

Impact of AI-driven Sustainable Human Resource Management Practices on Employee Performance

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Abstract

The rapid integration of Artificial Intelligence (AI) into human resource management has created new imperatives for understanding how AI-driven Sustainable HRM (AI-SHRM) practices shape employee outcomes. This study examines the impact of AI-SHRM on employee performance (EP) and work-life balance (WLB) and the mediating role of employee well-being (EWB). Grounded in the Job Demands-Resources (JD-R) model and Conservation of Resources (COR) theory, a conceptual framework was developed and tested using primary survey data from 805 employees across seven industry sectors in India, including banking, manufacturing, information technology, healthcare, retail, education and government. Partial Least Squares Structural Equation Modelling (PLS-SEM), via Smart PLS 4.0, was used for analysis. The measurement model showed strong reliability and validity, with Cronbach's alpha above 0.89, Average Variance Extracted above 0.70 and satisfactory model fit. Data were analysed using IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA). AI-SHRM exerted significant positive direct effects on well-being, performance and work-life balance and well-being significantly influenced both performance and work-life balance. Mediation analysis showed that well-being partially and complementarily mediated the relationships between AI-SHRM and both outcomes. The model showed strong explanatory power, with R^2 values of 0.946, 0.896 and 0.917 for EP, EWB and WLB respectively. Employee well-being is identified as the primary transmission mechanism through which AI-SHRM investments generate downstream employee outcomes, with theoretical and managerial implications for the design and governance of AI-augmented HR systems.

Keywords: AI-driven Sustainable HRM, Employee Performance, Employee Well-being, Job Demands-resources Model, Work-life Balance.

Introduction

AI-powered Sustainable Human Resource Management (AI-SHRM) has become an important research area, as intelligent automation meets sustainable human resource management practices (1). Sustainable HRM as a conceptual framework fosters the maintenance of the well-being of employees, work-life balance and the building of organizational cultures (2). These practices allow organisations to provide personalised well-being interventions and proactively prevent performance issues before they occur (3). Past research has focused more on the benefits of productivity and cost reduction and less on the impact on individual workers, especially their psychological well-being, work-life balance and performance (4). However, no study has theoretically constructed or empirically investigated the mechanisms of mediation that connect AI-SHRM practices to employee outcomes (5).

Recent studies published between 2020 and 2024 on algorithmic HRM and digital HR transformation confirm that individual-level well-being pathways remain markedly under-theorised, reinforcing the need for the mediation model proposed here (6-8). Employee well-being is the central focus of any HRM practice. JD-R model suggests that well-being depends on the interaction between job demands and job resources at workers' disposal and that high levels of well-being constitute solid predictors of performance and life satisfaction (9). What constitutes good or bad implementation of AI-SHRM is crucial to the extent to which it results in improvements to well-being and algorithmic depersonalisation have a detrimental impact (10). This theoretical and empirical gap is discussed by examining the effect of AI-driven Sustainable HRM practices on two significant employee outcomes, employee performance and work-life balance.

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There are three main research objectives.

- a) to explore the moderating effect of AI-SHRM practices on employee well-being, performance and work-life balance.
- b) to explore how employee well-being impacts performance and work-life balance.
- c) to analyse whether employee well-being mediates the relationship between AI-SHRM practices and employee outcomes.

The research is based on primary survey data gathered from 805 employees in seven industries in India such as Banking, IT, Manufacturing, Healthcare, Education, Retail and Government. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the proposed hypothesised relationships. With organisations adopting AI-driven HR tools, the dynamics are set against a backdrop of stark disparity in employee skills, organisational cultures and how employees perceive the ways organisations are managed (11).

Literature Review and Theoretical Framework

This study builds on the JD-R model and Conservation of Resource theory, bringing them into the context of AI and exemplifying the employee well-being (12). The JD-R model specifies the structural mechanism as to how AI-SHRM tools recalibrate the ratio of job demands to job resources (13). COR theory, in contrast, explains the motivational and self-protective mechanism, why employees who experience AI-SHRM-driven resource gains subsequently reinvest those resources into performance and boundary-management behaviors.

Sustainable HRM brings into foreground the issue of employee life span, rather than conventional HRM models that emphasise short-term results maximisation (14).

Organizations with the developed AI-HRM capabilities came out with high employee engagement and low attrition rates (5). Similarly, a positive relationship between algorithmic HR transformation and perceived fairness of performance assessments is an important antecedent of employee motivation (6). However, in these studies the pathways between AI-SHRM and individual well-being and performance have not been sufficiently mapped.

H1: AI-driven Sustainable HRM practices positively influence employee well-being.

H2: AI-driven Sustainable HRM practices positively influence employee performance.

H3: AI-driven Sustainable HRM practices positively influence work-life balance.

Employee Well-being as Mediator

Employee well-being is a multi-faceted phenomenon that includes hedonic aspects and eudaimonic aspects (15, 16). HRM literature has recognised the theoretical connection among HRM practices, well-being and outcomes (17). HRM practices that convey a commitment to employees' wellbeing help encourage a positive change, which contributes to increased employee effort, decreased absenteeism and enhanced employee personal resource management, including work-life balance (18). Stress monitoring in real time, flexible scheduling and AI-driven workload management all contribute to well-being in ways that traditional HRM practices do only in a blunt and reactive manner (10).

H4: Employee well-being positively influences employee's performance.

H5: Employee well-being has a positive influence on work-life balance.

AI-SHRM, Employee Performance and the Mediating Role of Well-being

Employee performance can be classified into three domains: task performance, contextual performance and adaptive performance (19). Higher levels of psychological well-being are accompanied by increased levels of goal commitment, creative problem-solving and resilience to the demands of the task, which leads to improved performance (20).

H6: Employee well-being mediates the relationship between AI-driven Sustainable HRM practices and employee performance.

AI-SHRM, Work-Life Balance and the Mediating Role of Well-being

Work-life balance is a state of balance between work and life that is perceived and managed well by oneself (21). There is ample research on the link between HRM practices and WLB (22). The relationship between these two factors and well-being was mediated by well-being; employees who are aware that their psychological and physical resources are supported through effective HRM practices should be more able to manage the work/personal boundary (23).

H7: Employee well-being mediates the relationship between AI-driven Sustainable HRM practices and work-life balance.

Conceptual Framework

Based on the theoretical and empirical review, this study proposes a conceptual model in which AI-

driven Sustainable HRM practices exert both direct and indirect effects on Employee Performance and Work-Life Balance. All hypotheses were tested simultaneously within a PLS-SEM framework, permitting an integrated assessment of both the direct structural paths and the mediation effects. This conceptual model is depicted in Figure 1.

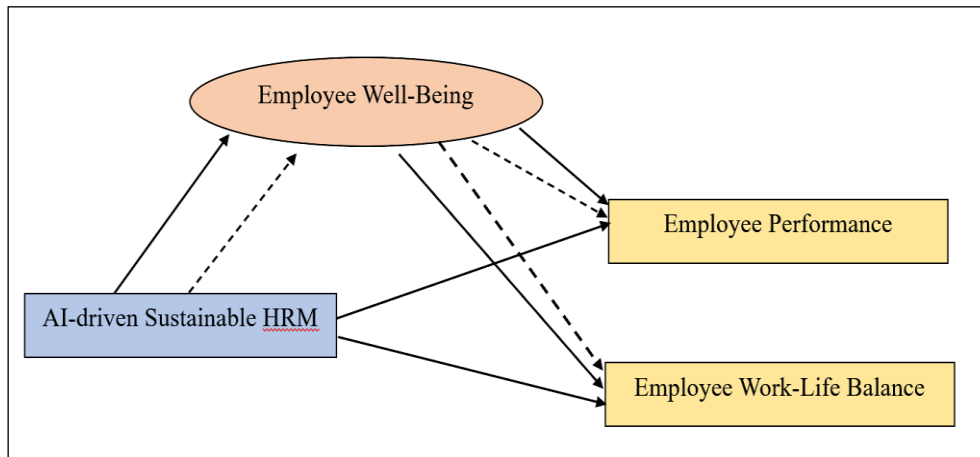


Figure 1: Conceptual Framework of the Study

Note: AI= Artificial Intelligence, HRM=Human Resource Management.

Methodology

Research Design and Philosophical Orientation

The present study adopted a quantitative, cross-sectional design with a positivist philosophical position. According to positivism, social phenomena, such as the behaviours of organisations and attitudes of employees, may be objectively measured and relationships among them may be identified and tested systematically through an empirical enquiry (24). This orientation seems to be fitting for the present study because the finding of a theoretically derived structural model between the relationships of AI-SHRM practices and employee well-being, employee performance and work-life balance is desired. The deductive approach used in this study, which starts from framework-derived hypotheses and then tests them through primary surveys and data analysis, helps build a knowledge base on AI-augmented HRM (25).

Several reasons guided the decision to use a cross-sectional survey design for this study. First, the goal of this study was to test the structural relationship between constructs at one point in time across a heterogeneous multisector sample; thus, it is an ideal study to support a cross-sectional design (26). Second, the large size of the target

population in terms of sectors and geographical distribution makes it impractical to perform longitudinal tracking within the resource restrictions of this study. Third, most studies in the field of organizational behaviour and HRM research that use PLS-SEM as an analysis tool have been conducted using cross-sectional survey designs (27).

Target Population and Sampling Strategy

The target population was full-time employees with work experience in seven major industry segments in India: IT, banking and financial services, including insurance, manufacturing, healthcare, education, retail and the government. India was chosen as the research context for two main reasons. First, India is one of the world's most prolific enterprise AI adopters, as evidenced by the rapid implementation of AI tools for human resources (HR) across various industries (11). Second, the Indian workforce is one of the most demographically and organizationally diverse employee populations, ensuring the maximum generalisability of findings in a national context, where exposure to AI, organizational culture and HRM practices widely vary.

A stratified purposive sampling strategy was used to provide adequate representation of various sectors, organizational sizes and employee designations. Forty-five organizational size categories were used to stratify the three employment sectors. In each stratum, respondents were selected via a mix of professional networks and institutional contacts and organizational HR managers with prior agreements to participate in the study. To ensure meaningful responses to the items related to AI-SHRM, a purposive criterion was applied in the sampling strategy, which means that only employees who had experience working with AI tools in the HR process were included in the sample.

Participating organizations were recruited through a combination of professional and alumni networks and pre-existing institutional research partnerships; HR managers at each organization were first approached to confirm the presence of AI-enabled HR tools and their willingness to circulate the survey internally. Strata were defined by sector, organisational size and employee designation and the number of respondents solicited within each stratum was set in proportion to publicly available sectoral employment shares rather than being left to convenience (11). Because participation depended on organisational gatekeepers, organisational-level response bias is a plausible concern: organizations with more mature or positively regarded AI-HR functions may have been more willing to participate. This possibility is acknowledged as a limitation of external validity and is one reason the sampling strategy is described here as stratified purposive rather than strictly probabilistic.

The final usable sample consisted of 805 respondents out of 1,000 survey instruments that were disseminated, resulting in a response rate of approximately 80.5%. This sample size well surpasses the suggested minimum number of observations required for PLS-SEM for models of moderate complexity, that is, 200, as well as the ten-times rule, which suggests a minimum of 10 observations per predictor path, which is well met in the present study (27). A large sample also provides adequate statistical power to reveal small-to-medium effect sizes at the standard level of significance ($\alpha = 0.05$) (28).

Survey Instrument and Measurement Scales

A structured, self-administered questionnaire in two parts was used to collect data. In the first part, demographic (profile) data of the organisations were collected. The second component was psychometric scales capturing the four key constructs: AI-driven Sustainable HRM practices (AI-SHRM), Employee Well-being (EWB), Employee Performance (EP) and Work-Life Balance (WLB). As is common in attitudinal and perceptual organizational behaviour studies, all psychometric items were 5-point Likert-type with Strongly Disagree (anchored at 1) to Strongly Agree (anchored at 5) (29).

Five items were used to measure AI-driven Sustainable HRM Practices (AI-SHRM) (3, 7). These items included aspects such as AI facilitating an equitable recruitment process, AI providing personalised learning delivery, AI enabling automated performance tracking, AI enabling well-being analytics and AI enabling workload optimisation. The rated items included the highest to lowest possible employee evaluation tools and AI tools for personalisation.

Employee Well-being (EWB) was assessed using five items adapted from the Warwick-Edinburgh Mental Well-being Scale and additional items on organizational well-being that measured psychological safety, job satisfaction, perceived support for health in the organisation, positive affect at work and sense of personal growth (17, 30).

Employee Performance (EP) was assessed using five statements that tapped effectiveness in completing tasks, quality of work output, adjustment to changing work requirements, initiative and self-direction and achievement of work performance goals (6, 19).

Work-Life Balance (WLB) was assessed by five items adapted from the scales that covered the following: workload manageability, flexibility accommodating personal responsibilities, boundary control between work and non-work and non-work conflict (21, 22).

Consistent with recent conceptual work distinguishing the dimensions of work-life balance (21, 22), work-life balance is conceptualized in this study specifically as perceived balance, that is, the employee's subjective appraisal that work and non-work roles are adequately accommodated,

rather than as the objective elimination of work-family conflict or as a measure of boundary-management style. The WLB items accordingly capture workload manageability, flexibility in accommodating personal responsibilities and boundary control, all assessed as perceived states rather than as behavioral conflict-reduction outcomes (23, 24, 26).

A pilot study was undertaken by testing the questionnaire with 45 respondents outside the sample taken up in the study but in the target population. The items were pilot-tested for clarity, speed of response, understanding of the scale and potential ambiguities. Based on the feedback obtained from the pilot test, three items were slightly modified to suit the age group and the modified instrument was used for data collection.

Rationale for PLS-SEM

The analytical method used in this study was Partial Least Squares Structural Equation Modelling (PLS-SEM) and the program used was SmartPLS 4.0 (31). Several theoretical and empirical considerations suggest the use of PLS-SEM instead of CB-SEM for this study. First, PLS-SEM is recommended for predictive and exploratory research that does not attempt to predict a priori, theory-driven covariance matrices of endogenous constructs (27). The prediction focus of PLS-SEM is epistemologically appropriate for this study, given its conceptual focus in the context of the theory development stage of AI-SHRM as a theoretical integration with existing HRM theories.

Second, PLS-SEM can be applied to complex models with several mediation pathways, whereas CB-SEM (for example, LISREL or AMOS) requires multiple distributional assumptions, such as multivariate normality (32). Third, PLS-SEM is well-suited to handle the reflective type of measurement model that was used in the present study and provided stable estimates of parameters despite moderate multicollinearity between the constructs, namely, AI-SHRM and EWB, EP and WLB and AI-SHRM and EP, which are consistent with the theorised relationships. Fourth, the large sample size ($n = 805$) and multisectoral nature of the data further strengthened the applicability of PLS-SEM, as PLS-SEM has greater estimation accuracy with increasing sample size (28).

A direct comparison with CB-SEM clarifies this choice. Although the sample size ($n = 805$) is large

enough to support CB-SEM and CB-SEM would be preferable if the primary aim were to confirm a well-established theoretical model against strict distributional criteria, CB-SEM assumes multivariate normality and is optimized for model confirmation rather than for maximizing explained variance in a newly integrated, theory-building context such as AI-SHRM (27). Given that this study is combining JD-R and COR into a new integrated framework rather than testing a fully established one and prioritises explaining variance in employee outcomes over confirming exact covariance structure, PLS-SEM's prediction-oriented, distribution-free estimation remains the more epistemologically appropriate choice, notwithstanding the sample size.

The analysis followed the two-step approach, where the measurement model was evaluated for construct validity and reliability, followed by the evaluation of the structural model to test the hypothesised relationships (33).

Measurement Model Assessment

The measurement model was assessed based on four commonly used criteria for reliability and validity in reflective PLS-SEM (27).

Cronbach's alpha (α) and composite reliability (ρ_a and ρ_c) were used to evaluate internal consistency and reliability. A Cronbach's alpha value of 0.70 is acceptable for social science research and a value of 0.90 or above is considered excellent (34). Composite reliability (ρ_c) is a more accurate indicator of reliability because it does not assume equal indicator loadings and this was compared to the recommended value of 0.70 (27).

The Average Variance Extracted (AVE) was used to establish convergent validity by calculating the percentage of variance of a construct in comparison to the overall measurement error. An AVE value of 0.50 or higher was considered a convergent validity criterion and the results of this study showed that the constructs met the criteria (35).

The Heterotrait-Monotrait (HTMT) ratio of correlations was used to assess discriminant validity, which is a more conservative and precise measure than the traditional Fornell-Larcker criterion (36). The threshold for acceptable discriminant validity is considered to be HTMT values below 0.85, values below 0.90 are considered as threshold.

The outer loadings of all reflective indicators were checked to assess the reliability of the indicators (27) and the minimum outer loading accepted was 0.7. Indicators with loadings less than 0.40 would be considered to be dropped and those with loadings between 0.40 and 0.70 would be considered to be dropped if doing so would improve the average variance extracted (AVE) or composite reliability.

Surveys conducted from a single source can suffer from Common Method Bias (CMB) (26). Procedural attempts to reduce CMB included not presenting items in contiguous sections of the survey, varying the wording of items to reduce consistency motivation and clearly affirming the confidentiality of item responses to reduce social desirability bias. A post-hoc Harman's single-factor test and full collinearity variance inflation factor (VIF) test were performed on all structural paths to determine the level of CMB. The VIF values for all the inner paths of the model were below 3.3, indicating that CMB has not critically inflated observed structural relationships (37).

It is acknowledged that Harman's single-factor test and the full-collinearity VIF test, while informative, are not sufficient in isolation to rule out common method bias when all constructs are reported by a single respondent (26). Both tests were therefore treated as complementary diagnostic checks rather than definitive proof of the absence of CMB and were interpreted alongside the a priori procedural remedies described above (temporal and psychological separation of items, reverse-worded anchors and assured confidentiality), which represent the primary safeguard against common method bias in this design; this combined procedural-and-statistical approach is noted explicitly as the basis for the CMB conclusions drawn in this study.

Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model was assessed using four criteria. The first step was to calculate the coefficient of determination (R^2) for each endogenous construct as a measure of the model's explanatory power. In behavioural research, R^2 values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak, respectively (27). Second, effect sizes (f^2) were calculated for each predictor-criterion path (28), with values of 0.02, 0.15 and 0.35, representing small, medium and

large effects, respectively. Third, path coefficients (β) were estimated using bootstrapping with 5,000 subsamples and bias-corrected confidence intervals for structural paths were calculated. Paths were deemed statistically significant when the confidence interval did not contain zero and the t-statistic was greater than 1.96 at the 5% significance level (27). Fourth, considering the significance of indirect effects via bootstrapped confidence intervals, mediation hypotheses (H6 and H7) were tested (38, 39).

The results of the model fit were checked using the Standardised Root Mean Square Residual (SRMR), which had a value of less than 0.08 to denote an acceptable model fit (40) and the Normed Fit Index (NFI), which had a value greater than 0.90 to denote an acceptable model fit (41). As additional model fit indices, d_ULS and d_G were provided (36).

In addition to R^2 , f^2 and path-significance criteria, the model's out-of-sample predictive power was evaluated using the PLS predict procedure with tenfold cross-validation and ten repetitions (17). The Q^2 predict values for all indicators of the endogenous constructs were positive and the PLS-SEM model's prediction errors were lower than those of a naive linear-model benchmark for the majority of indicators, jointly indicating that the model possesses medium-to-high predictive power beyond its in-sample explanatory strength.

Ethical Considerations

All respondents signed an informed consent form prior to data collection. All participation was voluntary and the respondents were informed of their right to withdraw at any time without consequences. No identifiable information was obtained and all responses were kept strictly confidential and used only for academic research purposes.

Results

Preliminary Overview

This section presents the empirical findings of this study in a structured sequence. The analysis was conducted in three stages.

- a) First, the demographic profile of the sample was described to establish the representativeness and diversity of the respondent base.
- b) Second, the measurement model was evaluated to confirm the reliability and validity of all four

- constructs before any structural relationships were interpreted.
- c) Third, the structural model results are presented, including direct path coefficients, coefficient of determination (R^2), effect sizes (f^2) and indirect mediation effects, each reported with bootstrapped significance statistics.

All results were generated using SmartPLS 4.0, with bootstrapping set to 5,000 subsamples. Statistical significance was evaluated at the 5% level ($p < 0.05$, two-tailed) and all findings were interpreted against the hypotheses formally stated (31). The full demographic breakdown is presented in Table 1.

Table 1: Demographic Profile of Respondents

Variables	Number of Employees	Percentage (%)
Gender		
Male	488	60.6
Female	317	39.4
Total	805	100.0
Age (years)		
Below 25	244	30.3
25-34	79	9.8
35-44	162	20.1
45-54	106	13.2
55+	214	26.6
Total	805	100.0
Marital Status		
Single	244	30.3
Married	186	23.1
Divorced	212	26.3
Widowed	163	20.2
Total	805	100.0
Education		
Diploma	106	13.2
UG	166	20.6
PG	320	39.8
MPHIL	107	13.3
PHD	106	13.2
Total	805	100.0
Sector of Employment		
IT	78	9.7
Banking	246	30.6
Manufacturing	185	23.0
Healthcare	80	9.9
Education	28	3.5
retail	82	10.2
Govt	106	13.2
Total	805	100.0
Designation		
Entry	296	36.8
Supervisor	104	12.9
Middle	104	12.9
Senior	191	23.7
Executive	110	13.7
Total	805	100.0
Experience (years)		
<2	235	29.2
2-5	82	10.2
6-10	190	23.6
11-15	246	30.6
>15	52	6.5
Total	805	100.0
Organisation Size		

50	268	33.3
51-249	108	13.4
250-999	183	22.7
1000-4999	112	13.9
5000	134	16.6
Total	805	100.0
AI HR Use		
00	160	19.9
yes	645	80.1
Total	805	100.0
AI Extent		
Low	160	19.9
Neutral	82	10.2
High	429	53.3
Very High	134	16.6
Total	805	100.0

The sample was predominantly male (60.6%) and skewed towards the youngest (below 25, 30.3%) and oldest (55+, 26.6%) age cohorts, reflecting a bimodal generational spread that captures both digitally native and transitioning employee perspectives on AI-driven HR systems. Postgraduate degree holders dominated the educational profile (39.8%), affirming the respondents' cognitive capacity to critically evaluate AI-SHRM practices. Banking (30.6%) and manufacturing (23.0%) account for the largest sectoral shares, consistent with the relatively advanced AI-HRM adoption rates in these industries in India (11). Entry-level employees form the largest designation group (36.8%), ensuring that frontline experiences of AI-SHRM, where direct exposure to automated HR tools is most frequent, are well represented alongside senior and executive perspectives (37.4% combined). Experience distribution is broadly spread, with the 11–15-year and under-2-year

bands jointly accounting for nearly 60% of respondents, mirroring the age distribution. Organizational size varies substantially, from microenterprises (33.3%) to very large organizations with 5,000 or more employees (16.6%), capturing a realistic range of AI-SHRM implementation intensities. Critically, 80.1% of respondents confirmed active AI HR tool usage in their organizations, with 53.3% characterizing the extent of use as high and a further 16.6% as very high, confirming that most of the sample had sufficient AI-HRM exposure to generate valid, experience-based construct assessments. Together, these characteristics establish the sample as diverse, multi-sector and empirically well-positioned to support the structural investigation that follows the study. The corresponding structural path diagram, showing standardised path coefficients across all constructs, is presented in Figure 2.

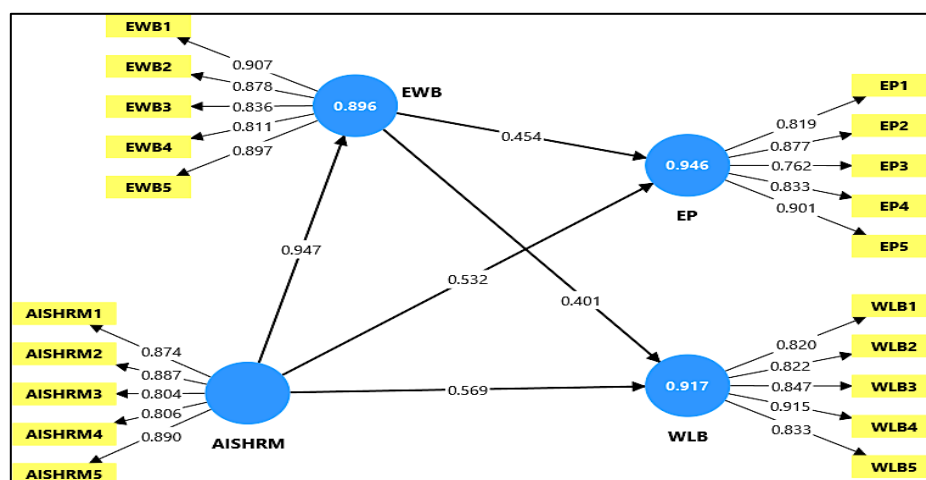


Figure 2: PLS-SEM Structural Model Results

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EWB = Employee Well-being, EP = Employee Performance, WLB = Work-Life Balance

Table 2: Direct Path Coefficients (Structural Model Direct Effects)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t Statistics (O/STDEV)	P Values
AI-SHRM -> EP	0.532	0.532	0.122	4.361	0.000
AI-SHRM ->EWB	0.947	0.947	0.103	9.194	0.000
AI-SHRM ->WLB	0.569	0.569	0.127	4.480	0.000
EWB -> EP	0.454	0.454	0.122	3.721	0.000
EWB ->WLB	0.401	0.402	0.127	3.157	0.000

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EWB = Employee Well-being, EP = Employee Performance, WLB = Work-life Balance. Path coefficients estimated via bootstrapping with 5,000 subsamples; significance based on two-tailed t-statistics ($t > 1.96$, $p < 0.05$).

Table 2 presents the direct path coefficients estimated via bootstrapping with 5,000 subsamples for the full sample. All five hypothesized direct paths were statistically significant ($p < 0.001$). The strongest direct effect is observed from AI-SHRM to EWB ($\beta = 0.947$, $t = 9.194$), indicating that AI-driven Sustainable HRM practices exert a near-complete and highly robust positive influence on employee well-being, the most powerful relationship in the entire model. AI-SHRM also exerts significant direct positive effects on WLB ($\beta = 0.569$, $t = 4.480$) and EP ($\beta = 0.532$, $t = 4.361$), confirming H2 and H3, respectively. In the

second-stage paths, EWB positively and significantly influenced both EP ($\beta = 0.454$, $t = 3.721$) and WLB ($\beta = 0.401$, $t = 3.157$), supporting H4 and H5. The close alignment between the original sample estimates and bootstrapped sample means across all paths confirmed the stability of these estimates and ruled out model overfitting. Collectively, these results establish that AI-SHRM practices operate as a powerful antecedent of both well-being and downstream employee outcomes, while well-being functions as a substantive predictor of performance and work-life balance.

Table 3: Indirect Path Coefficients (Mediation Effects)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t Statistics (O/STDEV)	P Values
AI-SHRM ->EWB ->EP	0.430	0.430	0.121	3.554	0.000
AI-SHRM ->EWB ->WLB	0.380	0.380	0.126	3.016	0.000

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EWB = Employee Well-being, EP = Employee Performance, WLB = Work-Life Balance. Path coefficients estimated via bootstrapping with 5,000 subsamples; significance based on two-tailed t-statistics ($t > 1.96$, $p < 0.05$).

Table 3 reports the bootstrapped indirect effects testing the mediating role of employee well-being in the AI-SHRM-EP and AI-SHRM-WLB relationships, respectively. Both indirect paths were statistically significant ($p < 0.001$). The indirect effect of AI-SHRM on EP through EWB is $\beta = 0.430$ ($t = 3.554$), confirming that employee well-being meaningfully transmits the performance-enhancing effects of AI-SHRM practices, supporting H6. Similarly, the indirect effect of AI-SHRM on WLB through EWB is $\beta = 0.380$ ($t = 3.016$), confirming partial mediation in the work-

life balance pathway, thus supporting H7. The substantive magnitude of both indirect effects, relative to the corresponding direct effects reported in Table 2, indicates that well-being is not a trivial mediator but a central transmission mechanism through which AI-SHRM converts its structural affordances into tangible employee outcomes. Both the direct and indirect paths are significant; the mediation pattern is classified as complementary partial mediation for both outcome variables (39).

Table 4: Coefficient of Determination (R^2)

	R-square	R-square adjusted
EP	0.946	0.946
EWB	0.896	0.896
WLB	0.917	0.917

Note: R-square = Coefficient of Determination, EP = Employee Performance, EWB = Employee Well-being, WLB = Work-life Balance.

Table 4 presents the coefficients of determination (R^2) for the three endogenous constructs in the model. All three R^2 values are exceptionally high, substantially exceeding the 0.75 threshold classified as having substantial explanatory power in behavioral PLS-SEM research (27). Employee Performance is the most strongly explained construct ($R^2 = 0.946$), indicating that the combined direct effects of AI-SHRM and EWB account for 94.6% of the variance in EP, reflecting the tight theoretical and empirical coupling between AI-driven HR practices, well-being

resources and performance outcomes. Work-Life Balance is explained at $R^2 = 0.917$ and Employee Well-being at $R^2 = 0.896$, both indicating that the model captures the overwhelming majority of systematic variance in these constructs. The near-zero gaps between R^2 and adjusted R^2 across all three endogenous constructs confirms that the high explanatory power is not an artifact of overfitting and holds under correction for the model complexity. These values collectively affirm the strong overall predictive adequacy of the proposed model.

Table 5: Effect Sizes (f^2)

	f-square
AI-SHRM -> EP	0.541
AI-SHRM ->EWB	0.649
AI-SHRM ->WLB	0.406
EWB -> EP	0.395
EWB ->WLB	0.402

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EP = Employee Performance, EWB = Employee Well-being, WLB = Work-life Balance, F-Square = Effect Size.

Table 5 presents the f^2 effect sizes, which measure the practical contribution of each predictor to the explained variance of its respective endogenous construct, independent of the overall R^2 (28). By convention, f^2 values of 0.02, 0.15 and 0.35 denote small, medium and large effects, respectively. All five paths in the model yielded large effect sizes, underscoring the substantive practical significance of each relationship beyond statistical significance alone. The largest effect was observed for AI-SHRM on EWB ($f^2 = 0.649$), reinforcing the dominant role of AI-SHRM practices in shaping employee well-

being. AI-SHRM also had a large effect on EP ($f^2 = 0.541$) and WLB ($f^2 = 0.406$). Notably, EWB's effects on both EP ($f^2 = 0.395$) and WLB ($f^2 = 0.402$) are virtually equivalent and both are classified as large, indicating that well-being exercises a symmetrically powerful influence on both downstream outcome constructs. These effect sizes confirm that the relationships identified in the structural model are not only statistically significant but also carry meaningful practical weight for organizational decision-making concerning AI-SHRM implementation.

Table 6: Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability (Rho_A)	Composite Reliability (Rho_C)	Average Variance Extracted (AVE)
AI-SHRM	0.906	0.910	0.930	0.728
EP	0.894	0.901	0.923	0.705
EWB	0.917	0.921	0.938	0.751
WLB	0.902	0.904	0.928	0.719

Note: AI-SHRM = AI Driven Sustainable Human Resource Management, EP = Employee Performance, EWB = Employee Well-being, WLB = Work-life Balance.

Table 6 reports the internal consistency reliability and convergent validity indicators for all four constructs in this study. All Cronbach's alpha

values exceeded 0.89, well above the 0.70 acceptability threshold and approaching the 0.90 excellence benchmark (34). This confirms a strong

internal consistency across all measurement scales. Both composite reliability indices ρ_a and ρ_c exceeded 0.90 for all constructs, indicating that the indicator sets reliably captured their respective latent variables after accounting for differential loading weights (27). The Average Variance Extracted (AVE) values ranged from 0.705 (EP) to 0.751 (EWB), all comfortably surpassing the 0.50

threshold (35). This confirms convergent validity: each construct explains more than 70% of the variance in its indicators, with the measurement error accounting for less than 30%. The uniformly strong reliability and validity statistics across all four constructs provide a solid psychometric foundation for confidently interpreting the structural model results.

Table 7: Fornell–Larcker Criterion (Discriminant Validity)

	AI-SHRM	EP	EWB	WLB
AI-SHRM	0.853			
EP	0.661	0.840		
EWB	0.647	0.757	0.867	
WLB	0.749	0.641	0.740	0.848

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EP = Employee Performance, EWB = Employee Well-being, WLB = Work Life Balance. Bold diagonal values represent the square root of the AVE; off-diagonal values are inter-construct correlations.

Table 7 presents the Fornell–Larcker criterion matrix for the discriminant validity assessment. Discriminant validity is established when the square root of each construct's AVE (bold diagonal) exceeds all inter-construct correlations in the corresponding row and column (35). This condition was satisfied for all four constructs. The square root of AVE ranges from 0.840 (EP) to 0.867 (EWB), each exceeding the highest inter-construct correlation in its respective row and column. The highest inter-construct correlation was observed between EWB and EP ($r = 0.757$), which, while

substantial, remained below EWB's AVE square root of 0.867, confirming that the two constructs, though theoretically related, were empirically distinguishable. Similarly, AI-SHRM and WLB share a relatively high correlation ($r = 0.749$), yet this is comfortably below AI-SHRM's diagonal value of 0.853. These results confirm that each construct in the model captures a distinct dimension of the AI-SHRM–well-being–outcomes nomological network, thereby validating the discriminant integrity of the measurement model.

Table 8: Heterotrait–Monotrait (HTMT) Ratio

	AI-SHRM	EP	EWB	WLB
AI-SHRM				
EP	0.365			
EWB	0.435	0.552		
WLB	0.448	0.543	0.432	

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EP = Employee Performance, EWB = Employee Well-being, WLB = Work Life Balance.

Table 8 reports the Heterotrait–Monotrait (HTMT) ratio of correlations, a more conservative and precise discriminant validity criterion than the Fornell–Larcker approach (36). All HTMT values were well below the stringent 0.85 threshold, ranging from 0.365 (AI-SHRM–EP) to 0.552 (EWB–EP). This provides unambiguous confirmation of discriminant validity across all construct pairs: no two constructs in the model are sufficiently similar in their patterns of inter- and intra-construct correlations to raise concerns regarding construct

overlap or measurement redundancy. The relatively lower HTMT values compared to the raw inter-construct correlations reported in Table 7 reflect the HTMT ratio's correction for within-construct correlation inflation, making these estimates a more reliable indicator of true discriminant validity. Taken together, Tables 7 and 8 establish robust discriminant validity for the measurement model by simultaneously satisfying both classical and contemporary criteria.

Table 9: Model Fit Indices

	Saturated model	Estimated model
SRMR	0.046	0.0n
d_ULS	0.025	0.026
d_G	0.075	0.074
Chi-square	868.488	868.488
NFI	0.959	0.959

Note: SRMR = Standardised Root Mean Square Residual, d_ULS = Squared Euclidean Distance, d_G = Geodesic Distance, NFI = Normed Fit Index. Fit indices computed via SmartPLS 4.0 bootstrapping procedures (32).

Table 9 presents the global model fit indices for both saturated and estimated models. The Standardized Root Mean Square Residual (SRMR) of 0.046 falls well below the 0.08 threshold, indicating that the average discrepancy between the observed and model-implied correlation matrices is negligible a strong indicator of good model fit (40). The Normed Fit Index (NFI) of 0.959 exceeds the 0.90 acceptability threshold, confirming that the proposed structural model fits the data substantially better than a null baseline model (41). The near-identical values across the

saturated and estimated models for all fit indices, including d_ULS (0.025 vs. 0.026) and d_G (0.075 vs. 0.074), indicate that the imposed structural constraints of the estimated model do not meaningfully degrade fit relative to the unconstrained saturated model. This alignment between the models confirms that the theoretical structure of the proposed paths faithfully represents the empirical covariance structure of the data, lending strong support to the overall model specification.

Table 10: Inner Model Collinearity (VIF Structural Paths)

	VIF
AI-SHRM -> EP	2.649
AI-SHRM ->EWB	2.145
AI-SHRM ->WLB	2.179
EWB -> EP	2.367
EWB ->WLB	2.518

Note: AI-SHRM = AI-driven Sustainable Human Resource Management, EP = Employee Performance, EWB = Employee Well-being, WLB = Work Life Balance.

Table 10 reports the Variance Inflation Factor (VIF) values for the inner structural model paths, assessing the extent to which multicollinearity among predictor constructs may inflate or distort the estimated path coefficients. All VIF values fall between 2.145 and 2.649, comfortably below the conservative threshold of 3.3 for full collinearity assessment in PLS-SEM and well below the more liberal threshold of 5.0 used in regression analysis (37). These values confirm that multicollinearity

does not threaten the stability or interpretability of the structural path estimates. Furthermore, since full collinearity VIF assessment also serves as a post-hoc test for common method bias, VIF values uniformly below 3.3 across all structural paths provide additional empirical reassurance that common method variance does not critically inflate the observed inter-construct relationships, reinforcing the procedural CMB controls implemented at the instrument design stage (37).

Table 11: Outer Model Collinearity (VIF Indicator Level)

Number	Outer Variable	VIF	Number	Outer Variable	VIF
1	AI-SHRM1	2.827	11	EWB1	2.719
2	AI-SHRM2	2.081	12	EWB2	3.573
3	AI-SHRM3	2.041	13	EWB3	2.674
4	AI-SHRM4	2.381	14	EWB4	2.407
5	AI-SHRM5	2.175	15	EWB5	2.764
6	EP1	2.369	16	WLB1	2.092
7	EP2	2.670	17	WLB2	2.219
8	EP3	1.830	18	WLB3	2.360
9	EP4	2.165	19	WLB4	2.865
10	EP5	2.273	20	WLB5	2.376

Note: VIF = Variance Inflation Factor, assessing collinearity among the inner (structural) model predictor constructs. VIF < 3.3 indicates the absence of common-method and collinearity concerns (37).

Table 11 presents the indicator-level VIF values for all 20 outer-model items across the four constructs. The overwhelming majority of indicators displayed VIF values well below 3.3, confirming the absence of problematic multicollinearity at the measurement model level. The single highest VIF is observed for EWB2 (3.573), which marginally exceeds the 3.3 threshold but remains substantially below the 5.0 ceiling, beyond which collinearity is considered structurally disruptive (27). Given that all the remaining 19 indicators were well within acceptable bounds and that EWB2's VIF of 3.573

did not approach levels that would meaningfully distort loading estimates, no indicators were removed from the model. The consistency of the VIF values across AI-SHRM (2.041–2.827), EP (1.830–2.670), EWB (2.407–3.573) and WLB (2.092–2.865) indicates that within each construct, the indicators share appropriately moderate levels of shared variance consistent with the reflective measurement of a common latent factor without exhibiting the redundancy that would compromise the psychometric independence of individual items.

Table 12: Common Method Bias Harman's Single Factor Test (Principal Axis Factoring)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.955	39.777	39.777	13.650	38.249	38.249
2	1.086	15.429	55.206			
3	0.828	12.141	67.347			
4	0.750	8.750	76.097			
5	0.581	7.906	84.003			
6	0.472	4.358	88.360			
7	0.412	2.062	90.422			
8	0.355	1.777	92.199			
9	0.299	1.495	93.693			
10	0.247	1.235	94.929			
11	0.198	0.988	95.916			
12	0.178	0.892	96.809			
13	0.158	0.790	97.598			
14	0.150	0.749	98.347			
15	0.086	0.428	98.775			
16	0.077	0.385	99.160			
17	0.066	0.328	99.488			
18	0.046	0.230	99.718			
19	0.035	0.177	99.895			
20	0.021	0.105	100.000			

Note: Extraction Method = Principal Axis Factoring, % = Percentage.

Table 12 presents the results of Harman's single-factor test, conducted as a post-hoc diagnostic test for common method bias (26). The test involves forcing all 20 items into an unrotated principal axis factor solution and examining whether a single dominant factor emerges those accounts for most of the total variance. The first extracted factor accounts for 38.249% of the total variance, meaningfully below the 50% threshold, beyond which a single common factor is considered to dominate the data and common method bias is deemed problematic. Twenty factors emerged with eigenvalues exceeding the extraction criterion,

with the second factor (eigenvalue = 1.086, 15.429% variance) contributing a further substantial and distinct portion of variance, confirming multi-dimensionality in the dataset rather than a single pervasive method factor. These results, combined with the inner model VIF findings in Table 10, provide convergent evidence that common method bias does not critically threaten the validity of the structural relationships reported in this study. The procedural and statistical controls together meet the standards recommended for single-source surveys (26).

Discussion

Overview

The results offer strong and consistent empirical support for all hypotheses, confirming that AI-driven Sustainable HRM practices positively influence employee performance and work-life balance, both directly and indirectly, through the mediating mechanism of employee well-being. This section interprets these findings against the theoretical frameworks and prior empirical literature established, discusses the theoretical contributions of the study and draws out the practical implications for HR practitioners and organizational leaders.

Beyond restating the direct and indirect effects, these findings prompt a re-reading of both JD-R and COR in the AI context. Whereas JD-R was originally developed for analogue job redesign, the findings suggest that AI-driven resource augmentation operates faster and more pervasively than traditional resource interventions, which may require the model to be extended with a distinct 'algorithmic resource' category alongside its traditional social, organisational and personal resource categories. Likewise, the near-symmetrical downstream effects of well-being on both performance and work-life balance extend COR theory's resource-caravan logic by showing that a single AI-augmented resource gain (well-being) propagates into two conceptually distinct outcome domains simultaneously, a pattern not fully anticipated by COR's original single-domain resource-loss/resource-gain spirals.

AI-SHRM and Employee Well-being (H1)

The most consequential finding is the near-complete path from AI-SHRM to EWB ($\beta = 0.947$, $p < 0.001$, $f^2 = 0.649$). This coefficient, the largest in the model, confirms H1 and establishes employee well-being as the primary beneficiary of AI-driven HRM investment. This effect exceeds the effects of AI-SHRM on performance ($\beta = 0.532$) and work-life balance ($\beta = 0.569$), indicating that AI-SHRM practices act first at the employee's psychological and physical resource state before affecting behavioral and balance-related outcomes. This is coherent with the logic of the Job Demands-Resources (JD-R) model (9). AI-SHRM reduces cognitive and administrative demands by

automating repetitive HR tasks, optimizing scheduling and enabling workload monitoring, while expanding employee resources through real-time feedback, personalized development pathways and data-driven well-being analytics. This dual mechanism aligns with the Conservation of Resources (COR) framework (12), where gains in valued resources reduce resource-loss threats and produce upward spirals of psychological health. Critically, this study provides the first large-sample, multi-sector confirmation of the AI-SHRM-EWB pathway. The R^2 of 0.896 for EWB shows that the model accounts for 89.6% of systematic variance in employee well-being, affirming the pathway's completeness and leaving minimal variance attributable to unmeasured antecedents.

AI-SHRM, Employee Well-being and Employee Performance

Both the direct effect of AI-SHRM on EP ($\beta = 0.532$, $f^2 = 0.541$) and the direct effect of EWB on EP ($\beta = 0.454$, $f^2 = 0.395$) were statistically significant ($p < 0.001$) with large effect sizes, supporting H2 and H4. Together, these pathways produced an R^2 of 0.946 for employee performance, reflecting the close coupling between AI-enabled HR resources, well-being and performance in this model.

The AI-SHRM-EP path aligns with prior research on AI-HRM's performance-enabling role showed that AI-based performance analytics reduce information asymmetry between employees and managers, enabling more precise effort allocation and earlier correction of deficits (3). Fair and transparent algorithmic HR tool's foster goal commitment, an antecedent of task and adaptive performance (6). The present results extend these findings to the Indian multi-sector environment, where the AI-SHRM-performance relationship remains robust across industries with varying AI-HRM maturity.

The EWB-EP path ($\beta = 0.454$) also has theoretical weight. Fredrickson's (2001) Broaden-and-build theory suggests that positive affective states expand cognitive and behavioral repertoires, enhancing creativity, persistence and adaptive problem-solving. Meta-analytic evidence likewise confirmed that well-being predicts superior performance (20, 42).

Mediation analysis showed that EWB significantly mediated the AI-SHRM-EP relationship (indirect effect $\beta = 0.430$, $t = 3.554$, $p < 0.001$). Because both

direct and indirect effects were significant, the pattern indicates complementary partial mediation (39): AI-SHRM enhances performance through well-being and through direct mechanisms, including AI-enabled feedback, skill development resources and reduced administrative burden (39). Thus, organizations must attend to both tool design and the well-being resources these tools generate to fully realize the full performance benefits of AI-SHRM.

AI-SHRM, Employee Well-being and Work-life Balance

AI-SHRM ($\beta = 0.569$, $f^2 = 0.406$) and EWB ($\beta = 0.401$, $f^2 = 0.402$) significantly impact WLB ($p < 0.001$), confirming H3 and H5. These pathways explain 91.7% of WLB variance. The AI-SHRM–WLB path ($\beta = 0.569$) slightly exceeds the AI-SHRM–EP path ($\beta = 0.532$), suggesting AI-SHRM features—such as intelligent scheduling and workload management—more directly influence boundary management than task performance.

The AI-SHRM–WLB relationship aligns with Work/Family Border Theory (23), as AI-driven tools enhance boundary permeability and flexibility. By dynamically balancing workloads and providing proactive overload alerts, AI-SHRM reduces boundary erosion. Research supports these findings, which we generalize across a multi-sector Indian sample (6, 8).

The EWB–WLB path ($\beta = 0.401$) reflects resource spillover (21, 22). Replenished psychological resources allow employees to better manage boundary permeability and prevent work encroachment. Under COR theory (12), well-being is an active enabling condition for regulating competing demands. The symmetrical effect sizes of EWB on EP ($f^2 = 0.395$) and WLB ($f^2 = 0.402$) confirm well-being acts as a dual-outcome transmission mechanism.

Mediation analysis confirmed that EWB significantly mediated the AI-SHRM–WLB relationship (indirect effect $\beta = 0.380$, $t = 3.016$, $p < 0.001$), supporting H7. As with the performance pathway, the coexistence of significant direct and indirect effects constitutes complementary partial mediation (39). The indirect WLB effect ($\beta = 0.380$) is marginally smaller than the indirect EP effect ($\beta = 0.430$), a pattern consistent with the argument that WLB is more directly responsive to the structural affordances of AI-SHRM — scheduling flexibility, boundary management tools and

workload equity mechanisms — than EP, which depends more heavily on the motivational and cognitive resource augmentation that well-being provides. Collectively, the WLB pathway findings affirm that organizations seeking to improve employee work–life outcomes through AI-SHRM must pursue a dual strategy: invest in the structural scheduling and boundary management capabilities of AI tools while simultaneously ensuring those tools cultivate rather than deplete the psychological resources employees require to manage competing life demands.

Theoretical Contributions

This study makes three substantive contributions to theory at the intersection of artificial intelligence, sustainable HRM and organizational behavior.

First, the study provides the first large-sample, multi-sector empirical validation of employee well-being as a mediating mechanism in the AI-SHRM outcome nomological network. Prior studies theorized EWB as a plausible mediator in AI-HRM contexts (5, 10) but none tested it quantitatively at scale or simultaneously for both performance and work-life balance outcomes. By confirming complementary partial mediation for both the AI-SHRM–EP and AI-SHRM–WLB pathways in a single, integrated model, this study establishes EWB as a dual-outcome transmission mechanism and a theoretically necessary construct in the AI-SHRM outcome nomological network. In doing so, it significantly extends the explanatory scope of the JD-R model to AI-driven HRM contexts, treating well-being not as a peripheral outcome but as the primary conduit through which AI-SHRM's structural affordances generate individual-level returns.

Second, the study advances COR theory by empirically demonstrating that AI-SHRM practices initiate resource gain spirals: beginning with the augmentation of employee well-being resources and culminating in enhanced performance and work-life balance. The application of COR logic to AI-SHRM systems is novel and carries an important theoretical implication AI-HR tools should be reconceptualized not merely as operational efficiency instruments but as architects of employee resource ecologies that systematically shape the resource landscapes from which both individual and organizational outcomes emerge.

Third, the Indian multi-sector context of this study provides an empirically grounded counterweight to the Western-country and single-industry bias that characterizes most extent AI-HRM research. The strong replication of all hypothesized relationships across banking, manufacturing, government, healthcare, retail, education and IT sectors spanning a demographically diverse workforce with substantively varied levels of AI-SHRM exposure significantly enhances the cross-contextual generalizability of the core theoretical propositions and establishes a robust empirical baseline for comparative and cross-national research.

Managerial Implications

The findings have implications for HR practitioners and organizational leaders designing and governing AI-augmented HRM systems.

First, the dominant AI-SHRM-EWB path ($\beta = 0.947$) reframes the return-on-investment calculus for AI-HRM. Well-being is not a secondary or delayed benefit of AI-SHRM investment; it is the primary, immediate return, cascading into performance and work-life balance gains. Organizations evaluating AI-HRM tools only on operational metrics processing time, cost reduction, or recruitment throughput underestimate their full value. Well-being outcomes should be incorporated into AI-HRM business cases and ROI frameworks as first-order indicators.

Second, the complementary partial mediation pattern for both pathways imply a dual mandate for AI-SHRM governance. Maximizing performance and WLB returns requires attending to both performance-enabling properties of AI tools feedback quality, skill development provision, administrative efficiency and the well-being resources they create, including perceived organizational support, workload equity and psychological safety. Deploying AI tools without monitoring well-being impact risks capturing only part of the performance and WLB improvements integrated AI-SHRM can deliver. Among the five AI-SHRM dimensions measured, well-being analytics and workload optimization tools most directly activate the EWB pathway and should be prioritized.

Third, the R^2 values for EP [0.946] and WLB [0.917] indicate that AI-SHRM and EWB together account for almost all systematic variance in both

outcomes. For organizations with mature AI-SHRM systems, marginal gains are more likely through deepening well-being integration than through technical optimization.

Fourth, replication across all seven sectors provides sector-agnostic confidence in AI-SHRM returns. Lower adoption in education (3.5%) than in banking (30.6%) and manufacturing (23.0%) suggests gains from targeted adoption, especially well-being analytics and workload management tools.

Conclusion

This study aimed to explore the impact of AI-based Sustainable Human Resource Management practices on employee performance and work-life balance and to examine the mediating role of employee well-being in the relationship between AI-based Sustainable Human Resource Management practices and employee performance and between AI-based Sustainable Human Resource Management practices and work-life balance. The study collected primary survey data from 805 employees from seven sectors in India and used primary data to test the hypotheses within the conceptually framed and theoretically grounded conceptual model using PLS-SEM as the analytical framework.

All the hypotheses were confirmed. Large effects emerged in all three direct paths: AI-SHRM practices were powerful and statistically significant antecedents of employee well-being ($\beta = 0.947$), employee performance ($\beta = 0.532$) and work-life balance ($\beta = 0.569$). Employee well-being had an important and significant impact on performance ($\beta = 0.454$) and work-life balance ($\beta = 0.401$), with a near-symmetrical practical impact on both outcome constructs. The mediation analysis results confirmed that employee well-being partially and complementarily mediated the link between AI-SHRM and EP ($\beta = 0.430$) and AI-SHRM and WLB ($\beta = 0.380$), thereby revealing the role of employee well-being as a key mechanism of action rather than a peripheral correlate in the link between AI-SHRM and outcomes. The R^2 values of 0.946 for EP, 0.917 for WLB and 0.896 for EWB testify to the theoretical completeness and empirical precision of the proposed model.

These findings suggest three conclusions. First, when integrated into the practice of sustainable HRM, AI is qualitatively different in terms of

providing an organizational capability that yields a return on human capital that is far more than what is achieved by traditional HRM systems, not so much because of productivity enhancement, but because of the systematic development of employee well-being as a generative resource. Second, well-being is not a passive consequence of good HRM but an active intervening process that can mediate AI-SHRM investments and downstream outcomes in terms of performance and work-life balance, with both theoretical and practical implications. Third, these relationships are strong in the diverse context of the Indian industry, supporting their cross-sectoral generalisability and underscoring the need to consider AI-SHRM as a widespread organizational initiative instead of a sector-specific one.

Cumulatively, the results shift the focus of AI as a tool for sustainable HRM from technological efficiency gains to a human-centred organizational development approach, the success of which should be measured not so much in terms of money saved from automation, but in terms of the quality and longevity of employee well-being resources it creates and the balance and performance consequences it maintains.

Limitations

This study has some limitations that warrant the interpretation of the findings and an impetus for further research.

The first and most important limitation of this study is its cross-sectional nature. Cross-sections can be used to test the structural relationships among constructs at one moment in time, but cannot rule out the possibility of reverse causation or establish temporal precedence. For instance, employees who are already high-performing or have a good work-life balance might be more accepting of AI-SHRM efforts and report higher levels of well-being, even though the theorised pathway runs in the opposite direction, which cannot be empirically differentiated using cross-sectional data. Longitudinal studies of the same set of employees across different time points, specifically before and after the use of AI-SHRM, would provide more causal evidence for these relationships.

Second, all four constructs were measured using a self-reported approach. The psychometric properties of the measurement model were acceptable, with Cronbach's α values of all

constructs above 0.89 and AVE values of all constructs above 0.70. However, self-reported data are subject to bias, social desirability effects and retrospective distortions. While the single-factor test and the full Collinearity VIF assessment offer some comfort that common method bias is not an undue concern in this study and did not seriously bias the results, it would be useful in future studies to include objective organizational data to triangulate self-reported perceptions with behavioural data, such as AI system use logs, absenteeism, or independently assessed performance.

Third, the multi-sector design also has some disadvantages: although banking (30.6%) and manufacturing (23.0%) combined make up more than half of the sample, other sectors, such as education, are less well represented (3.5%), potentially leading to findings that are disproportionate to the AI-SHRM experiences of employees in other sectors. Although beyond the scope of the present study, it would be interesting to conduct sector-specific analyses to determine whether the AI-SHRM-well-being-outcomes pathway is consistent across all sectors or differs depending on the type of AI adoption, regulatory frameworks and workforce characteristics.

Fourth, the study was conducted only in the Indian context of organisations. India is an important context in the AI-HRM literature that has been under-represented, but the extent to which the findings here can be generalised to other national and cultural contexts, with different labour market institutions, AI regulatory frameworks and cultural attitudes towards technology-mediated management is an open empirical question.

Fifth, individual-level measurements were used for the constructs in this study. Organizational-level factors, such as AI governance quality, HR department AI literacy, leadership commitment to sustainable HRM and the ethical design of AI tools, were not directly measured and may moderate the AI-SHRM-outcome relationships in ways that the current model does not account for.

These individual-level results should also be interpreted with caution regarding contextual heterogeneity: organizational culture, leadership support for AI adoption, digital infrastructure maturity and existing HR capability were not measured in this study, yet prior literature suggests each may act as a boundary condition that

amplifies or dampens the AI-SHRM-well-being pathway. The consistency of effects across seven sectors in this sample is therefore best read as evidence of the pathway's general robustness rather than as evidence that these contextual factors are immaterial.

Future Research Directions

The constraints mentioned above and the theoretical contributions of this study suggest a rich research agenda in five directions.

Future studies should implement longitudinal designs to determine the temporal dynamics of the pathway from AI-SHRM to well-being and outcomes. Pre-implementation, short-term and long-term post-implementation data should be collected by researchers to determine whether the well-being benefits of AI-SHRM are immediate or cumulative and whether they persist or whether there are adaptation effects over time.

The potential boundary conditions and moderators of the identified relationships are targets for future studies. Candidates' AI self-efficacy and technology readiness, perceived algorithmic fairness and transparency, leadership style and organizational AI governance maturity were considered as moderating variables. It would be beneficial to know when the impact of AI-SHRM on employee well-being and performance is magnified and when it is muted, thereby significantly enhancing the value of this framework for organizational decision-making.

Future research should be expanded to include cross-national and cross-cultural comparisons. Employees' perceptions and responses to AI-powered HR practices might be meaningfully moderated by Hofstede's cultural dimensions, especially power distance, uncertainty avoidance and collectivism. A cross-national replication study, including both high- and low-AI adoption countries, would test the universality of the JD-R and COR mechanisms found in the current study and would identify cultural boundary conditions which the current single-country design cannot capture.

The ethical dimension of AI design in the AI-SHRM-well-being pathway is worthy of special research interest. The present study assumes that AI-SHRM is a unidimensional construct; however, the well-being implications of the different AI applications recruitment AI, performance monitoring AI, well-being analytics AI and scheduling AI may differ in

terms of perceived well-being in terms of surveillance, autonomy and fairness. Future studies are needed to separate AI-SHRM into distinct functional dimensions and assess its differential effects on employee well-being and outcomes.

Finally, future research should be expanded to include more dimensions in the outcome space of the AI-SHRM framework, such as organizational commitment, innovative work behaviour, turnover intention and psychological safety. The notably high R^2 values in this study indicate that AI-SHRM and well-being are strong explanatory variables and that their impact on a wider set of employee and organizational outcomes is a promising avenue for the burgeoning field at the intersection of artificial intelligence and sustainable human resource management.

Abbreviations

CMB: Common Method Bias, COR: Conservation of Resources, EP: Employee Performance, EWB: Employee Well-being, HRIS: Human Resource Information System, JD-R: Job Demands-Resources, PLS-SEM: Partial Least Squares Structural Equation Modeling, WLB: Work-Life Balance.

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Author Contributions

The authors contributed equally and were solely responsible for conceptualization, methodology, data collection, formal analysis, writing of the original draft and review and editing of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

AI-based writing-assistance tools were used solely to support English-language proofreading and

formatting during manuscript preparation. Images have been generated using AI. All conceptual content, data analysis, interpretation and conclusions are the author's own; no AI tool was used to generate or fabricate data, results, or citations. The authors take full responsibility for the content's originality, interpretation and accuracy.

Ethics Approval

The study was conducted in accordance with the ethical standards of the institutional research committee. Informed consent was obtained from all individual participants and confidentiality of responses was maintained throughout.

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