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Can AI Adoption architect Sustainable HRM? Investigating the Moderated Mediation role of Techno-Complexity and Self-Efficacy

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Abstract

The current study addresses the central challenge of how organisations can manage AI-driven transformation while simultaneously sustaining employee well-being and advancing Sustainable HRM. Consequently, the study investigated the relationship between Artificial Intelligence Adoption (AIA) and sustainable Human Resource Management (SHRM) through the mediating mechanism of Job complexity (JC) and Resilience (Re) and the moderating role of Techno-Complexity (TC), Self-Efficacy (SE). The study has collected 881 data from Indian private and public sector enterprises through purposive and snowball sampling. Further, the study employed mediation and moderated mediation analysis in order to capture the associations among the variables. The result shows that AIA increases both JC (β = 0.478) and Re (β = 0.196), reflecting AI's dual impact on job demands and adaptive capability. Further, mediation analysis reveals that JC (β = 0.208) and Re (β = 0.046) partially mediates the effect of AIA on SHRM, while the direct relationship between AIA and SHRM (β = 0.356) remains positive and significant. In addition to this, moderated-mediation results indicate that TC (β=-0.019) weakens the positive pathway from AIA to SHRM via Re, whereas SE shows no significant moderating effect. The study suggests that although AI can strengthen SHRM, simplifying system interfaces, sequencing training with technological rollout, and fostering supportive learning environments emerge as critical policy levers for ensuring that AI-enabled transformation translates into long-term sustainable HR outcomes. The current study extends the existing literature by amalgaming technological readiness (AIA, TC) and human-centric factors (SC, Re, SE) in shaping sustainable HR outcomes.

1. Introduction

The integration of Artificial Intelligence (AI) practices into Human Resource Management (HRM) has transitioned from being a futuristic premise to an emerging necessity, especially after interpreting through the lens of sustainability (George & Thomas, 2019). Widely misunderstood as an approach of focussing on quick profits and meeting immediate needs, sustainable Human Resource Management (SHRM) can be clarified as the practice of considering human resources as assets and not just short-term resources. This can be achieved by focusing on their growth and well-being while promoting social fairness, environmental responsibility, and long-term economic success (Ehnert et al., 2016) through skill development and employee care. Integration of AI into SHRM can contribute towards sustainable practices by automating routine tasks, enhancing decision-making, predicting skill gaps, personalizing learning pathways, optimizing resource use, enabling flexible work arrangements, and tracking diversity and inclusion goals (Murugesan et al., 2023). Together, these applications ensure that organizations can balance efficiency with long-term human development and sustainability. This transformational transition from conventional to AI driven practices in organizational settings has resulted in advanced work culture in two ways (Murire, 2024). First, enhancing the work output through analyzing personalized growth plans rather than believing in one-size-fits-all annual appraisals. Second, by strengthening competitiveness via enabling smarter workforce planning, reducing HR overheads in routine tasks, freeing resources for strategic work, and global talent acquisition. However, outweighing the benefits of AI intervention in corporate scenario, voluminous existing literature have evidenced that the indispensable intervention of

AI has intensified the challenges of sustainable HRM. Specifically, concerns have grown around employee wellbeing due to reducing interpersonal interactions, declining traditional labour roles, automating administrative functions, diminishing the human touch in decision-making, and creating a sense of surveillance-driven work culture (Sharma et al., 2025). Amid this job-risk scenario, objecting the intervention of AI in organizational settings may significantly hamper competitiveness which may be achieved at the cost of sustainability commitment towards the employees.

Particularly in India, which is considered as a leading nation in AI adoption with 30% Indian entrepreneurs actively deriving value from its application, is also subjected to transitional challenges from conventional to AI-driven approach (Kumari, 2025). This transformation has stemmed from variations in Artificial Intelligence competency (AIC), perceptions of techno-complexity, and differing levels of self-efficacy (SE) among employees and HR professionals. Nevertheless, these temporary challenges are outweighed by development of AI competency, coupled with supportive social climates (SC) and initiatives to enhance self-efficacy, thereby facilitating smoother integration resulting in productive workforce sustainability. Although voluminous existing literature have discussed about the role of AI adoption in SHRM (Grace Herlina & Iskandar, 2025), but rarely any of those have clarified the interplay between technological readiness (AI competency, techno-complexity) and human-centric factors (SC, resilience, self-efficacy) in shaping sustainable HR outcomes. Magnifying further, the current study will overcome the existing gaps in the existing literature such as, first, AIA has been focussed in technology although AI adoption has been widely discussed in technology and management research, there is still a limited understanding of its role in advancing SHRM. Most existing studies focus on operational or efficiency outcomes of AI, but the strategic link to sustainability in HR practices remains underexplored (Gozgor et al., 2019). Second, while the literature recognises that AI adoption can reshape work processes, the mediating mechanisms through which it affects SHRM are less understood. In particular, the roles of job complexity (JC) and resilience (Re) as pathways that channel the impact of AI adoption toward sustainable outcomes are rarely examined in an integrated framework (Jones & Sackley, 2016). Third, prior studies often examine contextual factors such as social climate, techno-complexity, and self-efficacy in isolation. However, their combined influence on AI adoption and subsequent organisational outcomes remains underexplored, leaving a gap in understanding how both technological and human-centric factors interact to shape sustainable HRM practices. Finally, although SHRM is an emerging priority for organisations, there is a lack of comprehensive models that integrate technological readiness (AI competency, techno-complexity) and human-centric dimensions (Re, self-efficacy, SC) to explain how AI adoption contributes to long-term sustainability in HRM. India's diverse organizational landscape offers fertile ground to study how technological readiness (AI competency, techno-complexity) and human-centric factors (Re, self-efficacy, and SC) interact to drive sustainable HR outcomes. Although existing literature has touched upon AI adoption and SHRM separately, very few studies have explicitly examined this interplay within the Indian context, where unique socio-cultural and organizational dynamics amplify the importance of Re, adaptability, and supportive climates in shaping sustainable HRM practices. Based on these gaps, the objectives of this study are fourfold:

RO1: To study the role of AI competency and social climate in driving AI adoption within organizations.

RO2: To understand the mediating role of job complexity and resilience in shaping the relationship between AI adoption with SHRM.

RO3: To examine the role of techno-complexity and self-efficacy in moderating the mediation relationship of Resilience between AI adoption and SHRM.

2. Conceptual and Theoretical Framework

2.1. Theoretical Background

The present study builds its conceptual logic on multiple theoretical lenses to explain how AI adoption influences sustainable HRM through job complexity and resilience, and how this process is shaped by techno-complexity (TC) and self-efficacy. First, in order to understand how the adoption of AI in the workplace is facilitated by AI competency and a positive social environment a theoretical standpoint is necessitated which can be explained with the help of Technology Acceptance Model (TAM). TAM can be understood as the combination of perceived usefulness and ease of use which shape the intention of adopting a new technology (Davis, 1989; Tornatzky & Fleischer, 1990). In the current context, TAM can be used in understanding that AI competency reduces the complexity associated with AI tools which in turn increases confidence due to ease of use. Further, a supportive social environment encompassing of peer collaboration, encouraging management, and open knowledge sharing condenses the learning anxiety and lacking technical rigor, thereby enhancing perceived ease of use. As a result, the two core cognitive halves of TAM can be helpful in explaining how the adoption of AI in the workplace is facilitated by AI competency and a positive social environment (Venkatesh et al., 2003; Dwivedi et al., 2023). Second, mediation role of Job complexity and Resilience between AI Adoption and SHRM is grounded in Job Demands–Resources (JD-R) model that emphasizes on job demands and job resources. AI integration in workplace necessitates cognitive, technical, and adaptive demands for greater skill requirement, flexibility and learning agility, task interdependence, and handlings data-driven complexities. Adapting these complexities in AI-integrated work will enhance learning, innovation, skill development, long-term employee capability and adaptability which will ultimately contributes to SHRM. Similarly, resilience in employees can be a critical personal resource in JD-R as resilient employees develop adaptability and coping capacity which can help them to outweigh technological disruptions, and maintain well-being, thereby directly supporting a sustainable performance over time (Demerouti et al., 2001; Bakker & Demerouti, 2017). Third, Sustainable HRM theory provides a strong conceptual basis to explain this relationship by emphasizing that long-term organizational sustainability depends on maintaining a balance between technological advancement and their self-efficacy. After AI intervention in work, only resilient employees can adapt with the unprecedented changes, uncertainty, and sustain their performance resulting in SHRM. Nevertheless, in presence of high techno-complexity, the expectations and burden associated with advanced technologies on employees escalate limiting their ability to effectively utilize their resilience. From a Sustainable HRM perspective, such excessive technological strain disrupts the alignment between employee capabilities and organizational demands, thereby weakening the positive contribution of resilience toward SHRM. However, Self-efficacy can be helpful in

this situation as employees with higher confidence in their abilities are more likely to navigate complex technological environments, mitigate perceived difficulty, and sustain adaptive functioning, thereby partially restoring the pathway toward sustainable HR outcomes (Kramar, 2014; Ehnert et al., 2016).

2.2. Empirical Evidence

2.2.1. Relationship between AI Competency, Social Climate and AI Adoption

Organizational climate (OC) and AI competency (AC) plays a significant role in the AI adoption (AIA) as in one hand, AC drives AIA from internal capability and confidence, while on the other, OC drives AIA through external influence and social validation. OC refers to an employee's interpretation of quality of organization's internal environment (Fousiani et al., 2024) which determines to what extent it can shape their attitude, Re, motivation, and behaviour. This social support can meaningfully influence employees' interaction and interest in adopting AI (Yu et al., 2023) from the knowledge and experience of AI-skilled personnel, thereby promoting a culture of innovation and technological adoption. To illustrate this relationship further, evidence from the European public sector, OECD, Boston Consulting Group, and INSEAD indicates that the integration of technical expertise enhances AI implementation more effectively in the presence of innovative and supportive OC (European Commission Joint Research Centre, 2024; OECD/BCG/INSEAD, 2025). However, even if the support extended from external factors such as organizational encouragement or guidance from AI-skilled colleagues motivate the employee for AIA, but it is not sufficient to ensure successful AIA. The intrinsic desire of the employee to develop AC plays a critical role in determining the outcome. AC can be understood not just as proficiency in operating devices and programs through AI, but also using this ability to perform an AI-related task effectively, successfully, and beneficially (Chiu et al., 2024) Without a personal commitment to learning and improving their AI-related skills, employees may struggle to fully leverage the technology, even in a supportive environment. Hence, the motive to be AI competent can lead to AI adoption. Hence, based on supporting existing literature, it can be hypothesized that:

H1: AI Competency positively impacts AI Adoption

H2: Social Climate positively impacts AI Adoption

2.2.2. Relationship between AI Adoption, Job Complexity, and Sustainable Human Resource Management

The implementation of AI is fundamentally transforming organizational operations by modifying job roles and affecting the long-term efficacy of human resource management (HRM) strategies. In this context, incorporating AI into work obligations has complicated the long-standing work culture, as now workers need to learn new technical skills, devise innovative solutions to problems, and stay current with their knowledge (Chowdhury et al., 2023). The adoption of AI induces technical transformation, although its impact on JC is frequently paradoxical. In one hand, if adequate training and support system are

provided, employees may be encouraged to develop AI competency, which will further enhance their confidence in handling challenging activities. As a result, with adequate training, AI can facilitate their jobs by automating repetitive processes, alleviating cognitive burden, and optimising workflows, hence decreasing their workload (Wilson & Daugherty, 2018). In line with this, when organisations permit AI systems to manage repetitive and data-intensive tasks, organizations expect employees to use AI as a tool to analyze data, simulate scenarios, and generate insights to support better decision-making. Conversely, on the other hand, in the absence of such support, AI integration may heighten stress levels, and accelerate the risk of obsoleting the employee skills (Jarrahi, 2018) resulting in JC. Lack of AI competency among employees will hinder them from understanding, interpreting, and supervising multiple options in the systems generated by AI, thereby complexing their task. As a result, when employees perceive their jobs as complex, they are pushed to continuously develop new competencies to handle evolving demands, keeping in mind the fear of job insecurity imbued from the arrival of AI and automation (Bhaker, 2024). This adaptive learning not only augments their employability but also strengthens their skill, knowledge, and Re capacity which supports a culture of continuous learning resulting in sustainable HRM. Taken together these prior empirical works in understanding the relationship between AI, JC, and SHRM, this study asserts the followings:

H3: AI Adoption leads to Job Complexity

H4: Job Complexity positively impacts Sustainable Human Resource Management

H7: AI Adoption positively impacts Sustainable Human Resource Management

H8: Job Complexity significantly mediates the relationship between AI Adoption and Sustainable Human Resource Management

2.2.3. Relationship between AI Adoption, Resilience, and Sustainable Human Resource Management

Re can be understood as the ability to adapt, recover and learn in uncertain or rapidly changing environment (Lengnick-Hall et al., 2011). In the context of technological transformation, Re becomes critical as AIA often introduces new systems, processes and expectations that may feel unfamiliar or overwhelming to employees. While AIA has the potential to enhance efficiency, improve decision-making and strengthen organisational performance, it can also create unintended consequences such as stress, fear of reduced competence, or resistance to change (Patnaik et al., 2024). These reactions are particularly common when employees perceive AI as a threat to their skills, roles or job security. Employees with lower Re are therefore more likely to face difficulties in adapting to AI-driven changes, which indicates that AI adoption can negatively influence Re when not supported by adequate coping strategies and organisational support. At the same time, Re does not only determine how employees respond to technological challenges but also contributes to SHRM. SHRM focuses on achieving long-term organisational performance while promoting employee well-being, fairness and social responsibility (Kramar, 2014). Resilient employees are more willing to accept change, reskill themselves and align with

sustainable practices that balance organisational needs with employee development. Conversely, employees with low Re often struggle to adjust to change, which can reduce motivation, weaken engagement and create barriers to achieving sustainable outcomes (Song et al., 2025). Beyond this direct influence, Re also serves as a mediating factor between AI adoption and SHRM. While AI adoption may initially disrupt established routines and cause anxiety among employees (Daly et al., 2025), Re allows them to reinterpret AI as a tool that supports collaboration, growth and improved performance. Instead of perceiving AI as a competitor, resilient employees are able to transform potential risks into opportunities for professional development and organisational advancement. This adaptive mindset enables organisations to implement AI in ways that encourage innovation, ethical responsibility and sustainable workforce practices (Yu et al., 2023). In this way, Re becomes the bridge that connects technological adoption with sustainable human resource strategies, ensuring that the benefits of AI are realised without compromising employee well-being or long-term organisational success.

H5: AI Adoption positively impacts Resilience

H6: Resilience positively impacts Sustainable Human Resource Management

H9: Resilience significantly mediates the relationship between AI Adoption and Sustainable Human Resource Management

2.2.4. Moderated Mediating Role of Techno-Complexity on relationship between AI Adoption, Resilience, and Sustainable Human Resource Management

TC refers to the perception that digital technologies, including AI, are too complex, difficult to learn, or demanding to manage (Tarafdar et al., 2007). When employees experience high levels of techno-complexity, they may feel overwhelmed by constant technological change, which can increase stress and reduce their confidence in effectively using AI. This is particularly important in the context of Re, as Re reflects the ability of individuals to adapt, recover, and grow in the face of uncertainty (Lengnick-Hall et al., 2011). While Re enables employees to reinterpret AI adoption positively by viewing it as a tool for collaboration and growth (Yu et al., 2023), the presence of high TC can weaken this adaptive capacity. Employees who are constantly struggling to keep pace with complex systems may find it difficult to focus on long-term SHRM goals, such as fairness, well-being, and workforce development (Kramar, 2014). In contrast, when TC is perceived as low, employees are more likely to engage with AI adoption in a constructive manner. In such environments, resilient employees can fully utilise their adaptive capacity to support sustainable practices, including reskilling, innovation, and ethical workforce development (Song et al., 2025). However, when the perceived complexity of AI systems is high, the positive influence of Re on SHRM becomes weaker, as the psychological burden of handling complex technologies interferes with sustainable outcomes. In this sense, TC acts as a barrier that reduces the strength of Re in mediating the relationship between AI adoption and SHRM.

H10: Techno-Complexity negatively moderates the relationship of Resilience between AI Adoption and Sustainable Human Resource Management

2.2.5. Moderated Mediating Role of Self-efficacy on relationship between AI Adoption, Resilience, and Sustainable Human Resource Management

SE refers to an individual's belief in their ability to successfully perform tasks and manage challenges (Bandura, 1997). In the context of artificial intelligence adoption (AIA), SE shapes how employees perceive and respond to technological change. Employees with high SE are more confident in their ability to use AI tools effectively, while those with low SE may doubt their capacity to adapt, even when organisational support is available. This is particularly relevant to Re, which reflects an individual's ability to adapt, recover, and grow when facing uncertainty (Lengnick-Hall et al., 2011). Resilient employees can usually reinterpret AI adoption as a collaborative tool that supports innovation and professional growth (Yu et al., 2023). However, when SE is low, even resilient employees may struggle to fully utilise their adaptive capacity. Their doubts about personal capability can create anxiety and reduce engagement, making it difficult to achieve the long-term goals of SHRM, which emphasises fairness, employee well-being, and workforce development (Kramar, 2014). In contrast, when SE is high, employees feel empowered to reskill, experiment with new technologies, and actively support sustainable workforce practices (Song et al., 2025). Yet, paradoxically, very high SE can sometimes reduce the strength of Re as a mediator between AI adoption and SHRM. Employees who are overly confident may underestimate the challenges of AI integration, leading to complacency or resistance to collaborative learning. This can weaken the positive contribution that Re typically brings to sustainable outcomes (Patnaik et al., 2024). In this way, SE moderates how Re functions in the relationship between AI adoption and SHRM, either enabling or constraining the transformative role of Re.

H11: Self-efficacy positively moderates the relationship of Resilience between AI Adoption and Sustainable Human Resource Management

The conceptual framework for the proposed hypotheses is portrayed in Fig. 1 for the better understanding.

Insert Fig. 1

3. Data and Methodology

3.1 Data Collection Procedure

In order to analyse the effect of AI adoption on the sustainable HRM, an online survey was conducted throughout India during the time span of January 2025 to November 2025. Further, purposive sampling technique is used to select the targeted population, focusing specifically the Human Resource Managers of both private and public sector enterprises. In addition to this, the data is collected by using snowball sampling method, wherein initial respondents were asked to refer other participants, thereby facilitating a people-to-people reaching process. The survey questionnaire was designed in Google Forms and was shared through various mail and other social media platforms such as WhatsApp groups, Facebook, LinkedIn and Twitter. The Google Form was designed such that the initial page included an introductory

note outlining the objective of the survey, along with a clear assurance that the responses would be used strictly for academic purposes while maintaining complete confidentiality of the participants' information.

Before proceeding for the data collection process, a pilot study was conducted in order to examine the practicality and feasibility of the methods to be used in a subsequently larger and more comprehensive investigation (Viechtbaueret al., 2015). The pilot survey confirmed the feasibility of the current study demonstrating acceptable levels of preliminary validity and reliability of the constructs. This pre-test survey of 102 respondents demonstrated clarity in the questionnaire with no ambiguity, appropriateness of the sample size, and estimated time required for collecting the data. showed the study protocol's viability and a suitable data gathering timeline and sample size. Based on the findings of the pilot study, the final round of data collection was conducted and gathered 910 final responses. Out of 910 responses, 881 responses were considered and remaining 29 responses were discarded for incomplete response, thereby yielding a response rate of 96.81% which has the potential to minimize non responsiveness bias. Further, to cross-verify the targeted sample count, the study utilized Cochran's formula to determine the appropriate sample size, as it is most suitable when the population size is undefined (Althubaiti, 2022). Applying Cochran's formula with a 95% confidence level and a 5% margin of error, the calculated ideal sample size for the analysis was approximately 384 respondents. Exceeding the threshold limit of 384, the response count of 881 will represent greater statistical power, improved representativeness, and enhanced reliability of the study findings (Andrade, 2020). The demographic characteristics of the respondents, including age, gender, education, type of organization, and work experience, are presented in Table 1.

Insert Table 1

3.2 Instrument and Scaling

In developing the questionnaire and conceptualizing the proposed theoretical framework, this study reviewed and synthesized insights from prior literature. Since the primary objective is to examine the impact of Artificial Intelligence Adoption (AIA) on SHRM, with JC and Re serving as mediating variables, existing validated scales were carefully adapted and modified to align with the study context. The investigators adopted a five-point Likert scale to record all the responses (from 1: strongly disagree to 5: strongly agree). A 4-item AIC and 4-item SC constructs were measured using the scales developed by Chiu et al. (2025) and Cooper et al. (2019) respectively. The 4-items AIA construct was assessed using the scale proposed by Monteiro et al. (2023). Additionally, 5-items TC and 4-items SE construct were measured using the scales developed by Urukovičová et al. (2023) and Schwarzer et al. (1995) respectively. The mediating variables, 4-items JC and 5-items Re, were measured using the scales adapted from Huo et al. (2025) and Wagnild and Young (1993) respectively. Finally, 6-items SHRM was measured using the scale developed by Yu et al. (2021). The details of the items under each construct are tabulated under Table 2.

3.3 Statistical Analysis

3.3.1 Measurement Model

The data is collected at the same time using a single self-reported questionnaire; hence the study may be susceptible to common method bias (CMB). As a statistical measure, the presence of CMB was tested by accessing the common method variance (CMV). Hence, first, in order to verify whether a single factor accounts for the majority of variance, Harman single factor test was performed (Ma et al., 2025). As the findings revealed that not a single factor account for the majority of variance (36% < 50%), hence, there was no major issue of CMB. Second, a full collinearity variance inflation factor (VIF) approach was employed which showed that all the variables in the current work projected a VIF value less than a threshold limit of 3.3, thereby confirming the absence of CMB (Malhotra & Ramalingam, 2025).

Further, the investigators have considered using SmartPLS version 4.1.1.8 software for conducting partial least square structural equation modelling (PLS-SEM) and to trace the mediation, moderation and moderated mediation relationship among the variables. The current research work preferred PLS-SEM over CB-SEM as the study aimed at predicting the results and not at testing or confirming the theory. Further, the conceptual framework designed for the current analysis is complex and comprises of multiple mediating and moderating relationships, thereby providing a flexible and reliable analytical framework for PLS-SEM compared to CB-SEM (Vuković, 2024). However, before proceeding for the SEM analysis we assessed the internal consistency reliability of individual indicators through factor loading and at the construct level through Cronbach's alpha (α) and composite reliability (CR). Only items with significant factor loadings and more than 0.50 were retained (Dash et al., 2025). After every deletion, the effect of deletion on reliability and convergent validity was examined through Cronbach's alpha, Rho_a, and AVE to ensure that such a deletion did not compromise the quality of the measurement. As depicted in Table 2, the values of Cronbach's alpha and CR for both the lower and higher-order constructs were above the acceptable threshold (recommended value>0.6), representing good internal consistency) reliability (Hair et al., 2010).

Insert Table 2

The convergent validity was examined using the average variance extracted (AVEs) values for all latent constructs, and the results showed that all AVE values were more significant than 0.5, as Fornell and Larcker (1981) recommended. Further, the Heterotrait-Monotrait (HTMT) ratio is calculated to test the divergent validity among the constructs. The result ranged between 0.466 and 0.822, showing a satisfactory discriminant validity among the constructs (Hsu et al., 2016).

3.3.2 Structural Model

The current study has tested the structural model using coefficient of determination (R^2), predictive Relevance (Q^2) and effect size (f^2) to justify that the model is not just statistically significant, but also meaningful and predictive (Hair et al., 2017). First, in order to test how much of the variation in endogenous variable is explained by exogenous variables, R^2 is estimated. The results indicate that the model explains 29.1% of the variance in AIA, 49.4% in Re, 22.9% in JC, and 44.4% in SHRM, thereby

demonstrating a weak to moderate explanatory power across the endogenous constructs. Second, to understand importance of each variable, f^2 was estimated which revealed that it ranges from 0.003 and 0.297 that is higher than the threshold value of zero. Third, to verify the predictive relevance, Q^2 was tested which revealed that Q^2 value of AIA (0.286), Re (0.503), JC (0.238), and SHRM (0.300) noted to be greater than the threshold value of zero. The proposed conceptual model is tested by using a nonparametric bootstrapping method with 5,000 samples. Table 3 tabulates the direct association among the constructs. Further, the hypothesized relationships among latent constructs are tested using path coefficient (B), t-statistics and 95% confidence interval (CI) values.

4. Results and Discussion

4.1 Direct Path Analysis

Upon confirming the model's reliability and validity, a path analysis was employed to investigate the structural relationships (Figure 2), including direct, indirect, mediation, and moderated mediation effects among the proposed variable. As shown in the table 3, it is observed that AIC and SC are positively influencing the AIA. This indicates that, AI competency equips employees with the necessary skills and cognitive readiness to engage with advanced technologies, while a supportive SC fosters psychological safety and a shared commitment to innovation. Together, these factors reduce resistance, enhance learning, and facilitate the successful adoption and institutionalization of intelligent systems within organizations. In this regard, Uren & Edwards, (2023) explained that people, process and data readiness are required in addition to technology readiness to achieve long term operational success with AI. Which can be understood as if the people of an organization are well equipped with AI, then that will make the organization more capable in adopting AI in its operation. Further, in the context of SC, Fousiani et al., (2024) tested that in various organisation of UK, there is a positive relationship between competitive climate and employee AI use over time. While analyzing the direction relationship between AIA with JC and Re, it is found that AIA is significantly influencing both JC and Re. This can be understood as, adoption of AI transforms organizational work structures by automating routine tasks and expanding employees' analytical and decision-oriented responsibilities, thereby increasing JC. This evolution demands higher cognitive and technical competencies as employees collaborate with digital systems and interpret data-driven outcomes (Jarrahi, 2018). Although such complexity introduces new challenges, it also promotes adaptive learning and strengthens Re, enabling individuals and organizations to respond effectively to any uncertainty and changes (Duchek, 2020).

Insert Figure 2

In addition to this, the association JC and Re with SHRM, shows a significant and positive. This explains that, JC often enhances SHRM because, it requires diverse skills, independent decision-making, and creative problem-solving provide greater learning opportunities and strengthen intrinsic motivation (Al Kahtani & M. M., 2022), thereby improving employees' psychological capital and overall well-being. Such enriched work environments foster innovation, engagement, and retention fundamental components of

SHRM (Zhang et al., 2025). Further, in the context of Re, it can be understood that Re plays a crucial role in advancing SHRM by promoting employee well-being, adaptability, and long-term engagement. Resilient employees are better equipped to manage stress, maintain motivation, and adapt to organizational change, thereby supporting the human-centered goals of sustainability (Kramar, 2014). Through enhanced coping capacity and continuous learning, Re reduces burnout, strengthens retention, and fosters a proactive workforce capable of sustaining performance under dynamic conditions (Duchek, 2020). Last the from the direct path analysis it is observed that AIA is significantly influencing SHRM. This indicates that the integration of AI optimizes resource use, reduces human fatigue, and enhances work–life balance, aligning with the social and environmental goals of SHRM. Collectively, these outcomes strengthen organizational sustainability by balancing productivity with employee growth and welfare (Mahade et al., 2025).

4.2 Mediation and Moderated Mediation Analysis

In the second phase while analysing the mediating role of the proposed variables, it is observed that both the mediators i.e. JC and Re are partially mediating the association between AIA and SHRM, this indicates that the direct path between the independent variables (AIA) and the dependent variable (SHRM) remains significant even after including the mediators (JC and Re) in the model. Further, it can be understood from the findings that JC can significantly mediate the relationship between AIA and SHRM as when organizations adopt intelligent technologies, routine tasks are automated, and employees take on more complex, analytical, and decision-oriented roles. This increase in JC enhances learning, innovation, and intrinsic motivation, fostering employees' long-term adaptability and well-being ultimately resulting in SHRM. In this regard, Al-Ayed, (2024) found that in the private sector of Saudi Arabia, AI integration is enhancing the human resource management by enhancing the cognitive skills of employee. In addition to this, it is observed that Re is significantly mediating the association between AIA and SHRM, this explains that as AI reshapes job structures and introduces new challenges, resilient employees are better able to manage uncertainty, learn new skills, and maintain motivation in dynamic work environments. This adaptive capacity enables organizations to sustain productivity while safeguarding employee welfare, aligning with the core objectives of SHRM.

Insert Table 3

In the final phase the moderated mediation analysis is performed. The results indicate that the interaction between SE and AIA has no significant effect on Re ($\beta = 0.012$, $t = 1.413$, $p = 0.158$), suggesting that their combined influence does not meaningfully contribute to SHRM through Re. In contrast, the interaction between TC and AIA shows a significant negative effect on Re ($\beta = -0.019$, $t = 2.024$, $p = 0.043$), indicating that higher TC, when coupled with AIA, diminishes Re, thereby hindering SHRM outcomes. The result revealed that the non-significant interaction between SE and AIA suggests that employees' confidence in their capabilities alone does not significantly influence Re under conditions of technological transformation. Conversely, the significant negative interaction between TC and AIA indicates that when AI systems become increasingly complex, employees' Re tends to decline, potentially leading to stress, resistance, and reduced engagement. This weakened Re can, in turn, hinder the

realization of SHRM objectives, as sustainable HRM depends on maintaining employee adaptability, well-being, and long-term performance. In this regard, Liu et al., (2024) explained that digital transformation (including complexity) can have both positive and negative effects, and under certain regulatory focus conditions, complexity undermines Re.

5. Conclusion

The findings of the study revealed that AIA is a significant influencer in achieving SHRM directly and indirectly in Indian organizational settings. The direct path analysis confirmed that AIC and SC positively influence AIA, highlighting the critical role of both technical proficiency and supportive organizational environments in driving successful AI integration. Furthermore, AIA was found to significantly enhance JC and Re, indicating that AI-driven changes in the workplace not only increase the cognitive and analytical demands of employees but also strengthen their adaptive capacity. These outcomes collectively reinforce SHRM principles by promoting innovation, motivation, and employee well-being core elements of sustainable organizational growth. In addition to this, the mediation analysis revealed that JC and Re partially mediate the relationship between AIA and SHRM. As organizations adopt intelligent systems, routine tasks are automated, encouraging employees to engage in more complex and creative responsibilities. This not only improves learning and intrinsic motivation but also contributes to long-term adaptability essential for sustaining productivity and well-being. Likewise, Re enables employees to cope with rapid technological change, maintain motivation under pressure, and align their personal growth with organizational goals. In the moderated mediation analysis, a more nuanced understanding emerged. The interaction between SE and AIA was found to be insignificant in influencing Re, suggesting that confidence alone is insufficient for coping with the challenges of technological transformation. Conversely, the interaction between TC and AIA showed a significant negative effect on Re, indicating that excessive technological complexity can erode employees' Re. This implies that when AI systems become too intricate or demanding, employees may experience stress, cognitive overload, and resistance to change. Such conditions hinder the realization of SHRM objectives by weakening adaptability and reducing engagement levels within the workforce. Taken together, these findings stress upon the potential of AIA in enhancing SHRM, there by understanding that the success relies heavily on managing the balance between technological advancement and human adaptability.

6. Implications for Practice

This study contributes to theoretical advancement across multiple dimensions by synthesizing perspectives from organizational change, sociotechnical systems, and sustainability into a cohesive framework that links digital transformation with long-term human resource outcomes. First, by identifying employee capability and workplace climate as key precursors to technology engagement, the study extends traditional models of innovation acceptance and organizational readiness into the realm of sustainable people management shifting the emphasis from short-term efficiency to enduring workforce development. Second, by highlighting JC and Re as mediating factors, the research enriches the JDR model and COR theory, illustrating how evolving task demands and personal strengths interact to shape

sustainable HR trajectories. Third, the inclusion of task-related strain and self-belief as boundary conditions adds nuance by clarifying when Re can effectively translate disruption into positive HR outcomes, thereby sharpening the explanatory power of the proposed mechanisms. Overall, this study moves beyond the application of existing theories to offer a layered and integrative logic that connects organizational preparedness, human adaptability, and long-term sustainability providing a fresh and comprehensive lens on how digital transformation is reshaping the future of HR. In practice, organizations should not rely solely on AI infrastructure investments rather they must simultaneously build AI competency through structured capability development programs that reduces anxiety, strengthens confidence, and promotes meaningful engagement with AI tools. Further, creating a supportive SC is essential as managers should institutionalize peer-learning, mentoring by AI-literate employees, and psychologically safe spaces for experimentation to normalize AI adoption as a shared organizational practice rather than an individual burden. Third, the findings highlight that JC is not inherently negative but becomes problematic when unmanaged; thus, HR and line leaders should redesign work by pairing AI-enabled automation with workload rationalization, skill roadmaps, and gradual responsibility transitions to prevent role overload. Additionally, the moderating effects of indicate that HR leaders should actively monitor and manage psychological frictions by simplifying interfaces, sequencing training with system introduction, and strengthening employees' belief in their capability to cope with AI reduce friction and increase sustainability of change outcomes. Finally, by aligning AI adoption initiatives with fairness, long-term employability, and ethical workforce practices, organizations not only mitigate resistance but convert AI transformation into a strategic lever for sustainable, future-proof HR systems.

7. Limitations and Future Directions

In light of the findings, the present study is subject to three key limitations. First, it relies on cross-sectional data, which restricts the ability to infer causality, particularly because AI-driven organisational transformations and employee behaviours evolve over time. Hence, the future research can consider longitudinal designs to capture these dynamic changes more accurately. Second, the study is confined to the Indian context, selected due to its rapidly expanding industrial landscape; however, inclusion of a broader geographical scope could yield a more comprehensive understanding of AI adoption and sustainable HRM. Further, comparative studies across countries would also enable researchers to identify cross-cultural and institutional variations in these relationships. Finally, the study examines only two moderating variables TC and SE. Future research may incorporate additional moderating variables such as leadership style, digital maturity, learning culture, and organisational readiness to enhance the robustness and explanatory power of the model.

Declarations

Conflict of interest:

The authors declare that they have no conflict of interest. The authors have no relevant financial or non-financial interests to disclose.

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Ethical Statement

All procedures involving human participants performed in this study followed the ethical standards of the institutional research ethical committee of Kalinga Institute of Social Science bearing the reference number 1488/KISS-DU/2025.

Author Contribution

The first and third author has collected the data. The first and second authors have collectively contributed towards drafting the manuscript. The third authors have designed and performed the analysis. The fourth and fifth author have reviewed and edited the manuscript. All the authors have substantially contributed towards writing and editing the manuscript.

Data Availability

All procedures involving human participants performed in this study followed the ethical standards of the institutional research ethical committee of Kalinga Institute of Social Science bearing the reference number 1488/KISS-DU/2025.

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Tables

Table 1 Demographic Characteristics

Variables	Elements	Frequency	Percentage
Gender	Male	511	58
	Female	370	42
Education	Graduation	661	75
	Post Graduation and more	220	25
Age	21-30	176	20
	31-40	255	29
	41-50	141	16
	51-60	194	22
	61 and more	106	12
Organization Type	Public	405	46
	Private	476	54
Years of Experience	Less than 5 Years	150	17
	5 years to 15 years	335	38
	16 years to 25 Years	220	25
	16 Years and More	185	21

Table 2 Model Validity Measures

Constructs	Indicators	Factor Loadings	CR (rho_a)	CR (rho_C)	AVE	Cronbach
AI Adoption (AIA)	The company has implemented AI in all business processes. (AIA1)	0.786	0.811	0.875	0.636	0.810
	The implementation of AI had a high impact on business operations. (AIA2)	0.833				
	The implementation of AI, taking into account its potential for the company's business, was an extensive process. (AIA3)	0.784				
	The AI implementation allowed business processes to be substantially changed. (AIA4)	0.787				
AI Competency (AIC)	I can distinguish whether a tool is AI-based or not. (AIC1)	0.790	0.832	0.888	0.664	0.831
	I can create content with AI. (AIC2)	0.837				
	I can explain what AI is. (AIC3)	0.820				
	I know how to choose the right AI tools to effectively complete a task. (AIC4)	0.811				

Job Complexity (JC)	My current work tasks are very complex. (JC1)	0.818	0.785	0.859	0.604	0.781
	I have to make very complex decisions in my work. (JC2)	0.730				
	In my work, I need to apply all the knowledge and skills I possess. (JC3)	0.807				
	In my work, I need to continuously learn knowledge related to new things. (JC4)	0.750				
Self-Efficacy (SE)	I can always manage to solve difficult problems if I try hard enough (SE1)	0.782	0.771	0.852	0.59	0.769
	If someone opposes me, I can find the means and ways to get what I want. (SE2)	0.772				
	It is easy for me to stick to my aims and accomplish my goals. (SE3)	0.774				
	I am confident that I could deal efficiently with unexpected events. (SE4)	0.743				
Resilience (Re)	I usually take things in my stride. (Re1)	0.758	0.819	0.873	0.579	0.818
	I am friends with myself.	0.815				

	(Re2)					
	I feel that I can handle many things at a time. (Re3)	0.770				
	I am determined. (Re4)	0.746				
	I can get through difficult times because I've experienced difficulty before. (Re5)	0.713				
Social Climate (SC)	Employees have confidence in other employees' intentions and behaviour. (SC1)	0.761	0.86	0.898	0.637	0.857
	Employees are skilled at collaborating with each other to diagnose and solve problems. (SC2)	0.777				
	Employees view themselves as partners in charting the direction of the organization. (SC3)	0.834				
	Employees share information and learn from one another. (SC4)	0.780				
	Employees are aware and committed to the purpose and collective aspirations of the	0.836				

	organization. (SC5)					
Techno Complexity (TC)	I do not know enough about this technology to handle my job satisfactorily. (TC1)	0.772	0.839	0.886	0.609	0.839
	I need a long time to understand and use new technologies. (TC2)	0.791				
	I do not find enough time to study and upgrade my technology skills. (TC3)	0.800				
	I find new recruits to this organization know more about computer technology than I do. (TC4)	0.768				
	I often find it too complex for me to understand and use new technologies. (TC 5)	0.769				
Sustainable HRM (SHRM)	HRM follows a sustainable development orientation. (SHRM1)	0.767	0.908	0.927	0.68	0.906
	HRM adheres to the people-oriented principle. (SHRM2)	0.831				
	HRM adheres to the principles of fairness, neutrality, and	0.820				

openness. (SHRM3)	
HRM follows efficiency orientation. (SHRM4)	0.860
HRM policy includes a clear statement about sustainable development. (SHRM5)	0.867
The company promotes employees' innovative capacity through training. (SHRM6)	0.798

Table 3 Direct and Indirect Relationship Results

Path Analysis	Co-efficient (β)	T statistics	P values	LL	UL
Direct Path Analysis					
AIC -> AIA	0.248	5.833	0.000	0.165	0.332
SC -> AIA	0.343	8.637	0.000	0.266	0.422
AIA -> JC	0.478	17.491	0.000	0.424	0.531
AIA -> Re	0.196	6.011	0.000	0.132	0.262
JC -> SHRM	0.435	12.672	0.000	0.371	0.503
Re -> SHRM	0.237	6.875	0.000	0.168	0.303
AIA -> SHRM	0.356	11.996	0.000	0.297	0.414
Mediation Analysis					
AIA -> Re -> SHRM	0.046	4.960	0.000	0.029	0.066
AIA -> JC -> SHRM	0.208	9.920	0.000	0.169	0.251
Moderated Mediation Analysis					
TC x AIA -> Re -> SHRM	-0.019	2.024	0.043	0.000	0.036
SE x AIA -> Re -> SHRM	-0.012	1.413	0.158	-0.028	0.006

Figures

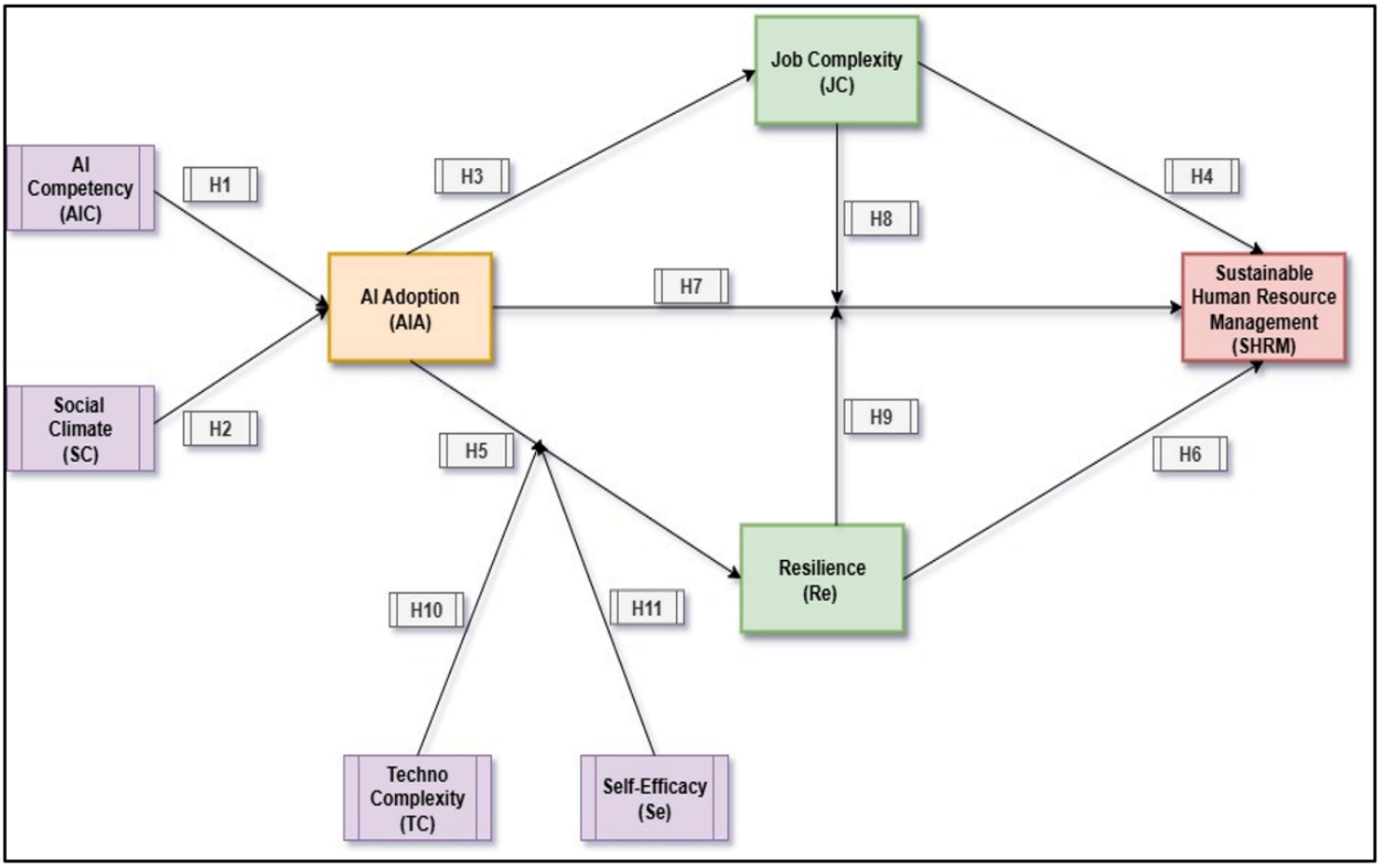


Figure 1

Conceptual Framework

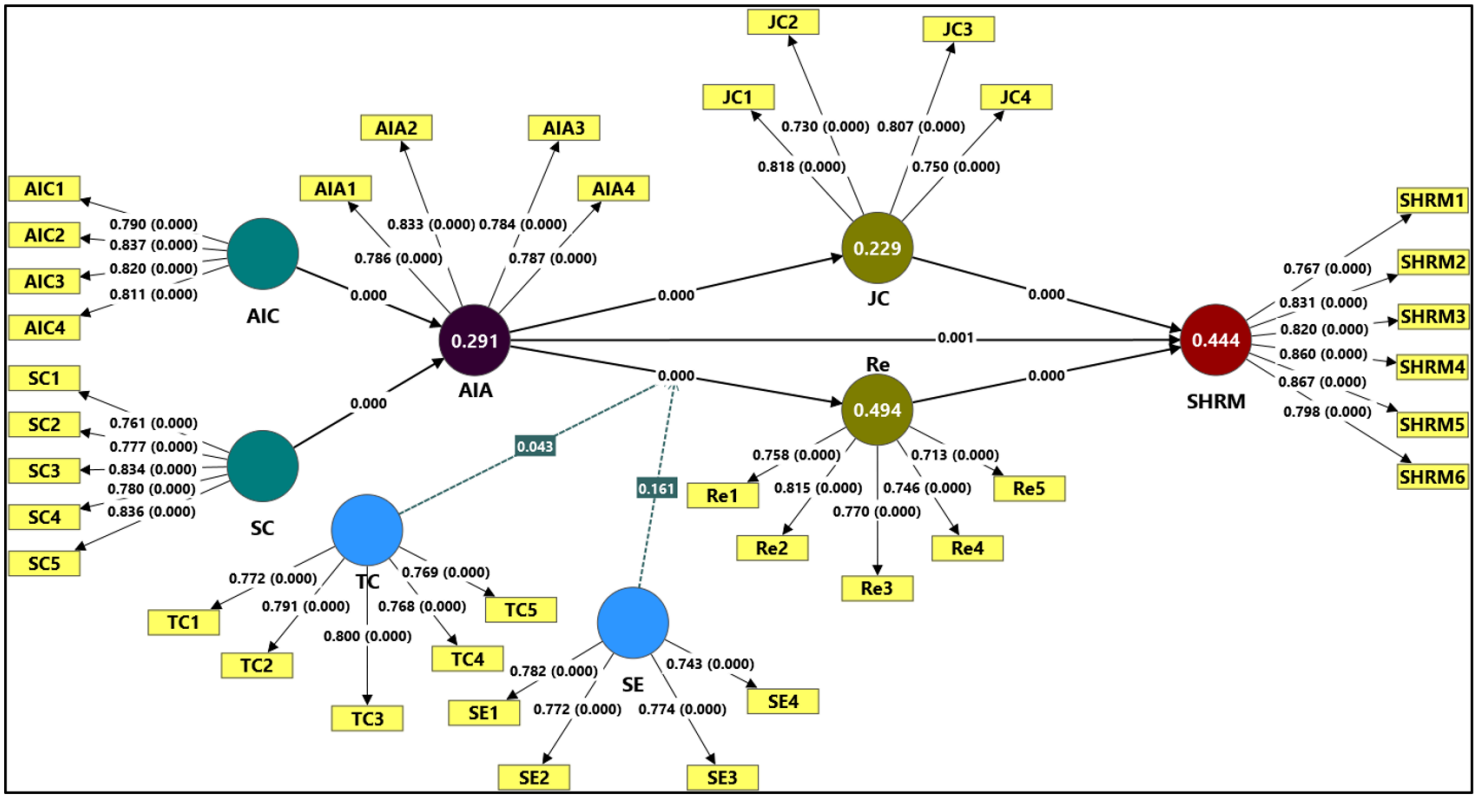


Figure 2

Results of Structural Equation Modelling