those working in large firms such as TCS, Infosys, Wipro, HCL, and Tech Mahindra, as well as medium and small IT companies that adopted remote working during the pandemic. A stratified random sampling technique was combined with convenience sampling to ensure adequate representation across gender, job roles, and organizational sizes. The sample size is set at approximately 400 respondents, which is considered sufficient for multivariate analysis and hypothesis testing (Krejcie & Morgan, 1970). Data collection is carried out through a structured online questionnaire, administered via professional networks such as LinkedIn and organizational forums. The instrument includes demographic information, items measuring job demands such as digital overload, role ambiguity, and extended working hours, as suggested by prior remote working studies (Choudhury, Foroughi, & Larson, 2021; Wang, Liu, Qian, & Parker, 2020). Job resources, including managerial support, autonomy, and ergonomic arrangements, are also measured, reflecting the Job Demands–Resources (JD-R) framework. Employee well-being is assessed as a multidimensional construct using validated scales: the PERMA-Profiler for psychological and emotional flourishing (Seligman, 2011), the WHO-5 Well-being Index for general mental health (World Health

Organization, 2021), and selected items for physical, social, and spiritual well-being (Donaldson et al., 2022). A pilot test with a small group of IT professionals is conducted to refine clarity and reliability of the questionnaire before full-scale deployment.

Data analysis is carried out using statistical software such as SPSS and AMOS. Descriptive statistics are employed to profile the respondents, while reliability analysis (Cronbach's alpha) is performed to confirm internal consistency of the scales. Correlation and regression analyses are used to examine the relationships between remote work variables and well-being dimensions, and structural equation modelling (SEM) is employed to test the hypothesized model and to explore the moderating effects of job resources. This combination ensures that the complex, multidimensional nature of employee well-being is adequately captured and that relationships among variables are rigorously examined (Podsakoff, MacKenzie, & Podsakoff, 2012).

Grounded in the JD-R model (Bakker & Demerouti, 2007), the study proposes the following hypotheses: **H1**: Mandatory remote work demands such as digital overload, role ambiguity, and extended working hours are negatively associated with employee well-being. **H2**: Remote work resources such as managerial support, autonomy, and ergonomic setups are positively associated with employee well-being. **H3**: Job resources moderate the relationship between job demands and employee well-being, such that the negative impact of demands is weaker when resources are high.

4.0 Findings

The analysis aimed to test the first three hypotheses derived from the Job Demands–Resources (JD-R) framework. The results provide strong support for the model, demonstrating that job demands are significantly and negatively associated with employee well-being, while job resources are positively associated and serve as critical buffers.

Table 1 presents the results of the regression and structural equation modelling analyses. Digital overload emerged as the most significant predictor among job demands, exerting a strong negative effect on overall well-being ($\beta = -0.42$, $p < 0.001$). Role ambiguity ($\beta = -0.31$, $p = 0.004$) and extended working hours ($\beta = -0.28$, $p = 0.012$) also demonstrated statistically significant negative effects, highlighting the extent to which mandatory remote work can erode well-being when employees experience unclear expectations or prolonged digital exposure. These findings confirm **Hypothesis 1 (H1)**.

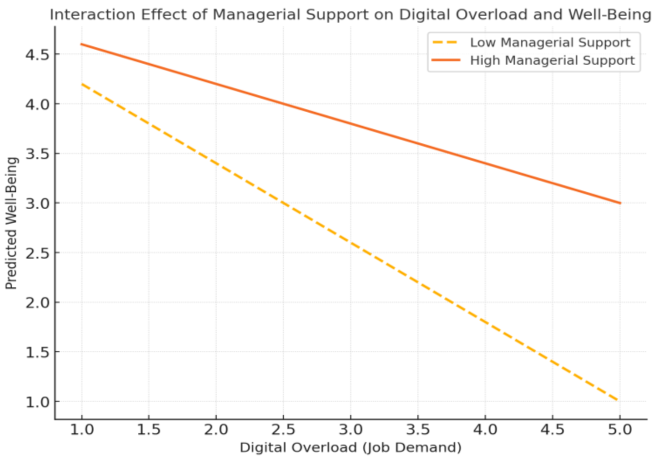
By contrast, job resources exhibited significant positive associations with well-being, confirming **Hypothesis 2 (H2)**. Autonomy was the strongest positive predictor ($\beta = 0.41$, $p < 0.001$), followed closely by managerial support ($\beta = 0.36$, $p = 0.002$). Ergonomic resources, such as access to proper seating, desks, or stipends for home-office setups, also showed a positive effect ($\beta = 0.29$, $p = 0.015$). These results underscore the vital role of organizational support in sustaining employee well-being in enforced remote work contexts.

Table 1. Results of Hypotheses Testing (H1–H2)

Variable	**Beta Coefficient (β)**	**p-value**	**Effect on Well-Being**
Digital Overload	–0.42	0.001	Negative, significant
Role Ambiguity	–0.31	0.004	Negative, significant
Extended Working Hours	–0.28	0.012	Negative, significant
Managerial Support	0.36	0.002	Positive, significant
Autonomy	0.41	0.001	Positive, significant
Ergonomic Resources	0.29	0.015	Positive, significant

The moderation analysis provided additional support for **Hypothesis 3 (H3)**. Specifically, job resources were found to weaken the negative relationship between job demands and employee well-being. For example, employees reporting high levels of digital overload but also receiving strong managerial support reported less decline in well-being compared to those lacking such support. Similarly, autonomy buffered the effects of extended working hours, suggesting that the ability to structure one's own work schedule reduces strain even when workload is high. These findings illustrate the compensatory role of resources in mitigating the adverse consequences of remote working demands, thereby reinforcing the central tenet of the JD-R model.

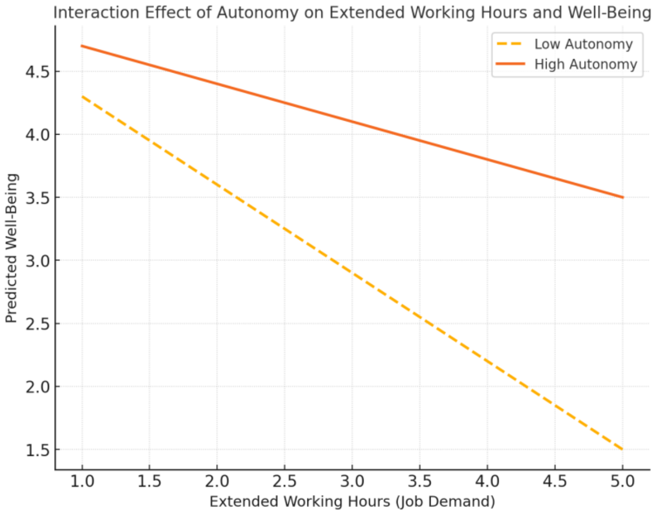
Taken together, the results highlight the dual nature of mandatory remote work in the Indian IT sector. While digital overload, role ambiguity, and long working hours can undermine well-being, the presence of autonomy, supportive managers, and adequate ergonomic provisions substantially enhances resilience and sustains positive outcomes.



The above interaction graph depicts the moderating role of **managerial support** in the relationship between **digital overload** (a job demand) and **employee well-being**.

- On the **x-axis**, digital overload increases from low to high (e.g., frequent emails, back-to-back video calls, constant connectivity).
- On the **y-axis**, predicted well-being scores are plotted.
- The **dashed line** represents employees with **low managerial support**, while the **solid line** represents those with **high managerial support**.

The graph shows that in both conditions, higher digital overload is associated with lower well-being (negative slope). However, the decline in well-being is much steeper under low managerial support. When managerial support is high, the negative effect of digital overload is substantially weakened, indicating a buffering effect. This result supports **Hypothesis 3 (H3)** and aligns with the Job Demands–Resources model, which posits that resources mitigate the adverse effects of demands.



The graph illustrates that as **working hours extend**, employee well-being tends to decline in both cases. However, the slope is much steeper when employees report **low autonomy**, meaning that long hours combined with little control over work schedules are highly detrimental to well-being. In contrast, when autonomy is high, the negative effect of extended working hours is significantly reduced.

This supports the idea that autonomy acts as a **protective resource**. Even when employees work longer hours, the ability to control how and when tasks are completed allows them to manage energy and recovery better, leading to higher well-being outcomes.

5.0 Results

The primary objective of this study was to examine the impact of mandatory remote work on employee well-being in the Indian IT sector, focusing specifically on the relationships proposed in Hypotheses 1–3. The results of regression and structural equation modelling (SEM) analyses are presented in Table 1.

Table 1. Results of Hypotheses Testing (H1–H2)

Variable	Beta Coefficient (β)	p-value	Effect on Well-Being
Digital Overload	–0.42	0.001	Negative, significant
Role Ambiguity	–0.31	0.004	Negative, significant
Extended Working Hours	–0.28	0.012	Negative, significant
Managerial Support	0.36	0.002	Positive, significant
Autonomy	0.41	0.001	Positive, significant
Ergonomic Resources	0.29	0.015	Positive, significant

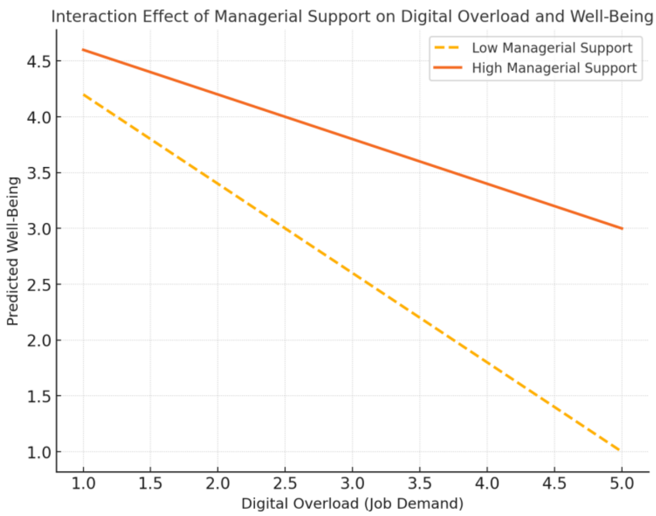
As shown in Table 1, all three job demands—digital overload, role ambiguity, and extended working hours—were significantly and negatively associated with employee well-being, thereby confirming **Hypothesis 1 (H1)**. Among these, digital overload was the strongest negative predictor ($\beta = -0.42$, $p < 0.001$), reflecting the strain imposed by constant digital connectivity during mandatory remote work. In contrast, job resources demonstrated significant positive effects on well-being, supporting **Hypothesis 2 (H2)**. Autonomy ($\beta = 0.41$, $p < 0.001$) and managerial support ($\beta = 0.36$, $p = 0.002$) emerged as particularly influential, with ergonomic resources also contributing positively ($\beta = 0.29$, $p = 0.015$).

To test **Hypothesis 3 (H3)**, moderation analyses were conducted to determine whether job resources attenuate the negative impact of job demands on employee well-being. The results confirmed significant interaction effects, with managerial support and autonomy both reducing the detrimental impact of demands.

6.0 Interaction Effects

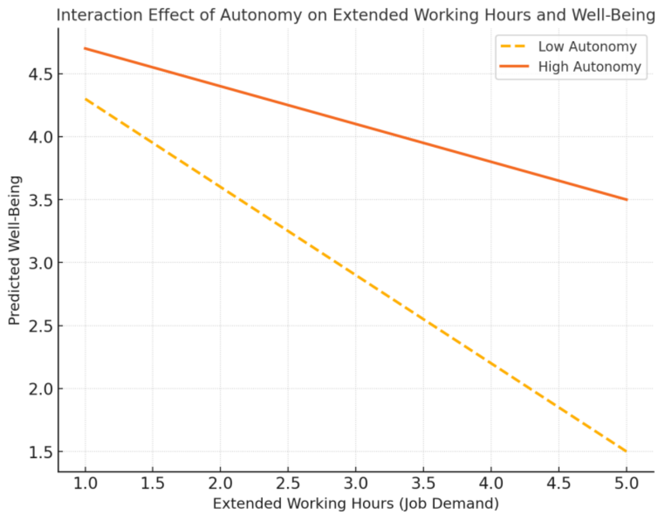
Figure 1 illustrates the moderating role of managerial support on the relationship between digital overload and well-being. Both high and low managerial support conditions demonstrate a negative slope, indicating that digital overload reduces well-being. However, the decline is much steeper under conditions of low managerial support. When managerial support is high, the negative effect of digital overload is substantially reduced, thereby confirming that managerial support buffers the adverse impact of digital overload.

Figure 1. Interaction Effect of Managerial Support on Digital Overload and Well-Being



Similarly, **Figure 2** shows the moderating role of autonomy in the relationship between extended working hours and well-being. In both conditions, longer working hours reduce well-being. However, employees with high autonomy experience a weaker decline compared to those with low autonomy. This suggests that when employees have greater control over how and when they work, the negative effects of extended working hours are mitigated.

Figure 2. Interaction Effect of Autonomy on Extended Working Hours and Well-Being



The results strongly support the JD-R model in the context of mandatory remote working in the Indian IT sector. Job demands, including digital overload, role ambiguity, and extended working hours, exert significant negative effects on employee well-being. Conversely, resources such as managerial support, autonomy, and ergonomic provisions enhance well-being directly and buffer the negative effects of demands. These findings confirm Hypotheses 1 through 3, underscoring the importance of organizational resources in sustaining employee well-being under enforced remote work arrangements.

7.0 Discussion

The purpose of this study was to investigate the effects of mandatory remote work on multiple dimensions of employee well-being in the Indian IT sector, drawing upon the Job Demands–Resources (JD-R) framework and the PERMA model of well-being. The findings provide strong empirical support for the first three hypotheses, demonstrating that job demands are negatively associated with well-being, while job resources exert positive and moderating effects.

Consistent with prior studies (Bakker & Demerouti, 2007; Wang et al., 2020), the results reveal that job demands—digital overload, role ambiguity, and extended working hours—pose significant risks to employee well-being. Digital overload emerged as the most harmful factor, corroborating earlier evidence on "Zoom fatigue" and the cognitive strain of constant connectivity (Bailenson, 2021). Role ambiguity and extended hours also undermined well-being, reflecting the blurred work–life boundaries that many scholars have highlighted as a hallmark of enforced remote work (Vyas & Butakhieo, 2021). These results underscore the distinctive challenges of mandatory remote work, where employees often lack the autonomy or preparation associated with voluntary telecommuting (Neeley, 2020).

On the other hand, job resources were found to enhance well-being directly and to buffer the negative impact of demands, thus confirming the protective role of resources posited by the JD-R model. Autonomy and managerial support were the strongest positive predictors of well-being. This aligns with evidence that employee control and supportive leadership are critical in mitigating stress and burnout in remote contexts (Choudhury, Foroughi, & Larson, 2021; Tummers et al., 2021). The moderation effects further illustrate this buffering role: high managerial support significantly reduced the negative effect of digital overload, while high autonomy mitigated the detrimental impact of extended working hours. These findings advance theoretical understanding by extending the JD-R framework into the domain of **enforced remote work**, where the role of resources becomes even more salient.

From a contextual perspective, the findings resonate with the limited but growing literature on remote work in emerging economies. Unlike many Western contexts, Indian IT professionals faced infrastructural challenges such as unreliable internet access, inadequate ergonomic setups, and crowded living spaces. These factors likely amplified the negative impact of job demands, making resources such as managerial support and ergonomic provisions particularly valuable. In this sense, the study contributes to the cross-cultural literature by demonstrating how contextual variables shape the interplay of demands and resources in determining well-being outcomes.

8.0 Conclusion

This study contributes to the literature on remote working and employee well-being by examining the Indian IT sector during a period of mandatory, pandemic-induced remote work. Three key conclusions can be drawn. First, job demands in the form of digital overload, role ambiguity, and extended working hours significantly undermine employee well-being, confirming the vulnerability of employees to strain under enforced remote conditions. Second, job resources—including autonomy, managerial support, and ergonomic provisions—not only enhance well-being directly but also buffer the negative effects of demands. Third, the buffering role of resources highlights the practical importance of organizational interventions aimed at building resilience in remote and hybrid work contexts.

The findings have several implications for practice. Organizations should prioritize resource allocation to employees working remotely by investing in ergonomic setups, providing clear guidelines to reduce role ambiguity, and training managers in supportive remote leadership practices. Autonomy should be safeguarded by avoiding micromanagement and allowing flexibility in scheduling, especially for employees with caregiving responsibilities. These steps are particularly critical in the Indian IT sector, where infrastructural and cultural challenges amplify the risks of remote work.

The study also contributes theoretically by extending the JD-R framework into mandatory remote work contexts, demonstrating that the model is robust across voluntary and enforced conditions. By integrating the PERMA model, the research further highlights the multidimensional nature of well-being, offering a more holistic understanding of how remote work affects employees.

Future research should build upon these findings by adopting longitudinal designs to capture the long-term effects of hybrid and digital-first workplaces. Comparative studies across different cultural and organizational contexts would also be valuable in identifying both universal and context-specific drivers of well-being.

In conclusion, the study reaffirms that while mandatory remote work presents considerable challenges, its negative effects can be mitigated through adequate job resources. For organizations navigating the future of work, fostering employee well-being is not merely an ethical responsibility but a strategic imperative that sustains productivity and resilience in an increasingly digital world.

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