

DIGITAL GREEN HRM AND EMPLOYEE ECO-WELLBEING: AN OVERLOOKED DUAL PATHWAY TO ORGANIZATIONAL SUSTAINABILITY IN PAKISTAN'S POLLUTING MANUFACTURING CLUSTERS

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Abstract

Human resource management (HRM) literature has mainly investigated how environmental HR practices generate green behavior, instead of their impact on employee well-being and their role. The body of research on green human resource management (GHRM) has centered on the influence of environmental HR practices on the generation of employee green behavior, rather than their impact on employee well-being and the role they play. Research on digital delivery remains fragmented. This gap is critical in polluting manufacturing clusters, where employees are both agents of environmental performance and the people most exposed to environmental harm. Drawing on the job demands-resources model and conservation of resources theory, we develop a dual-pathway framework in which digital GHRM advances organizational sustainability through a motivational pathway (employee green behavior) and a health-protection pathway (employee eco-wellbeing), with pollution exposure intensity, workforce digital readiness, and resource commitment as boundary conditions. We then test the GHRM core of the framework with a random-effects meta-analysis of 16 open-access studies ($N = 5,374$). GHRM was associated with employee green behavior ($r = .48$) and, to a similar degree, with employee wellbeing ($r = .51$). In a meta-analytic path model, GHRM retained a direct association with wellbeing ($\beta = .38$) after green behavior was controlled, and the indirect association through green behavior was smaller (.13), indicating that wellbeing is a parallel pathway rather than a by-product of green behavior. GHRM was also strongly associated with sustainability performance ($r = .68$). The GHRM-wellbeing association tended to be weaker in industrial

than in service samples, and no included study measured digitally delivered GHRM or environmental dimensions of wellbeing. We discuss the implications for theory, for managers in Pakistan's textile and leather clusters, and for primary research.

INTRODUCTION

The sustainability costs of manufacturing activity in emerging economies are doubled. Companies are required to decrease their ecological impact to meet regulators and foreign customers, and their own environmental policies. Companies need to lower their environmental impact to comply with regulators and international buyers, as well as their own environmental policies; employees often work in the pollution that firms create. Pakistan illustrates this tension sharply. The textile industry contributes approximately 8% of the national gross domestic product and 58.98% of export earnings, yet it is regarded as the country's most polluting domestic industry (Khan, Muhmood, et al., 2024). During the recent fieldwork, ambient air quality in Faisalabad, Pakistan's third-largest industrial zone, was not being monitored, and there were no wastewater treatment facilities in industrial centers in the city (Khan, Muhmood, et al., 2024). Around 600 tanneries are concentrated in Kasur, Karachi, and Sialkot, where waste discharge pollutes air, soil, and water (Syed et al., 2010). The degradation of the environment is not an abstract global problem, but is a working condition of the workers of these clusters.

The human cost is well documented. In 11 Faisalabad spinning mills, 36% of 206 workers experienced chronic cough, 17% at least one episode of bronchitis, and 22.3% experienced symptoms of byssinosis, with higher rates of work absence due to illness observed in dusty areas (Khan, Muhmood, et al., 2024). Almost fifty-four hours of work per week, and only 9.2% of female workers with permanent contracts were recorded, along with the absence of social security for 63% of workers and only 56% of workers being able to read, were significant factors in the adverse health outcomes of women workers, such as fatigue and blood in phlegm, which increased the risk significantly (Amir-ud-Din Khan, Khan, & Atif,

2025). Perhaps most tellingly for human resource management (HRM) scholars, all of the sample workers in Faisalabad said that the mill provided them with free face masks, but only 14% actually wore them (Khan, Muhmood, et al., 2024). The binding constraint was therefore not the availability of a protective resource but the people-management system that should have turned provision into practice.

The alignment of recruitment, training, performance management, rewards, and employee involvement with environmental objectives (also referred to as GHRM) is the main response to the question regarding how organizations mobilize employees for environmental goals (Renwick et al., 2013; Tang et al., 2018). Several studies indicate that GHRM positively influences employee green behavior (EGB) (Dumont et al., 2017; Norton et al., 2015; Saeed et al., 2019), and the Pakistani research findings also support the positive relationship between GHRM and the company's sustainable performance and environmental sustainability in manufacturing (Khaskhely et al., 2022; Wen et al., 2022). Recently, however, research has started to link GHRM to employee well-being. GHRM has been found to impact employees' subjective well-being by virtue of their green behaviour in manufacturing SMEs in Ghana (Gyensare et al., 2024), to positively influence employees' well-being and work engagement, which in turn partly mediates the effect on sustainable performance in Spanish wineries (ía et al., 2024), and to positively affect employees' well-being through psychological contract fulfilment in Pakistani readymade-garment exporters (Gilal et al., 2025).

Yet there are three blind spots in the field that diminish its relevance to polluting manufacturing clusters. First, wellbeing is defined in a general way, such as life satisfaction (Gyensare et al., 2024) or general wellbeing at work (ía et al., 2024), and

is typically included as a by-product of green behavior or another mediator between green behavior and the outcome. If the work environment itself poses an environmental risk, the wellbeing that is most important is environmental, that is, the physical effects of exposure, and the psychological impact of working in, and contributing to, a degraded environment. The study of the workplace implications of climate-related distress and eco-anxiety has only begun to emerge in the last few years and is mainly limited to the Global North and predominantly white-collar environments (Ayassamy & Francoeur, 2024; Brooks & Greenberg, 2023). *Second*, the digital transformation of HRM has been treated mainly as a performance lever. Electronic HRM (e-HRM) has been shown to strongly predict the uptake of GHRM practices (Alabaddi et al., 2020), and AI-driven sustainable HRM has been correlated with engagement and performance (Jia & Hou, 2024), the latest systematic review of 68 studies found that previous attempts to review GHRM neglected digital HR platforms and cautioned about the negative impacts of technostress on the same outcomes that digital tools are supposed to foster (Sarjaka et al., 2026). How digital GHRM affects wellbeing and how it functions among low-literacy shop-floor workforces remains unexamined. *Third*, context is under-theorised. The settings that dominate the GHRM-wellbeing stream (SMEs in Ghana, wineries in Spain, certified manufacturers in Thailand; Pokalai et al., 2026) are not high-exposure environments, and Pakistani GHRM studies rarely treat occupational exposure as anything other than background. Moreover, the evidence on whether GHRM benefits wellbeing at all, and whether that benefit is distinct from its effect on green behavior, is scattered across single studies and has not been synthesized. This study addresses these gaps through three questions. *RQ1: Through which pathways does digital green HRM contribute to organizational sustainability in polluting manufacturing clusters? RQ2: Under which conditions are these pathways strengthened or weakened? RQ3: What does the cumulative empirical evidence say about*

the GHRM core of the proposed dual pathway? Based on the job demands-resources (JD-R) model (Bakker & Demerouti, 2007; Demerouti et al., 2001), and the conservation of resources (COR) theory (Hobfoll, 1989; Hobfoll et al., 2018), we show that D-GHRM has two parallel pathways: a motivational pathway, where D-GHRM triggers employee green behavior that leads to an improvement in environmental sustainability, and an overlooked health protection pathway, where D-GHRM protects and enhances employee eco-wellbeing, which in turn sustains their social and economic pillars of organizational sustainability. We then test the parts of this framework that existing primary studies allow us to observe through a meta-analysis of 16 studies.

This study makes five contributions. First, it introduces *employee eco-wellbeing* as a dimensional construct (physical wellbeing and eco-psychological wellbeing) which is different from generic subjective wellbeing and appropriate to high-exposure work. Second, it reframes digital green HRM as a package that is both an eco-efficiency function and a protective-care function, thereby going beyond the administrative digitization of HRM. Third, it maps GHRM's effects onto the two processes of the JD-R model, giving theoretical structure to the 'dual' claims that are increasingly made in this literature but rarely grounded (Pokalai et al., 2026; Sarjaka et al., 2026). Fourth, it provides the first meta-analytic evidence that GHRM is as strongly associated with employee wellbeing as with green behavior, and that most of the wellbeing association is not channelled through green behavior. Fifth, it identifies pollution exposure intensity, workforce digital readiness, and resource commitment as boundary conditions, documents that digital GHRM has not yet been measured in this literature, and sets out a primary-research design tailored to Pakistan's textile and leather clusters.

The remainder of this paper is organized as follows. Section 2 explains the two-part research design. Sections 3 and 4 present the theoretical foundations and core constructs, respectively. Section 5 develops the dual-pathway framework

and propositions. Section 6 reports the meta-analysis. Section 7 discusses the findings, implications, limitations, and an agenda for primary research, and Section 8 concludes.

2. Research design

The study is a synthesis of theory building and quantitative testing. For the first part, an integrative review was employed for the development of the framework. A design like this is suitable for issues that lie between two distinct literatures and when the goal is to create new frameworks and propositions (Snyder, 2019; Torraco, 2005). We purposefully included a range of recent, openly accessible studies that span the literatures we connected to in our framework: GHRM and employee wellbeing (Gyensare et al., 2024; Martínez-Falcó et al., 2024), e-HRM and GHRM (Alabaddi et al., 2020; Sarjaka et al., 2026), workplace eco-anxiety (Ayassamy & Francoeur, 2024), and occupational health in the textile sector in Pakistan (Khan, Muhmood, et al., 2024; Khan, Amir-ud-Din, & Atif, 2025). We

supplemented this set by backward and forward citation chasing, compared the different conceptualizations of the construct of interest in the literature, and applied the integrative lenses of JD-R and COR theory to generate propositions and boundary conditions. A summary of the main studies, what each study adds, and each study's gap is provided in Table 1.

The second part involves the testing of the core relationships of the framework by conducting a meta-analysis of the relationships between GHRM, employee green behaviour, employee wellbeing and sustainability performance, as reported in independent primary studies (Section 6). Since the use of digitally delivered GHRM, or the environmental dimensions of wellbeing that this builds upon, has yet to be measured in a primary study, the meta-analysis examines the traditional GHRM foundation that provides a basis for the digital and exposure-specific propositions. The wellbeing pathway is represented by general measures of wellbeing as the closest available proxy.

Table 1. Principal studies informing the framework and the gaps they leave open.

Study	Context and design	Key finding	Gap addressed by this paper
Gyensare et al. (2024), <i>Business Strategy and the Environment</i>	249 employees and supervisors, manufacturing SMEs, Ghana; two waves three months apart	GHRM → EGB ($\beta = 0.39$); EGB mediates GHRM → subjective wellbeing (indirect effect = 0.23); effect stronger under high resource commitment	Wellbeing measured as life satisfaction; non-digital GHRM; low-exposure setting
Martínez-Falcó et al. (2024), <i>BMC Psychology</i>	196 Spanish wineries; executive respondents; PLS-SEM	GHRM → employee wellbeing ($\beta = 0.435$); wellbeing and work engagement partially mediate GHRM → sustainable performance	Employee wellbeing reported by executives; generic wellbeing; agri-food context
Gilal et al. (2025), <i>Evidence-based HRM</i>	67 managers and 217 employees, Pakistani readymade-garment	Psychological contract fulfilment mediates GHRM → OCBE and subjective wellbeing; environmental-	Exposure and digital delivery not considered

	exporters; multilevel (HLM)	orientation fit strengthens the effect.	
Alabaddi et al. (2020), <i>European Journal of Business and Management</i>	180 employees, 15 Jordanian pharmaceutical firms; PLS	e-HRM strongly predicts green recruitment, training, performance evaluation, and rewards ($\beta = 0.736-0.877$)	Outcomes stop at practice adoption; no employee outcomes; very high coefficients raise discriminant-validity questions.
Sarjaka et al. (2026), <i>F1000Research</i>	Systematic review of 68 Scopus-indexed articles, 2017–2026	GHRM acts as a ‘dual-performance’ engine; AI and digital HR emerge as a new context; technostress risk noted	Wellbeing treated as a mechanism towards performance; exposure context absent.
Ayassamy et al. (2024), <i>Frontiers in Sustainability</i>	Scoping review (10 studies) and Lewin’s change model	Workplace eco-anxiety is under-researched; GHRM can help employees understand and manage eco-anxiety and channel it into pro-environmental action.	Global North and conceptual; physical exposure absent
Khan, Muhmood, et al. (2024), <i>Journal of the Egyptian Public Health Association</i>	206 workers, 11 spinning mills, Faisalabad; two-week health diaries	36% chronic cough, 17% bronchitis, 22.3% byssinosis; dusty sections increase absence; masks supplied free but used by 14%	Health-economics lens; HRM mechanisms not examined
Khan, Amir-ud-Din, & Atif (2025), <i>Frontiers in Public Health</i>	541 female workers, 18 mills, Lahore and Faisalabad (data collected 2015)	≈54-hour week; 63% without social security; 56% illiterate; overtime raises odds of fatigue and blood in phlegm	Precarity lens; HRM and digital-literacy implications unexplored
Pokalai et al. (2026), <i>Business Strategy and the Environment</i>	796 employees, seven Thai manufacturers certified under the Green Industry Standard; SEM	Parallel cognitive (green innovation) and affective (job satisfaction) pathways from GHRM to EGB	Both ‘dual’ pathways end in EGB; wellbeing is not an outcome in its own right.

Khaskhely et al. (2022), <i>Frontiers in Psychology</i>	396 employees, Pakistani large-scale manufacturing incl. textiles; PLS-SEM	GHRM → corporate sustainable performance ($\beta = 0.198$); about 15% (social) and 5% (environmental) variance explained	Low explained variance suggests unmodelled mechanisms, consistent with a missing wellbeing pathway.
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Note: EGB = employee green behavior; OCBE = organizational citizenship behavior for the environment; HLM = hierarchical linear modelling; PLS-SEM = partial least squares structural equation modelling. The coefficients are as reported in the original studies.

3. Theoretical foundations

3.1 The job demands–resources model and its two processes

According to the JD-R model, all jobs contain demands (physical, psychological, social, or organizational demands that require sustained effort and involve physiological or psychological costs) and resources (aspects that facilitate work goal achievement, reduce the demands and their costs, or promote growth) (Bakker & Demerouti, 2007; Demerouti et al., 2001). Importantly, the model identifies two processes: the health impairment process, where chronic demands overwhelm employees resulting in health issues; and the motivational process, where resources help to engage employees and support their performance (Bakker & Demerouti, 2007). The health impairment effects of polluting cluster exposures are classic physical job demands, that is to say, cotton dust, tanning chemicals, heat, and effluents (Khan, Muhmood, et al., 2024).

Compared with previous studies of GHRM, the present study seems to have focused only on the motivational process, because in most cases, GHRM has been examined only as a source of abilities, motivation, and opportunities to trigger green behavior (Renwick et al., 2013). We use our framework to read GHRM via the JD-R processes. D-GHRM is a job resource that works in motivational (Pathway A) and protective ways (Pathway B) by reducing and/or buffering demands of the exposure. This mapping provides a theoretical foundation for the ‘dual pathway’ idea that is not tied to any specific mediators used in any one study.

3.2 Conservation of resources theory

COR theory proposes that people strive to obtain, retain, and protect valued resources, and that stress results when resources are threatened, lost, or not regained after an investment (Hobfoll, 1989). Two COR principles are central to our arguments. The *primacy of loss* principle holds that resource loss is disproportionately more salient than equivalent gain, while the *gain paradox* principle holds that resource gains become more salient, and thus more valuable, precisely in contexts of high resource loss. (Hobfoll et al., 2018). Workers in polluting clusters face continual loss of health, energy, and income due to illness and absence. Therefore, COR predicts that HR practices offering protective resources will be noticed, valued, and reciprocated more strongly in high-exposure settings than in low-exposure settings, a prediction that underpins our exposure-intensity proposition. COR also explains why resources travel in ‘caravans’: employees whose health and psychological resources are protected have more surplus resources to invest in discretionary behavior, including green behavior.

3.3 The AMO framework and signalling.

GHRM is commonly organized around the ability–motivation–opportunity (AMO) framework, in which HR practices raise performance by building abilities, motivating effort, and providing opportunities to contribute (Appelbaum et al., 2000; Renwick et al., 2013). AMO explains why D-GHRM affects EGB. Signalling logic adds that HR practices communicate organizational priorities; Pokalai et

al. (2026) show that GHRM signals operate through parallel cognitive (green innovation) and affective (job satisfaction) routes. We extend this logic by arguing that, in polluting clusters, what D-GHRM signals depends on whether it addresses the hazards workers actually experience. An eco-efficiency programme that asks workers to save paper and switch off lights while they breathe cotton dust may signal hypocrisy rather than environmental commitment.

4. Conceptual building blocks

4.1 From e-HRM to digital green HRM

e-HRM refers to the application of information technologies to support and network HR activities among actors within and beyond the organization (Strohmeier, 2007). Four decades of research have shown that the adoption and consequences of e-HRM depend heavily on users and context rather than on technology alone. (Bondarouk et al., 2017). In the green domain, Alabaddi et al. (2020) found that e-HRM was a strong predictor of green recruitment, training, performance evaluation, and rewards among 180 employees of 15 Jordanian pharmaceutical firms, and recommended linking employee incentives to the acquisition of new technology skills. Jia and Hou (2024) found that among 470 employees of

Chinese enterprises, AI-driven sustainable HRM increased engagement, which in turn raised performance, with conscientiousness strengthening the link. Sarjaka et al. (2026) identified digital knowledge-sharing systems, HR chatbots, and AI-enabled HRM as an emerging frontier of GHRM, but cautioned that such tools must be managed to avoid technostress.

We define **digital green HRM (D-GHRM)** as *the bundle of environmentally oriented HR practices that are designed, delivered, monitored, and fed back through digital infrastructure, with the dual aim of improving the organization's environmental performance and protecting employees from the environmental conditions of their work*. Two features distinguish this definition from prior e-HRM–GHRM work. First, digitalization is not treated merely as paperless administration, a common example of ‘green’ HR, but as an enabler of capabilities that are impossible or prohibitively costly in analog form: continuous exposure monitoring, real-time feedback, anonymous hazard reporting, and on-demand learning in local languages. Second, D-GHRM has a *protective-care function* alongside the familiar *eco-efficiency function*. Table 2 sets out five dimensions and illustrates both functions in the context of Pakistan’s clusters.

Table 2. Dimensions and functions of digital green HRM (D-GHRM) in polluting manufacturing clusters.

Dimension	Eco-efficiency function	Protective-care function	Illustration in Pakistan’s clusters
Digital green recruitment and onboarding	Screening for environmental values; paperless hiring	Digital induction on section-specific hazards; exposure-aware job allocation	Video onboarding in Urdu/Punjabi on dust control in spinning or chrome handling in tanneries
Digital green learning	E-modules on energy, water and waste saving.	Microlearning on protective-equipment use, hygiene and symptom recognition	Short audio-visual mobile lessons for workers with limited literacy (cf. 56% illiteracy; Khan, Amir-ud-Din, & Atif, 2025)

Digital green performance and exposure monitoring	Dashboards for energy, water, and waste per line	Sensor-based dust or chemical exposure tracking linked to rotation and break schedules.	Particulate sensors in spinning halls where city air quality is unmonitored (Khan, Muhmood, et al., 2024)
Digital green rewards and recognition	Digital points for resource-saving ideas	Recognition for consistent protective-equipment use and hazard reporting	Team-level recognition tied to mask use (cf. 14% use; Khan, Muhmood, et al., 2024)
Digital green voice and participation	Idea platforms for green improvements	Anonymous hazard and symptom reporting; online occupational safety and health committees	Messaging- or voice-based reporting channels accessible to women and contract workers

Note: Illustrations are design suggestions derived from the cited evidence, not reports of existing practices.

4.2 Employee eco-wellbeing.

Wellbeing in HRM research is usually defined broadly, spanning happiness, health, and relationship dimensions. (Guest, 2017; Van De Voorde et al., 2012). GHRM studies have operationalized it as life satisfaction (Gyensare et al., 2024, using the scale of Diener et al., 1985), job satisfaction (e.g., Adeel et al., 2022; Cui et al., 2026), or a general wellbeing-at-work scale (ia et al., 2024). These measures are valid but environmentally neutral: they cannot reveal whether GHRM affects well-being because of its environmental content or simply because it is good HRM. They are also insensitive to the physical consequences of environmental exposure that dominate workers' experience in polluting clusters.

We define employee eco-well-being as the physical and psychological well-being that employees experience in relation to the environmental conditions of their work and the environmental conduct of their organization. This construct has two dimensions.

Exposure-related physical wellbeing captures freedom from and perceived protection against work-related environmental harm: respiratory and dermatological symptoms, fatigue associated with heat and long hours in contaminated sections, and

the perceived environmental safety of one's workstation. It draws on the integrated view of occupational safety, health protection, and health promotion advanced by the Total Worker Health approach. (Schill & Chosewood, 2013) and epidemiological evidence from Pakistan's textile mills (Khan, Muhmood, et al., 2024; Khan, Amir-ud-Din, & Atif, 2025).

Eco-psychological wellbeing captures the affective and meaning-related side of employees' relationships with the environment: low levels of maladaptive eco-anxiety, together with positive experiences of environmental meaningfulness and efficacy at work. Eco-anxiety, the anxiety people experience in response to ecological crises. (Clayton & Karazsia, 2020; Hogg et al., 2024) is not uniformly harmful. Low to moderate levels can motivate pro-environmental action, whereas high levels can produce powerlessness and paralysis (Ayassamy & Francoeur, 2024; Verplanken et al., 2020). Pro-environmental behavior can itself regulate eco-anxiety when it produces rapid and concrete feedback. (Pihkala, 2020). For workers who live and work in polluted clusters, eco-psychological distress may also take the form of solastalgia, the distress caused by environmental change in one's home environment. (Albrecht et al., 2007), a concept

not yet applied to industrial workforces. Table 3 contrasts employee eco-wellbeing with the

wellbeing constructs currently used in adjacent research.

Table 3. Employee eco-wellbeing compared with wellbeing constructs used in adjacent research.

Construct	Typical measure	Focus	Sensitivity to environmental conditions	Use in related research
Subjective wellbeing	Satisfaction with Life Scale (Diener et al., 1985)	Global cognitive evaluation of one's life	Low	Gyensare et al. (2024)
Wellbeing at work	Generic seven-item wellbeing-at-work scale	General affective and occupational wellbeing	Low	Martínez-Falcó et al. (2024)
Climate/eco-anxiety	Climate Change Anxiety Scale (Clayton & Karazsia, 2020)	Distress about ecological crisis	Moderate (global rather than workplace-specific)	Ayassamy et al. (2024); Hogg et al. (2024)
Occupational respiratory health	Respiratory Health Questionnaire; health diaries	Physical symptoms of exposure	High, but not linked to HRM.	Khan, Muhmood, et al. (2024); Khan, Amir-ud-Din, & Atif (2025)
Employee eco-wellbeing (this paper)	Composite of exposure-related physical and eco-psychological dimensions	Wellbeing in relation to work environment and the organisation's environmental conduct	High, and theoretically linked to HRM	Proposed here

4.3 Organizational sustainability.

Following the triple bottom line (Elkington, 1997) we treat organizational sustainability as the joint achievement of environmental, social, and economic performance. This tripartite operationalization has already been used in GHRM research; Martínez-Falcó et al. (2024), for example, measured sustainable performance with economic, social, and environmental sub-scales. GHRM research has emphasized the environmental pillar, although reviews increasingly stress GHRM's implications for social

sustainability (Amrutha & Geetha, 2020). Notably, a study of 396 employees in Pakistani large-scale manufacturing found a significant effect of GHRM on corporate sustainable performance, but the model explained only about 15% of the variance in social performance and approximately 5% in environmental performance. (Khaskhely et al., 2022). We read this as a signal of unmodelled mechanisms. In polluting clusters, the social pillar includes worker health, retention, trust, and community legitimacy, and the economic pillar includes productivity losses from

sickness absence, which Khan, Muhmood, et al. (2024) show are concentrated in dusty sections.

5. A dual-pathway framework and propositions.

Figure 1 presents the framework. D-GHRM influences organisational sustainability through two pathways that correspond to the two processes of the JD-R model. Pathway A, the motivational

and behavioural route, runs from D-GHRM through employee green behaviour to environmental sustainability. Pathway B, the health-protection and wellbeing route, runs from D-GHRM through employee eco-wellbeing to social and economic sustainability. The two pathways are linked reciprocally and are conditioned by three boundary conditions.

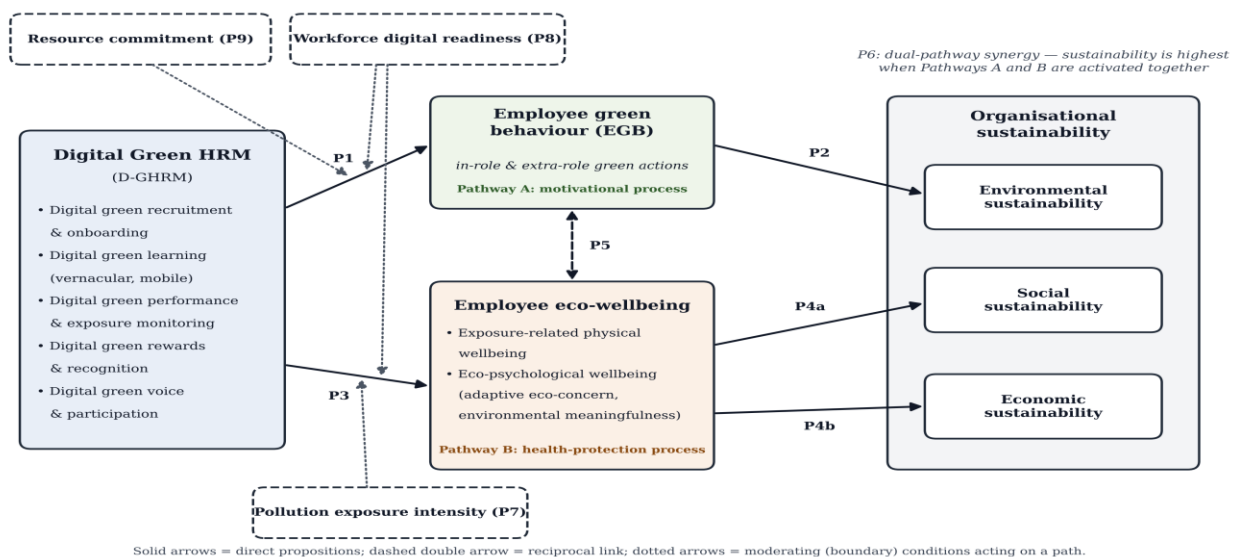


Figure 1. Dual-pathway framework linking digital green HRM to organisational sustainability through employee green behaviour and employee eco-wellbeing

5.1 Pathway A: the motivational route.

From an AMO perspective, each dimension of D-GHRM strengthens one or more drivers of green behavior. Digital green learning builds the *ability* to act in environmentally responsible ways; digital rewards and recognition raise *motivation*; and digital voice platforms create *opportunities* to contribute ideas and report problems (Appelbaum et al., 2000; Renwick et al., 2013). Single studies show that GHRM predicts supervisor-rated green behavior in Ghanaian manufacturing SMEs ($\beta = 0.39$; Gyensare et al., 2024), elicits workplace green behavior through psychological green climate (Dumont et al., 2017), promotes pro-environmental behavior through pro-environmental psychological capital (Saeed et al., 2019), and shapes environmental commitment and organizational citizenship behavior for the

environment via harmonious environmental passion (Iqbal et al., 2024). Digital delivery should extend these effects because it increases the reach, frequency, and immediacy of green signals. In particular, real-time dashboards provide rapid and concrete feedback that turns abstract environmental goals into actionable targets (Pihkala, 2020).

Proposition 1:

Digital green HRM is positively related to employee green behavior, both in-role and extra-role.

Green behavior, aggregated across employees, is a recognized micro-foundation of organizational environmental performance. (Norton et al., 2015). Employee-level evidence shows that HRM influences environmental performance through

employees' discretionary eco-initiatives (P. et al., 2014) and Pakistani evidence links GHRM to environmental sustainability in manufacturing SMEs (Wen et al., 2022).

Proposition 2: Employee green behavior is positively related to organizational environmental sustainability.

5.2 Pathway B: the health-protection route

Pathway B is the paper's central theoretical move. Through the lens of JD-R, the protective-care function of D-GHRM is a job resource that directly reduces exposure demands and buffers their health-impairment consequences. Exposure monitoring allows managers to rotate workers out of high-dust sections and schedule breaks; vernacular microlearning and team-level recognition can convert the provision of masks and other protective equipment into actual use; and anonymous digital reporting surfaces hazards and symptoms early enough for corrective action. The Faisalabad evidence is instructive: mask use was associated with approximately 2.4 fewer work hours lost to illness (significant at the 10% level), yet masks were used by only 14% of workers despite being supplied free (Khan, Muhmood, et al., 2024). The gap between provision and practice is precisely where HRM, rather than procurement, makes the difference. COR theory adds that protective resources preserve employees' health and energy, preventing the loss spirals that chronic exposure would otherwise trigger (Hobfoll, 1989; Hobfoll et al., 2018).

D-GHRM should also enhance eco-psychological wellbeing. Environmentally focused management practices can alleviate eco-anxiety by demonstrating organizational commitment, reducing uncertainty, building understanding, and providing a sense of purpose. (Ayassamy & Francoeur, 2024). Digital tools can make these effects tangible: when workers can see, through a dashboard, that dust levels in their section have fallen or that their reported hazard was fixed, environmental concern is converted into efficacy rather than helplessness. (Pihkala, 2020;

Verplanken et al., 2020). Single-study evidence that GHRM enhances wellbeing (Gilal et al., 2025; Gyensare et al., 2024; Martínez-Falcó et al., 2024) supports the general direction of this argument, although none of these studies isolated the environmental dimension of wellbeing.

Proposition 3a: Digital green HRM, particularly its protective care function, is positively related to employees' exposure-related physical well-being.

Proposition 3b: Digital green HRM is positively related to employees' eco-psychological well-being by converting environmental concern into efficacy and meaning rather than helplessness.

Eco-wellbeing should, in turn, sustain the social pillar of organizational sustainability. Employees who are healthier and who experience their organization's environmental conduct as genuine are more likely to stay, trust management, and act as positive ambassadors in the communities around industrial clusters; the mutual-gains perspective in HRM similarly holds that employee well-being and organizational performance can be complementary rather than competing. (Guest, 2017; Van De Voorde et al., 2012). Martínez-Falcó et al. (2024) found that employee well-being partially mediated the effect of GHRM on sustainable performance (indirect effect = 0.139).

Proposition 4a: Employee eco-well-being is positively related to organizational social sustainability.

The economic consequences of exposure are equally direct and immediate. An International Labour Organization estimate cited by Khan, Muhmood, et al. (2024) puts the cost of work-related sick leave, injury compensation, production interruptions, and medical expenses at approximately 4% of the annual world GDP. In Faisalabad's mills, illness-related absence was concentrated among workers in dusty sections (Khan, Muhmood, et al., 2024), and among female textile workers, overtime markedly increased the odds of fatigue (Khan, Amir-ud-Din, & Atif, 2025). Therefore, protecting eco-well-

being should reduce absence- and turnover-related losses and protect productivity.

Proposition 4b: Employee eco-well-being is positively related to organizational economic sustainability, partly through reduced sickness absence and turnover.

5.3 Interplay between the pathways.

The two pathways are not independent. Gyensare et al. (2024) showed that green behavior mediates the effect of GHRM on subjective wellbeing (indirect effect = 0.23), suggesting that acting in environmentally responsible ways is itself a source of wellbeing. Conversely, JD-R and COR imply that exhausted or unwell employees withdraw discretionary effort, whereas employees with protected resources can invest in extra-role green behavior. In the eco-anxiety literature, the link between employee eco-anxiety and green behavior has been examined in green restaurants. (Joshua et al., 2023) Moderate eco-concern can motivate action, while excessive anxiety can paralyze it (Ayassamy & Francoeur, 2024; Verplanken et al., 2020). These arguments imply a reciprocal relationship that unfolds over time.

Proposition 5: Employee green behavior and employee eco-well-being are reciprocally and positively related over time.

The pathways are also complementary at the organizational level. A D-GHRM portfolio that activates only Pathway A, for example, digital energy-saving campaigns without attention to exposure, risks being read by workers in high-exposure sections as greenwashing, which is likely to erode trust and, with it, the social pillar. A portfolio that activates only Pathway B may protect workers but miss the environmental gains available from their ideas and behavior. We therefore propose that the two pathways are synergistic, so that combined activation yields greater sustainability than either pathway alone. This proposition also offers an explanation for the modest variance in social and environmental

performance explained by GHRM-only models in Pakistani manufacturing (Khaskhely et al., 2022).

Proposition 6: The contribution of digital green HRM to organizational sustainability is greater when both pathways are activated than when only one pathway is activated. In polluting clusters, D-GHRM, which emphasizes eco-efficiency without protective care, yields weaker social sustainability outcomes.

5.4 Boundary conditions

Pollution exposure intensity. The COR's gain-paradox principle implies that protective resources matter most where losses are greatest. (Hobfoll et al., 2018). The same D-GHRM practice, for example, sensor-based exposure monitoring linked to rotation, should therefore matter more to a worker in a spinning hall or a chrome-tanning unit than to a worker in a finishing or packing section. Exposure intensity also shapes how D-GHRM is interpreted: in high-exposure units, protective content is likely to be read as care, whereas its absence is likely to be read as indifference.

Proposition 7: Pollution exposure intensity moderates the relationship between digital green HRM and employee eco-well-being, such that the relationship is stronger in high-exposure units than in low-exposure units.

Workforce digital readiness. e-HRM outcomes depend on users (Bondarouk et al., 2017) and technostress can lower productivity (Tarafdar et al., 2007). Shop-floor workforces in Pakistan's clusters include many workers with limited literacy (56% of the female textile workers surveyed by Khan, Amir-ud-Din, and Atif, 2025, were illiterate), uneven access to smartphones, and limited exposure to digital interfaces. Individual differences also matter: Jia and Hou (2024) found that conscientiousness strengthened the effect of AI-driven sustainable HRM on engagement. We define workforce digital readiness as employees' digital literacy, device access, and the linguistic accessibility of digital HR tools. Where readiness is low, and tools are not adapted (for example,

through voice-based, pictorial, or vernacular design), D-GHRM may generate technostress and exclusion, weakening both pathways.

Proposition 8: Workforce digital readiness moderates the relationship between digital green HRM and both employee green behavior and employee eco-wellbeing, such that these relationships are stronger when readiness is high; when readiness is low, and tools are not adapted, D-GHRM may induce technostress and weaken both pathways.

Resource commitment. Digital HR requires investments in hardware, software, and training. Gyensare et al. (2024) found that resource commitment to GHRM, measured with items covering financial, managerial, software, and

hardware investment. (Li, 2014) strengthened the effect of GHRM on employee green behavior (interaction $\beta = 0.19$), and that the indirect effect on well-being was significant only when resource commitment was high. D-GHRM, being more investment-intensive than analog GHRM, should be at least as sensitive to boundary conditions.

Proposition 9: Organizational resource commitment strengthens the relationship between digital green HRM and employee green behavior, and consequently, the indirect effects of D-GHRM on organizational sustainability.

Table 4 Summarizes the propositions, their theoretical anchors, and whether and how each is examined in the meta-analysis reported next.

Table 4. Summary of propositions and their examination in the meta-analysis.

No.	Proposition (abridged)	Theoretical anchor	Key supporting evidence	Meta-analytic test (Section 6)
P1	D-GHRM → employee green behaviour (+)	AMO; JD-R motivational process	Gyensare et al. (2024); Dumont et al. (2017); Saeed et al. (2019); Iqbal et al. (2024)	H1 supported for conventional GHRM ($r = .48$, $k = 10$); digital delivery not yet measured
P2	Employee green behaviour → environmental sustainability (+)	Micro-foundations of environmental performance	Norton et al. (2015); Paillé et al. (2014); Wen et al. (2022)	Not pooled (one study, $r = .33$)
P3a	D-GHRM (protective-care function) → exposure-related physical wellbeing (+)	JD-R health-impairment process; COR	Khan, Muhmood, et al. (2024); Khan, Amir-ud-Din, & Atif (2025); Schill & Chosewood (2013)	H2 supported with general wellbeing proxy ($r = .51$, $k = 6$); physical eco-wellbeing not yet measured
P3b	D-GHRM → eco-psychological wellbeing (+)	COR; eco-anxiety regulation	Ayassamy et al. (2024); Pihkala (2020); Martínez-Falcó et al. (2024)	As for P3a, eco-psychological wellbeing is not yet measured.

P4a	Eco-wellbeing → social sustainability (+)	Mutual-gains HRM	Guest (2017); Martínez-Falcó et al. (2024)	Provisional support (wellbeing-sustainability $r = .62$, $k = 2$)
P4b	Eco-wellbeing → economic sustainability (+), partly via absence and turnover	Health-production logic	Khan, Muhmood, et al. (2024); Khan, Amir-ud-Din, & Atif (2025)	As for P4a: pillars not separable in primary studies
P5	Employee green behaviour eco-wellbeing (reciprocal, +)	COR resource caravans; eco-anxiety regulation	Gyensare et al. (2024); Verplanken et al. (2020); Joshua et al. (2023)	H3 supported as an association ($r = .46$, $k = 3$); direction not testable
P6	Both pathways together > either alone; eco-efficiency without protection weakens social sustainability	Signalling; JD-R dual processes	Khaskhely et al. (2022); Pokalai et al. (2026)	Indirect support: wellbeing path largely direct ($\beta = .38$); not directly testable
P7	Exposure intensity strengthens D-GHRM → eco-wellbeing	COR gain paradox	Hobfoll et al. (2018); Khan, Muhmood, et al. (2024)	Not testable; industrial vs service contrast exploratory (RQ-B)
P8	Digital readiness strengthens D-GHRM → both pathways; low readiness may induce technostress.	e-HRM user dependence; technostress	Bondarouk et al. (2017); Tarafdar et al. (2007); Khan, Amir-ud-Din, & Atif (2025); Jia & Hou (2024)	Not testable: no study measured digital GHRM (RQ-C)
P9	Resource commitment strengthens D-GHRM → employee green behaviour.	Resource-based logic	Gyensare et al. (2024); Li (2014)	Not testable with available studies

6. Meta-analytic test of the GHRM core of the dual pathway.

6.1 Hypotheses and research questions

The meta-analysis examines the part of the framework that existing primary studies allow us to observe: the relationships among GHRM, employee green behavior, employee wellbeing, and sustainability performance. Following Propositions 1, 2, 3, 4, and 5, and recognizing that primary studies measure conventional rather than

digital GHRM and general rather than environmental well-being, we test four hypotheses.

Hypothesis 1: GHRM is positively associated with employee green behaviour.

Hypothesis 2: GHRM is positively associated with employee well-being.

Hypothesis 3: Employee green behavior is positively associated with employee well-being.

Hypothesis 4: GHRM and employee well-being are positively associated with organizational sustainability performance.

Three further questions are examined without directional predictions, either because the existing theory supports competing expectations or because the evidence base is thin.

Research question A: When employee green behavior is controlled, does GHRM retain a direct association with employee well-being, or is the well-being pathway largely channelled through green behavior?

Research question B: Do the associations differ between industrial and service samples and between South Asian and other samples?

Research question C: To what extent have primary studies measured digitally delivered GHRM or the environmental dimensions of well-being?

6.2 Method

6.2.1 Search and eligibility

On October 7 and 8, 2026, we conducted targeted searches of open-access sources, namely, the

Google-indexed scholarly web, PubMed Central, MDPI, Frontiers, DOAJ, Mendeley Data, and journal websites. Search strings combined ‘green human resource management’ or ‘green HRM’ with ‘employee green behavior’, ‘pro-environmental behavior’, ‘well-being’, ‘job satisfaction’, ‘happiness’, ‘environmental performance’ or ‘sustainable performance’, and with sector and country terms such as textile, chemical, manufacturing, Pakistan, and Bangladesh. Because the authors did not have institutional subscription access, retrieval was restricted to openly accessible full texts. Studies were eligible if they (a) were quantitative empirical studies, (b) measured GHRM practices overall or by dimension, (c) measured at least one of employee green behavior, employee wellbeing (subjective wellbeing, psychological wellbeing, or job satisfaction), or organizational sustainability or environmental performance, and (d) reported the sample size and a zero-order correlation or a latent inter-construct correlation from a Fornell–Larcker matrix. Studies reporting only heterotrait–monotrait (HTMT) ratios or path coefficients were excluded because these cannot be converted into correlations without further assumptions. Of 50 reports sought, 13 could not be retrieved, 37 were assessed in full text, and 16 met all criteria (Figure 2). Supplementary Material S1 lists every included, excluded, and unretrieved report, with reasons.

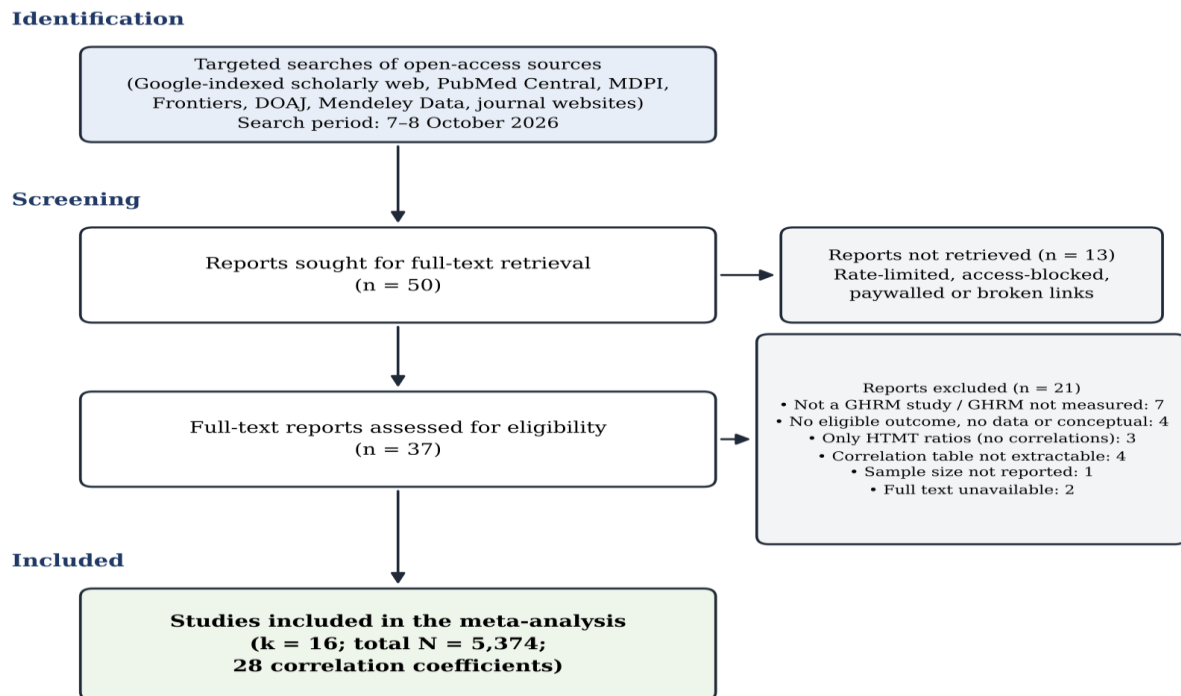


Figure 2. Flow of reports through the meta-analysis (PRISMA 2020-style diagram)

6.2.2 Coding

For each study, we coded the sample size, country, sector, wellbeing measure, rating source for green behavior, and type of correlation. Context was coded as industrial (manufacturing, extractive, chemical, energy, or utility samples), service (hospitality, tourism, health, and education), or mixed. Region was coded as South Asia (Pakistan and India) or other. We also coded whether GHRM was measured as a digitally delivered practice and whether wellbeing was measured with reference to the environment. When only GHRM dimensions were reported, the correlation of a unit-weighted GHRM composite with the outcome was computed as the sum of the dimension–outcome correlations divided by the square root of $k + 2 \times$ the sum of the dimension intercorrelations, where k is the number of dimensions (Hunter & Schmidt, 2004); this applied to three studies. One study reported

correlations of GHRM with two facets of green behavior without their intercorrelation, and these were averaged. Each study contributed at most one effect size per relationship.

6.2.3 Analysis

Correlations were converted to Fisher's z , pooled with random-effects models estimated by restricted maximum likelihood. (Viechtbauer, 2005) and back-transformed. We report 95% confidence intervals and 80% prediction intervals. (IntHout et al., 2016) Cochran's Q , I^2 , and τ (Higgins & Thompson, 2002). Robustness was examined with leave-one-out analyses and, where applicable, by excluding latent (Fornell–Larcker) correlations. Small-study effects were examined with Egger's regression test. (Egger et al., 1997) for the relationship based on ten studies. Moderators were examined with subgroup analyses and Q -between tests, where each subgroup contained at

least two studies. To address Research Question A, we fitted a path model to the pooled correlation matrix following the univariate meta-analytic structural equation modelling approach. (Viswesvaran & Ones, 1995), using the harmonic mean of the cumulative sample sizes of the three correlations involved ($N = 1,493$) and Monte Carlo confidence intervals for the indirect effect. A model including sustainability performance was not estimated because two of the required correlations rested on fewer than three studies. Analyses were run in Python (NumPy and SciPy); the extracted data and code are provided as supplementary material. Reporting follows the PRISMA 2020 statement where applicable. (Page et al., 2021).

6.3 Results

6.3.1 Study characteristics

The 16 studies (Table 5 and Figure 3) comprised 5,374 participants and yielded 28 correlations. Six were conducted in China, five in Pakistan, and one each in India, Indonesia, Ghana, Portugal, and the United Kingdom; six were from South Asia. Nine studies used industrial samples, four used service samples, and three used both. Wellbeing was measured as job satisfaction in five of the six wellbeing studies and as life satisfaction in one, and green behavior was supervisor-rated in one study. In answer to Research Question C, none of the 16 studies measured GHRM as a digitally delivered practice, and none measured well-being with reference to environmental conditions.

Table 5. Characteristics of the studies included in the meta-analysis.

Study	Country	Sector (context code)	N	Correlations	Wellbeing measure	Correlation type
Adeel et al. (2022)	Pakistan	Higher education (service)	337	GHRM-WB = .57; GHRM-SUS = .70; WB-SUS = .66	Job satisfaction	Pearson
Chen & Wu (2022)	China	Tourism, manufacturing, construction, pharmaceutical (ISO 14001) (mixed)	296	GHRM-EGB = .61	–	Pearson
Chen et al. (2021)	China	Oil and mining (industrial)	358	GHRM-EGB = .33	–	Pearson
Cui et al. (2026)	China	Manufacturing, utility and energy (environmentally sensitive firms) (industrial)	258	GHRM-EGB = .41; GHRM-WB = .43; EGB-WB = .44	Job satisfaction	Pearson
Gomes et al. (2024)	Portugal	Hospitality and tourism (service)	449	GHRM-EGB = .24; GHRM-SUS = .62; EGB-SUS = .33	–	Pearson

Guysare et al. (2024)	Ghana	Manufacturing SMEs (industrial)	249	GHRM-EGB = .58; GHRM-WB = .56; EGB-WB = .59	Subjective wellbeing (SWLS)	Pearson
Khan, Iqbal & Saba (2025)	Pakistan	Manufacturing (industrial)	303	GHRM-EGB = .43	–	Pearson
Khan, Yusliza, et al. (2024)	Pakistan	Textile manufacturing (industrial)	624	GHRM-WB = .42	Job satisfaction	Pearson
Kuo et al. (2022)	Pakistan	Chemical industry (industrial)	500	GHRM-SUS = .67	–	Latent (composite)
Manjula & Kumar (2025)	India	Services, manufacturing, IT (mixed)	350	GHRM-SUS = .67	–	Pearson
Muchsinati et al. (2026)	Indonesia	Hospitals (service)	200	GHRM-WB = .49; GHRM-SUS = .66; WB-SUS = .57	Job satisfaction	Latent
Naqvi et al. (2025)	Pakistan	Manufacturing (textile, cement, steel) (industrial)	400	GHRM-SUS = .75	–	Latent (composite)
Qureshi (2026)	United Kingdom	Hospitality (four-star hotels) (service)	344	GHRM-EGB = .60; GHRM-WB = .58; EGB-WB = .32	Job satisfaction	Pearson (composite)
Song et al. (2023)	China	Chemical, manufacturing, pharmaceutical, hotel (industrial)	207	GHRM-EGB = .56	–	Pearson
Zhu et al. (2021)	China	Manufacturing (18 industries) (industrial)	228	GHRM-EGB = .43	–	Pearson
Zhu, Wu & Shen (2022)	China	Mixed enterprises (mixed)	271	GHRM-EGB = .54	–	Pearson

Note: EGB = employee green behavior; WB = employee wellbeing; SUS = sustainability or environmental performance. Composite = correlation of a unit-weighted GHRM composite computed from dimension-level correlations. Full extraction details are provided in Supplementary Material S1.

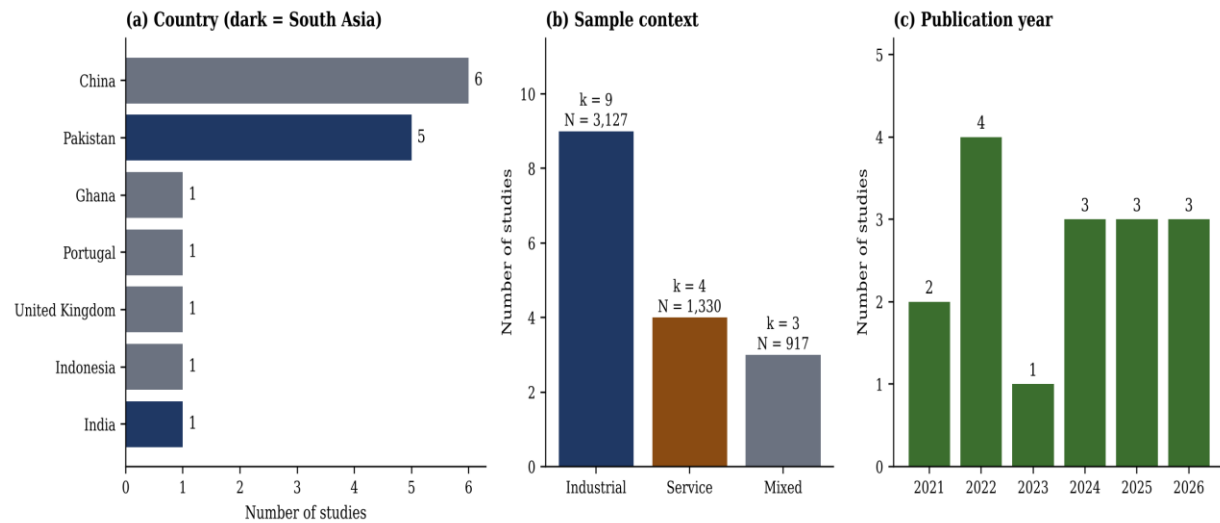


Figure 3. Characteristics of the 16 included studies by (a) country, (b) sample context and (c) publication year.

6.3.2 Pooled associations

Tables 6 and 4 report the pooled associations. GHRM was positively associated with employee green behavior ($r = .48$, 95% CI [.40, .55], $k = 10$, $N = 2,963$) and employee wellbeing ($r = .51$, 95% CI [.45, .57], $k = 6$, $N = 2,012$), supporting Hypotheses 1 and 2. Green behavior was positively associated with wellbeing ($r = .46$, 95% CI [.29, .60], $k = 3$, $N = 851$), supporting Hypothesis 3, although this estimate rests on three studies and its prediction interval is wide. GHRM was strongly associated with sustainability performance ($r = .68$, 95% CI [.64, .72], $k = 6$, $N = 2,236$), and wellbeing was associated with sustainability performance in the two studies that reported this relationship ($r = .62$, 95% CI [.52, .70], $k = 2$, $N = 537$), supporting Hypothesis 4, provisionally. The association between green behavior and sustainability performance was reported by a single study ($r = .33$) and was not pooled.

Heterogeneity was substantial for the GHRM-green behavior relationship ($I^2 = 88.4\%$, $\tau = .15$; 80% prediction interval [.29, .63]) and moderate to substantial for the GHRM-wellbeing ($I^2 =$

71.7%) and GHRM-sustainability ($I^2 = 65.7\%$) relationships. Even so, all prediction intervals for the relationships based on six or more studies were entirely positive. Leave-one-out estimates (Figure 5) ranged from .46 to .50 for GHRM-green behavior, .49 to .53 for GHRM-wellbeing, and .66 to .69 for GHRM-sustainability, and excluding latent correlations left the GHRM-wellbeing ($r = .51$, $k = 5$) and GHRM-sustainability ($r = .66$, $k = 3$) estimates essentially unchanged. The funnel plot for the GHRM-green behavior relationship (Figure 6) shows considerable scatter on both sides of the pooled estimate. Egger's test for this relationship was not significant at the .05 level (intercept = 13.67, $t(8) = 1.88$, $p = .098$), but with ten studies the test has limited power, and larger studies tended to report smaller correlations; therefore, some small-study bias cannot be ruled out.

Table 6. Random-effects meta-analytic correlations

Relationship	k	N	r	95% CI	80% PI	Q (df), p	I ² (%)	τ	Hypotheses
GHRM – employee green behaviour	10	2,963	.48	[.40, .55]	[.29, .63]	77.56 (9), p < .001	88.4	0.150	H1 supported
GHRM – employee wellbeing	6	2,012	.51	[.45, .57]	[.40, .61]	17.66 (5), p = .003	71.7	0.084	H2 supported
Employee green behaviour – wellbeing	3	851	.46	[.29, .60]	[–.10, .80]	17.33 (2), p < .001	88.5	0.165	H3 supported
GHRM – sustainability performance	6	2,236	.68	[.64, .72]	[.61, .74]	14.58 (5), p = .012	65.7	0.071	H4 supported
Employee wellbeing – sustainability performance	2	537	.62	[.52, .70]	–	2.71 (1), p = .100	63.1	0.083	H4 supported (provisional)
Employee green behaviour – sustainability performance	1	449	.33	[.24, .41]	–	–	–	–	Single study; not pooled

Note: k = number of studies; N = cumulative sample size; r = pooled correlation (REML random-effects, Fisher z back-transformed); CI = confidence interval; PI = prediction interval (not computed for k < 3). All pooled correlations were p < .001.

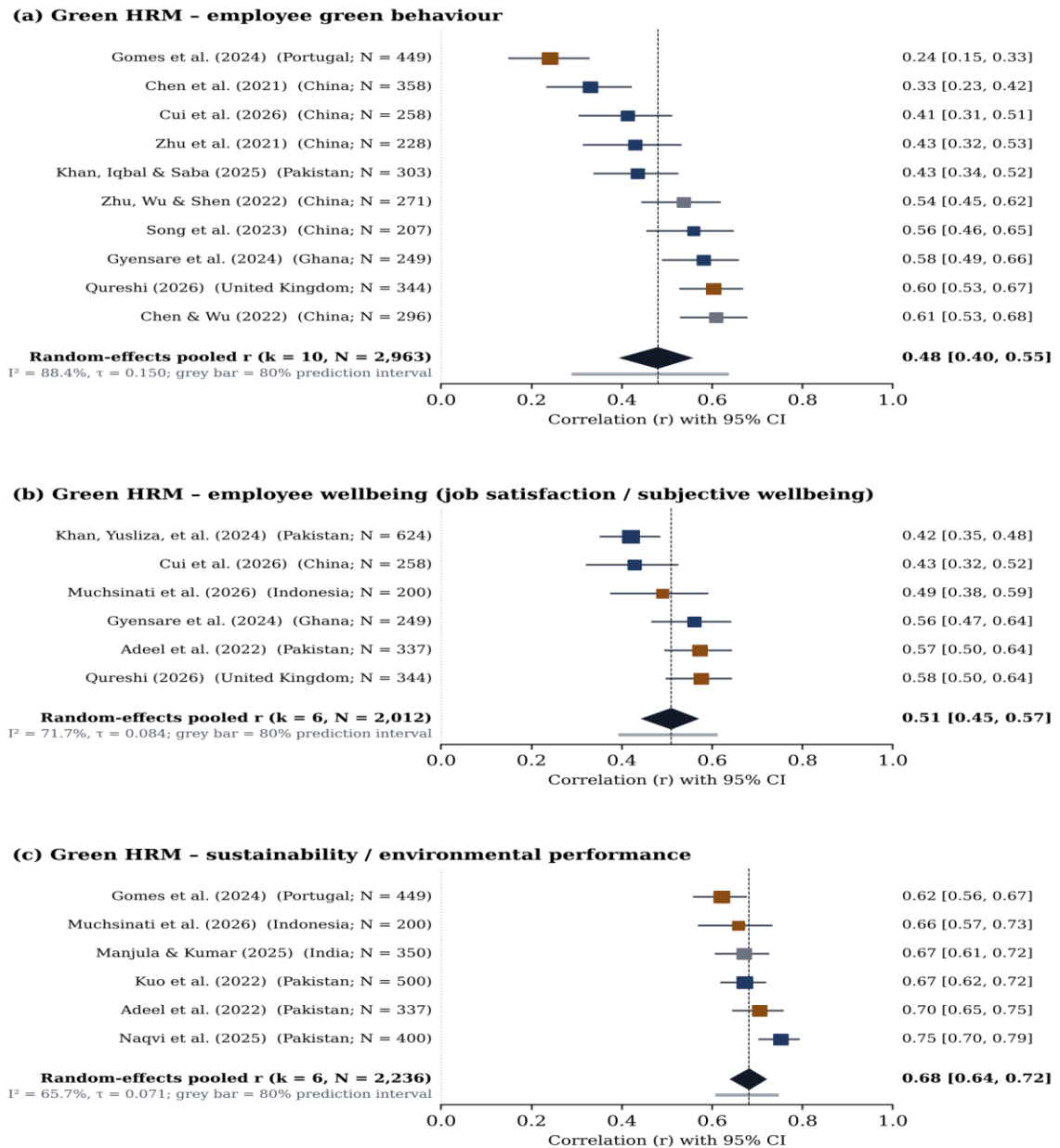


Figure 4. Forest plots of the pooled associations of green HRM with (a) employee green behaviour, (b) employee wellbeing and (c) sustainability performance

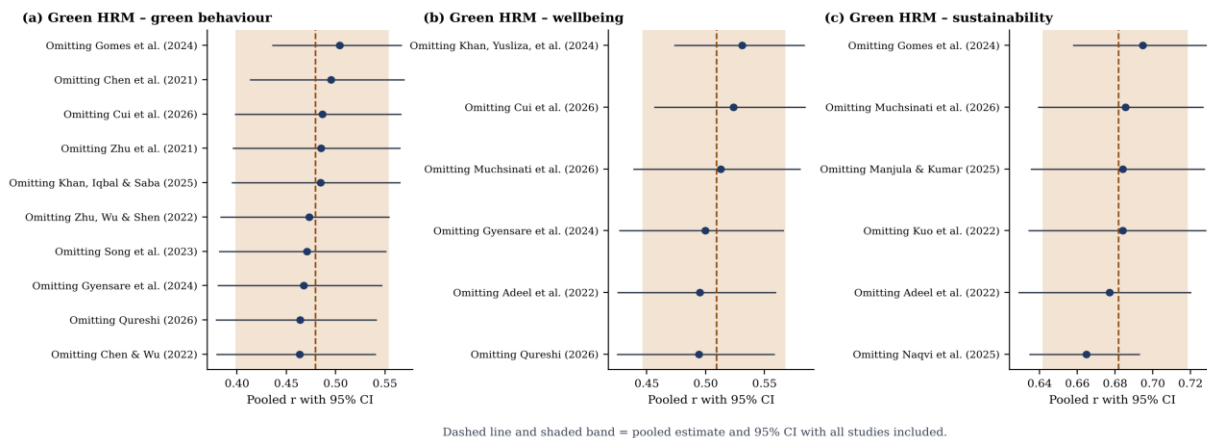


Figure 5. Leave-one-out sensitivity analysis: pooled correlation recomputed after omitting each study in turn.

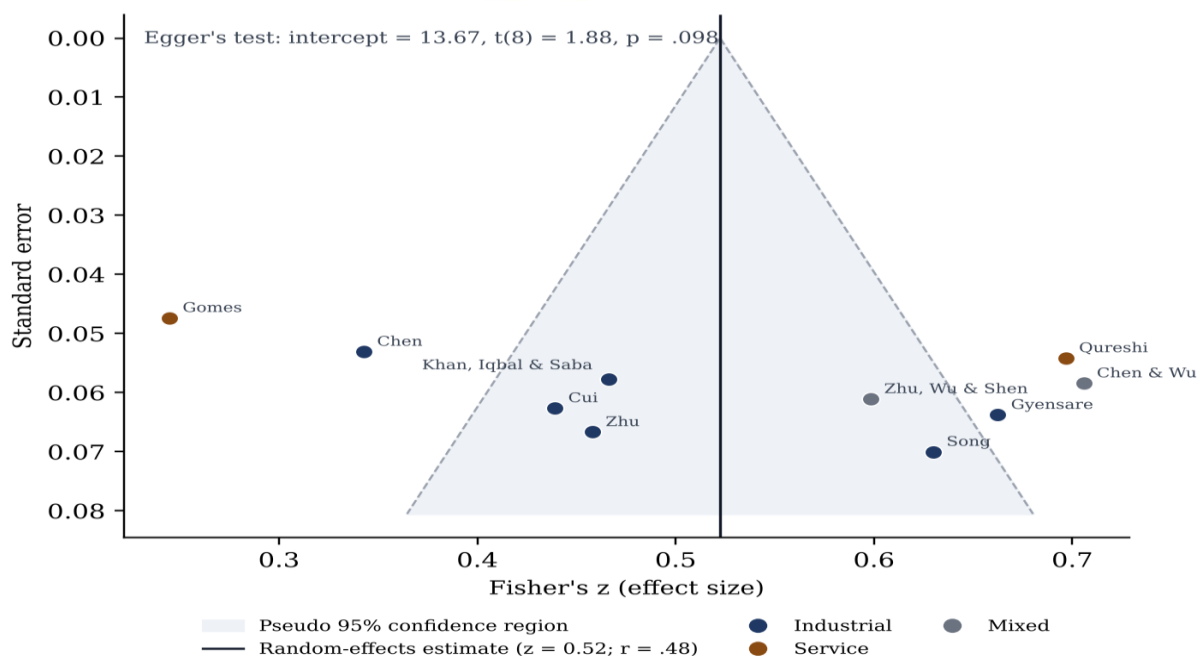


Figure 6. Funnel plot of the green HRM – employee green behaviour correlations (k = 10), with pseudo 95% confidence limits around the random-effects estimate

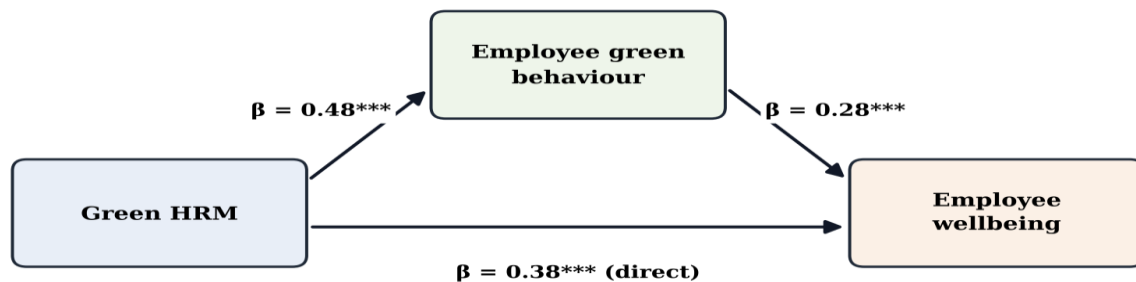
6.3.3. Is the well-being pathway a byproduct of green behavior?

Figure 7 presents the meta-analytic path model addressing RQ A. GHRM was associated with green behavior ($\beta = .48$, $p < .001$), and green behavior was associated with wellbeing ($\beta = .28$, $p < .001$). Crucially, GHRM retained a substantial

direct association with wellbeing when green behavior was controlled ($\beta = .38$, $p < .001$). The indirect association through green behavior was .13 (95% CI [.11, .16]), so that about three-quarters (74%) of the total GHRM-wellbeing association of .51 was not channelled through green behavior. The model explained 23% of the

variance in green behavior and 32% of the variance in wellbeing. Because the univariate approach does not propagate between-study heterogeneity into the path estimates, the standard

errors are likely to be optimistic; the paths nevertheless remained clearly significant when the smallest cell sample ($N = 851$) was used instead of the harmonic mean.



Indirect effect via green behaviour = 0.13, 95% CI [0.11, 0.16]; $R^2(\text{green behaviour}) = 0.23$; $R^2(\text{wellbeing}) = 0.32$

Standardised coefficients from the pooled correlation matrix; harmonic-mean $N = 1493$. *** $p < .001$

Figure 7. Meta-analytic path model of green HRM, employee green behaviour and employee wellbeing.

6.3.4 Moderators

Tables 7 and 8 present the subgroup analyses for RQ-B. The GHRM-well-being association tended to be weaker in industrial samples ($r = .47$, 95% CI [.37, .55], $k = 3$) than in service samples ($r = .56$, 95% CI [.51, .60], $k = 3$), although the difference did not reach conventional significance ($Q\text{-between}(1) = 3.21$, $p = .073$). The GHRM-green behavior association did not differ between industrial ($r = .46$, $k = 6$) and service samples ($r = .44$, $k = 2$; $Q\text{-between}(1) = 0.01$, $p = .91$), and the

GHRM-sustainability association did not differ between industrial ($r = .71$, $k = 2$) and service or mixed samples ($r = .66$, $k = 4$; $Q\text{-between}(1) = 1.18$, $p = .28$). The GHRM-well-being association was similar in South Asian ($r = .50$, $k = 2$) and other samples ($r = .52$, $k = 4$; $Q\text{-between}(1) = 0.06$, $p = .81$). A regional comparison for green behavior was not possible because only one South Asian study reported it. Given the small number of studies per subgroup, these analyses were exploratory in nature.

Table 7. Subgroup (moderator) analyses.

Relationship	Moderator	Subgroup	k	N	r [95% CI]	Q-between (df), p
GHRM – wellbeing	Context	Industrial	3	1,131	.47 [.37, .55]	3.21 (1), $p = .073$
		Service	3	881	.56 [.51, .60]	
GHRM – wellbeing	Region	South Asia	2	961	.50 [.33, .63]	0.06 (1), $p = .808$

		Other regions	4	1,051	.52 [.45, .58]	
GHRM – green behaviour	Context	Industrial	6	1,603	.46 [.38, .53]	0.01 (1), $p = .910$
		Service	2	793	.44 [.03, .72]	
		Mixed	2	567	.57 [.50, .64]	Three-group test: 4.79 (2), $p = .091$
GHRM – sustainability	Context	Industrial	2	900	.71 [.63, .78]	1.18 (1), $p = .278$
		Service/Mixed	4	1,336	.66 [.62, .70]	

Note: Subgroups were analyzed only when they contained at least two studies; a regional comparison for GHRM – green behavior was not possible (one South Asian study). Results are exploratory given the small number of studies per subgroup.

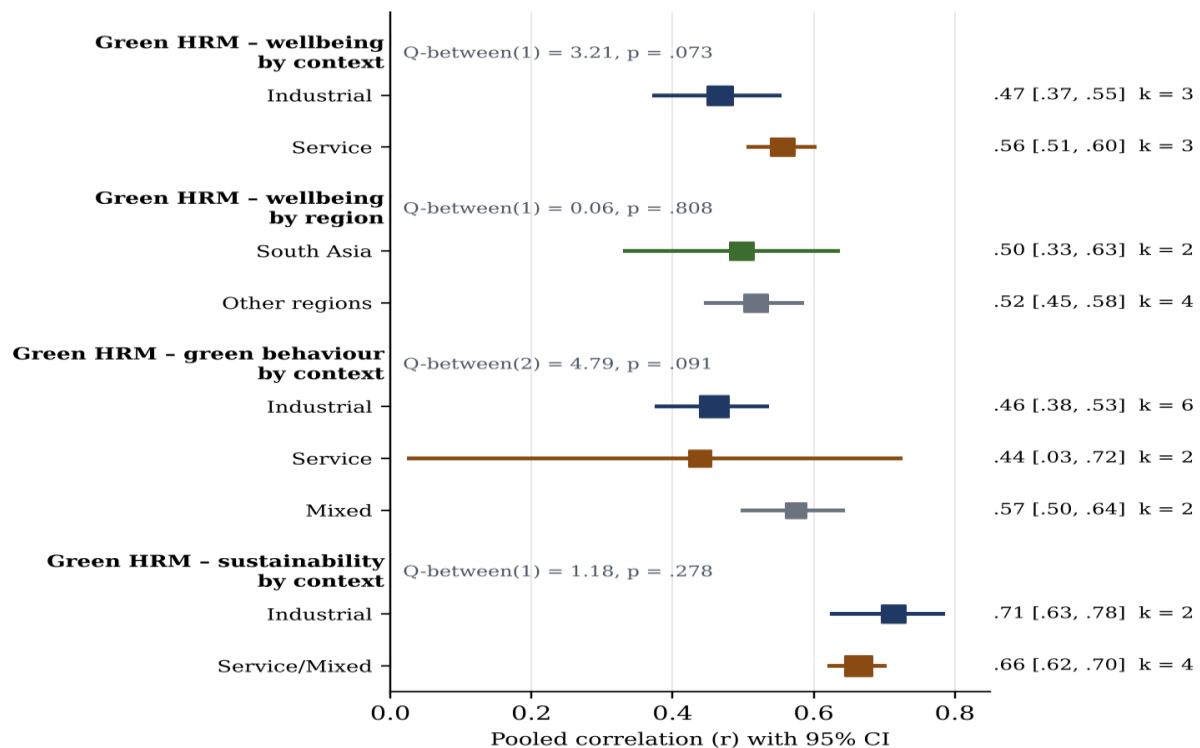


Figure 8. Subgroup (moderator) analyses: pooled correlations with 95% confidence intervals by sample context and region; marker size is proportional to cumulative N

7. Discussion

7.1 What the evidence shows

The meta-analysis supports the GHRM core of the dual-pathway framework. Across 16 studies, GHRM was associated with employee well-being at least as strongly as with employee green behavior, and most of the well-being association was not explained by green behavior. This pattern is difficult to reconcile with the dominant view that well-being is a downstream by-product of green behavior, and it is consistent with our reading of GHRM through both processes of the JD-R model: GHRM appears to work as a resource that motivates green behavior and, in parallel, supports well-being directly. The tentative finding that the GHRM–well-being association was weaker in industrial than in service samples is also consistent with this framework. If conventional GHRM in industrial settings is dominated by eco-efficiency practices and offers little protective care, as propositions 6 and 7 imply, it should deliver smaller well-being gains precisely where environmental demands are highest. This interpretation must remain provisional, given the small number of studies and the marginal significance of the difference.

This meta-analysis also documents what the literature has not yet measured. None of the included studies examined digitally delivered GHRM, and none measured well-being with reference to environmental conditions. Therefore, the digital and exposure-specific elements of the framework and the boundary conditions in Propositions 7 to 9 remain untested and define the agenda for primary research set out in Section 7.5.

7.2 Theoretical implications

This study contributes to theory in four ways. First, it re-centres wellbeing within GHRM. Existing studies treat wellbeing either as an outcome of green behavior (Gyensare et al., 2024) or as a mediator towards performance (Jia et al., 2024; Sarjaka et al., 2026). Our framework positions employee eco-wellbeing as a parallel pathway with its own sustainability consequences, and the meta-

analytic evidence that the wellbeing association is largely direct supports this repositioning. We also specify a wellbeing construct that is sensitive to environmental conditions, responding to Gyensare et al.'s (2024) call for research on wellbeing outcomes of GHRM beyond subjective wellbeing.

Second, the framework brings the health-impairment process of the JD-R model into GHRM. Reading GHRM only through motivational lenses such as AMO, social exchange, or signalling has made the field blind to the possibility that green HR practices also protect or fail to protect employees from environmental demands. Mapping GHRM onto both JD-R processes provides a parsimonious basis for dual-pathway models, which have been justified case by case (Pokalai et al., 2026).

Third, it extends e-HRM theory into the green domain. Prior work shows that e-HRM enables GHRM adoption (Alabaddi et al., 2020), and that AI-driven sustainable HRM can raise engagement (Jia & Hou, 2024). We add a protective care function and introduce workforce digital readiness as a boundary condition, answering Sarjaka et al.'s (2026) call to treat digital HR infrastructure as a moderator and bring technostress literature (Tarafdar et al., 2007) into contact with GHRM. The finding that none of the included studies measured digital GHRM gives this call empirical weight.

Fourth, this study advances contextualized theorizing. By treating pollution exposure intensity as a boundary condition grounded in COR's gain paradox, it explains why findings from low-exposure settings may misjudge the role of protective HR practices in polluting clusters. It also extends research on workplace eco-anxiety (Ayassamy & Francoeur, 2024) from the Global North and white-collar work to industrial workforces in the Global South, where environmental distress is physical and local as well as psychological and global.

7.3 Practical and policy implications

For managers in Pakistan's textile and leather clusters, the results suggest that GHRM is not only an environmental tool but also a lever for employee wellbeing, and that this second benefit may be under-delivered in industrial settings. Managers should therefore audit their GHRM portfolio for balance. Many green HR initiatives are eco-efficiency programmes; in high-exposure sections, protective-care practices should come first, both because they are likely to matter most there (Proposition 7) and because their absence undermines the credibility of eco-efficiency messages (Proposition 6). Digital tools should be designed for the workforce that will use them: short audio-visual lessons in Urdu or Punjabi, pictorial interfaces, interactive voice response, and messaging-based reporting are more likely to reach workers with limited literacy than text-heavy portals. Recognition schemes can target behaviors whose under-adoption is known, such as mask use, preferably at team level to build norms rather than individual competition. Exposure data should feed into rotation, break scheduling, and engineering controls and should not be used punitively.

For policymakers, the framework implies that environmental regulation under national and provincial environmental protection legislation (e.g., Pakistan Environmental Protection Act, 1997) and occupational health policy should be considered together. Cluster-level shared monitoring infrastructure can lower the cost of exposure monitoring for SMEs that cannot afford it individually. The finding that social security entitlement was associated with markedly lower odds of excessive working hours among female textile workers (Khan, Amir-ud-Din, & Atif, 2025) suggests that labor protections and eco-wellbeing are interdependent. For international buyers, whose audits shape practices in export-oriented firms, the framework suggests including wellbeing indicators alongside environmental and compliance metrics.

7.4 Limitations

This study has several limitations. First, the meta-analysis was restricted to openly accessible full texts, and several relevant reports could not be retrieved; therefore, the 16 included studies are a subset of the available literature, and studies in subscription journals may differ systematically. Second, some relationships rest on few studies (three for green behavior-wellbeing, two for wellbeing-sustainability), and the moderator analyses had low power; therefore, these results should be treated as provisional. Third, heterogeneity was substantial, and the univariate approach to meta-analytic path modelling does not propagate between-study heterogeneity into the path estimates; a two-stage structural equation modelling approach (Chan, 2005) would be preferable as the evidence base grows. Fourth, the primary studies were cross-sectional and mostly single-source; therefore, the pooled associations cannot establish causality and may be inflated by common method variance. Fifth, wellbeing was measured mainly as job satisfaction, which is a proxy for, not a measure of, the eco-wellbeing construct proposed here. Sixth, three effect sizes were derived from GHRM dimensions using a composite formula and three were latent rather than observed correlations, although excluding latent correlations did not change the conclusions. Seventh, several included studies were published in regional journals or proceedings whose review standards may vary. Finally, some of the occupational-health evidence that motivates the framework is dated: the survey of female textile workers was conducted in 2015, although published in 2025 (Khan, Amir-ud-Din, & Atif, 2025).

7.5 Agenda for primary research in Pakistan's clusters

The untested elements of the framework call for primary data. We propose a multi-source field survey of approximately 300 shop-floor employees in 15–20 textile and leather firms, stratified so that approximately half of the employees work in high-exposure sections (e.g., spinning, beam house, and

chrome tanning) and half in low-exposure sections (e.g., finishing and packing). Employees would report perceived D-GHRM, eco-wellbeing, perceived green hypocrisy, digital readiness, illness-related absence, and intention to stay; supervisors would rate green behavior and protective safety behavior, so that predictors and mediators come from different sources (Podsakoff et al., 2003); and section-level exposure would be measured with portable particulate monitors, complemented by the 'dusty' versus 'less dusty' classification used in Pakistani textile research (Khan, Muhmood, et al., 2024; Khan, Amir-ud-Din, & Atif, 2025). Women and contract workers should make up at least 30% of the sample, and questionnaires should be translated into Urdu, administered orally where needed, and piloted with 30–50 employees. For partial least squares

structural equation modelling, approximately 275 observations are needed to detect a path coefficient of 0.15 at the 5% level with 80% power (Kock & Hadaya, 2018); therefore, approximately 300 usable responses would suffice for the individual-level propositions; firm-level propositions require 30 or more firms (Maas & Hox, 2005). Table 8 lists candidate measures. Partial least squares structural equation modelling (Hair et al., 2022) and conditional process analysis (Hayes, 2022) would suit the analysis. Digital exposure monitoring can become an instrument of surveillance; therefore, studies should secure informed consent, protect anonymity in hazard reporting, and examine whether workers perceive D-GHRM data as used for protection or for discipline.

Table 8. Candidate measures for primary research in Pakistan's clusters

Construct	Source / respondent	Candidate measure	Adaptation required
Digital green HRM	Employees	GHRM practice scale (Tang et al., 2018) with digital-delivery stems; e-HRM items (Alabaddi et al., 2020)	New protective-care items; content validation and pilot; Urdu translation
Employee green behaviour	Supervisors	Five-item in-role/extra-role green behaviour scale (Bissing-Olson et al., 2013; Dumont et al., 2017), as used by Gyensare et al. (2024)	Shop-floor examples (e.g., reporting leaks, sorting waste)
Exposure-related physical wellbeing	Employees	Respiratory symptom items (Khan, Amir-ud-Din, & Atif, 2025); illness-related absence days (Khan, Muhmood, et al., 2024)	Add perceived environmental safety items
Eco-psychological wellbeing	Employees	Climate Change Anxiety Scale (Clayton & Karazsia, 2020)	Re-frame from global climate to local pollution; develop environmental-meaningfulness items

Perceived green hypocrisy	Employees	Three items developed for this study	Content validation and pilot
Pollution exposure intensity	Section level	Portable particulate monitoring; 'dusty' vs 'less dusty' classification (Khan, Muhmood, et al., 2024; Khan, Amir-ud-Din, & Atif, 2025)	Standardise across textile and tannery processes
Workforce digital readiness	Employees	Digital literacy and device-access items; technostress (Tarafdar et al., 2007)	Oral administration for low-literacy respondents
Employee-level outcome proxies	Employees	Illness-related absence days (economic pillar); three intention-to-stay items (social pillar)	Firm-level sustainability deferred to studies with ≥ 30 firms
Subjective wellbeing (discriminant check)	Employees	Satisfaction With Life Scale (Diener et al., 1985)	Report change from 7-point to 5-point format
Controls	Employees; manager form	Age, gender, tenure, contract type, overtime, smoking; firm sector, size and export status	Smoking and export status follow Khan, Muhmood, et al. (2024) and Khan, Amir-ud-Din, & Atif (2025)

Future research could pursue field experiments, for example randomizing vernacular digital microlearning on protective-equipment use across sections; qualitative studies of how women and contract workers experience digital HR tools; longitudinal studies of whether D-GHRM shifts eco-anxiety from paralysis towards efficacy; and

8. Conclusion

In Pakistan's polluting manufacturing clusters, the people expected to deliver environmental improvement are also those who bear the environmental costs of production. GHRM research has asked how HR practices can make employees greener; it has rarely asked how those practices can protect employees from the environmental conditions of their work, or how

updated meta-analyses that include subscription journals and test the industrial-service difference with more studies. Researchers should also examine the darker side of D-GHRM, including surveillance, data privacy, and gendered access to devices, which could turn a protective resource into an additional job demand.

that protection contributes to sustainability. This study argues that digital GHRM can do both, through a motivational pathway built on employee green behavior and an overlooked health-protection pathway built on employee eco-wellbeing. A meta-analysis of 16 studies shows that GHRM is as closely associated with employee wellbeing as it is with green behavior, and that most of this wellbeing association does not run

through green behavior, while also revealing that digital GHRM and environmental wellbeing have not yet been measured. Recognizing the second pathway changes what counts as good green HRM: in a spinning hall or a tannery, a green HR system that does not protect the people working there is unlikely to be sustainable in any of the three senses of the term.

Data availability statement

This study analyzed correlations reported in published studies; no new primary data were collected. The extracted effect sizes, coding decisions, lists of included, excluded, and unretrieved reports, and the analysis code are provided as Supplementary Materials S1 and S2.

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