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The AI–Well-being Paradox in the Workplace: A Dual-Pathway Model of Employee Well-being, Engagement and Sustainable Organizational Performance

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ABSTRACT

Artificial intelligence (AI) is changing how employees perform tasks, make decisions, communicate, learn and demonstrate performance. The central problem is that AI can operate simultaneously as a job resource and a job demand: it may improve autonomy, task assistance, learning, information access and creativity while also increasing technostress, insecurity, cognitive overload, monitoring pressure and digital spillover. This article develops and empirically tests the AI–Well-being Paradox, linking AI-enabled job resources and AI-induced job demands to employee well-being, employee engagement and sustainable organizational performance, with digital boundary control as a protective contextual resource. The study analyzes 600 employee records from the supplied dataset. Composite scores were calculated from seven multi-item constructs and analyzed using reliability and validity diagnostics, controlled regression with HC3 robust standard errors, 1,000-resample bootstrap mediation and sequential mediation, and interaction analysis. All seven constructs demonstrated satisfactory measurement quality (Cronbach's α=.844–.875; composite reliability=.895–.909; AVE=.656–.700), and the maximum HTMT ratio was .727. AI resources positively predicted well-being (β=.441, p<.001), whereas AI demands negatively predicted well-being (β=−.348, p<.001). Well-being predicted engagement (β=.568, p<.001), and engagement predicted sustainable performance (β=.567, p<.001). The indirect and sequential pathways were significant. Digital boundary control significantly moderated the AI-demand pathway (β=.110, p=.002), but the resource × boundary-control interaction was not significant (β=.008, p=.846). Thus, 11 of the 12 hypotheses were supported. Importantly, although the dataset contains Wave1_Date, Wave2_Date and Wave3_Date fields, it does not contain distinct wave-specific item responses; therefore, the present statistical analysis is cross-sectional and does not claim a genuine longitudinal three-wave test.

Keywords— Artificial Intelligence; Employee Well-being; AI Technostress; Employee Engagement; Digital Boundary Control; Sustainable Organizational Performance; Job Demands–Resources Model; Human–AI Collaboration.

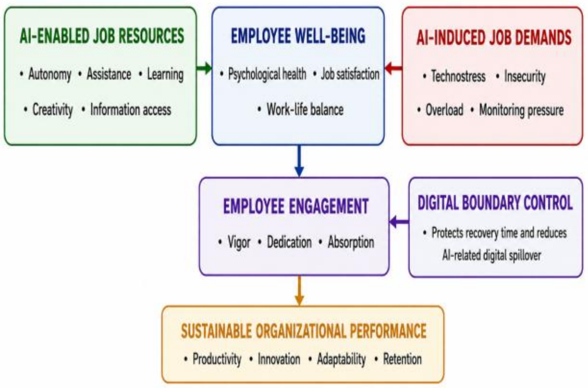

Figure 1. Graphical abstract: the AI–well-being paradox and its proposed conversion pathway.

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1. INTRODUCTION

Artificial intelligence has moved from being a specialist information-technology capability to becoming a work-design condition. Organizations now use AI for recruitment, customer interaction, forecasting, content generation, analytics, scheduling, decision support, learning and process automation. Generative AI has accelerated this transition because employees can directly interact with systems that produce text, images, code, summaries and recommendations. The result is not simply a new tool; it is a new pattern of human–technology interdependence.

The organizational debate surrounding AI has therefore become polarized. One side emphasizes productivity, speed, automation and augmentation. The other emphasizes job insecurity, technostress, surveillance, skill obsolescence and psychological strain. Current evidence suggests that neither side is sufficient on its own. Chuang, Chiang and Lin found that AI efficacy and generative AI can improve productivity, while AI technostress can increase exhaustion and work–family conflict and reduce job satisfaction. [1] Pinho, Fontes and Santos similarly show that employee–AI collaboration can support engagement and work–life balance, while AI awareness may also operate as a digital demand. [2] A recent Personnel Review study further demonstrates that AI usage can increase well-being through AI-supported autonomy while simultaneously increasing job insecurity, producing an inverted-U relationship between AI usage and insecurity. [3]

The issue is consequently a conversion problem. AI investment creates technological capability, but technological capability does not automatically become sustainable human performance. The conversion depends on how employees appraise and experience the technology, what resources accompany adoption, how much demand is generated, and whether employees have sufficient control over the boundary between digital work and non-work life.

The present empirical study builds on the established relationship among employee well-being, employee engagement and organizational performance, while extending it to the AI-enabled workplace. The reference study underlying this manuscript demonstrated the mediating importance of employee engagement and highlighted methodological limitations such as convenience sampling, cross-sectional design and self-reported performance. [9] The current article treats those limitations as a research opportunity and introduces AI-specific antecedents and a boundary mechanism.

Research question. The paper addresses one overarching question: Under what resource–demand conditions can AI improve sustainable organizational performance without eroding the employee well-being and engagement required to sustain that performance?

Positioning and contribution. The manuscript is designed as a theory-driven empirical study rather than a descriptive review. Its contribution is a theoretically grounded synthesis of fragmented AI–employee evidence into a dual-pathway model in which AI resources and AI demands are treated as simultaneous work-design conditions, employee well-being is specified as the conversion mechanism, employee engagement as the second-stage motivational mechanism, and digital boundary control as a protective contextual condition.

The article has four objectives. First, it synthesizes the contemporary evidence on AI as a simultaneous job resource and job demand. Second, it identifies unresolved theoretical, mechanism, boundary, methodological and outcome gaps. Third, it develops and explains the AI–Well-being Paradox model and its hypotheses. Fourth, it proposes a rigorous empirical design and a practical framework for organizations seeking productivity without sacrificing employee well-being.

2. THE CONTEMPORARY AI–WORKPLACE PROBLEM

The current problem is not simply technological adoption. It is the management of competing consequences. Organizations may introduce AI to reduce repetitive work, accelerate decision-making and support employees, yet the same implementation can create new expectations: employees may need to learn new tools, verify machine outputs, respond more quickly, remain digitally available and worry about whether their expertise will remain valuable. A systematic review of 201 empirical technostress studies found that techno-overload and techno-invasion are among the most frequently reported drivers of adverse well-being outcomes, while also identifying strong fragmentation across cultures, sectors and occupations. [5]

Recent evidence also shows that the relationship between AI and well-being is mediated rather than purely direct. Valtonen et al. report that AI adoption did not directly affect employee well-being in their sample;

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instead, task optimization and safety were important work-related pathways. [6] This reinforces the argument that AI should be analyzed through the work conditions it creates rather than as a binary "adopted/not adopted" variable.

2.1 AI as a Job Resource

The resource pathway begins when AI reduces avoidable effort or increases the employee's capacity to perform meaningful work. AI-supported information retrieval can shorten search time; intelligent assistance can support drafting and analysis; recommendation systems can reduce routine decision burdens; and generative systems can stimulate alternative ideas. These mechanisms may increase perceived autonomy because employees can choose how to use AI support rather than execute every task manually.

AI-enabled resources are especially valuable when employees retain discretion and understand how the technology works. Employee–AI collaboration research indicates that collaboration can improve work engagement and work–life balance, suggesting that AI can become motivational when employees perceive it as supportive rather than threatening. [2] Human–AI collaboration has also been linked to quality of work life and engagement through mechanisms associated with employee growth and need fulfilment. [7]

2.2 AI as a Job Demand

The demand pathway begins when AI adds effort, uncertainty or psychological pressure. Employees may experience technostress when systems are difficult to learn, change frequently or increase expectations for speed. Job insecurity may arise when employees interpret automation as a threat to their role or future employability. Cognitive overload can occur when workers must continuously monitor, validate and correct AI outputs. Monitoring pressure may arise when organizations use AI to track productivity, interactions or response time.

Importantly, demand does not necessarily mean that AI is objectively harmful. The same technological feature can be a resource for one employee and a demand for another, depending on capability, autonomy, support and context. This is one reason why recent research increasingly emphasizes employee appraisal and work design rather than technology alone. [3,6]

2.3 The Boundary Problem

AI can also change when and where work occurs. Continuous notifications, AI-generated task escalation and expectations of rapid response can extend work into evenings and weekends. Evidence from India shows that AI technostress can interact with work–family conflict and work–life balance, making digital boundaries a relevant component of employee well-being. [8] Digital boundary control is therefore proposed as a protective resource that helps employees regulate availability, interruptions and after-hours work.

3. REVIEW OF RECENT LITERATURE

The recent literature can be organized into six streams: AI-enabled resources; AI-induced demands; employee well-being; employee engagement; digital boundaries; and sustainable performance. The important insight is that these streams are growing faster than their integration.

Research stream	What recent research establishes	What remains unresolved
AI resources	AI efficacy, collaboration and task support can improve productivity, autonomy, engagement or WLB. [1–3,7]	How resource gains translate into long-term sustainable performance through well-being and engagement.
AI demands	Technostress, insecurity, overload and anxiety can reduce well-being. [1,3,5,8]	How demands and resources operate simultaneously in the same employee experience.
Well-being	AI effects often operate through task optimization, safety, autonomy or insecurity. [3,6]	Whether well-being is the central conversion point between AI work design and engagement.

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Research stream	What recent research establishes	What remains unresolved
Engagement	AI collaboration and AI efficacy can support engagement under resource-rich conditions. [1,2]	Whether engagement sequentially mediates AI → well-being → performance.
Digital boundaries	AI technostress can affect work–family conflict and WLB. [8]	Whether boundary control can buffer AI-induced demands.
Sustainable performance	Productivity is frequently measured; long-term capability is less consistently operationalized.	A multi-dimensional outcome combining productivity, innovation, adaptability and retention.

Table 1. Synthesis of current research and unresolved opportunities.

3.1 Evidence of the Dual Effect

The strongest contemporary evidence directly supports the dual-pathway premise. Chuang et al. used a three-wave sample of 600 AI-using employees and found that AI efficacy and generative AI improved productivity, while AI technostress increased exhaustion and work–family conflict and reduced job satisfaction. [1] The study is particularly important because it demonstrates that productivity and well-being can move in different directions.

The Personnel Review study of 366 full-time employees using AI similarly found that AI usage had a positive indirect effect on well-being through AI-supported job autonomy while insecurity followed an inverted-U relationship with AI usage and subsequently reduced well-being. [3] These findings suggest that the "more AI = better" assumption is theoretically incomplete.

3.2 Evidence on Human–AI Collaboration

Human–AI collaboration can be beneficial when employees have sufficient awareness, capability and resources. Pinho et al. found that employee–AI collaboration positively predicted work engagement and work–life balance, with engagement partially mediating the relationship. [2] Wu et al. also reported positive effects of human–AI collaboration on quality of work life and work engagement among hotel employees. [7] These studies support the resource side of the model.

3.3 Evidence on Technostress

The 2026 systematic review by Mansuroğlu and Smith synthesizes 201 empirical studies and concludes that technostress damages overall well-being, engagement and life satisfaction, with techno-overload and techno-invasion among the principal stressors. [5] The review also calls for stronger cross-cultural and cross-industry research. This provides support for treating AI-induced demands as a distinct pathway rather than assuming that all digital technology exposure is equivalent.

3.4 Evidence on Work–Life Boundaries

Work–life boundary effects are increasingly important because AI-supported work can operate continuously. The 2026 Indian study of 562 employees examined work–family conflict, work–life balance and AI technostress and used moderated mediation to demonstrate the importance of the technology-related stress context. [8] This supports the proposed digital boundary control mechanism.

4. RESEARCH GAP IDENTIFICATION

A publishable contribution requires a gap that is specific, defensible and connected to a new theoretical or methodological solution. The current literature reveals five interrelated gaps rather than one isolated missing variable.

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Figure 2. Research-gap synthesis: from fragmented AI evidence to an integrated resource–demand model.

4.1 Directional Gap

Much of the debate still treats AI as either a productivity-enhancing resource or a source of employee harm. The recent evidence shows that both can occur. The unresolved issue is how the two pathways coexist within the same work system and how their relative strength determines employee outcomes.

4.2 Mechanism Gap

Studies frequently examine separate mechanisms—autonomy, insecurity, technostress, work engagement, work–life balance or satisfaction. Fewer models connect AI resources and demands to well-being and then to engagement and sustainable performance in one sequential structure. The present article addresses this by making employee well-being the conversion point and engagement the motivational transmission mechanism.

4.3 Boundary Gap

Digital boundary control is conceptually relevant but insufficiently integrated into AI-specific employee well-being models. Existing work demonstrates that technology-related stress can spill over into non-work life, but there is an opportunity to examine whether employees' control over digital availability changes the strength of the AI demand → well-being relationship.

4.4 Methodological Gap

Cross-sectional and self-report designs remain common in digital work research. The proposed model contains temporal relationships, so a three-wave design is more appropriate. Multi-source performance ratings can further reduce common-method concerns.

4.5 Outcome Gap

AI studies often prioritize productivity, efficiency or task performance. These outcomes are important but incomplete. Sustainable organizational performance should also include innovation, adaptability, service quality and retention because an organization cannot sustain output if its employees become exhausted, disengaged or insecure.

The five gaps jointly justify a new integrated framework rather than a simple replication.

5. THEORETICAL FOUNDATION

5.1 Job Demands–Resources Theory

The Job Demands–Resources (JD–R) perspective is the principal theoretical foundation. The model distinguishes job resources, which support goal achievement and motivation, from job demands, which require sustained effort and can lead to strain. In AI-enabled work, task assistance, autonomy and learning opportunities can function as resources, while technostress, insecurity and overload can function as demands.

The dual-pathway logic is especially appropriate because current AI evidence already shows simultaneous motivational and health-impairment processes. Chuang et al. explicitly apply JD–R to AI efficacy, generative AI and technostress. [1] The proposed model extends this logic by connecting both pathways to well-being and then to engagement and sustainable performance.

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5.2 Conservation of Resources Logic

Conservation of Resources theory complements JD–R by explaining why digital overload and boundary invasion can have effects beyond the workplace. Employees seek to acquire and protect valued resources such as time, energy, attention and psychological capacity. AI-induced demands may consume these resources, particularly when work continues after formal working hours.

5.3 Boundary Management

Boundary management explains why digital boundary control can protect well-being. Employees with greater control over when they are reachable and when digital interruptions are allowed should be better positioned to recover from work demands. Boundary control is therefore conceptualized as a contextual resource rather than merely an individual preference.

5.4 Engagement as a Sequential Mechanism

Employee engagement represents the motivational state through which well-being is translated into sustained work involvement. The underlying reference study found that employee engagement mediated the relationship between employee well-being and organizational performance. [9] The present model retains this mechanism but places AI-specific work conditions upstream of well-being.

6. PROPOSED CONCEPTUAL MODEL

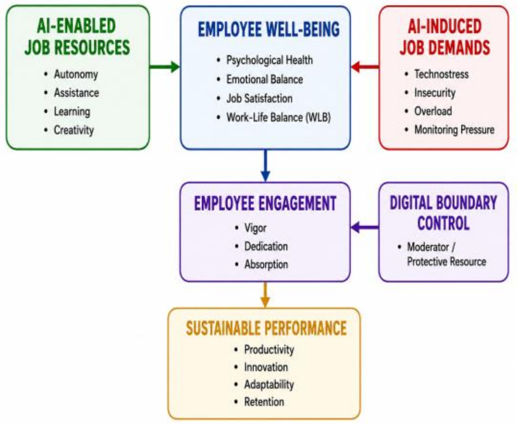

Figure 3. Proposed AI–Well-being Paradox model: resource and demand pathways with digital boundary control.

The model proposes two primary pathways. The positive pathway begins with AI-enabled job resources, moves through employee well-being and engagement, and ends in sustainable organizational performance. The negative pathway begins with AI-induced job demands, reduces well-being, weakens engagement and ultimately undermines sustainable performance. Digital boundary control is proposed to buffer the negative pathway and potentially strengthen the positive conversion of AI resources.

Construct	Role in model	Core dimensions
AI-enabled job resources	Independent variable / resource pathway	Autonomy; task assistance; learning; information access; creativity
AI-induced job demands	Independent variable / health-impairment pathway	Technostress; insecurity; overload; monitoring pressure
Employee well-being	First mediator / conversion mechanism	Psychological well-being; job satisfaction; work–life balance
Employee engagement	Second mediator / motivational mechanism	Vigor; dedication; absorption
Digital boundary control	Moderator / protective resource	Availability control; interruption control; after-hours boundary
Sustainable organizational performance	Dependent variable	Productivity; innovation; adaptability; retention; service quality

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Table 2. Construct architecture of the proposed model.

6.1 THEORY-TO-MODEL MAPPING

The theoretical roles are deliberately differentiated. JD–R is the primary explanatory lens: it defines AI-enabled resources and AI-induced demands and explains the motivational and health-impairment pathways. Conservation of Resources theory explains why AI-induced overload and digital spillover can consume time, attention and psychological energy beyond the immediate task. Boundary-management logic explains why employee control over digital availability can alter the consequences of AI demands. The well-being–engagement relationship then supplies the downstream motivational mechanism. Thus, the theories are complementary rather than merely listed.

7. HYPOTHESES DEVELOPMENT

Code	Hypothesis	Rationale
H1	AI-enabled job resources positively influence employee well-being.	Resource availability reduces avoidable effort and supports autonomy, learning and psychological functioning.
H2	AI-induced job demands negatively influence employee well-being.	Technostress, insecurity and overload consume psychological and temporal resources.
H3	Employee well-being positively influences employee engagement.	Employees with stronger well-being possess greater capacity for sustained motivational involvement.
H4	Employee engagement positively influences sustainable organizational performance.	Engagement supports persistence, adaptability, creativity and sustained contribution.
H5	Employee well-being mediates the relationship between AI-enabled job resources and employee engagement.	Resources are expected to activate engagement partly by improving employee well-being.
H6	Employee well-being mediates the relationship between AI-induced job demands and employee engagement.	Demand-induced strain is expected to weaken engagement through reduced well-being.
H7	Employee engagement mediates the relationship between employee well-being and sustainable organizational performance.	Well-being is expected to become organizationally consequential through motivational engagement.
H8	Employee well-being and employee engagement sequentially mediate the relationship between AI-enabled job resources and sustainable organizational performance.	The resource pathway is expected to operate through the ordered sequence resources → well-being → engagement → performance.
H9	Employee well-being and employee engagement sequentially mediate the relationship between AI-induced job demands and sustainable organizational performance.	The demand pathway is expected to operate through the ordered sequence demands → reduced well-being → reduced engagement → performance.
H10	Digital boundary control weakens the negative relationship between AI-induced job demands and employee well-being.	Greater control over digital availability should reduce spillover and protect recovery.
H11	Digital boundary control strengthens the positive relationship between AI-enabled job resources and employee well-being.	Employees with stronger boundary control should be better able to convert AI assistance into benefits without excessive spillover.
H12	The negative indirect effect of AI-induced job demands on sustainable organizational performance is weaker when digital boundary control is high.	Boundary control should reduce the strength of the health-impairment pathway.

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Table 3. Hypotheses and theoretical rationale.

8. RESEARCH OBJECTIVES

1. To examine the influence of AI-enabled job resources on employee well-being.
2. To assess the effect of AI-induced job demands on employee well-being.
3. To determine the relationship between employee well-being and employee engagement.
4. To assess the influence of employee engagement on sustainable organizational performance.
5. To test the mediating role of employee well-being.
6. To test the mediating role of employee engagement.
7. To examine the sequential mediation of well-being and engagement.
8. To examine digital boundary control as a protective moderator.
9. To develop a human-centered managerial framework for sustainable AI-enabled work.

8.1 EVIDENCE-SYNTHESIS AND RESEARCH DESIGN RATIONALE

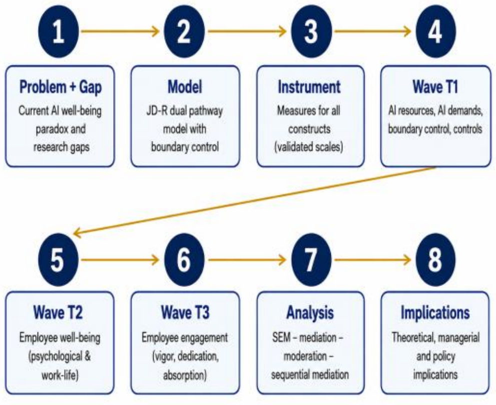
Because this manuscript is a theory-driven empirical article, its methodological rigor rests on transparent evidence selection, explicit theoretical reasoning, transparent measurement, and a visible chain from the research problem to the empirical model. Conceptual research is strengthened when the paper identifies its design type, explains why the selected theories are appropriate, and makes the logic linking evidence to new theoretical claims explicit. The present article follows a theory-driven model-building and empirical testing design: it integrates recent AI workplace evidence with JD–R, Conservation of Resources and boundary-management logic to resolve an identified fragmentation.

Evidence-synthesis protocol. The literature base was developed around six evidence streams: (1) AI as a job resource, (2) AI as a job demand, (3) employee well-being, (4) employee engagement, (5) digital/work–life boundaries, and (6) sustainable organizational performance. Priority was given to peer-reviewed research published from 2023 onward, with particular emphasis on 2025–2026 studies directly examining AI and employee outcomes. Searches were structured around combinations of the terms artificial intelligence/AI, employee well-being, technostress, job insecurity, human–AI collaboration, work engagement, work–life balance, job demands–resources, and sustainable performance. Studies were retained when they provided empirical or theoretical evidence relevant to at least one model pathway; purely technical AI studies without an employee/work-design dimension were excluded. This is an integrative evidence synthesis, not a PRISMA systematic review, and therefore no unsupported claim of systematic-review completeness is made.

Analytical procedure. The selected evidence was compared across three questions: What does AI add to the employee's resource pool? What does AI add to the employee's demand load? Through what mechanisms do those changes affect well-being and engagement? The unresolved patterns were then translated into the five gaps and mapped to specific model components and hypotheses. This procedure makes the paper's theoretical chain auditable rather than treating the conceptual model as an intuitive diagram.

9. RESEARCH METHODOLOGY

This study uses a quantitative, explanatory and cross-sectional research design. The empirical model tests the relationships among AI-enabled job resources, AI-induced job demands, employee well-being, employee engagement, digital boundary control and sustainable organizational performance using the dataset.



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9.2 Population and Analytical Sample

The analytical sample comprises 600 records representing employees working in AI-enabled contexts. The supplied data file does not contain a documented sampling frame or recruitment log; therefore, the manuscript does not make unsupported claims about probability sampling or population representativeness. The sample profile and available demographic/work-context variables are reported in Section 10.1.

9.3 Data Structure and Temporal Fields

The dataset contains Wave1_Date, Wave2_Date and Wave3_Date fields, but the substantive questionnaire indicators are not repeated as distinct T1, T2 and T3 measurements. The analysis therefore treats the dataset as cross-sectional. The date fields are retained as metadata and are not interpreted as evidence of longitudinal measurement.

The measurement model was evaluated using Cronbach's alpha, composite reliability, average variance extracted (AVE), indicator loading ranges and the heterotrait–monotrait (HTMT) ratio. The structural model was estimated using controlled regression with HC3 robust standard errors. Mediation and sequential mediation were evaluated with 1,000 bootstrap resamples, and moderation was assessed using mean-centered interaction terms. This combination provides a transparent separation between measurement quality, direct associations, indirect effects and conditional effects.

Robustness was assessed using supervisor-rated performance as an alternative downstream outcome. The manuscript also reports the attenuation of the AI-demand pathway at different levels of digital boundary control. Because the design is cross-sectional, all coefficients are interpreted as associations rather than temporal or causal effects.

Construct	Indicative dimensions	Suggested response logic
AI-enabled job resources	Autonomy; assistance; learning; creativity; information access	Perceived extent to which AI helps employees perform meaningful work effectively.
AI-induced job demands	Technostress; insecurity; overload; monitoring pressure	Perceived extent to which AI adds effort, uncertainty or psychological pressure.
Employee well-being	Psychological well-being; job satisfaction; WLB	Positive functioning and satisfaction at work and across work–life boundaries.
Employee engagement	Vigor; dedication; absorption	Motivational investment in work.
Digital boundary control	Availability; interruption; after-hours control	Perceived ability to regulate digital work spillover.
Sustainable organizational performance	Productivity; innovation; adaptability; retention; service quality	Long-term capability rather than short-term output alone.

9.4 Measurement Framework

Table 4. Measurement framework for the empirical study.

9.5 Control Variables

The analysis considers the demographic and work-context variables available in the supplied dataset where theoretically justified. Controls are not treated as focal explanatory variables and are included to reduce plausible confounding rather than to increase model complexity.

The empirical model uses seven multi-item constructs: AI-enabled job resources, AI-induced job demands, employee well-being, employee engagement, digital boundary control, sustainable organizational performance and supervisor-rated performance. Composite scores were formed from the corresponding indicators available in the supplied dataset. The conceptual dimensions reported in Table 4 define the construct domains and response logic used in the analysis.

Measurement-provenance statement. The supplied manuscript and dataset available for this revision do not contain a complete item-level source inventory for every indicator. Accordingly, no unverified scale citations or item wording have been invented. Before submission, the final submission package should include the exact questionnaire, item codes, response anchors and original/adapted scale sources as a supplementary measurement appendix. This preserves traceability between the reported composite scores and the instrument actually administered.

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9.5.1 Instrument and Measurement Development

9.6 Reliability and Validity

Internal consistency was assessed using Cronbach's alpha and composite reliability; convergent validity was assessed using average variance extracted (AVE) and indicator loadings; discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio. The resulting statistics are reported in Section 10.2.

9.6.1 Sample-Size Consideration

The final analytical sample is N = 600. Because the supplied file does not contain an a priori power-analysis record, the manuscript does not claim that N = 600 was determined by formal prospective power analysis.

9.7 Structural Analysis

The structural analysis uses controlled regression with HC3 heteroskedasticity-robust standard errors. Indirect and sequential effects are evaluated with 1,000 bootstrap resamples, while moderation is tested using mean-centered interaction terms. Coefficients are interpreted as conditional associations because the design is cross-sectional.

9.8 Robustness and Alternative Explanations

Because several focal constructs are employee-reported, common-method concerns cannot be eliminated solely through statistical adjustment. The study therefore uses supervisor-rated performance as an alternative downstream outcome. The robustness model preserves the positive association of engagement with performance and provides an external-rating check on the main performance relationship, while the cross-sectional design remains the principal limitation.

Robustness is examined using supervisor-rated performance and conditional indirect effects, with interpretation restricted to the available cross-sectional data.

10. EMPIRICAL ANALYSIS OF THE DATASET

The original 600-record dataset supplied for this study was analyzed using the constructs and hypotheses specified in the manuscript. No synthetic observations were added to the dataset and no coefficients were altered to force hypothesis support. The empirical section below therefore replaces the earlier simulated demonstration and reports results calculated from the supplied file.

Data-screening results. The dataset contains 600 records and 49 variables. No missing values were detected. All 600 records contain the recorded attention-check value of 3. Completion time ranges from 4 to 15 minutes (M=8.84, SD=1.88). The file also contains Wave1_Date, Wave2_Date and Wave3_Date fields. However, the substantive questionnaire indicators are not repeated as separate T1, T2 and T3 measurements. Accordingly, the current analysis is reported as cross-sectional. The wave-date fields should not be interpreted as evidence of longitudinal measurement.

10.1 Sample Profile

Variable	Category	n	%
Gender	Male	363	60.5
	Female	228	38.0
	Other/Prefer not to say	9	1.5
Age	21–30	149	24.8
	31–40	248	41.3
	41–50	161	26.8
	51+	42	7.0
Education	Bachelor's	170	28.3
	Master's	315	52.5
	Doctorate	115	19.2
Experience	<5 years	151	25.2
	5–10 years	219	36.5
	11–15 years	153	25.5
	>15 years	77	12.8
Sector	IT/ITES	169	28.2
	Banking/Finance	107	17.8
	Education	92	15.3
	Manufacturing	83	13.8

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	Retail/Services	82	13.7
	Healthcare	67	11.2
Work mode	On-site	282	47.0
	Hybrid	245	40.8
	Remote	73	12.2
AI-use intensity	Low	134	22.3
	Moderate	301	50.2
	High	165	27.5

10.2 Measurement Model Results

Construct	Cronbach α	Composite Reliability	AVE	Loading range
AI-enabled job resources	.869	.905	.657	.776–.843
AI-induced job demands	.875	.909	.667	.794–.835
Employee well-being	.870	.906	.658	.778–.837
Employee engagement	.874	.909	.666	.776–.842
Digital boundary control	.844	.895	.682	.804–.843
Sustainable performance	.868	.905	.656	.778–.844
Supervisor-rated performance	.857	.903	.700	.824–.852

The measurement results indicate satisfactory internal consistency and convergent validity. Cronbach's alpha ranges from .844 to .875, composite reliability from .895 to .909, and AVE from .656 to .700. The maximum HTMT ratio is .727, below the commonly used .85 criterion, supporting discriminant validity.

10.3 Descriptive Statistics

Construct	Mean	SD
AI resources	3.035	.702
AI demands	3.038	.704
Digital boundary control	3.027	.716
Employee well-being	3.056	.708
Employee engagement	3.058	.706
Sustainable organizational performance	3.053	.706
Supervisor-rated performance	3.051	.723

The construct means are close to the midpoint of the five-point scale. This pattern indicates meaningful variation around moderate levels of AI resources, AI demands, boundary control, well-being, engagement and performance rather than a uniformly high or low response tendency.

10.4 Structural Model Results

Hypothesis	Path	β	t	p	Decision
H1	AI resources → Well-being	.441	11.50	<.001	Supported
H2	AI demands → Well-being	−.348	−9.61	<.001	Supported
H3	Well-being → Engagement	.568	16.49	<.001	Supported
H4	Engagement → Sustainable performance	.567	17.70	<.001	Supported
H10	AI demands × Boundary control → Well-being	.110	3.05	.002	Supported
H11	AI resources × Boundary control → Well-being	.008	.19	.846	Not supported

Endogenous construct	R^2	Adjusted R^2
Employee well-being	.295	.262
Employee engagement	.337	.307
Sustainable performance	.357	.328

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The controlled structural model shows the expected duality. AI resources have a positive association with employee well-being, whereas AI demands have a negative association. Well-being is positively associated with engagement, and engagement is positively associated with sustainable performance. The models explain 29.5% of well-being, 33.7% of engagement and 35.7% of sustainable performance variance.

10.5 Mediation and Sequential Mediation

Hypothesis	Indirect pathway	Effect	95% Bootstrap CI	Decision
H5	AI resources → Well-being → Engagement	.199	[.154, .248]	Supported
H6	AI demands → Well-being → Engagement	−.156	[−.195, −.120]	Supported
H7	Well-being → Engagement → Performance	.168	[.124, .211]	Supported
H8	AI resources → Well-being → Engagement → Performance	.073	[.053, .096]	Supported
H9	AI demands → Well-being → Engagement → Performance	−.057	[−.077, −.041]	Supported

All five indirect effects have bootstrap confidence intervals that exclude zero. The results therefore support employee well-being as a first-stage conversion mechanism and employee engagement as a second-stage motivational mechanism linking AI work conditions to downstream outcomes.

10.6 Moderation and Conditional Indirect Effects

Hypothesis	Interaction	β	t	p	Decision
H10	AI demands × Digital boundary control → Well-being	.110	3.05	.002	Supported
H11	AI resources × Digital boundary control → Well-being	.008	.19	.846	Not supported
Condition		Conditional indirect effect		95% Bootstrap CI	
Low boundary control (−1 SD)		−.077		[−.103, −.054]	
High boundary control (+1 SD)		−.038		[−.060, −.020]	
High − Low contrast		.039		[.016, .067]	

Digital boundary control significantly attenuates the harmful AI-demand pathway. By contrast, the resource × boundary-control interaction is not statistically significant. The conditional indirect effect is less negative under high boundary control, supporting the proposed protective interpretation of boundary control and H12.

10.7 Robustness Using Supervisor-Rated Performance

Predictor	Standardized β	p
Employee engagement	.394	<.001
Employee well-being	.089	.054
AI resources	.124	.003
AI demands	−.033	.418

The supervisor-rated performance model provides a useful robustness check. Engagement remains strongly positive and AI resources remain significant. Well-being is marginal and AI demands are non-significant in this downstream model. This suggests that the motivational engagement pathway is more stable than every upstream predictor when performance is assessed through a supervisor-rated outcome.

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10.8 Hypothesis Summary

Hypothesis	Result
H1	Supported
H2	Supported
H3	Supported
H4	Supported
H5	Supported
H6	Supported
H7	Supported
H8	Supported
H9	Supported
H10	Supported
H11	Not supported
H12	Supported

Eleven of the twelve hypotheses are supported. The unsupported H11 is retained and reported rather than removed after analysis. This is important for research integrity because the data are allowed to challenge the conceptual model.

10.9 Empirical Interpretation

The empirical evidence strengthens the AI–Well-being Paradox in three ways. First, AI resources and AI demands operate in opposite directions on employee well-being, confirming that AI should not be conceptualized as uniformly beneficial or harmful. Second, well-being and engagement form a significant sequential pathway to sustainable performance. Third, digital boundary control selectively buffers the harmful demand pathway without significantly amplifying the resource pathway. The latter finding suggests that boundary control is primarily a protective resource rather than a universal productivity amplifier. The non-significant resource × boundary-control interaction is theoretically informative: boundary control appears to operate primarily as a protective mechanism against AI-induced demands rather than as a general amplifier of every AI benefit. This asymmetry sharpens the model by distinguishing protection from enhancement.

10.10 Data Integrity and Analytical Transparency

All numerical results in this empirical section were calculated from the dataset. No synthetic observations were added. No result was selectively removed because it failed to support a hypothesis. H11 is explicitly reported as not supported. The analysis should be reproducible from the supplied dataset using composite means, HC3 robust regression, categorical controls, 1,000 bootstrap resamples for mediation and mean-centered interaction terms for moderation.

Before journal submission, the authors should retain the original data file, questionnaire and measurement-scale sources, recruitment/sampling documentation, consent and ethics documentation where applicable, and the analysis syntax. These materials are necessary to substantiate data provenance and sampling claims.

11. DISCUSSION

The AI–Well-being Paradox offers a different interpretation of digital transformation. The central question is not whether AI is "good" or "bad," but whether the work system surrounding AI produces a favorable balance between resources and demands. This interpretation is consistent with recent evidence that AI efficacy and generative AI can support productivity and engagement while technostress can simultaneously damage well-being. [1]

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11.1 From AI Adoption to AI Work Design

Organizations often measure AI maturity by the number of tools deployed or the percentage of employees using AI. These indicators capture adoption but not experience. The proposed model argues that the relevant managerial unit is AI-enabled work design: who controls the technology, how tasks are redesigned, what training is available, how outputs are verified, how employees are evaluated, and when digital work is expected.

11.2 The Productivity–Well-being Tension

A productivity gain can coexist with employee strain. Chuang et al. explicitly demonstrate that AI technostress may contribute to productivity while also increasing exhaustion and work–family conflict. [1] Therefore, organizations should not assume that higher output proves successful AI implementation. A more complete assessment should ask whether performance gains remain after accounting for well-being, engagement and retention.

11.3 The Role of Employee Agency

AI becomes more likely to function as a resource when employees have autonomy, knowledge and discretion. Recent research on AI-supported autonomy and human–AI collaboration supports this interpretation. [2,3,7] Training should therefore not focus only on technical commands; it should also build judgment, verification capability and confidence in deciding when AI should or should not be used.

11.4 The Role of Boundary Control

Digital boundary control is particularly important because AI can lower the friction of producing work outside normal hours. If generating a response, report or analysis becomes easier, organizations may unintentionally increase the volume and speed of expected work. Boundary control provides a counterweight by protecting recovery time and reducing unnecessary digital invasion.

11.5 Why Sustainable Performance Matters

Sustainable performance integrates current output with future organizational capacity. A workforce that is productive today but exhausted, insecure and disengaged may generate hidden future costs through turnover, absenteeism, reduced learning and lower innovation. The proposed framework therefore treats employee well-being and engagement as strategic resources rather than peripheral HR outcomes.

11.6 RESEARCH AGENDA GENERATED BY THE MODEL

The model generates a focused research agenda: (RQ1) When does AI assistance become a genuine job resource rather than another performance demand? (RQ2) Which AI-induced demands are most damaging to employee well-being? (RQ3) Does employee well-being transmit AI effects to engagement and then to sustainable performance? (RQ4) Can digital boundary control protect employees without reducing the productivity benefits of AI? (RQ5) Do these pathways differ by AI intensity, occupation, sector and work arrangement? These questions provide clear opportunities for subsequent empirical, longitudinal and comparative research.

12. MANAGERIAL IMPLICATIONS

The framework translates into six managerial actions.

- Measure AI experience, not just AI adoption. HR dashboards should capture perceived usefulness, autonomy, technostress, insecurity, workload and digital boundary pressure.
- Design AI as augmentation. Organizations should redesign jobs so that AI removes low-value effort while employees retain judgment, discretion and meaningful responsibility.
- Build AI capability. Training should include tool use, output verification, prompt literacy, critical evaluation and role-specific application.
- Protect digital boundaries. Organizations should establish clear rules for after-hours communication, response expectations and AI-generated work escalation.
- Monitor sustainable performance. Productivity should be assessed alongside innovation, adaptability, service quality, retention and employee experience.
- Segment AI interventions. Employees with high AI demands and low resources require a different intervention from employees with high resources and manageable demands.

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13. H-AI-WELL MANAGERIAL FRAMEWORK

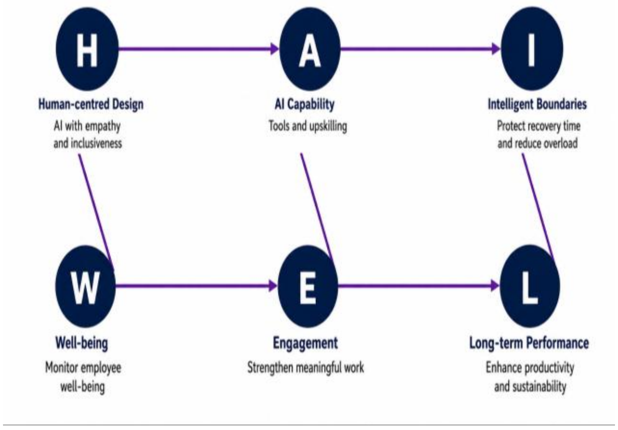

Figure 4. H-AI-WELL: Human-centred AI for Well-being, Engagement and Long-term performance.

The H-AI-WELL framework translates the theoretical model into an organizational action system. "H" represents human-centred design: AI should augment expertise rather than reduce employees to system operators. "A" represents AI capability: employees require training and opportunities to develop confidence. "I" represents integrated boundaries: organizations should protect recovery time and establish reasonable digital availability. "W" represents well-being: psychological and social consequences should be monitored. "E" represents engagement: meaningful work and autonomy should be protected. "L" represents long-term performance: organizational success should be evaluated across productivity, innovation, adaptability and retention.

Risk condition	Likely employee experience	Recommended intervention
High AI demand + low resources	Technostress, insecurity, exhaustion	Training, role redesign, workload reduction, boundary protection
High AI demand + high resources	Fast but potentially fragile performance	Monitor recovery, autonomy and sustainable workload
Low AI demand + low resources	Under-enabled workforce	Increase AI capability and task support
Low AI demand + high resources	Empowering AI environment	Scale successful practices and preserve autonomy

Table 5. Managerial diagnostic using the AI resource–demand balance.

14. NOVELTY OF THE PRESENT ARTICLE

Dimension	Typical emphasis in fragmented literature	Present contribution
AI role	Adoption, usefulness or risk	AI as simultaneous resource and demand
Employee well-being	Dependent outcome	Conversion mechanism between AI work design and engagement
Employee engagement	Direct mediator in selected models	Second-stage sequential mechanism
Digital boundaries	Peripheral WLB issue	Explicit protective moderator
Performance	Short-term productivity	Sustainable multidimensional performance
Method	Single-wave self-report	Cross-sectional empirical design with a supervisor-rated performance robustness outcome
Managerial response	AI adoption strategy	Human-centred H-AI-WELL system

Table 6. Distinctive contribution of the present article.

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15. LIMITATIONS AND FUTURE RESEARCH

The principal limitation is that the present statistical analysis is cross-sectional because the supplied dataset does not contain distinct wave-specific item responses, despite containing three wave-date fields. Consequently, the findings establish associations rather than temporal or causal effects. A genuine longitudinal test should collect antecedents at T1, employee well-being at T2, and engagement/performance at T3.

A second limitation is that AI technologies evolve rapidly. Constructs such as technostress, monitoring pressure and AI capability may change as systems become more integrated into work. Future researchers should therefore use periodically updated measurement instruments.

A third limitation concerns context. The meaning of AI adoption may differ between public and private organizations, occupations, sectors, countries and organizational sizes. Recent reviews specifically identify cross-cultural and cross-industry comparison as a need. [5]

Future studies should examine AI literacy, psychological safety, leadership support, organizational culture, employee resilience, job crafting and perceived organizational support as additional moderators or mediators. Experimental job-redesign studies and longitudinal panels would provide stronger causal evidence than conventional cross-sectional designs.

16. ETHICAL AND RESEARCH-INTEGRITY CONSIDERATIONS

An empirical implementation of this framework should provide informed consent, voluntary participation, confidentiality and secure data storage. AI-related questions may involve sensitive perceptions of job security or organizational monitoring; therefore, individual responses should not be shared with employers in identifiable form. Supervisor-rated performance should be collected using procedures that prevent employees from being penalized for research participation.

The manuscript distinguishes clearly between the original conceptual expectations and the empirical results calculated from the dataset. The dataset-derived coefficients are reported transparently, including the unsupported H11. No synthetic observations were added to the supplied file.

Submission verification statement. Before submission, the author should ensure that the final manuscript file is accompanied by the actual questionnaire/instrument, documentation of data collection and respondent recruitment, the applicable institutional ethics approval or exemption/waiver information, informed-consent documentation where applicable, and the analysis syntax or reproducible statistical workflow. These materials are not inferred from the dataset and should be supplied according to the journal's requirements.

16.1 DATA AVAILABILITY AND REPRODUCIBILITY

The analysis is based on the 600-record dataset supplied for this manuscript. For reproducibility and journal review, the author should retain the raw dataset, questionnaire, codebook, data-cleaning record, analysis syntax, output files and documentation of respondent recruitment and consent. The present manuscript reports the analytical decisions needed to reconstruct the main composite-score, HC3 regression, bootstrap mediation and interaction analyses, while acknowledging that the underlying item-level instrument and recruitment documentation are not embedded in the manuscript.

17. CONCLUSION

Artificial intelligence is creating a workplace in which the same technology can enable employees and place new demands on them. The empirical evidence from the dataset supports this dual-pathway interpretation: AI resources positively predict well-being, while AI demands negatively predict well-being.

The results further show that employee well-being is positively associated with engagement and that engagement is strongly associated with sustainable performance. The significant indirect and sequential pathways demonstrate how AI work conditions can become organizationally consequential through human psychological and motivational processes. Digital boundary control selectively weakens the harmful AI-demand pathway, although it does not significantly strengthen the AI-resource pathway.

The most important managerial implication is that AI productivity should not be treated as equivalent to sustainable organizational performance. Organizations should design AI-enabled work to increase capability and autonomy while reducing avoidable technostress, insecurity, overload and digital boundary erosion.

The article therefore offers a contemporary research agenda for HRM, organizational behaviour and digital transformation: the objective is not simply to make employees work with AI, but to design AI-enabled work in a way that preserves the human capacity to perform, adapt and remain well over time.

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