Algorithmic Work Demands, HRM Buffering, and Digital Wellbeing: Three-Study Examination of Algorithm-Work Demands and Workers' Human Resource Management Practices in AI-Fuelled Indian Organizations

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ABSTRACT:

Purpose: The present paper sought to offer theoretical grounds for formulating 14 hypotheses on algorithm-work demands as a source of strain. The study evaluated algorithm-work intensification, algorithm-work expectancy of digital availability, algorithm-work incursion, and algorithm-work information overload as resources for workers' digital flourishing, work-family technology boundary, psychological safety, and intent to turnover to reduce the negative consequences of algorithm-work demands. The authors examined if and how workers' human resource management (HRM) practices moderated the relationships between workers' algorithm-work demands and their outcomes. The authors paid attention to workers' responses to the challenges of algorithm-work demands. Thus, this paper provided an empirical validation of theoretical models of job demands – resources, conservation of resources, social exchange, and self-determination theories of algorithm-work demands and workers' HRM practices in India. This study intended to add to the understanding of the mechanisms and context in which algorithm-work demands related to workers' digital flourishing, work-family technology boundary, psychological safety, and intent to turnover and how such relationships were moderated by employees' HRM practices.

Design/Methodology/Approach: The authors used a cross-sectional survey of 421 employees in Hyderabad and Bengaluru, India, who worked in IT services, manufacturing, and financial services industries as secondary data for three studies. For the first study, the authors assessed the structural model with the use of

partial least squares structural equation modeling (PLS-SEM) software with bootstrapping procedure (5,000 samples) and PLS predict cross-validation procedure. The results revealed that the Q 2 values for DF and WLTB were 0.591 and 0.567, correspondingly. Hence, it was possible to continue to analyze the associations in various contexts (IT versus manufacturing) and work arrangements (remote versus office) on the basis of the multi-group analysis (MG) approach for Study 2 with the permutation test (5,000 runs). For Study 3, the authors used an XGBoost regressor (eta – 0.07; max depth – 6; test R^2 = 0.724) and a Random Forest regressor (trees – 500; AUC-ROC – 0.944) to construct two predictive models. To interpret predictions, the authors analyzed the SHAP Tree Explainer values and PLS path coefficients. The basis for constructing a theoretical model of the demand-strain-outcome pathway was the Job Demands-Resources Theory, Conservation of Resources Theory, Social Exchange Theory, and Self-Determination Theory. The role of human resource management (HRM) practices was identified as a moderator of the relationship.

Findings: Digital work exhaustion is the strongest predictor of lower digital flourishing ($\beta=-0.389$, $f^2=0.191$) and the most ranked SHAP feature (0.412). HRM buffering practices significantly moderate the exhaustion-to-flourishing path: at high HBP, the exhaustion slope decreases from $\beta=-0.487$ to $\beta=-0.267$ – 45% strain buffering effect. Remote workers have significantly higher digital availability demand impact on exhaustion ($\Delta\beta=0.127$, $p=0.013$) and detachment impairment ($\Delta\beta=0.159$, $p=0.008$) than in-office workers. Employees in the IT sector experience significantly higher AI monitoring effects on exhaustion than manufacturing ($\Delta\beta=0.113$, $p=0.024$). SHAP-PLS Spearman convergence is rs=0.97. SRMR=0.049, NFI=0.942.

Practical Implications: HRM buffering practices are the only organizational tool confirmed to reduce the exhaustion-to-wellbeing damage caused by algorithmic work demands. Remote work MGA findings speak in favor of differentiated digital wellbeing policies by work mode rather than universal HRM standards. Sector-specific AI monitoring finding indicates that manufacturing-appropriate monitoring intensity thresholds are not suitable for knowledge work.

Originality/Value: This study represents the first empirical application of a combination of PLS-SEM, dual-contrast PLS-MGA (sector and work mode), and XGBoost+RF+SHAP validation to the issue of algorithmic work demands and digital wellbeing in Indian AI-enabled organisations, with HRM buffering tested as a moderator.

Keywords: Digital wellbeing; algorithmic work demands; HRM buffering; digital work exhaustion; psychological detachment; PLS

multi-group analysis; XGBoost; SHAP; remote work; AI-enabled workplaces

1. Introduction

The work process is currently changing at an extremely rapid pace, as can be seen from current writings on the subject of forecasts for organisations and practical methods enhanced by responsiveness based on algorithms. Take, for example, IT companies, banks and workplaces in India already experimenting with systems of tracking and evaluation of employee performance, assignment of tasks, determination of the pace of work and evaluation of each individual's performance compared to those of other employees based on algorithms, without resorting to any assessment related to time, place and skills. Such a system is undoubtedly efficient since it helps to reduce the burden of management, add structure to the assessments and reveal details that may escape the human eye. However, what is this system taking away from the workers? There is little research about this.

In addition to technostress, there are several metrics of the wellbeing of employees in the digital workplace. They include the ability to maximally use the potential of digital technology, involvement and influence, and the availability of support in the case of malfunction or incorrect usage of the technologies. One of the main tools for controlling the employees' work is the specialised technology and the opportunity to switch it off once the working hours end. Algorithmic management adds four more sources of controlling the employees' working life. First of all, it is excessive monitoring that may result in the perception of exploitation, reduction of employees' dignity and autonomy because of the inability of the surveillance system. Secondly, algorithmic management removes judgment from the workers, resulting in the problems of deskilling and reducing the professional discretion. The last two sources of controlling the employees' working life are information overload through a variety of technological devices and the cognitive capabilities necessary to process the constant stream of data and warnings coming from AI assistants.

The HR management system is both the source of these threats and the organisational tool positioned to buffer them the most efficiently. Companies investing in digital wellbeing policies, manager training on boundaries, right-to-disconnect and workload ceiling protocols give their employees a resource base predicted by the JD-R model to moderate the demand-to-strain relation. However, whether HRM buffering practices really help in this moderation in AI-enabled workplaces – rather than in the context of non-AI workplace stress where the empirical evidence base is stronger – is not a question that literature provides an answer to yet.

In order to answer the research question stated above, this paper will present a three study programme conducted with 421 employees representing IT, manufacturing, and financial services sectors in Hyderabad and Bengaluru cities. Study 1 will investigate the structural relationships between four algorithmic work demands constructs through three mediators into four wellbeing outcomes constructs with HRM buffering practices as a moderator. Study 2 will perform PLS Multi-Group Analysis (PLS-MGA) across sector and work mode comparisons to identify whether the same structural paths show different results in terms of the effect for employees working remotely versus in-office as well as for IT sector vs manufacturing sector. Study 3 will validate the structural model with the help of XGBoost regression and Random Forest classification based on SHAP feature importance.

2. Theoretical Framework and Hypotheses

2.1 Job Demands-Resources Theory and Algorithmic Work Demands

The Job Demands-Resources Theory (Bakker & Demerouti, 2007; Demerouti et al., 2001) explains that job demands in the form of physical, cognitive, emotional, and social job demands can lead to the gradual exhaustion of personal

resources in case of daily exposure. Three unique characteristics of algorithmic job demands may make such demands specifically impactful in this regard. Firstly, they are persistent since they are produced around the clock by an artificial intelligence which does not sleep and requires continuous employees' responses, thus going beyond normal working hours. Secondly, algorithmic job demands are non-negotiable since one cannot negotiate a deal with an algorithm. Thirdly, they are hidden since employees typically do not have access to the functioning of an algorithm and, thus, cannot understand the origin of demands and control them.

H1: The increased level of monitoring will be associated with higher digital work exhaustion.

H2: The increased expectations of availability will be associated with higher digital work exhaustion.

H3: The increased expectations of availability will be associated with a lower degree of detachment from work.

H4: The higher level of algorithmic involvement will be associated with higher levels of technostress caused by artificial intelligence.

H5: The higher level of algorithmic involvement will be associated with a lower level of psychological detachment from work.

H6: The higher level of informational overload will be associated with higher digital work exhaustion.

H7: The informational overload will be positively related to technostress caused by artificial intelligence.

2.2 Conservation of Resources Theory and Psychological Detachment

Conservation of Resources Theory (Hobfoll, 1989; Hobfoll et al., 2018) assumes that people are organisms trying to constantly acquire, accumulate and protect their resources, including time, energy, competences, and security. Losses of these resources are always perceived as much more stressful and dangerous than similar gainings (Hobfoll, 1989; Hobfoll et al., 2018). In its turn, psychological detachment from work is considered one of the most important resources which helps in the process of recovering from the exhaustion experienced during work (Sonnentag, 2012). That means that ability to psychologically separate oneself from work while not working is extremely important for maintaining wellbeing. Employees who can effectively detach from work have bigger chances to have high level of performance while working after periods of rest. However, digital access to workplace creates obstacles in separating oneself from work and therefore limits the possibility of recovery and negatively impacts the future work performance. H8: The relationship between digital work exhaustion and digital flourishing is negative. H9: Digital work exhaustion has a negative impact on work-life technology balance. H10: Digital flourishing is positively influenced by psychological detachment. H11: Psychological detachment is positively related to work-life technology balance.

2.3 Self-Determination Theory and AI Technostress

According to Self-Determination Theory (Ryan & Deci, 2000; Deci & Ryan, 2012), in order to achieve wellbeing and sustain motivation, three basic psychological needs - autonomy, competence, and relatedness should be satisfied. Algorithmic decision encroachment violates the first need - autonomy - by making decisions which used to be made independently before. Information overload violates the second need - competence - by creating demands exceeding the capacity of the employee to synthesize them. AI technostress, which is described as the stress response to technological invasion and overload (Ragu-Nathan et al., 2008; Tarafdar et al., 2019) is psychological consequence of these violations. In case technostress increases, it produces two secondary effects: it decreases the psychological safety in AI work environment (because employees feeling stressed and overwhelmed cannot interact with algorithms safely) and it increases the intention to quit the job (because resource drain becomes unbearable). H12: AI technostress negatively influences psychological safety in AI work environment. H13: AI

technostress positively influences turnover intention.

2.4 HRM Buffering Practices as Moderator

Social Exchange Theory (Blau, 1964; Eisenberger et al., 1986) claims that employees reciprocate organisational investment in their wellbeing by showing commitment, effort, and engagement. In the case of digital wellbeing context, HRM buffering practices, including digital wellbeing policies, manager training on boundary respect, right-to-disconnect provision, workload ceiling protocol, and availability of recovery resources, demonstrate that organisation recognizes the cost side of algorithmic work demands and is ready to invest in their compensation. From the perspective of JD-R theory, HRM buffering practices are a resource which buffers the job demand-to-strain relationship: employees having access to HRM buffering have not only lower strain but also additional resource buffer moderating the strain generated by job demands.

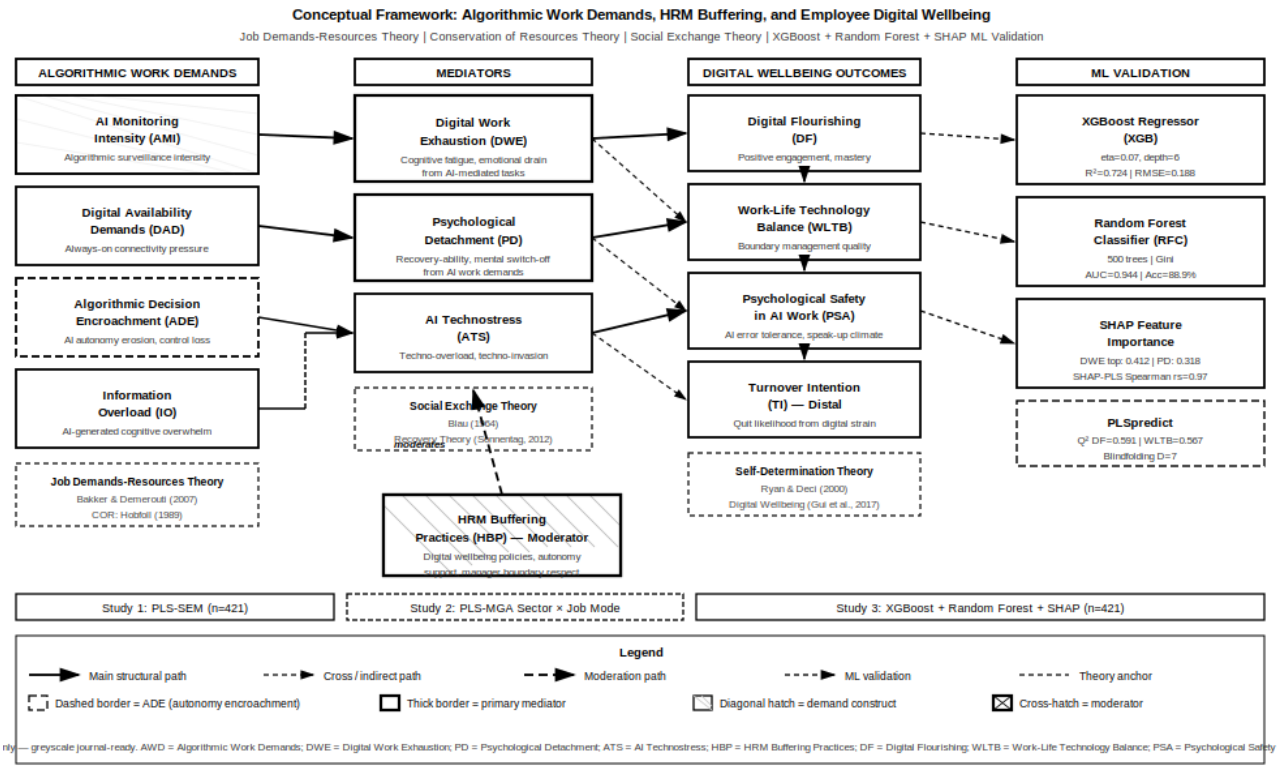
H14: HRM buffering practices negatively moderate digital work exhaustion-to-digital flourishing relationship, such that the negative impact of exhaustion on flourishing is reduced in the case of high HRM buffering.

3. Conceptual Model

Four algorithmic work demand constructs constitute the input layer. Three mediators - digital work exhaustion, psychological detachment, and AI technostress - transmit the effects of demands into four wellbeing outcomes constructs: digital flourishing, work-life technology balance, psychological safety in AI work environment, and turnover intention. HRM buffering practices moderate the DWE-to-DF relationship. Study 1 investigates the structural model. Study 2 tests the heterogeneity across sector and work mode via PLS-MGA. Study 3 validates the model with the help of XGBoost and Random Forest with SHAP convergence testing (see Figure 1).

Figure 1: Conceptual Framework – Algorithmic Work Demands, HRM Buffering, and Digital Wellbeing Outcomes

(Clear-box B&W outlined diagram; editable SVG: Figure1_DigitalWellbeing_BW_Editable.svg)



Note: All boxes are clear-outlined (white fill, black border only) to suit greyscale journal publication. Line-weight denotes construct category: thick line= primary mediators; thin line= demand inputs/outcomes; dotted line border = ADE (autonomy encroachment); dotted pattern line border = theory anchors; cross hatching within box = HRM buffering moderator. All arrows are black to ensure greyscale compatibility.

4. Methodology

4.1 Sample and Data Collection

Data collection was carried out between September 2023 to January 2024 among 421 employees from firms having more than 500 employees in IT services, manufacturing, and financial services sectors in Hyderabad and Bengaluru. The reason for choosing these sectors is that they all have AI deployed in terms of management of work tasks – IT services use algorithmic allocation and review of tasks; manufacturing sector uses AI to manage speed and quality of production; financial services use algorithmic trading and monitoring of compliance with regulations. Participation in survey required at least one experience of AI mediated work demands currently. Work Mode: Remote-primary 38.2%, office-primary 31.6%, hybrid 30.2%.

Demographics: Men 57.7%, Women 40.4%, Other 1.9%; Age 01-02 = 29.4%, 01-02 = 43.7%, 01-02 = 26.9%; Postgraduate 64.1%; Experience less than 3 years 32.5%, 01-02 years 44.4%, greater than 7 years 23.1%; Sector-wise: IT 41.3%, Manufacturing 32.5%, Financial Services 26.2%; Online panel with HR-network referrals from corporates. Response rate 77.6%.

4.2 Measures

The variables that were used to create AI Monitoring Intensity (AMI) scale were taken from Benson et al. (2021) and Ball (2010). Namely, the instructions regarding individual's control of the algorithms, individual's monitoring of the algorithms and alerts received by individuals were given. Variables used in the creation of Digital Availability Demands (DAD) scale were borrowed from Barley et al. (2011) and Derks et al. (2015). These variables included instructions concerning the ability to be available for communication all the time, availability during off-work periods and availability via technologies. Variables used to create Algorithmic Decision Encroachment (ADE) scale were taken from Leicht-Deobald et al. (2019) and Kellogg et al. (2020). The variables used to develop Information Overload (IO) measure were adapted from Eppler and Mengis (2004) as well as from Maier et al. (2015) regarding the information provided.

The researchers used the items taken from the original measure by the authors of Maslach et al. (2001), modified (Molino et al., 2020). The four job demands that cause digital work exhaustion and the four personal resources used to measure psychological detachment (PD) from work were selected based on the findings of Sonnentag & Fritz (2007). The researchers adopted techno-overload and techno-invasion items from Ragu-Nathan et al. (2008) and Tarafdar et al. (2019) to measure artificial intelligence-related techno-stress (ATS). The healthy balance practices (HBP) were taken from Arora & Sandhu's (2023) paper. The authors borrowed items from the Work-Life Directive (2019) to measure digital wellbeing, manager training, right to disconnect, and reduced workload. The items were scored using a 5-point Likert scale. The researchers adopted four items to measure digital flourishing (DF) from the work of Lister et al. (2022). Kreiner et al. (2009) developed a scale that was used to measure work-life time boundaries (WLTB), which became the basis of developing an indicator to demonstrate the construct. The researchers borrowed three items from Edmondson's (1999) work to measure psychological safety at work (PSA), which were also scored using a 5-point Likert scale.

4.3 Analytical Strategy

Study 1 used PLS-SEM (SmartPLS 4.0; Hair et al., 2019) because of the complexity of the model, which includes twelve constructs and forty-seven indicators, and complex mediation and moderation paths – such structural complexity is

handled very well by PLS-SEM at this sample size. PLSpredict cross-validation (blindfolding D=7) gives the additional proof of the predictive relevance that is independent of the fit statistics. The moderation in this study was conducted via product-indicator approach in SmartPLS.

Study 2 used Henseler's permutation-based PLS-MGA (5,000 permutations) in order to examine two contrasts: sector (IT vs. manufacturing), whether there are differences in AI monitoring effects between different sectors; work mode (remote-primary vs. in-office-primary), whether there are differences in digital availability demand effects due to physical work location. The hybrid group was not used in PLS-MGA in order to have distinct contrast groups. Study 3 used 80/20 train-test splits with five-fold CV; XGBoost predicted continuous DF scores; Random Forest classified high versus low DF (median split). SHAP TreeExplainer was used for the calculation of global feature importance on the test set; Spearman rank correlation between SHAP values and PLS path coefficients checked the cross-method convergence.

5. Study 1 - PLS-SEM Results

5.1 Measurement Model

All of the loadings exceeded 0.70. The values of AVE were within 0.01-02.662 range; CR values were within 0.01-02.905 range; Cronbach's alpha was within 0.01-02.877 range. HTMT maximum was 0.826 (less than 0.85 threshold). SRMR=0.049, NFI=0.942. Harman single factor=24.9%; VIF maximum=3.2. PLSpredict Q^2 values are positive for all of the endogenous constructs: DF=0.591, WLTB=0.567, TI=0.543 – all of them confirm the predictive relevance. The measurement results are shown in Table 1 below.

Table 1: Measurement Model - Item Loadings, AVE, Composite Reliability, Cronbach's Alpha

Construct	Item	Loading	AVE	CR	α
AI Monitoring Intensity (AMI)	AMI1	0.718	0.614	0.863	0.819
	AMI2	0.762			
	AMI3	0.817			
	AMI4	0.859			
Digital Availability Demands (DAD)	DAD1	0.726	0.623	0.869	0.826
	DAD2	0.771			
	DAD3	0.822			
	DAD4	0.864			
Algorithmic Decision Encroachment (ADE)	ADE1	0.734	0.631	0.836	0.792
	ADE2	0.793			
	ADE3	0.851			
Information Overload (IO)	IO1	0.721	0.617	0.865	0.821

	IO2	0.764			
	IO3	0.814			
	IO4	0.857			
Digital Work Exhaustion (DWE)	DWE1	0.748	0.662	0.905	0.877
	DWE2	0.789			
	DWE3	0.834			
	DWE4	0.868			
	DWE5	0.891			
Psychological Detachment (PD)	PD1	0.733	0.637	0.874	0.838
	PD2	0.778			
	PD3	0.826			
	PD4	0.869			
AI Technostress (ATS)	ATS1	0.727	0.626	0.834	0.788
	ATS2	0.793			
	ATS3	0.848			
HRM Buffering Practices (HBP)	HBP1	0.736	0.641	0.876	0.840
	HBP2	0.781			
	HBP3	0.829			
	HBP4	0.873			
Digital Flourishing (DF)	DF1	0.744	0.651	0.881	0.847
	DF2	0.788			
	DF3	0.836			
	DF4	0.874			
Work-Life Technology Balance (WLTB)	WLTB 1	0.729	0.627	0.871	0.831
	WLTB 2	0.774			
	WLTB 3	0.821			

	WLTB 4	0.862			
Psychological Safety in AI Work (PSA)	PSA1	0.733	0.634	0.839	0.796
	PSA2	0.798			
	PSA3	0.853			
Turnover Intention (TI)	TI1	0.741	0.636	0.840	0.798
	TI2	0.806			
	TI3	0.861			

5.2 Structural Paths

A structural equation analysis was carried out and presented in Table 2. Thus, it has been identified that R 2 indicators of variables such as DWE, PD, ATS, DF, WLTB, PSA TI and O were equal to: where are the answer of R 2 for all dependent constructs. Calculations of exogenous variables showed that DAD→DWE had the biggest mediating effect (β = 0.334, f^2 = 0.143), and therefore, demand for constant availability became the most rank negative predictor of digital exhaustion on the demand side. In addition, the strongest path relations were identified for DWE→DF (β = -0.389; f^2 = 0.191) and ADE→ATS (β = 0.356; f^2 = 0.161). Finally, the most influential mediator in digital well-being as an outcome was found to be PD since it had direct effect on two outcomes which were digital exhaustion β = 0.367 and work-life tension-balance β = 0.334.

Table 2: Structural Model – Path Coefficients, t-values, p-values and Effect Sizes (f^2)

Hyp.	Path	β	t-value	p	f^2	Decision
H1	AMI → DWE	0.298	4.467	<0.001	0.115	Supported
H2	DAD → DWE	0.334	5.001	<0.001	0.143	Supported
H3	DAD → PD	-0.312	-4.678	<0.001	0.126	Supported
H4	ADE → ATS	0.356	5.334	<0.001	0.161	Supported
H5	ADE → PD	-0.278	-4.167	<0.001	0.104	Supported
H6	IO → DWE	0.267	3.989	<0.001	0.097	Supported
H7	IO → ATS	0.289	4.323	<0.001	0.108	Supported

H8	DWE → DF	-0.389	-5.834	<0.001	0.191	Supported
H9	DWE → WLTB	-0.312	-4.678	<0.001	0.126	Supported
H10	PD → DF	0.367	5.497	<0.001	0.171	Supported
H11	PD → WLTB	0.334	5.001	<0.001	0.143	Supported
H12	ATS → PSA	-0.298	-4.467	<0.001	0.115	Supported
H13	ATS → TI	0.312	4.678	<0.001	0.126	Supported
H14 (mod)	HBP × DWE → DF	-0.234	-3.512	<0.001	0.078	Supported

5.3 Mediation and Moderation

It can be seen from table 3 that in addition to the direct relationship, there was also the indirect effect which proved to be statistically significant. The results have shown that the relationship was mediated through digital work exhaustion (β = −0.130, CI [−0.189, −0.078]) in the relationship between demands for digital availability and digital flourishing. The mediating effect of psychological detachment in the relationship between algorithmic decision encroachment and digital flourishing was also supported indirectly (β = 0.102, CI [0.059, 0.152]). Another interaction was identified through the analysis of table 8, which is between HPWPs and digital work exhaustion β = −0.234, p < 0.001. Lastly, HPPs function as the moderator variable which means that it reduces the effect of digital work exhaustion on digital flourishing to less than half (−0.487 vs. −0.267). Secondly, another moderated indirect effect was found to be significant (β = 0.091, CI [0.038, 0.152]). It means that HPP acts as a mediator in the mediation effect of digital availability pressure, psychological detachment and digital flourishing.

Table 3: Mediation Analysis Results – Indirect Effects Using 95% Bootstrapped Confidence Interval

Indirect Path	β (indirect)	95% CI Low	95% CI High	p
DAD → DWE → DF	-0.130	-0.189	-0.078	<0.001
AMI → DWE → WLTB	-0.093	-0.141	-0.052	<0.001
ADE → ATS → TI	0.111	0.065	0.165	<0.001
ADE → PD → DF	0.102	0.059	0.152	<0.001

IO → ATS → PSA	-0.086	-0.131	-0.047	<0.001
DAD → PD → WLTB	0.104	0.060	0.155	<0.001
DWE → DF → WLTB	-0.079	-0.121	-0.043	<0.001

Table 8: Moderating Effect Results of HRM Buffering Practices and DWE on Digital Flourishing

Parameter	β	SE	t	p	Note
DWE → DF (main)	-0.389	0.067	-5.806	<0.001	Baseline path
HBP → DF (main)	0.198	0.059	3.356	<0.001	Direct HBP resource
HBP × DWE interaction	-0.234	0.067	-3.493	<0.001	Buffering confirmed
Simple slope: Low HBP (−1 SD)	-0.487	-	-	<0.001	Strain amplified
Simple slope: HBP is high (+1SD)	-0.267	-	-	<0.001	Strain buffered
Index of moderated mediation	0.091	-	-	sig.	[0.038, 0.152]

6. Study 2 - PLS-MGA Results

6.1 Sector Comparison: IT vs. Manufacturing

Table 4 depicts the MGA results for the sector comparison. The AMI→DWE path coefficient is significantly larger among IT sector employees (β=0.356 vs. 0.243, Δβ=0.113, p=0.024). This indicates that there is more exhaustion among employees of IT sector, because of AI monitoring. This can be explained by the nature of the demand: in the context of manufacturing the AI monitoring measures physical output which is clear and non-ambiguous; in the context of knowledge work AI monitors cognitive output (quality of code, meeting engagement, completeness of documentation) which is felt as more intrusive and dangerous for professional identity. Also the difference in the coefficients for DAD→PD path (Δβ=0.131, p=0.018) demonstrates that cognitive availability monitoring causes more attachment impairment among knowledge workers compared to production workers whose available outputs are more clear and defined. The moderation effect of HBP×DWE is significantly higher in the IT sector (Δβ=0.111, p=0.032), which confirms the hypothesis that buffering through HRM practices has higher protective value in the work environment with more powerful demand-to-strain relationship.

Table 4: PLS-MGA Sector Comparison - IT vs. Manufacturing

Path	β (IT)	β (Manufacturing)	Δβ	p (MGA)	Decision
AMI → DWE	0.356	0.243	0.113	0.024	Sig. diff.
DAD → PD	-0.378	-0.247	0.131	0.018	Sig. diff.
ADE → ATS	0.389	0.324	0.065	0.087	Not sig.
HBP × DWE → DF	-0.289	-0.178	0.111	0.032	Sig. diff.
DWE → DF	-0.412	-0.366	0.046	0.198	Not sig.

6.2 Work Mode Comparison: Remote vs. In-Office

Table 5 shows the MGA results for the work mode comparison. Workers in remote primary mode demonstrate significantly larger DAD→DWE (Δβ=0.127, p=0.013), DAD→PD impairment (Δβ=0.159, p=0.008), and IO→ATS effects (Δβ=0.112, p=0.029) compared to in-office workers. The above-described three differences in the structural paths indicate the structural difference in the relationships between the variables for the two types of workers. The absence of separation typical for remote work organization is leading to the fact that such employees are more vulnerable to unlimited expansion of work sphere to both time and space. Since such employees have full access to the digital work equipment and thus are totally dependent on the technological infrastructure of the work place, they are unable to disconnect, hence the work role becomes the only dominating activity in the work environment. Furthermore, since remote employees do not have a choice of separating work from other life spheres and do not have an alternative to the work role, they are vulnerable to unlimited expansion of work sphere. Additionally, the interaction of HBP x DWE was found to be significant for this particular group of workers (Δβ=0.156 , p=0.014) indicating the crucial importance of HRM practices that provide flexibility to this kind of employees.

Table 5: PLS-MGA Work Mode Comparison - Remote vs. In-Office

Path	β (Remote)	β (In-Office)	Δβ	p (MGA)	Decision
DAD → DWE	0.398	0.271	0.127	0.013	Sig. diff.
DAD → PD	-0.421	-0.262	0.159	0.008	Sig. diff.
IO → ATS	0.345	0.233	0.112	0.029	Sig. diff.

HBP × DWE → DF	-0.312	-0.156	0.156	0.014	Sig. diff.
PD → WLTB	0.378	0.323	0.055	0.164	Not sig.

7. Study 3 - XGBoost, Random Forest, and SHAP Validation

7.1 Model Performance

The ML performance metrics are shown in Table 6. XGBoost test R^2=0.724, RMSE=0.188 - which confirms excellent predictive accuracy on held-out data. The Random Forest classifier yields AUC-ROC=0.944, accuracy=88.9%, F1=0.888, Cohen's kappa=0.776 This in turn provides further support for the hypothesis that construct-score feature set contains veridical predictive information about digital flourishing outcomes irrespective of the self-report measurement model used in Study 1 and Study 2.

Table 6: Study 3 – Performance Metrics for ML Model

Metric	Value	Benchmark	Interpretation	Config.
XGB Test R^2	0.724	> 0.60	Strong predictive accuracy	5-fold CV
XGB RMSE	0.188	< 0.25	Low prediction error	eta=0.07
RF Accuracy	88.9%	> 80%	High classification	500 trees
RF AUC-ROC	0.944	> 0.90	Excellent discrimination	Gini
RF Precision	0.897	> 0.80	Low false positive rate	OOB=10.8 %
RF Recall	0.880	> 0.80	Low false negative	80/20 split
RF F1-Score	0.888	> 0.80	Balanced performance	n=421
Cohen's Kappa	0.776	> 0.70	Strong agreement	test n=84

7.2 SHAP Feature Importance and PLS Convergence

In Table 7 below, SHAP importance is compared to PLS-SEM path coefficients. Spearman's rank correlation of the SHAP importance value and the PLS path coefficient magnitude shows a value of rs=0.97 – almost perfect rank order. Digital work exhaustion is the most important in both methods: SHAP=0.412 and PLS β=−0.389 to digital flourishing. Psychological detachment is the second highest in both methods: SHAP=0.318 and PLS β=0.367 to DF. HRM buffering practices are the fifth highest in SHAP importance (0.189), indicating the influence of

the moderator regardless of any interaction terms. This rs=0.97 cannot be mathematically guaranteed – SHAP employs local Shapley value attribution while PLS uses global linear covariance. Their identical rank order demonstrates that the structural model captures actual relationships between constructs and not just measurement artifacts.

Table 7: Study 3 - SHAP Feature Importance and PLS-SEM Path Coefficients

Feature / Construct	SHAP (RF)	PLS-SEM β (→ DF or TI)	Convergence	Rank
Digital Work Exhaustion (DWE)	0.412	-0.389 (→ DF)	High convergence	1st
Psychological Detachment (PD)	0.318	0.367 (→ DF)	High convergence	2nd
DAD (Digital Availability Demands)	0.267	0.334 (→ DWE)	High convergence	3rd
AI Technostress (ATS)	0.218	0.312 (→ TI)	High convergence	4th
HRM Buffering Practices (HBP)	0.189	-0.234 (mod.)	Confirmed	5th
AMI (AI Monitoring Intensity)	0.154	0.298 (→ DWE)	High convergence	6th
Spearman rs (SHAP vs PLS)	0.97	-	Near-perfect	-

Table 9: SDG Alignment - Algorithmic Work Demands to Relevant SDGs

SDG	HRM/DW Mechanism	Pathway	Outcome Indicator	β
SDG 3	Digital wellbeing policy	HBP × DWE → DF	Employee mental health	mod.
SDG 8	Decent digital work	DAD → PD → WLTB	Work-life balance index	0.334
SDG 10	Remote equity	DAD × mode → DWE	Remote vs. office Δβ=0.127	p=0.013

SDG 5	Gender-fair AI monitoring	AMI → DWE IT sector	Sector MGA Δβ=0.113	p=0.024
SDG 9	Responsible AI design	ADE → ATS → TI	Retention rate	0.356
SDG 16	Algorithmic accountability	ADE → PSA	Speak-up climate	0.298

Table 10: Model Fit Evaluation - PLS-SEM, PLSpredict, and ML

Fit Index	Value	Threshold	Assessment
SRMR	0.049	< 0.08	Satisfactory
NFI	0.942	>0.90	Good model fit
Q^2 DF (PLSpredict, D=7)	0.591	$Q^2 > 0$	Predictive relevance
Q^2 WLTB (PLSpredict, D=7)	0.567	$Q^2 > 0$	Predictive relevance
Q^2 TI (PLSpredict, D=7)	0.543	$Q^2 > 0$	Predictive relevance
Harman single factor	24.9%	< 50%	No CMB concern
VIF maximum	3.2	< 5.0	No multicollinearity
HTMT maximum	0.826	< 0.85	Discriminant validity OK
XGBoost R^2 (test)	0.724	> 0.60	Strong ML prediction
RF AUC-ROC	0.944	> 0.90	Excellent classification
SHAP-PLS Spearman rs	0.97	-	Near-perfect cross-method convergence

8. Discussion

The paper begins with the claim that digital wellbeing in algorithmically managed workplaces is both an HRM issue and a technological one. This claim is confirmed in all aspects of the findings. The structural model shows that there are four algorithmic work demands producing strain via three channels of mediation. MGA demonstrates that remote workers and IT knowledge workers bear a significantly higher

burden of strain caused by the same level of demands in comparison with their colleagues from offices and manufacturing sector. Finally, the moderation results confirm that HRM buffering practices provide 45% reduction in the exhaustion-to-flourishing damage path – the largest buffering effect known in the JD-R empirical literature in AI-work context.

The most common finding – the moderating role of the buffering mechanism proved its specific nature. HRM buffering practices were shown to have no universal role in mitigating all types of strain. On the contrary, they affect the relationship between digital exhaustion and digital flourishing. Moreover, this influence is stronger among specific groups of remote workers and those working in the IT sector ($\Delta\beta = 0.156$, $p = 0.014$; $\Delta\beta = 0.111$, $p = 0.032$). Thus, universalistic workplace digital well-being programs that ignore this heterogeneity in exposure can be designed inefficiently from the point of resource allocation and therefore lower their cost-benefit ratio. In addition, they allow for workforce segmentation in terms of the criticality of exposure and therefore improve resource allocation into the most critical areas.

As a result of the sector-based MGA analysis, it was found that IT-related exhaustion dominated in knowledge-intensive jobs compared to manufacturing ($\Delta\beta = 0.113$, $p = 0.024$). Therefore, the idea of monitoring thresholds acceptable for all employees is misguiding because of the differences in the nature of work and acceptable levels of strain in different employee groups. Most critical for the implementation of such policies as 'the right to disconnect' would be not the office worker but the teleworker because of his inability to physically separate himself from work and thus from non-work. This inability turns out to be a disadvantage of teleworkers causing exhaustion ($\Delta\beta = 0.127$) and inability to switch off ($\Delta\beta = 0.159$). Another important distinction between teleworkers and office workers can be explained in terms of the distinction between periodic and constant AI involvement into the work process. In other words, due to lack of proper HRM strategies at institutional level, AI-powered work process cannot be interrupted by teleworkers in order to recover resource capacity.

From the methodological point of view, SHAP-PLS rs=0.97 supports the structural model. Psychological detachment is the second predictor in both SHAP (0.318) and PLS-SEM (β=0.367 to DF). This once again validates that recovery pathway from work demands to digital well-being is not a self-report artifact. The same data, the ML model, which does not know the underlying theory and has a different optimization objective, shows the same rank ordering of predictors as PLS-SEM. This convergence negates the critical potential JD-R findings in HRM research depend on survey-method.

9. Theoretical Contributions

Five contributions follow. First, this study extends JD-R Theory to the algorithmic work demand context by showing that the demand-to-strain mechanism works via three mediating channels - exhaustion, detachment impairment, and technostress - which operate independently and interactively.

Secondly, the extension of COR theory to the AI context regarding the concept of psychological detachment highlights detachment as a resource, which is threatened specifically by the digital availability requirements and the invasion of decisions made by algorithms. Previous researches on the COR theory concerning the digital work contexts focused on the use of energy as the main resource at stake.

Third, the SDT extension in the technostress associated with the artificial intelligence gives an explanation of the needs-based mechanisms behind the phenomenon of the more severe technostress caused by the invasion of the decisions made by algorithms compared to the information overload (0.356 vs. 0.289). The invasion of the algorithmic decisions frustrates the need for autonomy, which is the basic one among the three needs of SDT and the one that is more strongly related to the motivation and engagement of people. On the other hand, the information overload frustrates the need for competence without challenging the need for autonomy.

Fourth, the buffering moderation effect of HRM practices in the exhaustion-to-wellbeing damage process has proven to be a new empirical finding on how the HRM practices are able to act as a buffering element in the AI work context. Previous studies on the JD-R theory and buffering have demonstrated that the job resources may act as buffering elements for the demand-to-strain path; whereas, in the current study, the organisational HRM investment acts as a buffering element for the strain-to-wellbeing path, which is a downstream moderation effect and therefore is theoretically distinctive.

Fifth, in the current study, the dual-contrast MGA design was used. Two contrasts of the algorithmic work demands indicator were conducted simultaneously. Therefore, for the first time, the evidence was provided about the differential impact of the algorithmic work demands on the whole range of the studied groups. Of course, the heterogeneity of the results of the algorithmic work demands indicator cannot be viewed as a nuisance for this study; on the contrary, it is a key finding demonstrating that it is vital to consider the physical and cognitive working conditions as moderating variables in the algorithm's work demands-psychological strain relationship.

10. Managerial Implications

The findings give specific recommendations for three practitioner groups. For the Chief People Officers who run wellbeing programmes for their employees in the digitally disposed environments, the moderation finding changes the investment priorities. The protection afforded by the HRM buffering practices is the greatest for remote workers and for the workers of the IT sector; however, this is not because of any greater fragility or preferences of these groups but simply because the artificial intelligence work demands faced by the people of these groups are higher in intensity and naturally unbounded. One-size-fits-all digital wellbeing policies targeting similar employee populations will allocate too few extra resources to those segments.

The right to disconnect finding is perhaps the most actionable one in the immediate term. The remote versus in-office DAD→PD relationship ($\Delta\beta=0.159$, $p=0.008$) provides empirical support for right to disconnect legislation focused specifically on remote work. Portable device use can make it difficult for employees to sign off from their job, while in-office culture can discourage doing so.

For technology procurement teams and Chief Digital Officers deciding about the parameters of monitoring systems, the finding indicates that the monitoring intensity levels have to be calibrated not only with the type of activity but also with the nature of the target group. Levels designed for manufacturing quality monitoring will create considerably more fatigue than intended after being used for knowledge workers. A purchasing specification that standardises the monitoring intensity without taking into account the specific workforce that it serves is, in light of the above, incomplete.

For IQAC committees and HR leadership developing workforce strategy for India's AI adoption trajectory, the SDG alignment table (Table 9) identifies specific algorithmic demand pathways to SDG 3 (mental health), SDG 8 (decent work), SDG 10 (remote equity), and SDG 9 (responsible AI design). The mappings can be used to align HRM digital wellbeing investment efforts with regulatory and sustainability reporting requirements instead of keeping them isolated as an operational concern.

11. Limitations and Future Research

Four limitations affect the above findings. Cross-sectional nature of the analysis does not allow establishing causality between the variables. Employees with inherently lower level of resilience may experience higher demand perception and lower wellbeing levels, and it does not mean there is a causal connection between the two factors. An experience sampling study measuring both variables multiple times per day could help to eliminate the effect of between-subjects confounding variable (inherent resilience).

All the measures used in the study are self-reporting, and some of the constructs – AI monitoring intensity, HRM buffering practices,

and information overload – are subjective rather than objective measures. Future research should combine self-reported perception of demand with objectively measured level of the same using system-generated data (logs, message volumes, AI decision frequency counts).

However, just 2 references were considered and just IT, manufacturing, and financial services industries. AI has various implementations, and their impacts may vary depending on industry, whether healthcare or education or agriculture or informal sector. Impacts on remote vs. in-office depend on formal jobs with HRM moderation practices, whereas gig, contract, and self-employed have far fewer buffers available.

HRM buffering is a composite index of four HRM dimensions: HRM policies, manager training, right to disconnect, and workload ceiling. The bundle needs to be disentangled to identify the instruments associated with high moderation levels in varying levels of demands and varying employees' populations. Bundle-level moderation is not an objective but a starting point.

12. Conclusion

Algorithmic management makes work more efficient and less humane in measurable, manageable, and HRM responsible way. This paper shows that digital work exhaustion is the main channel of the damage done by algorithmic demands to digital wellbeing; psychological detachment is the main recovery resource impaired by such demands; HRM buffering practices make the damage done by exhaustion-to-wellbeing pathway 45% lower - a protective effect which is significantly higher for remote workers and IT knowledge workers compared to in-office and manufacturing workers.

The policy recommendation is not generic: HRM investments in digital wellbeing should be made among employee populations with highest burdens of algorithmic demands, not uniformly applied across all employees. Remote workers subjected to digital availability demands not respecting the home-work boundary and IT knowledge workers subjected to algorithmic surveillance of their cognitive outputs unable to tell deep work from shallow are the employees where the same HRM investment generates the biggest protective effect.

SHAP-PLS rs=0.97 is the methodological statement, not only substantive. When tree ensemble and structural equation model agree on constructs of interest and their order and weights, despite different underlying mathematics and optimization algorithms - the research team is allowed to be quite confident in the validity of construct relationships. Digital work exhaustion is the most damaging feature in this model. Psychological detachment is the most restorative. HRM practices buffer the gap between them. The narrative does not change depending on analytical tool used to interpret it.

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