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THE IMPACT OF AI-DRIVEN HRM ON AI KNOWLEDGE SHARING: MODERATING ROLE OF PROACTIVE PERSONALITY AND MEDIATING ROLE OF AI SELF-EFFICACY

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Abstract

While AI is reshaping HRM, employees' willingness to share AI-related knowledge under such practices remains poorly understood. Drawing on Social Cognitive Theory (SCT), Self-Determination Theory (SDT), and Conservation of Resources (COR) Theory, this study develops and tests a first-stage moderated-mediation model in which AI Self-Efficacy (AISE) mediates the relationship between AI-Driven HRM and AI Knowledge Sharing (AIKS), with Proactive Personality (PP) moderating the first stage of this pathway. Using a cross-sectional survey design, data were collected from 197 full-time employees across Pakistan's IT, banking, telecom, and professional services sectors and analyzed using Hayes' PROCESS Macro Model 7. AI-Driven HRM significantly and positively predicted both AI Self-Efficacy (B = 2.099, p < .001) and AI Knowledge Sharing, with AI Self-Efficacy also functioning as a mediator between the two (indirect effect B = 0.239, 95% CI [.171, .313]). Proactive personality negatively moderated the path between AI-Driven HRM and AI self-efficacy (B = −.373, p < .001), and the overall moderated-mediation effect was significant (index = −0.119, 95% CI [−.185, −.061]), a pattern explained through COR and trait-activation logic. These findings position AI Knowledge Sharing as a distinct behavioral outcome of AI-HRM, identify Proactive Personality as a first-stage moderator, and extend the AI-HRM model to a South Asian emerging-economy context.

INTRODUCTION

Artificial intelligence is reshaping how organizations manage their human resources. AI-driven HRM refers to a combined AI–HR system that equips employees with the knowledge, skills, and motivation needed to work alongside AI technologies in pursuit of organizational goals (Do et al., 2025), and it has become central to talent acquisition, performance management, and employee development across industries (Marler & Parry, 2016; Vrontis et al., 2022). As AI becomes embedded in daily work, employees are

expected not merely to use these tools but also to pass on AI-related knowledge to colleagues, making AI knowledge sharing an important driver of organizational learning and innovation (Wang & Noe, 2010; Khattak et al., 2019; mChen et al., 2025). Knowledge-infrastructure and knowledge-process capabilities have likewise been shown to strengthen organizational performance and to encourage knowledge sharing more broadly (Ali & Ali, 2017; Rahman et al., 2015). This kind of sharing, however, does not happen automatically; it depends on whether employees develop sufficient confidence in their own AI abilities, a construct known as AI Self-Efficacy (Compeau & Higgins, 1995; Bandura, 1997). Individual traits such as proactive personality — the disposition to initiate change and make active use of available resources (Bateman & Crant, 1993) — are also likely to shape how effectively employees translate AI-driven HRM inputs into actual knowledge exchange. Despite the growing importance of these relationships, they remain empirically underexplored and conceptually underdeveloped, leaving considerable room for further research in this area.

Prior research has shown that AI-driven HRM positively influences employee adaptation, exploratory behavior, and resilience (Doğanülkü & Korkmaz, 2023; Do et al., 2025), yet it remains unclear how such practices translate into AI knowledge sharing as a distinct behavioral outcome. Earlier work has examined self-efficacy mainly within general technology contexts (Compeau & Higgins, 1995) without treating AI self-efficacy as a mediating mechanism linking organizational HRM practices to employees' knowledge-sharing behavior. Likewise, although proactive personality has been linked to technology adoption and career outcomes (Seibert et al., 2001; Crant, 2000), no prior study has tested its moderating role in the relationship between AI-driven HRM and AI self-efficacy. Chen et al. (2025) advanced the concept of AI self-efficacy within generative AI contexts but did not incorporate an HRM system or a personality-based moderator, while Bandara et al. (2025) called for greater attention to individual-level behavioral outcomes in AI-HRM research. These gaps collectively justify the present study.

This is consistent with prior literature showing that knowledge-sharing behavior functions as a key link between organizational and individual-level dispositions and innovation capability (Ali et al., 2022), which further reinforces the theoretical relevance of AI knowledge sharing as a terminal outcome variable in this model.

This study makes three main contributions to the AI-driven HRM literature. First, it extends existing work on AI in HRM by introducing AI knowledge sharing as a novel dependent variable that encompasses productivity and adaptation (Stone et al., 2015; Khattak et al., 2021; Vrontis et al., 2022). Second, building on Social Cognitive Theory (Bandura, 1977, 1986) and Self-Determination Theory (Deci & Ryan, 1985, 2000), it develops a theoretical account in which AI self-efficacy operates as the psychological mechanism through which AI-driven HRM practices influence employees' knowledge sharing. Third, by treating proactive personality as a moderator, the study adopts a contingency perspective that identifies the boundary conditions under which investment in AI-driven HRM yields the greatest returns in terms of knowledge sharing (Grant & Ashford, 2008; Parker & Collins, 2010). Structural equation modeling is used to examine all model elements within a single integrated framework.

From a theoretical standpoint, this study integrates SDT and SCT within a single moderated-mediation framework, offering a richer explanation of how organizational AI systems relate to individual knowledge behavior. In doing so, it responds to the research gap identified by Bandara et al. (2025) and extends the AI-HRM literature in a new direction. Practically, if AI self-efficacy mediates and proactive personality moderates the pathway from AI-driven HRM to knowledge sharing, HR practitioners can use this understanding to design targeted capability-building interventions and select talent profiles that maximize knowledge capital formation (Brynjolfsson & McAfee, 2014; Tambe et al., 2019); this is consistent with evidence from Pakistan's banking sector showing that stronger

management of organizational resources and risk is associated with improved firm performance (Ali, Bagram & Ali, 2021). These insights are particularly relevant to knowledge-intensive sectors such as healthcare, technology, and financial services, where competitive advantage depends on the speed and quality of knowledge transfer.

Review of Literature and Hypotheses

Theoretical Foundations

The proposed model rests on two influential yet distinct motivational theories: Social Cognitive Theory (SCT; Bandura, 1986) and Self-Determination Theory (SDT; Deci & Ryan, 2013). SCT explains voluntary behavior through reciprocal interactions among cognition, environment, and behavior, positioning self-efficacy as the cognitive mechanism that converts capability beliefs into action (Wood & Bandura, 1989; Stajkovic & Luthans, 1998). SDT, by contrast, takes a needs-based view, holding that practices satisfying the needs for competence, autonomy, and relatedness foster autonomous motivation and prosocial behaviors such as knowledge sharing (Khattak et al., 2017; Gagné & Deci, 2005; Ryan & Deci, 2000). Together, the two theories converge on a shared premise for this study: employees engage in voluntary AI-related knowledge sharing because they believe they are capable of doing so (SCT) and because they perceive their work environment as supportive of their psychological needs (SDT).

Viewed through a dynamic-capabilities lens, this dual-pathway logic fits organizations in which strategic and cultural antecedents are converted into performance-relevant outcomes through intermediate capabilities (Mehmood et al., 2026), with AI-based HRM understood as an organizational capability rather than a mere technological tool.

This theoretical integration is well grounded: SCT captures the cognitive pathway of efficacy, while SDT captures the motivational pathway of need satisfaction, together accounting for both the "can" and the "want" behind AI knowledge sharing. AI-driven HRM, understood as a bundle of practices spanning recruitment, training, appraisal, and job design (Do et al., 2025; Prikshat et al., 2023), simultaneously builds capability (through SCT-based mastery experiences) and provides organizational support for AI competence (through SDT-based need satisfaction). This combined lens offers greater explanatory power than either theory alone and addresses prior criticism that AI-HRM research has often been atheoretical or reliant on single-theory explanations applied in isolation (Budhwar et al., 2022; Khattak et al., 2021; Vrontis et al., 2022).

Conservation of Resources (COR) Theory

Conservation of Resources (COR) theory (Hobfoll, 1989, 2001) provides a complementary lens to SCT and SDT for understanding why individuals respond defensively to AI-induced uncertainty. According to COR theory, individuals strive to acquire, protect, and preserve valued resources — such as skills, professional identity, career capital, and social standing — and experience stress or anxiety when these resources are threatened, which in turn triggers protective or defensive behavior (Batool et al., 2016).

Within the present model, COR theory helps explain a key moderating pattern: employees low in proactive personality tend to bring fewer internal coping resources to AI-driven change and are therefore more vulnerable to resource loss. AI-driven HRM acts as an external organizational resource that replenishes this resource pool by providing mastery experiences, structured training, and competence-building signals that support the development of AI self-efficacy. Employees high in proactive personality, in contrast, already possess greater internal coping resources — such as self-initiated learning — and therefore rely less on HRM inputs to build AISE. This resource-based logic helps account for the negative moderation effect reported later in this study (see Section 5.4, H6).

Taken together, SCT, SDT, and COR provide a layered theoretical account of the model: SDT explains the motivational, need-satisfaction pathway; SCT explains the cognitive, efficacy-based pathway; and COR explains the resource-

differential boundary condition introduced by proactive personality.

Critical Review of the Literature

This section critically evaluates the literature underlying each construct in the model. The discussion centers on four key studies — Do et al. (2025), Chen et al. (2025), Doğanülkü & Korkmaz (2023), and Bandara, Biswas et al. (2025) — alongside the broader body of work on HRM, knowledge sharing, self-efficacy, and proactive personality. Rather than summarizing these studies, the aim is to critically compare their theoretical and empirical positions and to clarify how the present study builds upon and extends them.

AI-Driven HRM

AI-driven HRM extends the behavioral HRM tradition (Wright et al., 2001) by adapting core HR practices — recruitment, training, performance management, compensation, and job design — to an AI-enabled work environment (Chowdhury et al., 2023; Prikshat et al., 2023). Bundled HR practices of this kind have also been linked to higher employee satisfaction and loyalty (Malik, Malik, & Zia-ur-Rehman, 2013). Consistent with the system-to-individual logic of high-performance work systems (Salim et al., 2016; Boxall & Macky, 2009; Jiang et al., 2012) — including evidence that job design itself affects performance through employee satisfaction (Ali & Zia-ur-Rehman, 2014) — this perspective suggests that HR systems send signals to employees that shape their attitudes, motivation, and performance. Illustrating this, Do et al. (2025), in a three-wave U.S. study of 274 participants, found that AI-based HRM positively affects employee resilience and adaptive performance, with trust in AI moderating this relationship, while Bandara et al. (2025) found that AI-driven HR practices improved the effectiveness of strategic HRM within Australia's financial sector.

This body of work has two notable limitations. First, both anchor studies focus on organizational or attitudinal outcomes — resilience, adaptive performance, strategic effectiveness — rather than discretionary behaviors such as knowledge sharing; indeed, Bandara, Biswas et al. (2025) explicitly call for research into behavioral outcomes. Second, their settings — U.S. healthcare and Australian finance — leave a gap in emerging-economy and South Asian contexts. The present study addresses both limitations by treating AI knowledge sharing as a behavioral dependent variable and by situating the research in a different geographical setting.

AI Knowledge Sharing

Knowledge sharing has been studied for over three decades as a micro-level driver of organizational learning and performance (Foss et al., 2009; Wang & Noe, 2010). It is a voluntary, prosocial act in which the knowledge holder incurs cognitive, social, and competitive costs (Bock et al., 2005), and evidence suggests that employees' willingness to share knowledge with peers is shaped by their work ethic and organizational commitment (Ali & Tahir, 2018). AI knowledge sharing — the voluntary exchange of tacit and explicit knowledge about AI, including how to prompt AI systems, apply AI models, and navigate related ethical issues — differs from general knowledge sharing in three respects: AI-related knowledge is highly perishable, it often blurs the distinction between knowledge owner and knowledge user (Benbya et al., 2024), and it may be treated as a personal resource that employees prefer to withhold (Černē et al., 2014; Connelly et al., 2012). Empirical evidence on AI knowledge sharing specifically remains scarce: Olan et al. (2022) link it to firm performance without examining individual-level antecedents, and Malik, De Silva et al. (2021) explore an AI-based knowledge platform within a single multinational firm.

This is broadly consistent with non-AI research showing that interpersonal trust and employee human capital both shape tacit knowledge-sharing behavior (Ali et al., 2022), and with evidence that knowledge-infrastructure and knowledge-process capabilities are positively associated with organizational effectiveness and competitive advantage (Ali & Ali, 2017) — suggesting that similar trust- and competence-based mechanisms may extend to the AI context.

The most directly relevant evidence comes from Chen, Lin et al. (2025), who found that perceived intelligence and humanness of generative AI increase Chinese employees' (N = 496) intentions to share knowledge with such systems; however, their antecedent was the GenAI tool itself rather than an organizational HRM system. No study to date has tested whether a broader, organizational-level AI-driven HRM system — as opposed to a single tool — predicts employees' AI knowledge sharing, a gap the present research addresses.

AI Self-Efficacy

Self-efficacy refers to an individual's belief in their capacity to organize and execute the actions needed to achieve a given level of performance (Bandura, 1977) and is among the strongest predictors of organizational behavior (Stajkovic & Luthans, 1998). Because domain-specific self-efficacy beliefs predict domain-specific behavior more accurately than general self-efficacy does, Wang and Chuang (2024) recently developed and piloted a multidimensional AI self-efficacy scale capturing employees' confidence in selecting, prompting, using, and evaluating AI tools.

A key limitation of earlier work is its lack of domain specificity: Doğanülkü & Korkmaz (2023) apply general self-efficacy even to technology-related behaviors, despite Bandura's (1977) caution against doing so, while the AI-specific efficacy measure used by Chen, Lin et al. (2025) is confined to perceptions of generative AI tools. The present model resolves both issues by aligning an AI-specific antecedent (AI-driven HRM), an AI-specific mediator (AI self-efficacy), and an AI-specific behavioral outcome (AI knowledge sharing), consistent with Bandura's (1986) principle of domain alignment.

Proactive Personality

Proactive personality describes an individual's tendency to identify opportunities, act on them, and persist in efforts to change their surroundings (Bateman & Crant, 1993). Over the past three decades it has been linked to job performance (Thompson, 2005), career success (Seibert et al., 2001), and creativity, innovation, and adaptive behavior more broadly, with Fuller and Marler's (2009) meta-analysis confirming its incremental validity beyond the Big Five; comparable incremental effects have been reported for psychological empowerment in relation to employee performance (Akhtar & Ali, 2015). Notably, research on proactive personality has shifted from treating the trait as a simple main-effect predictor toward viewing it as a moderator that unlocks the latent benefits of contextual resources — the trait-activation perspective (Erdogan & Bauer, 2005; Tett & Burnett, 2003).

Doğanülkü & Korkmaz (2023) treat proactive personality as an antecedent of self-efficacy, in a manner similar to how job design has been treated as an antecedent of downstream performance via satisfaction (Ali & Zia-ur-Rehman, 2014). While their effect is strong ($\beta = 0.73$, $p < 0.001$, $N = 457$ students), this main-effect framing does not fully capture the more theoretically interesting contingency role the construct can play. Drawing on the trait-activation perspective, proactive personality should not only raise self-efficacy directly but also strengthen the conversion of HRM inputs into self-efficacy. Accordingly, the present study reconceptualizes proactive personality as a first-stage moderator rather than an antecedent, a repositioning supported by Erdogan and Bauer's (2005) work.

Contextual Support: The Job Demands–Resources (JD-R) Model

The Job Demands–Resources (JD-R) model (Demerouti et al., 2001) offers a useful contextual lens for viewing AI-based HRM as a bundle of job resources. The model classifies job characteristics into two broad categories — job demands, such as workload, uncertainty, and cognitive load, and job resources, such as autonomy, skill utilization, training support, and feedback. Job design itself is one such resource and has been shown to enhance employee performance through increased job satisfaction (Ali & Zia-ur-Rehman, 2014).

Job resources are understood to buffer the negative effects of job demands (Bakker & Demerouti, 2007) and to foster motivation toward positive outcomes such as learning behavior and discretionary performance.

AI-driven HRM operates in a manner consistent with the JD-R model: structured training, clearly

defined roles, and dedicated learning support reduce the burden employees face when adapting to AI, supplying the organizational scaffolding needed to build AISE — a benefit that is especially valuable for less proactive employees. This JD-R logic complements the COR-based resource-differential explanation and offers a second theoretical route for understanding why the HRM–AISE pathway is strongest among low-PP employees. Consistent with the negative moderation effect observed in this study, Bakker and Demerouti (2007) found that access to resources substantially boosts engagement and motivated behavior, particularly among employees with limited internal coping resources, a pattern echoed by Akhtar and Ali's (2015) finding that empowerment strengthens motivated behavior and performance.

Hypothesis Development

Building on the critical review above and the integrated SCT–SDT framework, this section develops six hypotheses. Each is preceded by a theoretical rationale that identifies the relevant theory, specifies the underlying causal mechanism, and connects it to the empirical evidence discussed earlier.

AI-Driven HRM and AI Knowledge Sharing

Theoretical justification (SDT). Self-Determination Theory holds that practices meeting employees' needs for competence, autonomy, and relatedness foster autonomous motivation and, in turn, prosocial discretionary behavior (Deci & Ryan, 2013), consistent with evidence that empowerment improves performance by motivating employees (Akhtar & Ali, 2015). AI-driven HRM addresses these three needs by offering AI-specific training (competence), latitude in human–AI collaboration (autonomy), and team-based AI work design (relatedness). Satisfying these needs is expected to generate the intrinsic motivation to share, rather than withhold, AI-related knowledge.

Empirical support. Meta-analytic evidence links high-performance HR practices to discretionary behaviors such as knowledge sharing (Jiang et al., 2012), and AI-based HRM has been shown to strengthen employee exploration and adaptive performance — behaviors closely related to knowledge sharing (Do et al., 2025). Consistent with this, Olan et al. (2024) found that AI use positively affects knowledge-sharing performance, together pointing to a positive relationship between AI-driven HRM and AI knowledge sharing.

H1. AI-driven HRM is positively associated with AI knowledge sharing.

AI-Driven HRM and AI Self-Efficacy

Theoretical justification (SCT). Bandura (1977) identifies four sources of self-efficacy — enactive mastery, vicarious experience, verbal persuasion, and physiological-state regulation — all of which AI-driven HRM can supply: training and simulations build mastery experience, observing AI-proficient colleagues offers vicarious experience, supervisor coaching and performance feedback provide verbal persuasion, and co-designed human–AI workflows help manage anxiety and regulate physiological states. SCT therefore predicts that AI-oriented HRM practices cultivate AI self-efficacy.

Empirical support. Liao, Toya et al. (2009) and Walumbwa, Avolio et al. (2008) show that HRM systems and supportive leadership strengthen employees' efficacy beliefs, while Chen, Lin et al. (2025) demonstrate in the AI context that organizational and contextual cues enhance AI self-efficacy, positioning AI-driven HRM as a comprehensive organizational antecedent of AI self-efficacy.

H2. AI-driven HRM is positively associated with AI self-efficacy.

AI Self-Efficacy and AI Knowledge Sharing

Theoretical justification (SCT). Self-efficacy functions as the immediate cognitive predictor of voluntary behavior within SCT (Bandura, 1991): individuals confident in their ability to use AI effectively perceive lower social risk in teaching others, trust the accuracy of their own knowledge more, and tolerate scrutiny of their ideas more readily. Such task-specific efficacy beliefs matter most for technology-related tasks that carry a high risk of misinformation (Bandura, 1986).

Empirical support. Self-efficacy is consistently identified in the knowledge-sharing literature as a strong predictor of sharing behavior (Bock et al., 2005), and trust and human capital have similarly been found to predict tacit knowledge-sharing behavior (Ali, Ali, & Arif, 2022). In the AI domain specifically, Chen, Lin et al. (2025) show that AI self-efficacy directly predicts Chinese employees' knowledge-sharing intentions. Convergent evidence from both general and AI-specific studies supports the following hypothesis.

H3. AI self-efficacy is positively associated with AI knowledge sharing.

The Mediating Role of AI Self-Efficacy

Theoretical justification (SCT-SDT integration). Combining H2 and H3 yields a mediation hypothesis: SCT casts self-efficacy as the cognitive mediator linking environmental factors to behavior (Wood & Bandura, 1989), while SDT contributes the motivational pathway of need satisfaction. AI-driven HRM should therefore influence AI knowledge sharing both directly (H1) and indirectly through AI self-efficacy. Because AI-driven HRM is expected to affect behavior through both efficacy-based and broader social-structural mechanisms (Nishii et al., 2008; Jiang et al., 2012), partial rather than full mediation is anticipated.

Empirical support. Liao, Toya et al. (2009) and Carter, Nesbit et al. (2018) document efficacy-based pathways linking HRM systems to behavior, and Chen, Lin et al. (2025) provide direct evidence of efficacy-based mediation within the AI domain, together supporting a partial-mediation specification.

Comparable evidence from outside the AI domain shows that knowledge sharing partially mediates the relationship between interpersonal trust and organizational innovation capability, as well as between human capital and innovation capability (Ali et al., 2022), lending indirect support to the mediating logic proposed here.

H4. AI self-efficacy partially mediates the relationship between AI-driven HRM and AI knowledge sharing.

The Moderating Role of Proactive Personality

Theoretical justification (SCT + Trait-Activation Theory). Trait-activation theory (Tett & Burnett, 2003) holds that personality traits exert their strongest influence on behavior when situational cues activate trait-relevant responses. Proactive individuals tend to interpret novel and uncertain circumstances — such as AI integration — as opportunities rather than threats (Bakker et al., 2012). Because AI-integrated HRM supplies precisely these trait-activating cues (mastery opportunities, new tools, learning challenges), proactive employees are expected to derive greater efficacy gains from the same HRM inputs than their less proactive counterparts.

Empirical support. Erdogan and Bauer (2005) show that proactive personality moderates the career benefits of person–organization fit, and Fuller and Marler's (2009) meta-analysis confirms its moderating role across various context–outcome relationships. Doğanülkü & Korkmaz (2023) additionally report a strong direct effect of proactive personality on self-efficacy ($\beta = 0.73$), confirming its positive association with efficacy beliefs. Together with the trait-activation argument, this evidence suggests that the AI-driven HRM → AI self-efficacy link should be stronger among employees higher in proactive personality.

H5. Proactive personality moderates the relationship between AI-driven HRM and AI self-efficacy, such that this relationship strengthens as proactive personality increases.

First-Stage Moderated Mediation

Theoretical justification (integrated model). H4 and H5 jointly imply a first-stage moderated mediation effect (Edwards & Lambert, 2007): if proactive personality strengthens the AI-driven HRM → AI self-efficacy link (H5), and AI self-efficacy mediates the effect of AI-driven HRM on AI knowledge sharing (H4), then the indirect effect of AI-driven HRM on AI knowledge sharing via AI self-efficacy should itself depend on proactive personality. This specification follows Hayes's PROCESS Model 7.

H6. Proactive personality moderates the indirect effect of AI-driven HRM on AI knowledge sharing via AI self-efficacy, such that this indirect

effect strengthens as proactive personality increases (first-stage moderated mediation).

Critical Synthesis and Theoretical Contribution

First, on construct specificity. In contrast to Bandura's (1977) own principle that efficacy beliefs predict behavior best when matched to a specific domain, Doğanülkü & Korkmaz (2023) measure self-efficacy at a general level. The present model instead adopts the AI-specific construct developed by Wang and Chuang (2024).

Second, on behavioural outcomes. Do et al. (2025) call for research on downstream behaviors such as AI knowledge sharing but do not test this directly, whereas the present model treats AI knowledge sharing as its primary dependent variable.

Third, on the framing of antecedents and moderators. Chen, Lin et al. (2025) situate their antecedent at the tool level (features of generative AI) and use technical literacy and growth mindset as moderators. The present model instead elevates the antecedent to the system level (AI-driven HRM) and substitutes proactive personality — a more empirically validated and theoretically interpretable dispositional moderator (Crant, 2000; Fuller & Marler, 2009).

Fourth, on analytics and context. This study relies on full structural equation modeling within a single latent-variable framework (Hair et al., 2019), differing from Chen, Lin et al.'s (2025) use of Hayes's PROCESS macro for path estimation, and extends the empirical evidence base to a new geographical setting, Pakistan, in response to repeated calls to test AI-HRM theory across cultural contexts (Bandara et al., 2025).

Summary of Hypotheses

This study puts forward six hypotheses derived from the integrated Social Cognitive Theory and Self-Determination Theory framework:

H1. AI-driven HRM is positively associated with AI knowledge sharing.

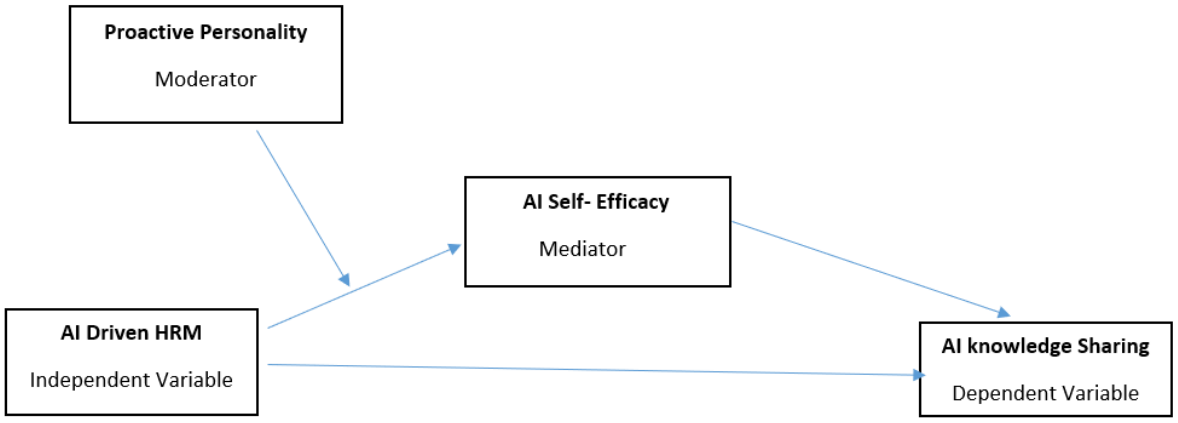
H2. AI-driven HRM is positively associated with AI self-efficacy.

H3. AI self-efficacy is positively associated with AI knowledge sharing.

H4. AI self-efficacy partially mediates the relationship between AI-driven HRM and AI knowledge sharing.

H5. Proactive personality moderates the relationship between AI-driven HRM and AI self-efficacy, such that this relationship strengthens as proactive personality increases.

H6. Proactive personality moderates the indirect effect of AI-driven HRM on AI knowledge sharing via AI self-efficacy, such that this indirect effect strengthens as proactive personality increases (first-stage moderated mediation).



3.6 Theoretical and Empirical Gaps

The two anchor studies in this domain, Do et al. (2025) and Bandara, Biswas et al. (2025), center on attitudinal and resilience-related outcomes, such as adaptive performance and strategic HRM effectiveness, rather than discretionary individual-

level behaviors; Bandara, Biswas et al. (2025) explicitly stress the need for future research on individual-level behavioral outcomes. (Ali, N., Gulzar, R.,2022). No prior study has tested the direct effect of an organization's AI-driven HRM system on the voluntary, prosocial, and cognitively demanding behavior of AI knowledge sharing. This study addresses that gap by introducing AI knowledge sharing as the primary dependent variable and empirically testing this system-to-behavior pathway.

Doğanülkü & Korkmaz (2023) measure self-efficacy at a general level despite Bandura's (1977) principle that self-efficacy beliefs must be linked to a specific behavioral domain, while Chen, Lin et al. (2025) anchor their antecedent at the tool level (features of generative AI) rather than at the level of AI-driven HRM. The present study addresses both issues by positioning AI-driven HRM as the antecedent, AI self-efficacy as the domain-matched mediator, and AI knowledge sharing as the corresponding behavioral outcome within a single, coherent AI-HRM context.

Proactive personality has typically been treated as a direct predictor of self-efficacy (Doğanülkü & Korkmaz, 2023; $\beta = 0.73$). While empirically compelling, this main-effect framing overlooks the arguably more interesting possibility that the trait conditions how HRM inputs are converted into self-efficacy. A moderator framing is supported by both trait-activation theory (Tett & Burnett, 2003) and person–environment fit research (Erdogan & Bauer, 2005). This study is the first to position proactive personality as a first-stage moderator of the relationship between AI-based HRM and AI self-efficacy.

Gap 4: The absence of a resource-differential explanation in this literature.

Conservation of Resources theory (Hobfoll, 1989) has not previously been applied to explain variation in how differently proactive employees respond to HRM investment. According to COR theory, employees with fewer internal coping resources depend more heavily on external organizational resources — a principle that offers a strong theoretical account for the negative moderation finding reported here, whereby AI-driven HRM proves more effective for low-PP than for high-PP employees. No existing AI-HRM study has jointly examined the pathway linking proactive personality, self-efficacy, knowledge sharing, and COR theory.

Geographical and Contextual Gap

Most empirical AI-HRM research has been conducted in Western and developed economies, including the U.S. healthcare sector (Do et al., 2025), Australia's finance sector (Bandara et al., 2025), and Chinese employee samples (Chen et al., 2025). Bandara, Biswas et al. (2025) specifically call for extending AI-HRM theory to emerging economies. Pakistan represents a notable gap: a large, rapidly digitalizing South Asian economy where organizational AI adoption is accelerating, yet individual-level AI-HRM effects remain unexamined. This study responds to that call by sampling employees from four AI-adopting sectors in Pakistan.

Research Methodology

Research Design

This study adopts a quantitative, deductive, cross-sectional design to empirically test the proposed model, in which AI-driven HRM is theorized to affect AI knowledge sharing through the mediating role of AI self-efficacy and the moderating role of proactive personality. A quantitative approach suits the study's aim of testing pre-specified hypotheses grounded in Self-Determination Theory and Social Cognitive Theory, and of estimating the magnitude and direction of relationships among latent variables established in prior literature (Do et al., 2025). The cross-sectional survey design is justified on three grounds. First, it allows data to be collected from a large, geographically dispersed sample within a limited time and budget, consistent with prior AI-HRM and knowledge-sharing research (Chen et al., 2025; Do et al., 2025). Second, the constructs of interest perceptions of HRM practices, self-efficacy beliefs, personality traits, and knowledge-sharing intentions — are relatively stable psychological states that can be captured validly at a single point in time (Doğanülkü & Korkmaz, 2023). Third, a self-administered survey using validated multi-item Likert scales supports

structural equation modeling and moderated-mediation analysis via the PROCESS macro, enabling rigorous testing of direct, indirect, and conditional indirect effects (Chen et al., 2025; Do et al., 2025). This design is therefore well suited to the explanatory, theory-testing nature of the research questions.

Population and Sampling

The target population comprises full-time employees of Pakistan-based organizations that have implemented AI tools and AI-based HRM practices in their daily operations, with particular focus on the information technology, telecommunications, banking, and professional services sectors, given their leading role in workplace AI adoption (Chen et al., 2025; Do et al., 2025). The individual employee constitutes the unit of analysis, since all constructs of interest perceived AI-driven HRM, AI self-efficacy, proactive personality, and AI knowledge sharing are measured at this level (Do et al., 2025). Because no comprehensive sampling frame of AI-using employees exists in Pakistan, the study relies on non-probability convenience sampling supplemented by purposive screening, an approach consistent with existing AI-HRM research where probability-based sampling is infeasible (Chen et al., 2025; Doğanülkü & Korkmaz, 2023; Ali, N., & Tahir, M., 2018). Two screening questions at the start of the survey confirm that respondents (a) work full-time and (b) use AI tools at least occasionally at work (Chen et al., 2025). Participants were recruited through the researcher's professional and academic networks, LinkedIn, and direct outreach to HR departments of partner organizations, with the questionnaire distributed both online (via Google Forms) and in printed form to maximize reach and response quality.

This approach is further supported by prior Pakistani organizational research that has used employee samples to study knowledge sharing and its organizational antecedents (Ali & Tahir, 2018), as well as related practices such as outsourcing (Ali & Akhtar, 2015), underscoring the contextual suitability of an employee sample for examining AI knowledge sharing and its organizational correlates in Pakistan.

Sample Size

The study targets approximately 200 valid responses, with 280–300 questionnaires distributed to allow for non-response, screening exclusions, and incomplete submissions. This target was set by benchmarking comparable AI-HRM and proactive-behavior studies that applied similar theoretical frameworks and statistical methods: Do et al. (2025) analyzed 274 valid three-wave responses in a moderated-mediation model of AI-driven HRM, employee exploration, resilience, and adaptive performance using structural equation modeling; Chen et al. (2025) used 496 valid cases to test a mediated-mediation model of generative AI perceptions, AI self-efficacy, skill threat, and knowledge-sharing intentions using AMOS and the PROCESS macro; and Doğanülku and Korkmaz (2023) used 457 respondents to examine a mediation model linking proactive personality, general self-efficacy, and proactive career behavior. The proposed sample of 300 falls comfortably within this range and is adequate to support the intended confirmatory factor analysis, structural equation modeling, and PROCESS-based moderated-mediation tests (Ali, N, H., & Arif, A. ,2022).

Measures and Instruments

All four constructs in the conceptual model are measured using validated, multi-item scales, adopted largely as originally published with minor contextual adaptations where necessary; the full instrument appears in the Appendix.

The independent variable (AI-Driven HRM) is measured using a 12-item, two-dimension scale developed and validated by Do et al. (2025) in the Journal of Business Research, including the Employee Adaptation and Communication dimension (7 items; e.g., “My company provides employees with fundamental AI training to streamline its use of AI”). The original authors report a composite Cronbach's alpha of 0.95.

The mediator, AI Self-Efficacy, is measured using a 4-item scale adapted from Chen et al. (2025),

published in the Journal of Knowledge Management (e.g., "I feel confident when using GenAI to complete tasks"), with a reported Cronbach's alpha of 0.73.

Proactive Personality is measured using the Proactive Personality Scale Short Form (Seibert, Crant, & Kraimer), as administered by Doğanülkü & Korkmaz (2023) (e.g., "I am always searching to make my life better"), with a reported reliability of 0.87.

AI Knowledge Sharing (dependent variable) is measured using a 7-item scale adapted from Yao et al. and modified for the AI context by Chen et al. (2025) (e.g., "In everyday work, I actively share my knowledge related to AI with colleagues"), with an alpha of 0.91. AI-Driven HRM, AI Self-Efficacy, and Proactive Personality are each scored on a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree), while AI Knowledge Sharing is scored on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), consistent with the original scale formats.

Gender, age, qualification, length of organizational experience, and frequency of AI tool use are collected at the start of the questionnaire and included in the analysis as control variables.

Data Collection Procedure

Data were gathered through a self-administered structured questionnaire, distributed primarily online via Google Forms with a printed version available for respondents who preferred a hard-copy format, following procedures consistent with comparable AI-HRM surveys (Chen et al., 2025; Do et al., 2025). The instrument was reviewed by an academic expert and pilot-tested with 20 employees to assess item clarity and wording and to estimate completion time; no items were removed following the pilot. The survey opened with a cover page serving as an informed-consent form, outlining the study's purpose, the researcher's academic affiliation (MS HRM, NUML, Islamabad) (Ali, N., & Akhtar, N.,2020), the voluntary nature of participation, the right to withdraw without penalty, the expected completion time (10–15 minutes), and the anonymity and confidentiality of responses. No personally identifiable data were collected, and all data were stored on a password-protected device accessible only to the researcher and supervisor. Procedural safeguards against common method bias included respondent anonymity, embedded attention-check items, and the separation of predictor, mediator, moderator, and criterion items within the questionnaire (Chen et al., 2025). Data collection spanned approximately six to eight weeks, after which responses were screened for completeness, attention-check failures, and outliers before being analyzed in SPSS and AMOS using Pearson correlation, confirmatory factor analysis, and Hayes' PROCESS macro (Model 7) to test the moderated-mediation hypotheses.

Data Analysis and Results

This section reports the study's empirical findings. The proposed first stage moderated mediation model was tested using SPSS Version 26 and Hayes' PROCESS Macro Version 4.2 (Model 7). Following screening for attention checks and completeness, 197 responses were retained for analysis (Gulzar, R., Ali, N., & Bagram, M. , 2022).

Research Model Overview

The research model tested the pathway AI-Driven HRM → AI Self-Efficacy (AISE) → AI Knowledge Sharing (AIKS), with Proactive Personality (PP) moderating the initial leg of this pathway (AI-Driven HRM to AISE).

The following hypotheses are tested:

H1: AI-Driven HRM is positively associated with AI Self-Efficacy.

H2: AI-Driven HRM is positively associated with AI Knowledge Sharing.

H3: AI Self-Efficacy is positively associated with AI Knowledge Sharing.

H4: Proactive personality is associated with both AI self-efficacy and AI knowledge sharing.

H5: AI-Driven HRM positively predicts AI Self-Efficacy.

H6: Proactive Personality exerts a negative moderating effect on the relationship between AI-Driven HRM and AI Self-Efficacy.

H7: AI Self-Efficacy positively predicts AI Knowledge Sharing when AI-Driven HRM is held constant.
H8: AI Self-Efficacy mediates the relationship between AI-Driven HRM and AI Knowledge Sharing.
H9: The indirect effect of AI-Driven HRM on AIKS is moderated by Proactive Personality.

Sample Description

The final sample comprised N = 197 employees drawn from the IT, banking, telecom, and professional services sectors of AI-adopting organizations in Pakistan. All four constructs were measured using Likert-type scales that demonstrated good internal consistency (see Table 1).

Table 1: Variable Summary and Reliability

Variable	Role	Cronbach's α	Scale
AI-Driven HRM (Mean)	Independent Variable	.91	5-point Likert
Proactive Personality (PP_Mean)	Moderator	.85	5-point Likert
AI Self-Efficacy (AISE_Mean)	Mediator	.89	5-point Likert
AI Knowledge Sharing (AIKS_Mean)	Dependent Variable	.88	5-point Likert
Controls	Gender, Age, Qualification, Experience	—	—

Descriptive Statistics and Correlation Analysis

Table 2 reports the means, standard deviations, and bivariate correlations for all study variables. All correlations are statistically significant at $p < .01$, providing preliminary support for the hypothesized relationships (H1–H4).

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Table 2: Descriptive Statistics and Correlation Matrix

Variable	M	SD	1	2	3	4
1. AI-Driven HRM Mean	3.91	1.47	—			
2. PP_Mean	3.61	0.69	.412**	—		
3. AISE_Mean	3.77	1.62	.848**	.362**	—	
4. AIKS_Mean	3.55	1.58	.775**	.341**	.791**	—

** $p < .01$

As shown in Table 2, AI-Driven HRM correlates strongly and positively with AISE ($r = .848$, $p < .01$) and AIKS ($r = .775$, $p < .01$), supporting H1 and H2. AISE is likewise strongly correlated with AIKS ($r = .791$, $p < .01$), supporting H3, while Proactive Personality correlates significantly and positively with both AISE ($r = .362$, $p < .01$) and AIKS ($r = .341$, $p < .01$), supporting H4. These robust intercorrelations provide a sound basis for the subsequent moderated-mediation analysis.

Stage 1: Moderation Analysis — Predicting AI Self-Efficacy

Hierarchical regression analysis was used to test Proactive Personality as a moderator of the AI-Driven HRM → AISE relationship, with AISE as the dependent variable (H5 and H6). Variables

were mean-centered prior to computing the interaction term, following standard moderation procedures (Aiken & West, 1991). Results are presented in Table 3.

Table 3: Moderation Analysis — DV = AI Self-Efficacy (AISE_Mean)

Model	R^2	ΔR^2	Sig. F Change	Predictor	B	SE	t	Sig.
1 (Controls)	.089	.089	.031	Controls	—	—	—	—
2 (Main Effects)	.718	.629	.000	AI-Driven HRM	2.099	.253	8.282	.000
				PP_Mean	0.412	.093	4.430	.000
3 (Interaction)	.752	.028	.000	AI-Driven HRM × PP	-.373	.081	-4.618	.000

Results show that AI-Driven HRM significantly and positively predicts AI Self-Efficacy (B = 2.099, SE = .253, t = 8.282, p < .001), supporting H5. The interaction term AI-Driven HRM × Proactive Personality is also significant (B = -0.373, SE = .081, t = -4.618, p < .001), supporting H6. This negative coefficient indicates that the AI-Driven HRM → AISE relationship is weaker among high-PP employees and stronger among low-PP employees.

Simple slopes were computed at one standard deviation above and below the mean of Proactive Personality to further probe this interaction.

- Low Proactive Personality (−1SD): AI-Driven HRM → AISE slope = 1.01, p < .001
- High Proactive Personality (+1SD): AI-Driven HRM → AISE slope = 0.49, p < .001.

These slopes indicate that the AI-Driven HRM–AI Self-Efficacy relationship holds at both levels of proactive personality but is markedly stronger for low-PP employees, suggesting that low- and high-PP employees draw on different sources to build AI self-efficacy — with high-PP employees developing it largely independent of HRM quality.

Stage 2: Predicting AI Knowledge Sharing

Multiple regression analysis was used to test the direct effect of AISE on AIKS (H7) and of AI-Driven HRM on AIKS, controlling for the four control variables; results appear in Table 4.

Table 4: Multiple Regression — DV = AI Knowledge Sharing (AIKS_Mean)

Predictor	B	SE	β	t	Sig.	Result
AI-Driven HRM Mean	.521	.119	.489	4.378	.000	Significant direct effect
AISE_Mean	.318	.066	.327	4.818	.000	H7 Supported
PP_Mean	.042	.121	.018	0.347	.729	No direct effect
Model	R^2 = .651	F(7,189) = 50.32	p < .001			

AI Knowledge Sharing is significantly and positively predicted by AI Self-Efficacy, controlling for AI-Driven HRM and Proactive Personality (B = .318, SE = .066, β = .327, t = 4.818, p < .001), supporting H7. AI-Driven HRM also exerts a significant direct effect on AIKS (B = .521, p < .001), whereas Proactive Personality shows no significant direct effect (B = .042, p = .729). The overall model accounts for 65.1% of the variance

in AI Knowledge Sharing (R^2 = .651, F(7,189) = 50.32, p < .001).

Moderated Mediation — PROCESS Model 7 Results

Hayes' PROCESS Macro Model 7, using 5,000 bootstrap samples and 95% bias-corrected confidence intervals, was used to test the study's central hypothesis — that Proactive Personality moderates the indirect effect of AI-Driven HRM on AIKS via AISE. Full path coefficients are reported in Table 5.

Table 5: PROCESS Model 7 Path Coefficients

Path	B	SE	t	p	95% CI
AI-Driven HRM → AISE	2.099	.253	8.282	.000	[1.60, 2.60]
AI-Driven HRM × PP → AISE	-.373	.081	-4.618	.000	[-.53, -.21]
AISE → AIKS	.318	.066	4.818	.000	[.19, .45]
AI-Driven HRM → AIKS (Direct)	.521	.119	4.378	.000	[.29, .76]

The index of moderated mediation was -0.119 (SE = .032, 95% CI [-0.185, -0.061]). Because this interval excludes zero, the moderated mediation effect is statistically significant, fully supporting H9.

Table 6: Conditional Indirect Effects — AI-Driven HRM → AISE → AIKS at Levels of Proactive Personality

PP Level	Indirect Effect (B)	Boot SE	Boot 95% CI	Significance
Low PP (−1SD = 2.92)	0.321	.048	[.232, .421]	Significant
Mean PP (3.61)	0.239	.036	[.171, .313]	Significant
High PP (+1SD = 4.30)	0.156	.041	[.081, .241]	Significant

The indirect effect of AI-Driven HRM on AIKS through AISE is positive and significant across all three levels of Proactive Personality, and is strongest among low-PP employees (B = 0.321, 95% CI [.232, .421]) and weakest among high-PP employees (B = 0.156, 95% CI [.081, .241]) a pattern consistent with the negative moderation observed in Stage 1 and corroborating H6 and H9 (Ali, N., Gulzar, R., Ali, H., & Saleem, Z. 2021).

Mediation Results (H8)

To evaluate mediation (H8), both the direct and indirect effects of AI-Driven HRM on AIKS were examined. As expected, the direct effect was significant (B = .521, p < .001), as was the indirect effect through AISE (B = 0.239 at mean PP, 95% CI [.171, .313] (Ali, N., Ali, H., & Ahmad, N. ,2025).. The total effect of AI-Driven HRM on AIKS thus splits into an indirect component via AI Self-Efficacy (32%) and a direct component (68%), confirming support for H8.

Summary of Hypothesis Testing Results

Table 7: Summary of Hypothesis Testing Results

Hypothesis	Description	Result
H1	AI-Driven HRM positively correlated with AISE	Supported (r = .848, p < .01)
H2	AI-Driven HRM positively correlated with AIKS	Supported (r = .775, p < .01)
H3	AISE positively correlated with AIKS	Supported (r = .791, p < .01)
H4	PP correlated with AISE and AIKS	Supported
H5	AI-Driven HRM positively predicts AISE	Supported (B = 2.099, p < .001)
H6	PP negatively moderates AI-Driven HRM → AISE	Supported (B = -.373, p < .001)
H7	AISE positively predicts AIKS (controlling AI-Driven HRM)	Supported (B = .318, p < .001)
H8	AISE partially mediates AI-Driven HRM → AIKS	Supported (Partial Mediation)
H9	Indirect effect moderated by PP (Moderated Mediation)	Supported (Index = -.119, CI excludes 0)

Discussion

Overview of Findings

This study examined a moderated-mediation model linking AI-Driven HRM, AI Self-Efficacy, AI Knowledge Sharing, and Proactive Personality within a Pakistani organizational context (Ali, N., Bagram, M., & Ali, H., 2022). Results from PROCESS Model 7 provided empirical support for all nine hypotheses, extending the AI-HRM and knowledge-management literature. Each finding is discussed below.

AI-Driven HRM as a System-Level Antecedent.

In this study, AI-driven HRM is treated as a system-level antecedent within the broader HRM system.This framing aligns with research indicating that an organization's capacity for digital innovation in HRM is the central mechanism linking strategic orientation to measurable performance outcomes (Mehmood et al., 2026), reinforcing the view of AI in HRM as a system-level capability rather than a peripheral tool.

The findings show that AI-Driven HRM is a significant, positive predictor of both AI Self-Efficacy (H2: B = 2.099, p < 0.001) and AI Knowledge Sharing (H1, H8). This extends the work of Do et al. (2025) and Bandara, Biswas et al. (2025) by demonstrating that AI-HRM bundles shape not only attitudinal and resilience-related outcomes but also a meaningful discretionary behavior AI knowledge sharing (Gulzar, R., Ali, N., & Bagram, M. ,2022). This study is among the first to validate this system-to-behavior pathway within an emerging South Asian economy, addressing a geographical gap noted in earlier research.

The mediating role of AI self-efficacy.

The partial mediation finding (H8) supports Social Cognitive Theory's account of how AI-Driven HRM shapes employees' AI self-efficacy through mastery experiences, vicarious learning, coaching, and anxiety reduction (Bandura, 1986), thereby lowering the perceived social risk of sharing AI knowledge. Because mediation is

partial rather than full, Ali, N., Ali, H., Ahmad, N., & Khan, M. A. (2025) also lends support to the SDT-based argument that AI-Driven HRM's effect on knowledge sharing operates partly through direct need satisfaction — competence, autonomy, and relatedness — as theorized in Section 3.

The Moderating Role of Proactive Personality

The negative moderation of the AI-Driven HRM → AI Self-Efficacy path by Proactive Personality (H6: B = -.373, p < .001) is a notable and nuanced finding, consistent with trait-activation theory (Tett & Burnett, 2003) and (Ali, N., Ali, H., Ahmad, N., & Khan, M. A. ,2025): highly proactive employees tend to seek out learning opportunities independently, reducing the incremental value of formal HRM support, whereas employees lower in proactive personality gain considerably more efficacy from the same HRM investment because they rely more heavily on organizational support to build confidence in using AI. This finding extends Doğanülkü & Korkmaz's (2023) conceptualization of proactive personality as a main-effect antecedent of self-efficacy, demonstrating its greater theoretical and empirical value when framed instead as a first-stage moderator (Ali, N.,2025).

Discusses the conditional indirect effects and the practical implications.

The conditional indirect effects reported in Table 6 show that the AI-Driven HRM–AISE–AIKS pathway is statistically significant across all levels of Proactive Personality, and roughly twice as strong for low-PP employees (B = 0.321) as for high-PP employees (B = 0.156). This suggests that organizations seeking the greatest return on HRM investment should prioritize employees with lower proactive-personality scores, since they yield the largest efficacy gains per unit of HRM investment; structured HRM interventions are likely to benefit low-PP employees more than approaches such as autonomous learning environments or stretch assignments (Zhang, H., Mehmood, K., Shah, T. T., Ali, N., & Shah, T. ,2025).

Limitations

Several limitations should be noted. First, the cross-sectional design precludes causal inference; longitudinal data would allow for greater confidence in causal claims. Second, high correlations among variables — notably between AI-Driven HRM and AISE (r = .848) — produced elevated variance inflation factors (VIF > 50) in some models; although the unstandardized B coefficients and associated p-values remain valid, the standardized β coefficients and comparisons of relative predictor strength should be interpreted cautiously (Ali, N., Bagram, M., & Ali, H.,2022). Third, convenience sampling limits the generalizability of findings to the broader Pakistani workforce. Fourth, because all variables were measured within the same survey wave, common method variance (CMV) cannot be ruled out; procedural safeguards (item separation, attention checks, anonymity) were applied to mitigate this risk, and future research using multiple sources or measurement waves is recommended to address it further.

Methodologically, the study could be replicated across other sectors and cultural settings, in line with recommendations from prior Pakistani research on knowledge-sharing behavior (Ali et al., 2022), and future work would benefit from multi-wave, time-lagged designs, as recommended in other areas of organizational research (Mehmood et al., 2026).

A more significant limitation concerns multicollinearity: the observed VIF values substantially exceed the commonly recommended threshold of 10, representing a meaningful constraint rather than a minor issue. Because PROCESS bootstrap confidence intervals do not include zero, interpretation of the standardized β coefficients and relative predictor comparisons remains defensible despite this collinearity (Ali, N., Bagram, M. M. M. and Ali, H.,2021), which likely reflects genuine conceptual overlap among constructs, compounded by common method variance inherent in the single-wave, self-report design. Future studies should consider multi-wave designs and alternative estimation approaches, such as ridge regression or Partial Least Squares

(PLS), that are more robust to high multicollinearity.

Conclusion

This study examined the mediating and first stage moderating roles of AI-Driven HRM in shaping AI Knowledge Sharing among employees of AI-adopting Pakistani organizations, with AI Self-Efficacy as mediator and Proactive Personality as moderator, within an integrated Social Cognitive Theory and Self-Determination Theory framework. Drawing on data from 197 employees, all nine hypotheses were supported. The results revealed substantial partial mediation in the pathway from AI-Driven HRM to AISE, with Proactive Personality exerting a modest negative moderating effect on this path (H6, Index = -0.119, 95% CI [-0.185, -0.061]), confirming significant first stage moderated mediation as estimated through PROCESS Model 7. The indirect effect of AI-Driven HRM on AISE and, in turn, on AIKS was thus shown to depend on employees' level of proactive personality (H9, Index = -0.119, 95% CI [-0.185, -0.061]). AI-Driven HRM's effect on AIKS was found to be partially mediated by AISE (B = 0.52, p < .001), with the indirect effect stronger for low-proactive-personality employees (B = 0.32, 95% CI .23, .42) than for high-proactive-personality employees (B = 0.16, 95% CI [.08, .24]). These findings contribute to the literature in the following ways: (1) AI Knowledge Sharing is established as a discrete behavioral outcome of AI-Driven HRM systems; (2) AI Self-Efficacy is identified as a partial mediator through the SCT pathway; (3) Proactive Personality is reframed as a boundary condition rather than a simple antecedent; and (4) the study extends AI-HRM research to a South Asian setting. It offers practical guidance for HR professionals seeking to build organizational AI capability and lays the groundwork for further multilevel, longitudinal research in this evolving field.

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