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The role of AI-enabled HRM practices and employee well-being: From digital wellness to organizational commitment

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Abstract: This study examines the associations among AI-enabled Corporate Wellness Systems (AI-CWS), Employee Well-Being (EWB), and Organizational Commitment (OC) among employees in Indian organizations. Using a quantitative, cross-sectional survey design, primary data from 1,259 respondents in technology, banking, healthcare, and education-related organizations were analysed using descriptive statistics, Pearson correlations, hierarchical regression, and bootstrapped mediation analysis. The results indicate a statistically significant negative association between AI-CWS and EWB ($B = -0.183, p < 0.001$) and a statistically significant positive association between AI-CWS and OC ($B = 0.323, p < 0.001$). EWB was positively associated with OC ($B = 0.160, p < 0.001$). The bootstrapped indirect association of AI-CWS with OC through EWB was negative and statistically significant (indirect effect = -0.029 , 95% CI $[-0.045, -0.016]$), while the direct association remained positive ($B = 0.352, p < 0.001$). The pattern is therefore consistent with an inconsistent or competitive mediation structure rather than positive partial mediation. Given the cross-sectional and self-reported nature of the data, the findings are interpreted as associations rather than causal effects. The study extends Job Demands–Resources and Perceived Organizational Support perspectives by showing that AI-enabled wellness systems may be perceived simultaneously as organizational support and as a potential technological demand.

Keywords: Artificial intelligence; AI-enabled corporate wellness systems; Employee well-being; Organizational commitment; Perceived organizational support; Job demands–resources theory.

1. Introduction

The implementation of artificial intelligence (AI) in contemporary organizations is reshaping human resource management, including approaches to employee wellness, engagement, and support. AI-enabled corporate wellness systems (AI-CWS) may incorporate digital wellness resources, automated support, predictive analytics, personalized recommendations, and real-time feedback. Prior literature identifies potential benefits of such technologies while also noting concerns related to privacy, surveillance, autonomy, and the quality of human–AI interaction [1,2,4]. Consequently, the organizational and psychological implications of AI-enabled wellness should be examined empirically rather than assumed to be uniformly beneficial.

Human-centred design is increasingly important in the integration of AI into human resource management. Human-centred AI emphasizes alignment between technological functionality, ethical governance, and users' welfare [2]. From this perspective, AI-CWS may provide accessible support and personalized information, but the same systems may also introduce perceived monitoring or uncertainty regarding the collection and use of employee data. The balance between potential resource and demand characteristics is therefore relevant to

understanding employee responses.

Recent research suggests that AI can support workplace health promotion through individualized information, risk identification, and digital interventions, although the empirical evidence remains developing [1,4,7]. These potential benefits do not imply that employees necessarily experience AI-enabled wellness as supportive. Digital monitoring, technological dependence, and concerns about data governance may alter employees' perceptions of the intervention and its consequences for well-being.

This issue is particularly relevant in India, where organizations are undergoing rapid digital transformation. Previous research on employee well-being programmes has reported positive associations with organizational commitment in conventional workplace settings [3]. However, evidence concerning AI-enabled wellness systems remains less developed, particularly regarding whether employee well-being represents a positive or negative pathway between technology-related wellness support and organizational commitment.

The organizational implications of AI-enabled wellness interventions therefore remain an empirical question. Systematic evidence indicates that AI applications in workplace health promotion are promising but still limited in scope, and implementation conditions matter [4]. Research on AI adoption and psychological safety likewise emphasizes supportive organizational practices, ethical governance, and attention to potential adverse effects [8].

Against this background, the present study addresses the following research question: What are the associations among AI-enabled corporate wellness systems, employee well-being, and organizational commitment in Indian organizations? Particular attention is given to whether employee well-being statistically mediates the association between AI-CWS and organizational commitment. Because the study is cross-sectional, the analysis does not establish temporal precedence or causal effects.

The study focuses on employees in Indian organizations across technology, banking, healthcare, and education-related settings. It examines self-reported perceptions and attitudes rather than objective outcomes such as turnover or absenteeism. The Indian context provides a relevant setting for examining the interaction between digital workplace practices, employee well-being, and organizational attitudes, while limiting generalizability to other national and institutional contexts.

The study contributes to the literature in three respects. First, it applies Job Demands–Resources (JD-R) and Perceived Organizational Support (POS) perspectives to AI-enabled workplace wellness. Second, it examines employee well-being as a potential statistical pathway linking AI-CWS with organizational commitment. Third, it highlights an empirically mixed pattern in which AI-CWS is positively associated with organizational commitment but negatively associated with employee well-being, producing a negative indirect association through well-being. This pattern provides a more cautious basis for evaluating AI-enabled wellness than an assumption of uniformly positive effects.

Ethical governance is particularly relevant to AI-enabled wellness because these systems may involve sensitive employee information, monitoring, or algorithmic decision-making. Prior literature emphasizes transparency, privacy, fairness, and human oversight [1,4,8]. The present study therefore treats these issues as possible contextual explanations for the observed negative association between AI-CWS and employee well-being rather than as empirically established mechanisms.

The study also contributes to the broader discussion of digital transformation by examining whether organizational commitment and employee well-being move

in the same direction when employees perceive greater AI-enabled wellness support. Existing research suggests that AI can have both supportive and potentially adverse implications for well-being depending on work design and implementation conditions [5,6]. The present findings are interpreted within this dual-pathway perspective.

The research specifically examines: (i) the association between AI-CWS and employee well-being; (ii) the association between AI-CWS and organizational commitment; and (iii) the indirect association between AI-CWS and organizational commitment through employee well-being. All relationships are interpreted as statistical associations because the study uses cross-sectional, self-reported data.

Overall, the study positions AI-enabled organizational wellness at the intersection of technology, employee psychology, and organizational behaviour. Rather than assuming that AI adoption improves employee outcomes, the analysis evaluates whether AI-CWS is associated with well-being and commitment in the same or different directions. This distinction is important because a technology may simultaneously be perceived as an organizational support signal and as a potential technological demand.

2. Literature Review

Research on AI and employee well-being has expanded as organizations increasingly incorporate digital technologies into human resource management. A systematic review identifies applications of AI in workplace well-being including mental-health monitoring, emotional support, personalized wellness programmes, identification of psychosocial risks, and training and development [1]. These applications indicate potential utility but do not establish that AI-enabled systems improve employee outcomes in all organizational settings.

Lange et al. [4] conclude that AI in workplace health promotion and prevention remains a relatively limited empirical field. Their review identifies potential for individualization and risk prediction but emphasizes the need for broader research, longitudinal evidence, and stronger reporting. This evidence supports examining AI-enabled wellness as a context-dependent intervention rather than assuming a uniformly beneficial effect.

Research on psychological safety further suggests that the organizational consequences of AI adoption depend on implementation conditions, including ethical governance, communication, and employee perceptions [8]. These considerations are compatible with the present study's use of JD-R and POS perspectives, which allow AI to function either as a resource or as a demand depending on how employees experience the technology.

Recent conceptual work emphasizes the dual potential of AI for employee well-being. Watermann et al. [6] argue that AI can influence work design in ways that may either enhance or undermine psychological well-being, depending on how technical and psychological considerations are balanced. This duality is relevant to the negative AI-CWS–EWB association observed in the present study.

Evidence concerning conventional employee well-being programmes indicates that organizational support can be positively related to organizational commitment [3]. However, this evidence should not be transferred directly to AI-enabled wellness systems because digital systems introduce additional issues of privacy, surveillance, autonomy, and technological pressure. The present study therefore examines the direct and indirect associations empirically.

Research on employee well-being in the digital era identifies both opportunities and risks, including improved efficiency alongside digital overload, stress, and burnout [5]. The broader literature therefore supports a balanced expectation: AI-enabled wellness may operate as a job resource in some

circumstances but may also generate job demands. The present study tests this possibility using employee well-being and organizational commitment as outcomes.

2.1 Theoretical Framework

The relationship between AI-enabled corporate wellness systems and employee outcomes is examined through Job Demands–Resources (JD-R) theory and Perceived Organizational Support (POS) theory. JD-R theory proposes that employee outcomes reflect the interaction between job demands and job resources. Digital technologies can operate as resources when they facilitate access to information, support, and coping resources, but they can also constitute demands when they increase monitoring, uncertainty, technological pressure, or perceived loss of autonomy [10].

POS theory proposes that employees develop general beliefs about the extent to which their organization values their contributions and cares about their well-being [11]. Organizational investments in employee support may therefore be associated with stronger organizational attitudes. In the context of AI-enabled wellness, however, the POS interpretation depends on whether employees perceive the technology as genuine organizational support rather than as surveillance or control.

The two perspectives provide a complementary framework for interpreting the present findings. JD-R theory is relevant to the relationship between AI-CWS and employee well-being because AI-enabled wellness may simultaneously provide resources and create technological demands. POS theory is relevant to the positive association between AI-CWS and organizational commitment because investment in wellness infrastructure may be interpreted as a signal of organizational support. The framework therefore does not require that AI-CWS have a uniformly positive effect.

Based on this framework, the study examines the association between AI-CWS and employee well-being, the association between AI-CWS and organizational commitment, and the indirect association between AI-CWS and organizational commitment through employee well-being. Given the cross-sectional design, these relationships are interpreted as associations rather than causal effects.

3. Materials and methods

The study used a quantitative, explanatory, cross-sectional survey design to examine the associations among AI-enabled corporate wellness systems, employee well-being, and organizational commitment among employees in India. The cross-sectional design permits estimation of statistical relationships but does not establish temporal ordering or causality. The analytical framework was informed by JD-R theory and POS theory, which allow AI-enabled wellness to be considered as either a potential job resource or a potential technological demand depending on employee perceptions and implementation conditions.

The empirical analysis focused on three constructs: AI-CWS, employee well-being, and organizational commitment. The analytical model examined their bivariate associations, adjusted regression relationships, and the indirect association between AI-CWS and organizational commitment through employee well-being. The direction of the observed relationships was determined empirically and was not assumed in the interpretation of the final results.

3.1 Data Sources and Sampling

The study used primary cross-sectional survey data collected from employees working in India between June and August 2025. The target population comprised currently employed individuals with sufficient exposure to organizational digital

or AI-enabled workplace practices to provide informed responses. Participants were invited and the questionnaire was disseminated via organizational contacts, professional networks and online professional groups. The questionnaire was self-administered and participation was voluntary. Before participation, respondents were informed about the academic purpose of the study, the confidentiality of their responses and their right to decline participation.

A total of 1,259 complete and usable responses were retained for the final analysis after screening for incomplete or inconsistent responses. As the questionnaire was disseminated through various open online channels like organizational contacts, professional networks and online professional groups, a complete record of the number of invitations or individuals who receive the survey is not available; hence, we cannot calculate the response rate. Age was collected as a continuous demographic variable in completed years and was retained as a continuous variable in the statistical analyses.

The Open Sourcing Mental Illness (OSMI) Mental Health in Tech Survey [12] was considered only as contextual background concerning workplace mental-health support. No formal statistical comparison or validation analysis was conducted with the OSMI dataset because measurement equivalence with the present questionnaire was not established. OSMI evidence is therefore not used to validate, externally replicate, or confirm the direction of the present study's statistical associations.

3.2 Instrument Development and Measures

The questionnaire comprised demographic questions and measures of AI-enabled corporate wellness support, employee well-being, and organizational commitment. Items were assessed using a five-point Likert response format ranging from 1 = strongly disagree to 5 = strongly agree. A pilot study involving 59 respondents was undertaken to assess item clarity, comprehensibility, and preliminary reliability.

AI-CWS was operationalized using indicators covering accessibility of digital wellness resources, personalized recommendations, chatbot-based support, predictive or preventive wellness functions, and perceptions of privacy and confidentiality. These indicators span multiple facets of AI-enabled wellness and should therefore be treated as an exploratory composite/index unless dimensionality is established statistically.

Employee well-being was operationalized using indicators relating to perceived stress, sleep quality, and burnout frequency. Items representing adverse states were reverse-coded so that higher scores indicated better reported well-being.

Organizational commitment was assessed using items relating to employees' attachment to the organization and intention to remain. Supervisor support and psychological safety should not be treated as interchangeable with affective organizational commitment unless their construct structure is empirically demonstrated. The reported OC composite was retained for the exploratory analysis, but its reliability coefficient ($\alpha = 0.670$) limits claims about measurement homogeneity.

The internal consistency estimates were $\alpha = 0.721$ for AI-CWS, $\alpha = 0.626$ for EWB, and $\alpha = 0.670$ for OC. These results provide acceptable exploratory evidence for AI-CWS but weaker evidence for EWB and OC. The measures should therefore not be described as uniformly reliable or psychometrically confirmed. Future research should use established scales and test construct validity through confirmatory factor analysis, composite reliability, convergent validity, and discriminant validity.

The composite measures are consequently treated as exploratory

study-specific or adapted indices. No claim of full construct validation is made. The absence of factor-analytic evidence and the relatively low internal consistency of EWB and OC are explicitly recognized as measurement limitations.

3.3 Data Analysis Procedures

Statistical analyses were conducted using SPSS and Python. Data were screened for incomplete or inconsistent responses, followed by descriptive statistics for the principal constructs and respondent characteristics. Internal consistency was assessed using Cronbach's alpha. Pearson correlations were used to describe bivariate associations among AI-CWS, EWB, OC, and age. Hierarchical ordinary least squares regression models estimated the associations of AI-CWS with EWB and OC while adjusting for age, company size, remote-work status, and industry category. A third regression model included AI-CWS and EWB simultaneously as predictors of OC.

The indirect association was estimated using non-parametric bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals. An indirect effect was considered statistically different from zero when its confidence interval excluded zero. Regression diagnostics included checks of linearity, homoscedasticity, multicollinearity, and distributional assumptions. Because the study is cross-sectional and based on self-reported measures, the coefficients and indirect effect are interpreted as statistical associations rather than causal effects.

No comparative statistical analysis using the OSMI dataset [12] was conducted. The OSMI Mental Health in Tech Survey was used only as contextual background and is not presented as an external validation sample, replication dataset, or source of equivalent variables.

4. Results

The empirical analysis examined the descriptive characteristics and statistical associations among AI-CWS, EWB, and OC. Preliminary diagnostics indicated low levels of missing data and no serious multicollinearity ($VIF < 3$ for all predictors). The results are reported as associations because the study is cross-sectional.

4.1. Descriptive Statistics

Table 1 reports the descriptive statistics. Age was collected as a continuous demographic variable by asking respondents to report their age in completed years. For analysis, age was retained as a continuous variable. The mean AI-CWS score was 2.64 ($SD = 0.98$), the mean EWB score was 3.63 ($SD = 1.17$), the mean OC score was 2.66 ($SD = 1.12$), and the mean age of respondents was 32.08 years ($SD = 7.29$) with ages ranging from 18 to 72 years. These values are descriptive characteristics of the sample and do not by themselves indicate causal or substantive effects.

Table 1. Descriptive Statistics for Key Constructs

	ai_cws_index	well_being_index	org_commitment_index	Age
count	1259	1259	1259	1259
mean	2.64	3.63	2.66	32.08
std	0.98	1.17	1.12	7.29
min	1	2	1	18
25%	1.83	2.5	1.67	27
50%	2.33	3.5	2.33	31
75%	3.17	5	3.67	36
max	5	5	5	72

The sample displayed variation in AI-CWS, EWB, and OC scores, with respondents ranging in age from 18 to 72 years. These descriptive statistics provide the empirical basis for the subsequent correlational and regression analyses.

4.1.1 Correlations

Table 2 shows Pearson correlation analysis indicated a statistically significant negative association between AI-CWS and EWB ($r = -0.131$, $p < 0.001$), a statistically significant positive association between AI-CWS and OC ($r = 0.197$, $p < 0.001$), and a statistically significant positive association between EWB and OC ($r = 0.126$, $p < 0.001$).

Table 2. Pearson Correlation Matrix (Key Constructs)

	ai_cws_index	well_being_index	org_commitment_index	Age
ai_cws_index	1	-0.131	0.197	0.149
well_being_index	-0.131	1	0.126	-0.05
org_commitment_index	0.197	0.126	1	-0.037
Age	0.149	-0.05	-0.037	1

The correlation pattern does not support an assumed positive association between AI-CWS and employee well-being. Instead, higher AI-CWS scores were associated with lower EWB scores in the present sample. Because the data are cross-sectional and self-reported, the direction of causality cannot be established.

Age showed a small positive association with AI-CWS ($r = 0.149$) and small negative associations with EWB ($r = -0.050$) and OC ($r = -0.037$). These coefficients are small and should not be interpreted as substantive effects without additional evidence.

4.1.2 Reliability and Measurement Quality

The internal consistency estimates were $\alpha = 0.721$ for AI-CWS, $\alpha = 0.626$ for EWB, and $\alpha = 0.670$ for OC (**Table 3**). The AI-CWS coefficient provides acceptable exploratory evidence of internal consistency, whereas the EWB and OC coefficients are below the commonly preferred threshold of 0.70.

The reliability evidence should not be characterized as uniformly strong. The lower coefficients for EWB and OC suggest that the component items may not form highly homogeneous reflective constructs, particularly because the measures combine conceptually distinct dimensions.

The composite indices were retained for the exploratory analyses, but the measurement limitations should be considered when interpreting the substantive findings. Future research should employ established scales and evaluate dimensionality and construct validity using confirmatory factor analysis and additional reliability and validity criteria.

Table 3. Reliability of Composite Scales (Cronbach's α)

Scale	Cronbach's α
AI-CWS composite	0.721
Well-Being composite	0.626
Organizational Commitment composite	0.67

4.1.3 Multivariate Regression Analysis

Three hierarchical regression models were estimated with controls for age, company size, remote-work status, and industry category. The reported coefficients are unstandardized regression coefficients (B).

Model A: AI-CWS and Employee Well-Being

Table 4 shows AI-CWS was negatively associated with EWB ($B = -0.183$, $SE = 0.036$, $t = -5.071$, $p < 0.001$, 95% CI $[-0.254, -0.112]$). Thus, after adjustment for the specified controls, higher AI-CWS scores were associated with lower EWB scores in this sample. Company size was positively associated with EWB ($B = 0.059$, $p = 0.006$), whereas age, remote-work status, and industry category were not statistically significant. The coefficient is an adjusted association and should not be interpreted causally.

Table 4. Regression A: Employee Well-Being ~ AI-CWS (+ Controls)

	Coef.	Std.Err.	t	P > t	[0.025	0.975]
const	3.995	0.203	19.722	0	3.598	4.393
ai_cws_index	-0.183	0.036	-5.071	0	-0.254	-0.112
Age	-0.005	0.005	-1.079	0.281	-0.014	0.004
company_size_num	0.059	0.022	2.73	0.006	0.017	0.102
remote_num	-0.017	0.019	-0.918	0.359	-0.054	0.02
tech_num	0.026	0.022	1.18	0.238	-0.017	0.069

Model B: AI-CWS and Organizational Commitment

AI-CWS was positively associated with OC ($B = 0.323$, $SE = 0.033$, $t = 9.705$, $p < 0.001$, 95% CI $[0.258, 0.389]$) (**Table 5**). Company size was negatively associated with OC ($B = -0.137$, $p < 0.001$), and industry category was positively associated with OC ($B = 0.054$, $p = 0.008$). Age and remote-work status were not statistically significant. The positive AI-CWS coefficient indicates an adjusted statistical association with organizational commitment, not a causal effect.

Table 5. Regression B: Organizational Commitment ~ AI-CWS (+ Controls)

	Coef.	Std.Err.	t	P > t	[0.025	0.975]
const	2.289	0.187	12.228	0	1.922	2.656
ai_cws_index	0.323	0.033	9.705	0	0.258	0.389
Age	-0.008	0.004	-1.831	0.067	-0.016	0.001
company_size_num	-0.137	0.02	-6.819	0	-0.176	-0.097
remote_num	0.002	0.017	0.131	0.896	-0.032	0.036
tech_num	0.054	0.02	2.655	0.008	0.014	0.094

Model C: AI-CWS, Employee Well-Being, and Organizational Commitment

When EWB was entered simultaneously with AI-CWS, both predictors remained statistically significant (**Table 6**). AI-CWS was positively associated with OC ($B = 0.352$, $SE = 0.033$, $t = 10.628$, $p < 0.001$), while EWB was also positively associated with OC ($B = 0.160$, $SE = 0.026$, $t = 6.184$, $p < 0.001$). The AI-CWS coefficient increased from 0.323 in Model B to 0.352 in Model C. This pattern is consistent with a negative indirect pathway rather than attenuation consistent with positive partial mediation. Mediation is therefore evaluated from the bootstrapped indirect effect rather than from coefficient reduction alone.

Importantly, the coefficient for AI-CWS in Model C is larger than that in Model B. Therefore, the present regression results do not support the manuscript's earlier

statement that the AI-CWS coefficient decreases after the mediator is introduced. The evidence for mediation must consequently be based on the bootstrapped indirect effect rather than on coefficient reduction alone.

Table 6. Regression C: Organizational Commitment ~ AI-CWS + Well-Being (+ Controls)

	Coef.	Std.Err.	t	P > t	[0.025	0.975]
const	1.652	0.211	7.815	0	1.237	2.066
ai_cws_index	0.352	0.033	10.628	0	0.287	0.418
well_being_index	0.16	0.026	6.184	0	0.109	0.21
Age	-0.007	0.004	-1.669	0.095	-0.015	0.001
company_size_num	-0.146	0.02	-7.377	0	-0.185	-0.107
remote_num	0.005	0.017	0.294	0.769	-0.029	0.039
tech_num	0.05	0.02	2.487	0.013	0.011	0.089

4.1.4 Bootstrapped Indirect Association

A non-parametric bootstrapping procedure with 5,000 resamples estimated the indirect association between AI-CWS and OC through EWB (**Table 7**). The indirect effect was -0.029 , with a 95% bias-corrected confidence interval of $[-0.045, -0.016]$. Because the interval excludes zero, the indirect association is statistically different from zero.

The negative indirect pathway is consistent with the negative first-stage association between AI-CWS and EWB combined with the positive association between EWB and OC. In statistical terms, higher AI-CWS scores were indirectly associated with lower OC through lower reported EWB.

At the same time, AI-CWS retained a positive association with OC when EWB was included in the model ($B = 0.352$, $p < 0.001$). The coexistence of a positive direct association and a negative indirect association is appropriately described as inconsistent or competitive mediation. The results do not support the claim that AI-CWS improves well-being and thereby increases commitment.

The observed pattern is better represented as two statistically distinguishable pathways: a positive direct association between AI-CWS and organizational commitment and a negative indirect association operating through employee well-being. The data do not establish why these pathways differ in direction; possible explanations such as perceived organizational support, privacy concerns, monitoring, technological pressure, or reverse causality require testing in future research.

Table 7. Bootstrapped Indirect Effect of AI-CWS on Organizational Commitment via Employee Well-Being

Indirect effect (a*b)	95% CI lower	95% CI upper	Bootstraps
-0.029	-0.045	-0.016	5000

The mediation results therefore do not support the previously proposed pathway of “AI wellness systems $\rightarrow$ improved well-being $\rightarrow$ increased commitment.” Instead, the empirical pattern indicates a positive direct association between AI-CWS and OC alongside a negative indirect association through EWB. This pattern is compatible with the dual-resource/demand interpretation offered by JD-R theory and the support-signalling interpretation offered by POS theory, but the present cross-sectional data cannot establish the underlying causal mechanism.

4.2 Graphical and Visual Diagnostics

Distribution of AI-CWS

Figure 1 displays the distribution of AI-CWS scores. The figure indicates substantial variation across respondents. The distribution should be treated as descriptive evidence of heterogeneity in reported AI-enabled wellness support rather than as evidence of organizational adoption or effectiveness.

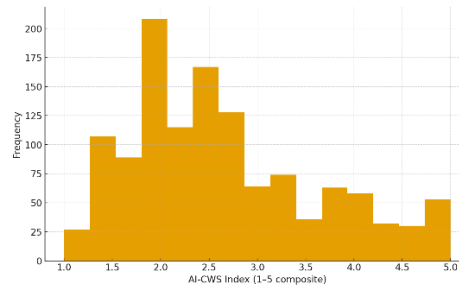


Figure 1. Distribution of AI-Driven Corporate Wellness Support (AI-CWS)

Bivariate Relationship Between AI-CWS and Organizational Commitment

Figure 2 illustrates the positive bivariate relationship between AI-CWS and organizational commitment. The upward regression line is consistent with the Pearson correlation reported in **Table 2** ($r = 0.197$, $p < 0.001$). The figure describes association and does not establish causality.

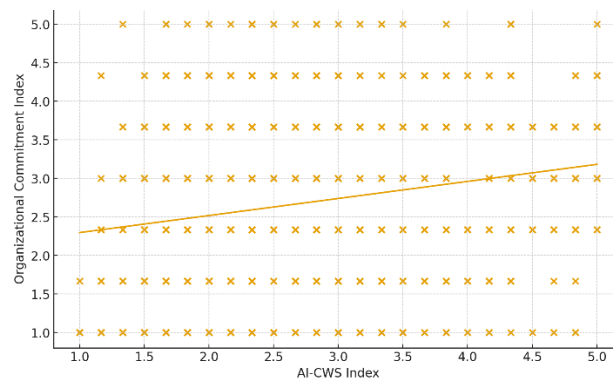


Figure 2. Relationship Between AI-Driven Wellness Support (AI-CWS) and Organizational Commitment

Organizational Commitment by Mental-Health Benefits Availability

Figure 3 presents mean organizational commitment across categories of mental-health benefits availability (1 = No, 3 = Maybe, 5 = Yes). The figure is descriptive and should not be interpreted as evidence that AI-enabled wellness benefits cause higher commitment. The category comparison is distinct from the multivariate mediation analysis reported in **Tables 4–7**.

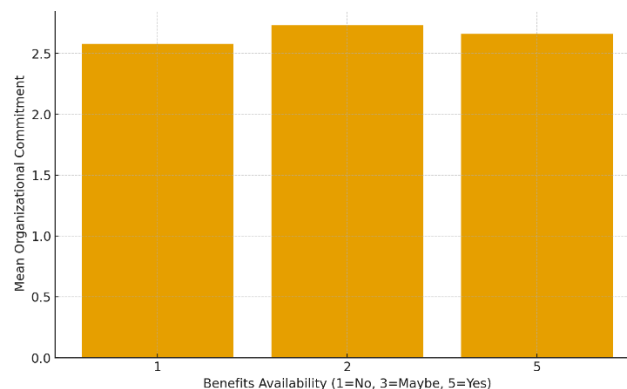


Figure 3. Mean Organizational Commitment by Mental-Health Benefits Availability

Conceptual Mediation Model

Figure 4 presents the tested mediation structure. The direct path from AI-CWS to OC is positive, while the indirect path through EWB is negative. The diagram should therefore be interpreted as an inconsistent or competitive mediation model rather than as a model of psychological enhancement.

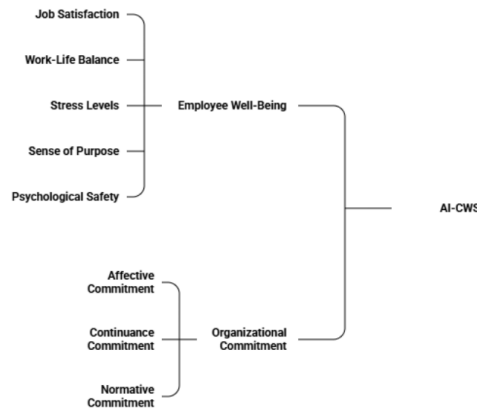


Figure 4. Conceptual Mediation Model

4.3 Summary of Results

Taken together, the results show a mixed pattern. AI-CWS was negatively associated with employee well-being, positively associated with organizational commitment, and indirectly associated with lower organizational commitment through employee well-being. The statistical pattern is therefore not consistent with a uniformly beneficial AI-enabled wellness pathway.

5. Discussion

The present study examined the relationships among AI-enabled Corporate Wellness Systems (AI-CWS), Employee Well-Being (EWB), and Organizational Commitment (OC) among employees in Indian organizations. The results show a mixed pattern: AI-CWS was positively associated with OC, negatively associated with EWB, and indirectly associated with lower OC through EWB. EWB itself was positively associated with OC. This pattern is more accurately described as inconsistent or competitive mediation than as positive partial mediation.

The positive direct association between AI-CWS and organizational commitment can be interpreted through Perceived Organizational Support theory. Employees may perceive organizational investment in wellness infrastructure as a signal that the organization recognizes employee needs and provides support. This interpretation is theoretically plausible and consistent with POS, but the cross-sectional design does not demonstrate that AI-CWS causes greater commitment.

The negative association between AI-CWS and employee well-being is theoretically important. From a JD-R perspective, the same technology may operate as a job resource for some employees while creating additional demands for others. Potential demands include perceived surveillance, uncertainty about data use, privacy concerns, reduced autonomy, and technological pressure. These explanations are plausible interpretations rather than mechanisms demonstrated by the present data.

The mediation analysis reinforces the mixed pattern. The indirect association of AI-CWS with OC through EWB was negative ($B = -0.029$, 95% CI $[-0.045, -0.016]$), while the direct association remained positive. The findings therefore do not support the pathway in which AI-CWS improves well-being and well-being subsequently increases commitment. Instead, the data indicate opposing direct and indirect associations.

Several explanations may account for the divergent pathways. Employees may simultaneously value organizational investment in wellness while experiencing discomfort related to digital monitoring or data collection. Alternatively, employees with lower well-being may be more likely to use or notice wellness technologies, creating possible reverse causality. Because the study does not establish temporal ordering, these explanations cannot be distinguished empirically.

The findings suggest that AI-enabled wellness should be evaluated not only by the presence of technological features but also by implementation quality, transparency, employee autonomy, perceived confidentiality, and access to human support. This interpretation is consistent with literature emphasizing both the potential and the limitations of AI in workplace health promotion [1,4,5,6,9]. Future research should test these contextual factors directly using longitudinal and multi-source designs.

5.1 Theoretical Implications

The findings refine the application of JD-R and POS perspectives to AI-enabled wellness. The negative AI-CWS–EWB association is compatible with a JD-R interpretation in which digital systems can generate demands as well as resources. The positive AI-CWS–OC association is compatible with POS insofar as employees may interpret organizational investment in wellness as a support signal. The opposing direct and indirect associations indicate that these mechanisms should not be collapsed into a single positive pathway.

5.2 Managerial Implications

The findings imply that AI-enabled wellness systems should not be evaluated solely on technological availability or organizational commitment outcomes. Organizations should establish transparent data-governance practices, communicate how employee information is collected and used, preserve employee autonomy, and maintain human support alongside digital tools. Employee well-being should be monitored after implementation because a system intended as support may also be experienced as a technological demand.

5.3 Limitations and Future Research

The study used non-probability convenience sampling with purposive eligibility criteria. As the survey was distributed through organizational contacts, professional networks, and open online professional groups, the total number of individuals exposed to the invitation could not be determined and a response rate could not be calculated. These limitations restrict the assessment of non-response bias and should be considered when interpreting the generalizability of the findings.

First, its cross-sectional design prevents causal inference and does not establish temporal ordering. Second, the principal variables are self-reported, which may introduce common-method and perceptual biases. Third, the EWB ($\alpha = 0.626$) and OC ($\alpha = 0.670$) composites have relatively low internal consistency, and no factor-analytic construct-validation evidence is reported.

6. Conclusion

This study examined the associations among AI-enabled Corporate Wellness Systems, Employee Well-Being, and Organizational Commitment among employees in Indian organizations. The empirical results indicate a mixed pattern: AI-CWS was positively associated with organizational commitment but negatively associated with employee well-being, while employee well-being was positively associated with organizational commitment. The bootstrapped indirect association from AI-CWS to organizational commitment through employee well-being was negative and statistically significant.

The findings therefore do not support the assumption that AI-enabled wellness necessarily improves employee well-being and subsequently increases

organizational commitment. Instead, the results are consistent with an inconsistent or competitive mediation structure in which a positive direct association coexists with a negative indirect association through well-being.

Theoretically, the findings are compatible with JD-R and POS perspectives. AI-CWS may be experienced as a digital job resource when it facilitates access to support, while simultaneously functioning as a job demand when it creates concerns about surveillance, privacy, autonomy, or technological pressure. Organizational investment in wellness technology may also be associated with stronger commitment when employees interpret it as organizational support.

Given the cross-sectional research design and self-reported measures, the findings should be interpreted as associations rather than causal effects. Future research should use longitudinal and multi-source designs, validated measurement instruments, and direct measures of the contextual factors that may explain why AI-enabled wellness is associated positively with commitment but negatively with well-being.

Overall, the study suggests that the value of AI-enabled workplace wellness depends on how the technology is designed, governed, communicated, and integrated with human support. Responsible implementation should therefore be evaluated not only in terms of organizational commitment but also in terms of employee autonomy, psychological well-being, privacy, trust, and responsible data use.

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