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Fostering faculty well-being: evidence on human resource practices for a psychologically healthy academia

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Abstract

Purpose – This study aims to examine how strategic human resource practices can help reduce stress among faculty members in higher education institutions (HEIs) by strengthening their internal psychological resources. It explores how different forms of intelligence – technological, emotional and spiritual – shape the effectiveness of these practices, offering a nuanced understanding of how institutions can better support academic staff in demanding and evolving work environments.

Design/methodology/approach – A structured questionnaire was distributed via an online survey to 438 faculty members across multiple HEIs in India, using a non-probability snowball sampling approach. This study used well-established psychometric scales to measure high-performance human resource practices (HPHRPs), psychological capital (PsyCap), artificial intelligence (AI), emotional intelligence, spiritual intelligence and perceived stress. Confirmatory factor analysis was conducted to establish construct validity, and moderated-mediation analyses were performed to test the hypothesized relationships.

Findings – The results indicate that HPHRPs play a meaningful role in alleviating stress by fostering greater psychological resilience among faculty members. PsyCap serves as a key pathway through which these practices exert their influence. Notably, the use of AI tools amplifies the positive effect of human resource practices on psychological resources. This relationship is further strengthened by individuals' emotional awareness and regulation abilities, which enhance the synergy between technology use and supportive work

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practices. Moreover, a sense of spiritual purpose and alignment with institutional values further buffers the impact of stress, reinforcing the role of deeper meaning and connection in sustaining well-being within academic environments.

Originality/value – This study sheds new light on how people-oriented management practices can ease workplace stress when embedded in environments that also nurture technological fluency, emotional awareness and spiritual meaning. Rather than treating these elements in isolation, the findings suggest that reducing stress in academic settings requires a broader view – one that sees human resource systems as deeply interconnected with how individuals experience purpose, connection and adaptability. When faculty feel supported not just by procedures but by values, emotions and enabling tools, they become more resilient and psychologically empowered. In doing so, this study challenges fragmented approaches to stress management and calls for more holistic strategies that recognize the full spectrum of what it means to thrive at work.

Keywords Artificial intelligence, Emotional intelligence, Spiritual intelligence, High-performance HR practices, Psychological capital, Higher educational institutions, India

Paper type Research paper

1. Introduction

Higher education institutions (HEIs) today are at a crossroads. Amid intensifying demands for performance, constant adaptation to digital platforms and growing expectations from students and administrators alike, faculty members are increasingly experiencing psychological strain. Reports of stress, emotional fatigue and burnout are no longer isolated incidents – they reflect deeper tensions between institutional pressures and personal well-being (e.g. Almaiah *et al.*, 2020; D'Souza *et al.*, 2023; Hammoudi Halat *et al.*, 2023; Mosleh *et al.*, 2022; Lim and Teo, 2023). In brief, faculty members now operate in environments that demand not only subject expertise but also emotional resilience, technological adaptability and alignment with institutional values – pressures that traditional academic support systems often fail to address.

In this context, high-performance human resource practices (HPHRPs) have gained prominence. These practices – designed to enhance employees' abilities, motivation and opportunities – aim to align individual capacities with organizational objectives (Chuang *et al.*, 2013; Jones and Wright, 1992). While widely associated with improved job satisfaction and performance outcomes (Jiang *et al.*, 2012; Miao *et al.*, 2016), their potential to alleviate psychological strain in complex academic environments remains underexplored. Existing research tends to emphasize operational effectiveness, leaving important questions about the emotional and existential effects of human resource (HR) design unanswered.

This study addresses this oversight by investigating how HPHRPs contribute to reduced perceived stress through the development of psychological capital (PysCap) – a multidimensional construct encompassing self-efficacy, hope, optimism and resilience (Avey *et al.*, 2010; Luthans *et al.*, 2007). PysCap is increasingly recognized as a foundational psychological resource that enables employees to withstand adversity, adapt to change and maintain well-being. Yet, its formation is not solely dependent on HR practices; it is shaped by contextual conditions that either facilitate or constrain its development.

To account for these contextual dynamics, the study introduces three critical forms of moderating capacity: emotional intelligence (EI), which supports emotional self-regulation and interpersonal effectiveness (Joseph *et al.*, 2015; Mayer and Salovey, 1997); artificial intelligence (AI), which influences how faculty interact with data, systems and administrative processes (Schepman and Rodway, 2022; Upadhyay and Khandelwal, 2018); and spiritual intelligence (SPINT), which enhances employees' sense of meaning, purpose and alignment

with organizational values (Ashmos and Duchon, 2000; Vasconcelos, 2020). Each of these capacities influences the relationship between HR practices, psychological resources and perceived stress in distinct but interconnected ways.

Despite growing interest in each of these elements – HPHRPs, PsyCap, AI, EI and SPINT – prior research has often treated them in isolation (e.g. Alston *et al.*, 2010; Jiang *et al.*, 2012; Hwa and Amin, 2016; Miao *et al.*, 2016; Sy *et al.*, 2006). Little is known about how they interact as part of a systemic approach to stress mitigation in higher education, leading to the following research question:

RQ1. How do high-performance human resource practices reduce perceived stress among HEI faculty through psychological capital, and how is this process shaped by the interacting roles of artificial, emotional, and spiritual intelligence?

To address it, the study surveyed 438 faculty members from HEIs across India and analyzed the data using moderated mediation techniques via PROCESS macro. The results confirmed that HPHRPs reduce perceived stress by enhancing PsyCap, which plays a critical mediating role. Crucially, the effects of HPHRPs on PsyCap are significantly amplified when faculty members actively engage with AI – especially those with high EI – demonstrating a powerful synergy between technological adaptability and emotional competence. SPINT further strengthens the stress-buffering role of PsyCap by anchoring employees in meaning and value alignment. These findings break new ground by showing that the effectiveness of HPHRPs is contingent not only on organizational design but also on how individuals harness digital, emotional and spiritual capacities. The study offers a paradigm shift: managing stress in academic settings requires an integrated approach that embeds AI readiness, emotional skills and existential purpose into human resource strategy.

The remainder of this paper organized as follows: In Section 2, we provide theoretical underpinnings and hypotheses development. In Section 3, we explain the methodology, and in Section 4, we explain the analysis. Section 5 is devoted to the discussion that includes the main findings, theoretical contributions, practical implications, limitations, suggestions for future research and conclusion.

2. Theoretical premises

This study draws on two complementary theoretical foundations: the ability–motivation–opportunity (AMO) framework (Appelbaum *et al.*, 2000) and conservation of resources (COR) theory (Hobfoll, 1989). Widely adopted in human resource management (HRM) research (Bos-Nehles *et al.*, 2023; Kim *et al.*, 2015), AMO theory provides a foundational lens for understanding how HPHRPs enhance employee effectiveness. According to this framework, organizational performance depends on three interlocking elements: employees' abilities (i.e. the psychological, cognitive and technical competencies to perform tasks effectively; Blumberg and Pringle, 1982; Marin-Garcia and Martinez Tomas, 2016), motivation (the desire and willingness to act; Bos-Nehles *et al.*, 2023; van Iddekinge *et al.*, 2018) and opportunity (external conditions that enable or constrain action; Blumberg and Pringle, 1982).

HPHRPs embody this triad through targeted practices that build skills, inspire effort and remove structural barriers to performance (Gardner *et al.*, 2011; Jiang *et al.*, 2012; Chuang *et al.*, 2013). When well-executed, these practices create work environments where faculty members are equipped, empowered and enabled to succeed (Kehoe and Wright, 2013). In the context of HEIs, such alignment is essential for attracting, developing and retaining talent capable of navigating complex academic demands. Building on prior evidence (Pham *et al.*, 2018), we propose that HPHRPs foster PsyCap

by reinforcing employees' confidence (ability), engagement (motivation) and behavioral agency (opportunity). Recent systematic reviews have affirmed the explanatory power of the AMO framework in linking HR practices to positive organizational outcomes (Kaur and Malik, 2025), further supporting its relevance to our study.

The second theoretical pillar is COR theory (Hobfoll, 1989; Hobfoll *et al.*, 2018), which emphasizes that individuals strive to acquire, protect and accumulate valued resources – tangible and intangible – to cope with stress and maintain performance. In academic settings, these resources range from personal attributes (e.g. self-efficacy and optimism) to material and social assets (e.g. technology access and collegial support). PsyCap, in this framework, represents a dynamic psychological resource that faculty members develop to adapt effectively to adversity, particularly in high-stress environments such as those shaped by the COVID-19 pandemic (Antony *et al.*, 2023; Siluvai *et al.*, 2023).

Consistent with Hobfoll's, (1989, p. 317) assertion that individuals "acquire resources to position themselves so that they are less vulnerable to future resource loss," faculty members proactively cultivate reservoirs of psychological resilience, often through professional development (e.g. learning new digital tools) or social investment. This resource-building process enhances their capacity to meet unpredictable demands. COR theory has been widely used to explain stress-related phenomena including burnout, work–family conflict and organizational citizenship behavior (Eldor and Harpaz, 2016; Halbesleben, 2006), making it especially well-suited to theorize the stress-mitigating role of PsyCap.

Together, AMO and COR offer a robust theoretical scaffold for understanding how HPHRPs reduce perceived stress by fostering PsyCap, and how this mediating process is conditioned by faculty members' technological, emotional and SPINTs. The hypothesized relationships are visually summarized in the conceptual model (Figure 1).

While AMO theory explains how HR practices enhance individual capabilities, motivation and opportunities for performance, it does not explicitly address how individuals respond to environmental demands that threaten well-being or psychological stability. This is where COR theory becomes essential. COR complements AMO by providing a stress-oriented lens, emphasizing how individuals deploy and protect psychological resources – such as PsyCap – when facing adverse conditions. By combining AMO and COR, our

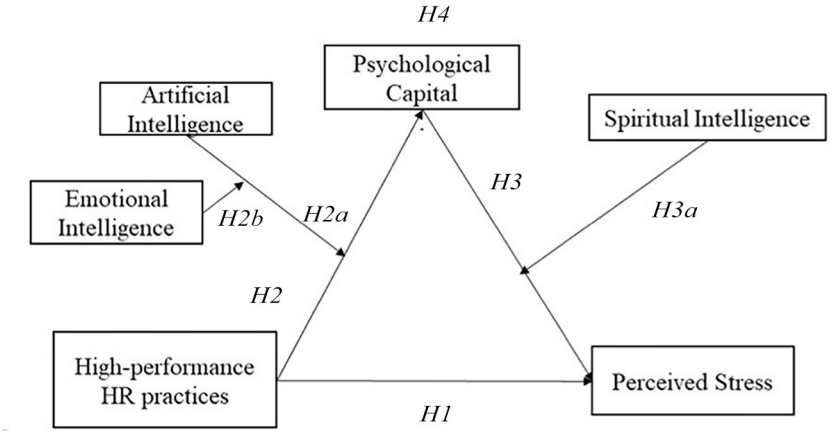

Figure 1. Conceptual model
Source: Authors' own elaboration

framework captures both the resource-enabling function of HR practices and the resource-conserving behavior of individuals under pressure. This theoretical integration allows us to model PsyCap not merely as a byproduct of HR systems but as a strategic mediating resource that links structural HR inputs to psychological outcomes. In doing so, we extend both theories: AMO by incorporating stress-related dynamics, and COR by embedding resource accumulation into systemic HR processes. This integrative lens also underpins the model's novelty – showing that the success of HR practices in reducing stress hinges on the alignment between organizational interventions and individual resource ecologies (Kiazad *et al.*, 2015).

2.1 Hypotheses development

Faculty members in various countries faced stress at work, particularly during the post-pandemic period, in Nigeria (Adekunle and Agboola, 2022), Malaysia (Ahmad and Hussain, 2023), Saudi Arabia (Al-Harbi, 2022), Jordan (Alqudah and Mohammed, 2022), Palestine (Al-Shobaki *et al.*, 2023), South Africa (Czerniewicz and Brown, 2022) and Singapore (Lim and Teo, 2023). When HR managers implement high-performing activities, employees are more likely to use their abilities, skills and competence to reduce perceived stress generated by work and the environment (Batta *et al.*, 2023; Boulet and Dextras-Gauthier, 2025; Iram *et al.*, 2024). A growing body of evidence suggests that HPHRPs can help alleviate perceived stress when implemented thoughtfully. For instance, Topcic *et al.* (2015) found that HPHRPs designed to increase job resources – such as participative decision-making and flexible working arrangements – can reduce employees' perceived stress, though practices framed as performance demands may increase it. Similarly, Jyoti *et al.* (2015), in their study of teachers in professional colleges, reported that bundled HPHRPs reduced emotional exhaustion, a key correlate of perceived stress. Sheehan and Garavan (2021) further demonstrated that supportive HR practices in HEIs were associated with lower levels of burnout and stress among faculty members. Collectively, these studies suggest that when HPHRPs are configured to emphasize employee development, empowerment and support, they can act as organizational resources that mitigate the stressors inherent in academic roles. Accordingly, we offer the following hypothesis:

H1. HPHRPs have a significant and negative influence on perceived stress.

Faculty members' PsyCap – comprising hope, self-efficacy, resilience and optimism – can be significantly enhanced when organizational HR practices are designed to empower, motivate and engage. HPHRPs, by promoting rigorous selection, targeted training and inclusive performance systems, serve as key organizational levers to develop such psychological strengths. This is supported by multiple empirical studies. For example, Miao *et al.* (2021) found a positive relationship between HPHRPs and PsyCap among employees in 44 Chinese firms. Similarly, Vuong (2022), surveying frontline bank employees in Vietnam, and Yıldırım *et al.* (2025), in a study of Turkish academics, both reported that employees exposed to high-performance HR systems developed stronger PsyCap. These findings reinforce the theoretical view that AMO-enhancing HR systems promote not only job performance but also internal psychological capacities (Luthans and Youssef-Morgan, 2017). In the context of HEIs, faculty members are particularly likely to build PsyCap when they are included in participatory training, collaborative work design and feedback-rich environments. Such interventions enhance their confidence, goal persistence and coping resources – essential for navigating the emotional demands of academic work:

H2. HPHRPs have a significant and positive influence on PsyCap.

Several studies in the past have empirically found that PsyCap is a guaranteed resource for employees to cope with stress (Abbas and Raja, 2015; Avey *et al.*, 2010; Li *et al.*, 2015). In a recent study conducted on 388 faculty members in India, researchers reported a negative relationship between PsyCap and stress (Bidi *et al.*, 2024). In another survey of 385 faculty members in Turkey, researchers found that PsyCap has lessened job stress (Toprak *et al.*, 2022). During the global pandemic, the researchers found that the four dimensions of PsyCap (hope, efficacy, resilience and optimism) were a practical resource for employees to cope with stress (Maykrantz *et al.*, 2021). In India, a recent study of 507 public sector employees revealed that PsyCap was beneficial in managing stress experienced during the pandemic (Pradhan *et al.*, 2024). Thus, we advance the following hypothesis based on abundant evidence and logos:

H3. PsyCap has a significant and negative influence on perceived stress.

While the direct effects of HPHRPs on perceived stress are understandable (as explained in *H1*), it is also possible that the direct effect may be lessened through PsyCap. By implementing HPHRPs, AMO dimensions help employees expand their PsyCap, which will alleviate perceived stress (Bello-Pintado, 2015; Boxall, 2012). In this study, we speculate a decisive mediating role of PsyCap in reducing the negative effect of HPHRPs on perceived stress. PsyCap as a mediator between organizational variables has been well documented in literature (Goswami and Agrawal, 2023; Shah *et al.*, 2023; Zhao *et al.*, 2025). For example, Vasudevan and Suganthi (2023) investigated the mediating role of PsyCap in the relationship between new working methods and life satisfaction. Working on similar lines, we propose to study the mediation of PsyCap between HPHRPs and perceived stress and state the hypothesis as follows:

H4. PsyCap mediates the relationship between HPHRPs and perceived stress.

With digital transformation, HEIs are switching their tuition practices by implementing the latest tools available for pedagogical purposes (Komljenovic, 2022; McGrath *et al.*, 2023), and several researchers documented the application of AI by faculty members in HEIs (Bearman *et al.*, 2022; Carvalho *et al.*, 2022; Luckin *et al.*, 2022). Mendy (2020) observed that HR development managers need to identify workplace stress and then design initiatives for such stress, and in this process, PsyCap plays a vital role (Luthans *et al.*, 2007). There is consensus among scholars that AI offers a personalized learning environment whereby faculty members can see each student's needs and provide helpful feedback (Abuhassna, 2024; Rahimi and Sevilla-Pavón, 2024). With the help of AI, faculty members can analyze student data and predict student success (Cerratto Pargman and McGrath, 2021) and incorporate AI tools for assessing student performance by automatic grading systems in managing large classes (Burrows *et al.*, 2015). Extant research reported that when faculty members who have high knowledge and proficiency in AI are successful in designing their course activities and engage in effective pedagogical techniques (Galindo-Domínguez *et al.*, 2023; Wang *et al.*, 2023).

While the direct effects of AI are understandable, this study argues that AI plays a moderating role by strengthening the positive relationship between HPHRPs and perceived stress mediated through PsyCap. The underlying logic for this proposition is that faculty members can divert their energies by adopting AI tools in pedagogical instructions and assessing students' performance. To our knowledge, no prior studies investigated such a moderating effect.

In addition, EI plays a vital role in achieving superior performance by understanding self and others emotions and managing the emotions in the workplace (Joseph *et al.*, 2015; Mayer *et al.*, 2008; Mayer and Salovey, 1997; Pekaar *et al.*, 2017), it will be interesting to see how EI interacts with AI to alleviate the perceived stress stemming from work. More precisely, when faculty members encounter stress due to implementing technological innovations with limited facilities, conflicts are more likely to erupt. How individuals manage these emotions plays a vital role in reducing, if not mitigating, the stress associated with performing tasks.

This research explores the three-way interaction between HPHRPs, AI and EI in enhancing PsyCap. Since none of the prior studies focused on this double moderation, we offer the following exploratory hypotheses:

H2a. AI positively moderates between HPHRPs and PsyCap such that at higher (lower) levels of AI, HPHRPs result in higher (lower) levels of PsyCap.

H2b. EI (second moderator) and AI (first moderator) influence the relationship between HPHRPs and perceived stress mediated through PsyCap.At higher (lower) levels of EI, higher (lower) AI interacts with HPHRPs to result in higher (lower) levels of PsyCap.

Several organizations have emphasized SPINT and workplace spirituality in maintaining smooth relationships and effective functioning (Nayyar *et al.*, 2024). For example, in HEIs in India, one study on 810 students found that SPINT is instrumental in developing leadership qualities (Prabhu and Mehta, 2023). In Indian organizations, some scholars found that workplace spirituality, which depends on SPINT, is significantly negatively related to stress (Saxena *et al.*, 2020). A study conducted on 473 respondents in India by Saini and Seema (2020) found that SPINT significantly negatively affects stress. In a recent study conducted on 381 respondents from universities in India, researchers found that SPINT reduced depression symptoms significantly (Rajan *et al.*, 2024). Expecting the positive effect of SPINT, we attempt to explore the moderating effect of SPINT in strengthening the negative relationship between HPHRPs and perceived stress. In other words, when people exhibit a high level of SPINT by finding meaning in their work and seeing that their work aligns with organizational goals, it is more likely that they will experience lower levels of stress. To our knowledge, the previous studies have yet to investigate this moderating effect of SPINT. Hence, we offer the following exploratory moderator hypothesis:

H3a. SPINT moderates the relationship between psychological capital and perceived stress such that at higher (lower) levels of SPINT, PsyCap results in lower (higher) levels of perceived stress.

3. Method

3.1 Sampling strategy

This study explores the effect of HPHRPs on perceived stress, mediated by PsyCap and moderated by AI, EI and SPINT. The context of the study is faculty members in HEIs in India – an occupational group experiencing increased stress due to pedagogical shifts and institutional demands post-COVID-19 (Pant and Srivastava, 2019; Pandit and Agrawal, 2022).

We used a structured questionnaire administered via Google Forms, consistent with current best practices in post-pandemic behavioral research (Antony *et al.*, 2023; Jayaraman *et al.*, 2023; Shaik *et al.*, 2023). Though pandemic restrictions had eased, online data

collection remains preferred for its reach and efficiency in targeting busy professionals (Newman *et al.*, 2014). Informed consent was obtained prior to participation.

Given the absence of an accessible sampling frame and the difficulty of accessing this population, we used a combination of convenience, non-probability and snowball sampling. Faculty known to the researchers were initially contacted and asked to share the survey with peers. Participants were assured anonymity and confidentiality. A total of 600 emails were sent.

We obtained informed consent from the respondents before participating in this study. We used convenience, non-probability and snowball sampling, though researchers do not prefer this data collection method. We first contacted known faculty members and procured their friends' emails, who were willing to participate in the survey. We assured the respondents that the data's anonymity and privacy would be protected. Through snowball sampling, we have sent 600 emails to the faculty members working in different parts of the country. We received 438 (73% response rate), and all the surveys were complete. Google Forms only allows a respondent to proceed further after responding to questions. Of the total number (438) faculty members, 210 (47.95%) are from Andhra Pradesh, 141 (32.19%) are from Telangana, 35 (7.99%) are from Tamil Nadu, 24 (5.48%) are from Karnataka, 10 (2.28%) are from Maharashtra, 12 (2.74%) are from Uttar Pradesh and 6 (1.37%) are from Rajasthan. We performed a nonresponse bias check by comparing the first 75 respondents with the last 75 respondents. We found no statistical differences between these two groups regarding all the study variables (Armstrong and Overton, 1977). The demographic profile of respondents is detailed in Table 1.

3.2 Higher education in India: the study context

Education is a powerful growth engine in any country, and India is no exception. A report by the Ministry of Education (2023), India reveals that the HEIs consist of over

Table 1. Demographic profile of respondents

Category	Profile	Total number	%
Gender	Male	255	58.2
	Female	183	41.8
Age (in years)	20–29 years	101	23.1
	30–39 years	157	35.8
	40–49 Years	100	22.8
	50–59 years	80	18.3
Educational qualification	Graduates [B. Tech degrees]	39	8.9
	Masters degrees and Ph. Ds	225	51.4
	Professional degrees [law, accountancy]	174	39.7
Annual income (INR / US $)	Less than Rs. 500,000 ($6,250)	193	44.1
	Rs. 500,000–900,000 ($6,250–$11,250)	102	23.3
	Rs. 900,000–1,400,000 ($11,250– $17,500)	96	21.9
	Rs. 1,400,000–1,900,000 ($17, 750–$23,750)	41	9.4
	Rs. 1,900,000–2,400,000 ($23,750–$30,000)	6	1.4
Employee designation	Assistant professor	261	59.6
	Associate professor	111	25.3
	Professor	66	15.1
Work experience	0–4 years	192	43.8
	5–9 years	73	16.7
	10–14 years	98	22.4
	Above 15 years	75	17.1

Source(s): Authors' own elaboration

1,000 universities (central universities, state universities, private universities, deemed universities and institutes of national importance such as IITs and NITs) and over 42,000 constituent colleges. HEIs are knowledge hubs. The faculty members play a vital role in disseminating knowledge, and the success of these organizations is heavily dependent on the quality of instructors. The administrators in HEIs use recruitment strategies to attract and retain competent faculty to remain competitive in a highly competitive environment. Furthermore, following the global pandemic, increasing competition for competent faculty who are flexible in a changing academic environment where pedagogical tools and instruments have undergone radical change necessitates HPHRPs in HEIs. In addition, the stress imposed by the pandemic has become common among employees in all sectors (Pandit and Agrawal, 2022), including HEIs, calls for a fresh look at HR practices and their impact on perceived stress.

3.3 Measures

We used well-established and tested measures in this study. The indicators for all the constructs were measured on a five-point Likert scale (5 = "strongly agree"; 1 = "strongly disagree").

HPHRPs were measured with three dimensions adapted from Chuang *et al.* (2013). Ability enhancing dimension of HPHRPs was measured with three indicators ($\alpha = 0.78$) and a sample item reads as "In my opinion selection of employees is totally based on their technical skills but not interpersonal skills." Motivation-enhancing dimension HPHRPs was measured with four items ($\alpha = 0.75$) and the sample item reads as: "In my opinion the selection of employees emphasizes their overall fit to the organization (values and personality)."

Opportunity enhancing dimension of HPHRPs was measured with three items ($\alpha = 0.77$), and the sample item reads as: "In my opinion the organization often arranges events for knowledge exchange (e.g. seminar and presentation)." The second-order latent construct HPHRPs has reliability coefficient of 0.81.

PsyCap was measured with seven items ($\alpha = 0.74$) adapted from Luthans *et al.* (2007) and the sample item reads as: "I feel confident in analyzing a long-term problem to find a solution."

EI was measured with four dimensions (self-emotion appraisal [SEA], others' emotional appraisal [OEA], use of emotions [UOE] and regulation of emotions [ROE]) adapted from Salovey and Mayer (1990). SEA dimension was measured with three indicators ($\alpha = 0.76$) and sample item reads as "I have good understanding of my own emotions."

OEA dimension was measured with three indicators ($\alpha = 0.79$) and sample item reads as "I am a good observer of others' emotions."

UOE dimension was measured with three indicators ($\alpha = 0.81$) and sample item reads as "I always tell myself I am a competent person."

ROE dimension was measured with three indicators ($\alpha = 0.76$) and sample item reads as "I am able to control my temper and handle difficulties rationally." The second-order latent variable EI has reliability coefficient of 0.82.

SPINT was measured with three dimensions – meaning at work, conditions for community and alignment with organization value adapted from Ashmos and Duchon (2000). SPINT (meaning at work) was measured with four indicators ($\alpha = 0.81$) and the sample item reads as: "I believe that my spirit is energized by my work." SPINT (conditions for community) was measured with four items ($\alpha = 0.75$), and the sample item reads as "I feel part of a community in my immediate workplace (department and unit)." SPINT (alignment with organization value) was measured with four items ($\alpha = 0.71$), and the sample item reads

as "In my opinion this organization cares about all its employees." The second-order latent construct of SPINT reliability coefficient of 0.78.

AI was measured with eight items (α = 0.76) adapted from Schepman and Rodway (2022), and the sample item reads as "I believe there are beneficial applications of AI."

Perceived stress was measured with nine items (α = 0.83) adapted from Cohen and Williamson (1988), and the sample item reads as "I felt upset because something happened unexpectedly."

3.4 Data analysis strategy

To test our conceptual model, we employed structural equation modeling (SEM) using SPSS. SEM is appropriate for this study given the presence of multiple latent variables and the need to assess both measurement and structural relationships simultaneously. We followed a two-step modeling approach (Anderson and Gerbing, 1988), beginning with a confirmatory factor analysis (CFA) to establish the validity and reliability of the measurement model, followed by estimation of the full structural model.

We assessed internal consistency using Cronbach's alpha and composite reliability (CR), and evaluated convergent and discriminant validity using average variance extracted (AVE) and Fornell–Larcker criterion. Model fit was assessed using indices including the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA) and Chi-square/df ratio, in line with accepted thresholds (Hair *et al*., 2014).

We tested mediation via PsyCap using (e.g. bootstrapping methods with 5,000 resamples) and moderation effects of AI, EI and SPINT using interaction terms created through mean-centered variables to minimize multicollinearity (Aiken and West, 1991).

4. Analysis and findings

4.1 Measurement model and confirmatory factor analysis

Before running the structural model, Anderson and Gerbing (1988) suggested the researchers check the measurement model to ensure the reliability and validity of the constructs (Anderson and Gerbing, 1988). Therefore, we first conducted CFA using the LISREL package of covariance-based SEM. Since this study has second-ordered constructs (HPHRPs have three dimensions, EI has four dimensions and SPINT has three dimensions), we presented the results of first-order latent variables in Table 2 and second-order latent constructs in Table 3.

A preliminary look at the table reveals that the factor loadings of all the constructs ranged from 0.71to 0.91, thus over the acceptable levels of 0.70 (Hair *et al*., 2014). Furthermore, the AVE estimates were well above 0.50, the CR was over 0.50 and the constructs' reliability coefficients were over 0.70. These statistics provide evidence that indicators measure the intended constructs, thus vouching for the reliability and convergent validity of the constructs (Montgomery *et al*., 2021). The second-order constructs (HPHRPs, EI and SPINT) also have reliability coefficients of over 0.70, AVE values of over 0.50 and CR values of over 0.70, providing evidence of convergent validity.

4.2 Descriptive statistics, convergent validity, discriminant validity and common method bias

The means, standard deviations and zero-order correlations between the variables were captured in Table 4.

The preliminary observation of correlations reveals that the highest correlation was 0.71 ($p < 0.01$) (between EI and SPINT), and the lowest correlation was −0.13 ($p < 0.01$) (between

Table 2. Confirmatory factor analysis

Constructs and the sources of constructs	Alpha	CR	Standardized loadings (λ_{yi})	Reliability (λ^2_{yi})	Variance [var(ε_{yi})]	Average variance extracted estimate $\Sigma(\lambda^2_{yi})/[(\lambda^2_{yi}) + (\text{var}(\varepsilon_i))]$
HPHRP [ability-enhancing dimension] (Chuang et al., 2013)	0.78	0.86				0.60
In my opinion selection of employees is totally based on their technical skills but not interpersonal skills			0.73	0.53	0.47	
I believe that selection of employees emphasizes teamwork ability			0.87	0.76	0.24	
In my opinion organization provides training to improve the interpersonal skills of employees to build good relationships			0.76	0.58	0.42	
In my opinion organization provides training to enhance team-building and teamwork skills of employees			0.74	0.55	0.45	
HPHRP [motivating enhancing dimension] (Chuang et al., 2013)	0.75	0.88				0.64
In my opinion the selection of employees emphasizes their overall fit to the organization (values and personality)			0.75	0.56	0.44	
In my opinion organization provides an extensive orientation program for new employees to learn the history, culture and values of the organization			0.78	0.61	0.39	
I believe the organization rewards employees for sharing new information and knowledge			0.91	0.83	0.17	
I believe employees' bonuses or incentive plans are based primarily on the organizational performance			0.75	0.56	0.44	
HPHRP [opportunity-enhancing dimension] (Chuang et al., 2013)	0.77	0.84				0.63
In my opinion the organization sponsors various social events to encourage contact and relationship building among employees			0.79	0.62	0.38	
In my opinion the organization often arranges events for knowledge exchange (e.g. seminar and presentation)			0.81	0.66	0.34	
In my opinion organization provides team training to facilitate social interaction			0.78	0.61	0.39	
Psychological capital (Luthans et al., 2007)	0.74	0.90				0.57
I feel confident in analyzing a long-term problem to find a solution			0.78	0.61	0.39	
I am confident in my performance that I can work under pressure and challenging circumstances			0.79	0.62	0.38	

(*continued*)

Table 2. Continued

Constructs and the sources of constructs	Alpha	CR	Standardized loadings (λ_{yi})	Reliability (λ^2_{yi})	Variance [var(ε_{yi})]	Average variance extracted estimate $\Sigma(\lambda^2_{yi})/[(\lambda^2_{yi}) + (\text{var}(\varepsilon_i))]$
I feel confident that I can accomplish my work goals			0.71	0.50	0.50	
At work, I always find that every problem has a solution			0.73	0.53	0.47	
If I have to face with bad situation, I believe that everything will change to be better			0.83	0.69	0.31	
I believe that success in the current work will occur in the future			0.72	0.52	0.48	
I usually take stressful things at work in stride			0.70	0.49	0.51	
Emotional intelligence [self emotion appraisal] (Salovey and Mayer, 1990)	0.76	0.81				0.58
I have good understanding of my own emotions			0.74	0.55	0.45	
I really understand what I feel			0.79	0.62	0.38	
I always know whether or not I am happy			0.76	0.58	0.42	
Emotional intelligence [others emotion appraisal] (Salovey and Mayer, 1990)	0.79	0.81				0.59
I am a good observer of others' emotions (OEA)			0.78	0.61	0.39	
I am sensitive to the feelings and emotions of others (OEA)			0.72	0.52	0.48	
I always know my friends' emotions from their behaviour (OEA)			0.80	0.64	0.36	
Emotional Intelligence [use of emotions] (Salovey and Mayer, 1990)	0.81	0.80				0.57
I always tell myself I am a competent person			0.75	0.56	0.44	
I am a self-motivated person			0.73	0.53	0.47	
I would always encourage myself to try my best			0.79	0.62	0.38	
Emotional Intelligence [regulation of emotions] (Salovey and Mayer, 1990)	0.76	0.80				0.57
I am able to control my temper and handle difficulties rationally			0.73	0.53	0.47	
I can always calm down quickly when I am very angry			0.74	0.55	0.45	
I have good control of my own emotions (ROE)			0.79	0.62	0.38	
Spiritual intelligence [meaning at work] (Ashmos and Duchon, 2000)	0.81	0.86				0.60
I experience joy in my work			0.75	0.56	0.44	
I believe others experience joy as a result of my work			0.79	0.62	0.38	
I believe that my spirit is energized by my work			0.83	0.69	0.31	

(*continued*)

Table 2. Continued

Constructs and the sources of constructs	Alpha	CR	Standardized loadings (λ_{yi})	Reliability (λ^2_{yi})	Variance [var(ε_{yi})]	Average variance extracted estimate $\Sigma(\lambda^2_{yi})/[(\lambda^2_{yi}) + (\text{var}(\varepsilon_i))]$
I see a connection between my work and the larger social good for my community			0.73	0.53	0.47	
Spiritual intelligence [conditions for community] (Ashmos and Duchon, 2000)	0.75	0.84				0.57
I feel part of a community in my immediate workplace (department and unit)			0.77	0.59	0.41	
I believe that my supervisor encourages my personal growth			0.72	0.52	0.48	
I feel that when I have fears I am encouraged to discuss them			0.71	0.50	0.50	
I am evaluated fairly here			0.81	0.66	0.34	
Spiritual intelligence [alignment with organization value] (Ashmos and Duchon, 2000)	0.71	0.85				0.59
In my opinion this organization cares about all its employees			0.72	0.52	0.48	
I feel that this organization is concerned about the poor in our community			0.77	0.59	0.41	
I feel positive about the values of the organization			0.80	0.64	0.36	
I feel connected with this organization's goals			0.78	0.61	0.39	
Artificial intelligence (Schepman and Rodway, 2022)	0.76	0.92				0.58
I believe there are beneficial applications of artificial intelligence			0.71	0.50	0.50	
I believe artificial intelligence can have positive impacts on people's well-being			0.79	0.62	0.38	
I believe artificial intelligence is exciting			0.74	0.55	0.45	
I believe artificial intelligent systems can perform better than humans			0.83	0.69	0.31	
I am interested in using artificial intelligent systems in my daily life			0.80	0.64	0.36	
I would like to use artificial intelligent systems in my own job			0.73	0.53	0.47	
I believe artificial intelligent systems can help people feel happier			0.75	0.56	0.44	
I love everything about AI			0.74	0.55	0.45	
Perceived stress (Cohen and Williamson, 1988)	0.83	0.94				0.63
I felt upset because of something happened unexpectedly			0.76	0.58	0.42	
I felt that I am unable to control important things in your life			0.79	0.62	0.38	
I felt nervous and stressed			0.72	0.52	0.48	

(*continued*)

Table 2. Continued

Constructs and the sources of constructs	Alpha	CR	Standardized loadings (λ_{yi})	Reliability (λ^2_{yi})	Variance [var(ε_{yi})]	Average variance extracted estimate $\Sigma(\lambda^2_{yi})/[(\lambda^2_{yi}) + (\text{var}(\varepsilon_i))]$
I found that I could not cope with all the things that I had to do			0.82	0.67	0.33	
I felt angry because of things that were outside of my control			0.81	0.66	0.34	
I did not feel confident about my ability to handle my personal problems			0.79	0.62	0.38	
I did not feel that things were going my way			0.85	0.72	0.28	
I could not control irritations in my life			0.75	0.56	0.44	
I did not feel that I was on top of things			0.86	0.74	0.26	

Source(s): Authors' own elaboration

Table 3. Second-order latent variables

Constructs and the sources of constructs	Alpha	Standardized loadings (λ_{yi})	Reliability (λ^2_{yi})	Variance [var(ε_i)]	Average variance-extracted estimate Σ (λ^2_{yi})/ [(λ^2_{yi}) + (var(ε_i))]
HPHRP CR = 0.83	0.81				0.63
HPHRP – Ability enhancing		0.74	0.55	0.45	
HPHRP – Motivating enhancing		0.83	0.69	0.31	
HPHRP – Opportunity enhancing		0.80	0.64	0.36	
Emotional intelligence CR = 0.84	0.82				0.56
Self-emotion appraisal (SEA)		0.83	0.69	0.31	
Others-emotion appraisal (OEA)		0.72	0.52	0.48	
Use of emotion (UOE)		0.70	0.49	0.51	
Regulation of emotion (ROE)		0.75	0.56	0.44	
Spiritual intelligence CR = 0.79	0.78				0.56
Spiritual intelligence [meaning at work]		0.74	0.55	0.45	
Spiritual intelligence [conditions for community]		0.79	0.62	0.38	
Spiritual intelligence [alignment with organization value]		0.72	0.52	0.48	

Source(s): Authors ‘own elaboration

Table 4. Correlations, reliability and validity

Variable	Mean	SD	1	2	3	4	5	6	Cronbach's alpha	Composite reliability	Average variance extracted
1. HPHRP	3.67	0.80	*0.79*						0.81	0.83	0.63
2. PsyCap	3.82	0.72	0.50**	*0.75*					0.74	0.90	0.57
3. AI	3.67	0.79	0.41**	0.40**	*0.76*				0.76	0.92	0.58
4. EI	3.86	0.59	0.45**	0.73**	0.36**	*0.75*			0.82	0.84	0.56
5. SPINT	3.72	0.59	0.58**	0.67**	0.44**	0.71**	*0.75*		0.78	0.79	0.56
6. Perceived stress	3.01	0.63	−0.13**	−0.12*	−0.16**	−0.28**	−0.55**	*0.79*	0.83	0.94	0.63

Note(s): **$p < 0.01$; HPHRP = high-performance HRM practices; PsyCap = psychological capital; AI = artificial intelligence; EI = emotional intelligence; SPINT = spiritual intelligence; Elements in diagonal and italic are the square root of average variance extracted (AVE)
Source(s): Authors' own elaboration

HPHRPs and perceived stress. Furthermore, the square root of AVEs between PsyCap and AI were 0.76 and 0.75, respectively and are greater than the correlations between PsyCap and AI (r = 0.40; p < 0.40). Similarly, the correlation between SP and perceived stress (r = −0.55; p < 0.01) was less than the square root of AVEs of 0.75 and 0.79 for SP and perceived stress, respectively. These statistics suggest that the data was not infected with multicollinearity (Tsui *et al.*, 1995). To assess the variance inflation factor (VIF) values for all the constructs, we found that these were less than 5, suggesting that the data did not have any problem of multicollinearity (Montgomery *et al.*, 2021).

Convergent validity is assessed by examining the AVE values of the indicators. As shown in Tables 2 and 3, the AVE values of each construct were well above 0.5, and convergent validity and internal consistency of the indicators were established (Hair *et al.*, 2014). Discriminant validity is confirmed when the square root of the AVE values of the variables is greater than the correlation between the variables (Henseler *et al.*, 2015). These statistics, CFA values and reliability coefficients (Cronbach's alpha and CR) confirm the discriminant validity of the six variables in this research.

This research is quantitative and survey based as we collected data on exogenous and endogenous variables from the respondents, and hence, common method bias (CMB) needs to be checked (Kraus *et al.*, 2020; Podsakoff and Organ, 1986). We tested CMB with several techniques. First, to minimize CMB, we randomized the survey questions as suggested by Podsakoff *et al.* (2012). Second, we did a traditional Harman's single factor test and found that a single factor accounted for 24.62% (50%) variance, suggesting that CMB is not a problem in this research (Podsakoff *et al.*, 2003). Second, we compared the 13 first-order factor model with 12 alternative measurement models (see Table 5) and found that the 13-factor model was the best fit of the data [χ^2 = 2548.42; df = 972; χ^2/df = 2.62; RMSEA = 0.052; root mean-square error (RMR) = 0.041; standardized RMR = 0.049; CFI = 0.93; non-normal fit index (NNFI) = 0.91; goodness of fit index (GFI) = 0.89]. In general, when RMSEA values are less than 0.08 and CFI values are over 0.90, it vouches for a good fit of the data to the model. On the contrary, the single-factor yielded poor fit [χ^2 = 3994.62; df = 1041; χ^2/df = 3.84; RMSEA = 0.094; RMR = 0.088; standardized RMR = 0.82; CFI = 0.60; GFI = 0.65]. As a third check, we performed a latent variable check recommended by Kock (2015) and loaded all the indicators into one factor each time and found that the inner VIF values of all the constructs were less than 3.3, indicating that the data was not infected by CMB. The summary of measurement properties of various models is presented in Table 5.

4.3 Testing hypothesis1–hypothesis4

To check direct hypotheses (*H1–H3*) and mediation hypothesis (*H4*), we used model number 4 of PROCESS macros (Hayes, 2018). The results are presented in Table 6.

The regression coefficient of HPHRPs on perceived stress was negative and significant (β = −0.26; t = −5,61; p < 0.001). The results based on 20,000 bootstrap samples show that the 95% bias-corrected confidence interval (BCCI) was −0.4491 (LLCI) and −0.0655 (ULCI). The model was significant and explains 15.9% variance in the perceived stress, and the magnitude is medium (f^2 = 0.19), [the effect size f^2 between 0.02 and 0.15 represents "small"; f^2 between 0.15 and 0.35 represent medium effect size and f^2 > 0.35 represents "large effect size" (Cohen, 1988)] and is statistically significant [R^2 = 0.159; F(1,436) = 11.35 p < 0.001]. These results support *H1* that HPHRPs were significant predictors of perceived stress.

The regression coefficient of HPHRPs on PsyCap, as proposed in *H2*, was positive and significant (β = 0.71; t = 17.06; p < 0.001). The 95% (BCCI) LLCI and ULCI were 0.6318 and 0.7963 respectively. The model was significant and explains 40.1% variance in PsyCap

Table 5. Comparison of measurement models

Model	Factors	χ^2	df	χ^2/df	$\Delta\chi^2$	RMSEA	RMR	Standardized RMR	CFI	TLI=NNFI	GFI
Null model		8872.30	1174								
Baseline model	Base line 13 factor model	2548.42	972	2.62		0.052	0.041	0.049	0.93	0.91	0.89
Model 1	12-factor model	2615.76	984	2.66	67.34**	0.059	0.052	0.056	0.92	0.89	0.88
Model 2	11-factor model	2641.31	995	2.65	92.89**	0.065	0.060	0.057	0.89	0.87	0.85
Model 3	10-factor model	2695.82	1005	2.68	147.4**	0.068	0.064	0.059	0.81	0.80	0.79
Model 4	Nine-factor model	2782.16	1014	2.74	233.74**	0.067	0.064	0.058	0.77	0.75	0.74
Model 5	Eight-factor model	2815.54	1022	2.75	267.12**	0.071	0.068	0.062	0.76	0.73	0.70
Model 6	Seven-factor model	3351.47	1029	3.26	803.05**	0.075	0.083	0.074	0.67	0.65	0.71
Model 7	Six-factor model	3462.74	1035	3.35	914.32**	0.076	0.080	0.076	0.66	0.65	0.71
Model 8	Five-factor model	3498.78	1040	3.36	950.36**	0.079	0.085	0.078	0.64	0.63	0.70
Model 9	Four-factor model	3585.51	1044	3.43	1037.09**	0.084	0.086	0.079	0.65	0.63	0.70
Model 10	Three-factor model	3655.47	1047	3.49	1107.05**	0.085	0.084	0.080	0.63	0.61	0.69
Model 11	Two-factor model	3845.29	1049	3.67	1296.87**	0.089	0.085	0.080	0.61	0.60	0.67
Model 12	One-factor model	3994.62	1050	3.80	1446.2**	0.094	0.088	0.082	0.60	0.60	0.65

Note(s): $^{**}p < 0.01$; HPHRPAE = high-performance HRM practices ability enhancing; HPHRPME = high-performance HRM practices motivation enhancing; HPHRPOE = high-performance HRM practices opportunity enhancing; PsyCap = psychological capital; EISEA = emotional intelligence self-emotional appraisal; EIOEA = emotional intelligence others-emotion appraisal; EIUOE = emotional intelligence use of emotions; EIROE = emotional intelligence regulation of emotions; SIMW = spiritual intelligence [Meaning at work]; SICC = spiritual intelligence [conditions for community]; SIAOV = spiritual intelligence [alignment with organization value]; AI = artificial intelligence; PSTR = perceived stress 12-factor model: HPHRPAE + HPHRPME; HPHRPOE; PSYCAP; EISEA; EIOEA; EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR 11-factor model: HPHRPAE + HPHRPME + HPHRPOE; PSYCAP; EISEA; EIOEA; EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR 10-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP; EISEA; EIOEA; EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR Nine-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA; EIOEA; EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR; Eight-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA; EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR Seven-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE; EIROE; SIMW; SICC; SIAOV; AI; PSTR; Six-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE; SIMW; SICC; SIAOV; AI; PSTR; Five-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE + SIMW; SICC; SIAOV; AI; PSTR; Four-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE + SIMW+ SICC; SIAOV; AI; PSTR Three-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE + SIMW + SICC + SIAOV; AI; PSTR; Two-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE + SIMW + SICC + SIAOV + AI; PSTR; One-factor model: HPHRPAE + HPHRPME + HPHRPOE + PSYCAP + EISEA + EIOEA + EIUOE + EIROE + SIMW + SICC + SIAOV + AI + PSTR

Source(s): Authors' own elaboration

Table 6. Testing *H1*, *H2* and *H3*

Hypotheses	Relationship	coeff	se	t	*p*	Boot LLCI	Boot ULCI	R^2 and F values	Result
H1	HPHRP → Perceived stress	−0.2621	0.0467	−5.6124	0.0003	−0.4491	−0.0655	0.159F (1,436) = 11.35	Supported
H2	HPHRP → PsyCap	0.7141	0.0419	17.0615	0.0000	0.6318	0.7963	0.401F (1,436) = 291.09	Supported
H3	PsyCap → Perceived stress	−0.3614	0.1089	−3.3196	0.0010	−0.5754	−0.1474	0.159F (2,435) = 15.62	Supported

Source(s): Authors' own elaboration

because of HPHRPs, and the effect size is large [R^2 = 0.401; $F(1,436)$ = 291.09; $p < 0.001$; f^2 = 78.7], thus supporting *H2*.

H3 proposes that PsyCap is negatively associated with perceived stress. The results reveal that the regression coefficient of PsyCap on perceived stress was negative and significant ($\beta = -0.36$; $t = -3.31$; $p < 0.001$; BCCI LLCI = −0.5754; BCCI ULCI = −0.1474). The model is significant and explains 15.9% of the variance in PsyCap, and the effective size is medium [R^2 = 0.159; $F(2,435)$ = 15.62; $p < 0.001$; f^2 = 21.4]. These results render support for *H3*.

PsyCap as a mediator between HPHRPs and perceived stress (*H4*) was checked by verifying whether the indirect effect was significant (Hayes, 2018). Table 7 shows the mediation results, and Table 8 shows the indirect effect.

The total effect of HPHRPs on perceived stress consisted of a direct effect (−0.1061) and an indirect effect (−0.1560), which comes to −0.2621. Furthermore, the indirect effect (−0.1560) was a product of the effect of HPHRPs on PsyCap (0.4319) and the effect of PsyCap on perceived stress (−0.3614). As can be seen from Table 8, the result based on 20,000 bootstrap samples shows that the indirect effect is significant [Boot LLCI = −0.0419; and Boot ULCI = −0.0384], and since zero was not contained in the confidence intervals, the mediation hypothesis is supported.

4.4 Testing moderation hypotheses H2a, H2b and H3a

We used PROCESS macros to test the two-way interaction (*H2a*), three-way interaction (*H2b*) and two-way interaction (*H3a*) and presented the results in Table 9.

As shown in Table 9, the regression coefficient of the interaction term (HPHRPs × AI) was significant [$\beta_{\text{HPHRP x AI}} = 0.36$; $t = 3.31$; $p < 0.001$; Boot LLCI (0.1474); Boot ULCI (0.5754)]. These results support *H2a*, which shows that AI moderates the relationship between HPHRPs and PsyCap. The visualization of two-way interaction is presented in Figure 2.

Table 7. Results of mediation analysis (HPHRP→PsyCap→perceived stress)

Relationship	Coeff	se	*t*	*p*	Boot LLCI	Boot ULCI
HPHRP→Perceived stress	−0.1061	0.0304	−3.4901	0.0010	−0.3747	−0.0375
HPHRP→PsyCap	0.4319	0.0419	10.3078	0.0000	0.6318	0.7963
PsyCap→Perceived stress	−0.3614	0.1089	−3.3196	0.0010	−0.5754	−0.1474
Total effect of HPHRP→Perceived stress	−0.2621	0.0467	−5.6124	0.0003	−0.4491	−0.0655

Source(s): Authors' own elaboration

Table 8. Indirect effect (*H4*)

Relationship	Effect	se	Boot LLCI	Boot ULCI
HPWP→ PsyCap → Perceived stress	−0.1560	0.0365	−0.0419	−0.0384

Note(s): Total Effect of HPWP → Perceived stress = Direct effect (−0.1061) + Indirect effect (−0.1560) = −0.2621 Indirect effect = (0.4319) (−0.3614) = −0.1560; *n* = 438; Boot LLCI refers to the lower bound bootstrapping confidence intervals. Boot ULCL refers to the upper bound bootstrapping confidence intervals. Number of bootstrapping samples for this bias corrected bootstrapping confidence intervals are 20,000. The level of confidence for all confidence intervals in output was 0.95. We have four decimal digits for bootstrap results because some values may be very close to zero
Source(s): Authors' own elaboration

Table 9. Results of moderation analysis

Hypotheses	Relationship	coeff	se	*t*	*p*	Boot LLCI	Boot ULCI	R^2 and F values	Result
H2a	HPHRP × AI→PsyCap	0.3614	0.1089	3.3196	0.0010	0.1474	0.5754	0.661F (3,434) = 119.87	Supported
H2b	HPHRP × AI × EI→PsyCap	0.3201	0.0990	3.2346	0.0013	0.1256	0.5145	0.563F (7,430) = 182.63	Supported
H3a	PsyCap × SPINT→Perceived stress	0.4077	0.0480	8.5007	0.0000	0.3134	0.5020	0.389F (3,434) = 25.93	Supported

Source(s): Authors' own elaboration

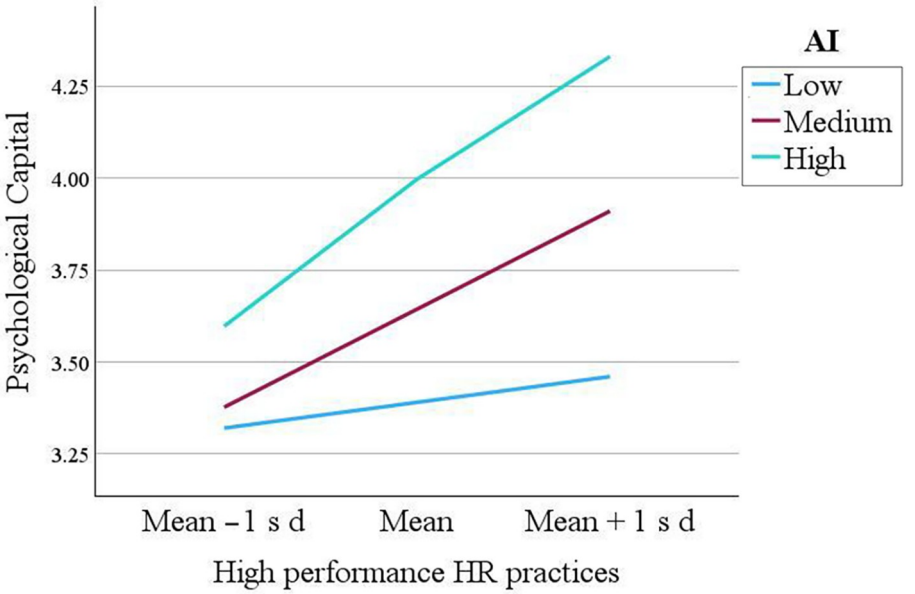

Figure 2. AI moderates between high-performance HR practices and psychological capital
Source: Authors' own elaboration

As shown in Figure 2, HPHRPs result in higher PsyCap when AI is high compared to lower levels of AI. Furthermore, when HPHRPs increase from low to high levels, PsyCap increases rapidly when AI is higher compared to lower levels of AI. The differences in the slopes of these curves representing "low", "medium" and "high" levels of AI are visible, and these curves render support for the moderation *H2a*.

H2b posits that EI moderates the relationship between HPHRPs and AI to influence PsyCap. The regression coefficient of the three-way interaction term (HPHRPs × AI × EI) was significant [$\beta_{\text{HPHRP x AI x EI}} = 0.42$; $t = 3.23$; $p < 0.01$; Boot LLCI (0.1256); Boot ULCI (0.5145)], thus supporting *H2b*. The visual presentation of three-way interaction is shown in Figure 3.

In Figure 3, we can see two panels. Panel A shows the interaction of HPHRPs and AI at low levels of EI. Panel B shows the interaction of HPHRPs and AI at a lower EI. As seen in Panel A, the PsyCap is higher when AI is higher and lower when AI is low (when the EI levels are low). However, when we move to Panel B, we can see a significant difference in the slopes of curves representing lower, middle and higher levels of AI when HPHRPs move from low to high. These panels render support to *H2b*.

The conditional effects of the focal predictor (PsyCap) at values of moderators (AI × EI) were captured in Table 10, and the conditional X*W interaction (HPHRPs × AI) at values of moderator *Z* (EI) was presented in Table 11.

H3a predicts that SPINT moderates the relationship between PsyCap and perceived stress. As shown in Table 9, the regression coefficient of the interaction term (PsyCap × SPINT) was significant [$\beta_{\text{HPHRP x SPINT}} = 0.41$; $t = 8.5$; $p < 0.001$; Boot LLCI (0.3134); Boot ULCI (0.5020)]. These results support *H3a*, which shows that SPINT moderates the

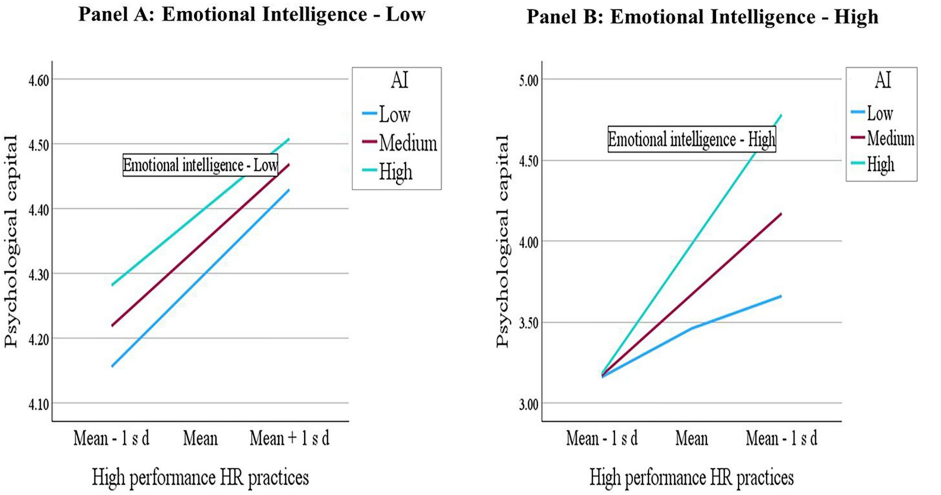

Figure 3. Panel A: Interaction of high-performance HR practices and AI at low levels of emotional intelligence. Panel B: Interaction of high-performance HR practices and AI at high levels of emotional intelligence

Source: Authors' own elaboration

relationship between PsyCap and perceived stress. The visualization of two-way interaction is presented in Figure 4.

As shown in Figure 4, at higher levels of SPINT, the effect of PsyCap on perceived stress was significantly lower than that of lower levels of SPINT. Furthermore, when PsyCap increases from "low" to "high," the perceived stress significantly decreases when SPINT is high (the slope of the curve representing the high level of SPINT is negative). In contrast, the perceived stress will be high when SPINT is low (the slope of the curve representing the low level of SPINT). These lines corroborate the support for *H3a*.

5. Discussion

This study examined the impact of HPHRPs on perceived stress among faculty members in Indian HEIs, using AMO and COR theories as its conceptual foundation. Drawing on data from 438 faculty members, the study confirmed all seven hypotheses in the proposed model. Importantly, each result not only supports existing frameworks but also reveals novel theoretical and practical dynamics, expanding the field's understanding of how cognitive, emotional, artificial and existential resources interact in stress regulation.

First, *H1* established a significant negative relationship between HPHRPs and perceived stress. AMO theory (Appelbaum *et al.*, 2000; Bos-Nehles *et al.*, 2023) explains this by framing HPHRPs as resource-generating mechanisms: ability-enhancing practices (e.g. training and skill development), motivation-enhancing activities (e.g. performance-based rewards) and opportunity-enhancing structures (e.g. participative decision-making) work in tandem to increase faculty members' capacity to navigate complex academic demands (Kehoe and Wright, 2013; Gardner *et al.*, 2011; Jiang *et al.*, 2012). This study extends the theory by illustrating how such HR systems transform stress from a reactive condition to a proactively managed outcome. Rather than merely confirming that HPHRPs reduce stress

Table 10. Conditional effects of the focal predictor (PsyCap) at values of moderators (AI × EI)

AI	EI	Effect	se	*t*	*p*	LLCI	ULCI
Low	Low	0.0824	0.0487	1.6920	0.0914	−0.0133	0.1781
Low	Medium	0.1264	0.0414	3.0493	0.0024	0.0449	0.2078
Low	High	0.1704	0.0480	3.5502	0.0004	0.0760	0.2647
Medium	Low	0.1482	0.0422	3.5085	0.0005	0.0652	0.2312
Medium	Medium	0.1519	0.0304	5.0016	0.0000	0.0922	0.2116
Medium	High	0.1556	0.0364	4.2705	0.0000	0.0840	0.2272
High	Low	0.2139	0.0544	3.9340	0.0001	0.1070	0.3208
High	Medium	0.1774	0.0415	4.2778	0.0000	0.0959	0.2589
High	High	0.1409	0.0496	2.8376	0.0048	0.0433	0.2384

Moderator value(s) defining Johnson–Neyman significance region(s)

Value	% below	% above
3.4017	21.0046	78.9954

Source(s): Authors' own elaboration

Table 11. Conditional X*W interaction (HPHRP × AI) at values of the moderator *Z* (EI)

EI	Effect	se	*t*	*p*	LLCI	ULCI
1.0000	0.2761	0.0831	3.3233	0.0010	0.1128	0.4394
1.2000	0.2590	0.0781	3.3174	0.0010	0.1056	0.4125
1.4000	0.2420	0.0732	3.3070	0.0010	0.0982	0.3858
1.6000	0.2249	0.0684	3.2905	0.0011	0.0906	0.3593
1.8000	0.2078	0.0637	3.2652	0.0012	0.0827	0.3330
2.0000	0.1908	0.0591	3.2277	0.0013	0.0746	0.3070
2.2000	0.1737	0.0547	3.1732	0.0016	0.0661	0.2813
2.4000	0.1567	0.0506	3.0949	0.0021	0.0572	0.2562
2.6000	0.1396	0.0468	2.9837	0.0030	0.0476	0.2316
2.8000	0.1225	0.0433	2.8279	0.0049	0.0374	0.2077
3.0000	0.1055	0.0403	2.6143	0.0093	0.0262	0.1848
3.2000	0.0884	0.0379	2.3301	0.0203	0.0138	0.1630
3.4000	0.0714	0.0362	1.9689	0.0496	0.0001	0.1426
3.4017	*0.0712*	*0.0362*	*1.9655*	*0.0500*	*0.0000*	*0.1424*
3.6000	0.0543	0.0353	1.5364	0.1252	−0.0152	0.1237
3.8000	0.0372	0.0353	1.0549	0.2921	−0.0321	0.1066
4.0000	0.0202	0.0361	0.5585	0.5768	−0.0508	0.0912
4.2000	0.0031	0.0377	0.0823	0.9344	−0.0711	0.0773
4.4000	−0.0140	0.0401	−0.3481	0.7279	−0.0927	0.0648
4.6000	−0.0310	0.0430	−0.7210	0.4713	−0.1156	0.0535
4.8000	−0.0481	0.0464	−1.0354	0.3011	−0.1393	0.0432
5.0000	−0.0651	0.0502	−1.2967	0.1954	−0.1639	0.0336

Note(s): The values in bold represent the cutoff points of significant zones of interaction effect
Source(s): Authors' own elaboration

(Allen *et al.*, 2022; Sheehan and Garavan, 2021), we reveal that faculty reinterpret workplace demands as developmental challenges when HPHRPs activate all three AMO components.

Second, findings showed that HPHRPs significantly increased PsyCap, supporting *H2*. PsyCap – comprising hope, efficacy, resilience and optimism (Luthans *et al.*, 2007; Luthans and Youssef-Morgan, 2017) – is bolstered when faculty members are embedded in

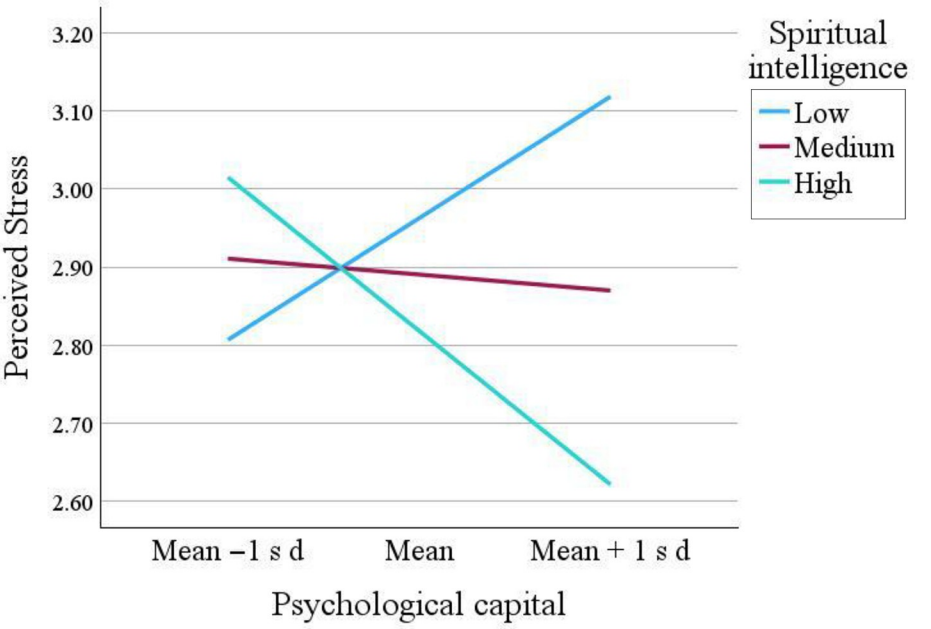

Figure 4. Spiritual intelligence moderates between psychological capital and perceived stress
Source: Authors' own elaboration

environments that provide structured developmental opportunities and foster intrinsic motivation (Miao *et al.*, 2021; Vuong, 2022). This study contributes to AMO theory by showing that PsyCap acts as a latent psychological capability mobilized by HPHRPs. In this sense, PsyCap is not simply an outcome, but a dynamic mediator that enables faculty to respond to future uncertainty with agency and perseverance. Our findings also align with COR theory (Hobfoll, 1989; Hobfoll *et al.*, 2018), where PsyCap functions as a gain resource – catalyzing resource accumulation in the face of pressure.

Third, consistent with *H3*, PsyCap significantly reduced perceived stress. This aligns with previous research (Avey *et al.*, 2010; Abbas and Raja, 2015; Bidi *et al.*, 2024; Li *et al.*, 2015; Pradhan *et al.*, 2024), but our study deepens the theoretical interpretation by suggesting that PsyCap is not just a stress buffer, but a cognitive-affective schema through which challenges are reappraised as surmountable (Maykrantz *et al.*, 2021; Toprak *et al.*, 2022). This highlights PsyCap's dual role as both a psychological filter and an energy-conserving resource (Hobfoll, 1989), reducing the emotional and cognitive toll of ambiguous demands.

Fourth, *H4* confirmed that PsyCap significantly mediates the HPHRPs–perceived stress relationship. Theoretically, this underscores a sequential resource path: HPHRPs activate AMO mechanisms, which enhance PsyCap, which in turn reduces stress. This mediation clarifies how HR systems influence mental health not only through direct provision of supports but through resource internalization. This aligns with recent extensions of COR theory emphasizing resource caravans (Hobfoll *et al.*, 2018), and complements emerging calls to conceptualize HR practices as psychological enablers rather than structural levers alone (Kaur and Malik, 2025; Pham *et al.*, 2018).

Fifth, the study confirmed *H2a*: AI positively moderated the relationship between HPHRPs and PsyCap. Faculty who positively perceive AI – via adaptive automation, smart scheduling or AI-enhanced teaching – experience enhanced benefits from HPHRPs. Theoretically, this finding contributes to the intersection of HRM and digital transformation literature (Bajpai and Ghosh, 2019; Huang *et al.*, 2019; Parry and Battista, 2019) by showing that AI functions as an enabling resource amplifier. Rather than replacing human agency, AI enhances the resource-generating effects of HR practices, particularly when aligned with employees' task focus and decision latitude (Abuhassna, 2024; Rahimi and Sevilla-Pavón, 2024; Galindo-Domínguez *et al.*, 2023).

Sixth, consistent with *H2b*, EI significantly moderated the interactive effect of HPHRPs and AI on PsyCap. Faculty members high in EI – who can recognize, interpret and regulate affect – derive amplified benefits from the synergy of HPHRPs and AI. This introduces a triadic perspective into resource theory: HPHRPs and AI co-construct opportunities, but EI enables their meaningful emotional assimilation (Mayer and Salovey, 1997; Joseph *et al.*, 2015; Pekaar *et al.*, 2017). Importantly, our study surfaces a new pathway for EI: not as a stress buffer *per se*, but as an orchestration mechanism that integrates institutional practices and technological systems into coherent experiences of self-efficacy and purpose.

Finally, the findings supported *H3a*: SPINT significantly moderated the relationship between PsyCap and stress. This highlights SPINT's role as an existential anchoring mechanism: when individuals connect their work to transcendent meaning and shared values (Ashmos and Duchon, 2000; Vasconcelos, 2020), PsyCap's stress-mitigating effects are magnified. Faculty with high SPINT likely draw on value-aligned identity narratives that protect them from existential depletion, in line with COR's claim that deeply held values function as conservation resources (Gold, 2011; Nayyar *et al.*, 2024; Pinto *et al.*, 2024; Saini and Seema, 2020; Saxena *et al.*, 2020).

In sum, this study not only validates the conceptual model but also makes four theoretical contributions. First, it reframes HPHRPs as mechanisms for stress reappraisal, not just job enrichment. Second, it positions PsyCap as both a resource and a resource-enabler within COR gain spirals. Third, it introduces a triadic interaction (HPHRPs × AI × EI) that unlocks new synergies across cognitive, emotional and technological domains. Finally, it brings SPINT into mainstream HRM theory as a moderator of resource-to-outcome transmission. These findings advance an integrated theory of human, artificial, emotional and existential resources in organizational stress management.

5.1 Theoretical contributions

This study makes several important theoretical contributions to the HRM literature by elucidating how HPHRPs reduce perceived stress through PsyCap, and how this process is shaped by AI, EI and SPINT. It introduces a novel framework that bridges psychological, technological and spiritual domains to advance theoretical understanding of stress mitigation in knowledge-intensive work environments.

First, the study contributes directly to HRM theory by demonstrating that HPHRPs – when implemented comprehensively across ability-, motivation- and opportunity-enhancing dimensions – function not only as performance enablers but also as protective mechanisms against perceived stress. While past studies emphasized productivity-related outcomes (Jiang *et al.*, 2012; Kehoe and Wright, 2013), our findings underscore a wellbeing-oriented function of HPHRPs. This reconceptualization positions HPHRPs as dual-purpose interventions: fostering performance while simultaneously reducing psychological strain through structural support, participatory culture and developmental investments. This insight is especially

significant in the post-pandemic higher education context, where the burden of uncertainty and workload has intensified (Sheehan and Garavan, 2021; Allen *et al.*, 2022).

Second, the study meaningfully advances AMO theory. It extends the AMO framework beyond its traditional performance-centric applications by providing evidence that AMO mechanisms also contribute to psychological resilience and stress regulation. By showing that well-structured recruitment, training and participative opportunities not only improve task performance but also mitigate perceived stress, we demonstrate that AMO elements can serve as latent affective resources. This reveals a previously underappreciated dimension of AMO theory, where each component – especially motivation and opportunity – can be interpreted not only in behavioral terms but also as enablers of psychological safety and cognitive control.

Third, the study deepens and updates COR theory by positioning HPHRPs as deliberate organizational mechanisms for resource gain. Rather than focusing solely on resource loss avoidance, as is common in stress literature, this study shows that HPHRPs systematically equip faculty with internal (PsyCap) and external (AI, EI and SPINT) resources that preemptively buffer future stress. In particular, the mediating role of PsyCap illustrates how COR processes can be strategically initiated through HRM configurations, not just passively experienced. We therefore contribute to COR theory by showing how resource-building can be intentionally engineered through organizational systems rather than left to individual adaptation.

Fourth, the study strengthens the conceptual and empirical foundation of PsyCap as a mediating mechanism linking HRM to employee wellbeing. While previous works have noted PsyCap's role in enhancing performance (Luthans and Youssef-Morgan, 2017; Miao *et al.*, 2021), our study underscores its function as a psychological buffer that transforms structural HR practices into reduced perceived stress. Importantly, we show that this is not merely a linear effect but one that interacts dynamically with contextual intelligences – thus moving the PsyCap literature toward more situated and relational models of resource development.

Fifth, the study introduces AI as a novel moderator in HRM theory, not simply as a process automation tool but as a psychological enabler. Employees who positively perceive AI report stronger relationships between HPHRPs and PsyCap, suggesting that AI can be reframed as a cognitive resource amplifier. This enriches both AMO and COR perspectives by integrating digital technologies into resource-based models of stress mitigation (Galindo-Domínguez *et al.*, 2023; Wang *et al.*, 2023).

Sixth, the study identifies a three-way interaction involving HPHRPs, AI and EI. This advances emerging literature that connects emotional and technological competencies by showing that emotionally intelligent faculty are better equipped to translate AI-supported HR systems into personal psychological gains (Joseph *et al.*, 2015; Mayer and Salovey, 1997). In effect, EI operates as a translational capacity, allowing individuals to integrate technological affordances with emotional self-regulation – creating a synergy that enhances PsyCap.

Seventh, the study reveals the moderating role of SPINT in the PsyCap–stress relationship. While SPINT has been linked to meaning-making and moral grounding (Pinto *et al.*, 2024; Saini and Seema, 2020), our findings empirically show that SPINT enhances the stress-buffering capacity of PsyCap by reinforcing existential alignment. Faculty members with high SPINT appear more capable of contextualizing challenges within broader personal and professional values, which contributes to resilience and emotional regulation under pressure.

Finally, and most distinctively, this study proposes a comprehensive, integrative model that consolidates psychological, technological and spiritual resources within the domain of

HRM. This model challenges siloed approaches to employee wellbeing by showing that optimal outcomes arise not from isolated practices but from synergistic configurations – where structural HR systems interact with AI perceptions, emotional competencies and spiritual frameworks. In doing so, the study lays the groundwork for a multidimensional theory of resource-based stress mitigation, applicable to future research across knowledge-intensive and emotionally demanding sectors.

5.2 Practical implications

This study provides critical insights into how HPHRPs can be strategically leveraged to reduce workplace stress and enhance employee performance. The findings emphasize that HR managers must integrate ability-, motivation- and opportunity-enhancing strategies into their recruitment, selection and training processes (Abuhassna, 2024; Rahimi and Sevilla-Pavón, 2024). Specifically, HR professionals should focus on structured training programs, mentorship initiatives and continuous learning opportunities to strengthen employees' PsyCap, thereby fostering resilience and reducing stress levels (Bidi *et al.*, 2024; Pradhan *et al.*, 2024).

Policymakers and administrators should institutionalize EI training as a core component of professional development. Regular workshops and peer-coaching sessions can be implemented to help employees recognize and regulate their emotions while improving interpersonal relationships. Embedding EI training into leadership development programs will enable managers to support their teams effectively, reduce workplace conflicts and create a positive work climate.

Organizations should also prioritize the integration of AI into daily operations by raising employee awareness of AI's benefits and providing hands-on training sessions. AI-powered tools can be used to automate repetitive administrative tasks, allowing employees to focus on more strategic and fulfilling work, thereby alleviating work-related stress. Implementing AI-assisted decision-making systems can also enhance employees' confidence in their problem-solving abilities, further strengthening PsyCap.

For HEIs, stress among faculty members remains a significant concern, particularly in post-pandemic environments where digital transformation continues to evolve. HEI administrators should proactively offer tailored support programs, such as faculty wellness initiatives, time management training and workload redistribution mechanisms, to prevent burnout. Creating structured forums for faculty to share best practices and collaborate on teaching methodologies can also enhance engagement and reduce isolation.

To leverage SPINT as a stress-buffering mechanism, institutions should encourage employees to find meaning in their work and align their personal values with organizational goals. This can be facilitated through initiatives such as values-driven leadership programs, organizational storytelling and community engagement activities. By fostering a work environment where employees feel a strong sense of purpose and connection, organizations can significantly mitigate perceived stress and enhance job satisfaction.

Finally, HR policies should be reviewed and adapted to create a holistic support system for employees. This includes offering flexible work arrangements, recognizing and rewarding contributions beyond performance metrics and establishing mentorship networks. Organizations should actively measure the impact of these interventions through periodic employee feedback and well-being assessments to ensure continuous improvement.

By implementing these actionable strategies, organizations – especially in academic and knowledge-intensive sectors – can enhance employee resilience, optimize performance and create a sustainable work environment that prioritizes both well-being and productivity.

5.3 Limitations and suggestions for future research

We acknowledge some of the limitations of this study. First, this research focused on faculty members in higher educational institutions in India, and hence, the results should be interpreted carefully when applied to other industries. However, the variables described in the conceptual model can be generalized regarding the HPHRPs carried out in all sectors. Second, we considered a relatively more minor sample ($n = 438$), though the faculty members are from different institutions from various parts of the country. Third, we focused on only limited variables – HPHRP, PsyCap, AI, SPINT, EI and perceived stress. Fourth, we used non-probability sampling to collect data from faculty members, which may constitute a limitation in this study. Even though we justified using snowball sampling as a data collection method, some sampling bias may be inherent. However, we took adequate care to ensure that the sample collected was representative. Fifth, as with any survey-based research, the intrinsic limitations of CMB and social desirability bias should be acknowledged. Even though we conducted various statistical tests to check CMB and anonymized the survey results to the respondents to ensure that data will not be infected by social desirability bias, with certainty, no one can say that these biases are eliminated.

This study provides several avenues for future research. First, researchers may involve much bigger samples to test the conceptual model. It is also advantageous to conduct longitudinal studies to see the time lag in the causal sequence of variables. Second, future studies may include other variables such as emotional exhaustion, role conflict, role ambiguity, knowledge management and turnover intentions that influence the relationship between HPHRPs and perceived stress. Third, researchers can compare the differences between developing and developed countries and see if cultural differences influence the proposed relationships conceptualized in Figure 1. Fourth, future studies may investigate any differences in HPHRPs in other developing countries (e.g. Pakistan, Sri Lanka and Bangladesh) that influence PsyCap and perceived stress. Further, studies may examine the differences in AI, SPINT and employees' EI in other developing countries that affect relationships.

6. Conclusions

This study set out to understand how stress among university faculty – often framed as an individual burden – is shaped by organizational systems and broader constellations of human, technological, emotional and existential resources. Drawing on data from Indian HEIs, the findings reveal that HPHRPs do not operate in isolation; rather, they serve as entry points into a more complex ecosystem that shapes how faculty make sense of demands, mobilize inner resources and navigate uncertainty.

At the heart of this ecosystem lies PsyCap, which this study identifies not simply as a mediator, but as a dynamic capacity-building mechanism. HPHRPs build PsyCap; PsyCap lowers stress. But this relationship is far from linear. It is amplified, shaped and sometimes redirected by how faculty engage with AI, how they regulate and interpret emotions (EI) and how they draw on deeper sources of purpose and meaning (SPINT). These dimensions are not decorative – they are decisive. Faculty do not just react to their work environments; they process them through layers of perception, interpretation and identity. The inclusion of AI, EI and SPINT in this study was not merely instrumental – it reflects the lived complexity of modern academic work, where performance metrics intersect with affective labor and existential reflection. What emerges is a multilayered view of organizational life: HPHRPs enable agency, AI amplifies potential, EI orchestrates inner clarity and SPINT grounds it all in something enduring. Together, these elements construct a system where stress is not merely reduced but recontextualized – as a condition that can be managed, reframed and sometimes even transformed.

By empirically validating this integrative framework, the study calls on HRM scholars and practitioners to move beyond isolated interventions or one-dimensional solutions. In environments defined by rising demands, technological change and blurred personal–professional boundaries, effective HR systems must speak to the whole person. They must engage minds, technologies, emotions and values. For academic institutions – and potentially other knowledge-intensive sectors – this means designing HR practices not just for performance, but for coherence: systems that help people stay grounded, focused and resilient in an increasingly complex world.

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