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Contact to corresponding author: Waiphot Kulachai, waiphot.ku@ssru.ac.th

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Adi Prasetyo Tedjakusuma
University of Surabaya, Indonesia
Chaoyang University of Technology, Taiwan
orcid.org/0000-0003-0794-2124

Waiphot Kulachai
Suan Sunandha Rajabhat University, Thailand
orcid.org/0000-0002-3476-9462

Ching-Te, Lin
Chaoyang University of Technology, Taiwan
orcid.org/0000-0003-2765-2327

Joshi Maharani Wibowo
University of Surabaya, Indonesia
University of Helsinki, Finland
orcid.org/0000-0002-2070-1950

Capability conversion in green manufacturing: Green HRM, ethical AI, and dual sustainability performance under the NRBV

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Abstract

Research background: Manufacturing firms in emerging economies face simultaneous pressures to decarbonise and digitalise, yet how green human resource systems, responsible AI governance, and green innovation jointly translate into sustainability outcomes remains insufficiently understood.
Purpose of the article: Grounded in the Natural Resource-Based View, this study tests a capability-conversion model linking green human resource management practices (GHRMPs), ethical AI (EA), green innovation performance (GIP), environmental performance (ENP), and operational economic performance (ECP) in Thai manufacturing.
Methods: Cross-sectional online survey data were obtained from 422 key informants, with one supervisory, managerial, or executive respondent representing each medium-sized or large Thai manufacturing firm. The model was analysed using two-stage partial least squares structural equation modelling, a reflective–formative higher-order specification of GHRMPs, and 10,000-subsample bootstrapping.
Findings & value added: GHRMPs were positively associated with EA (β = .846), EA with GIP (β = .733), and GIP with ENP (β = .810) and ECP (β = .765), whereas the direct GHRMP–ENP and GHRMP–ECP relationships were nonsignificant. The serial indirect associations through EA and GIP were significant for ENP (β = .502) and ECP (β = .475). These findings support an indirect capability-conversion pattern in which green HR architecture functions as a distal enabling capability, EA as an intermediate governance capability, and GIP as the proximal mechanism associated with environmental improvement and operational resource cost efficiency. The environmental coefficients were descriptively larger than the economic coefficients, but these differences were not formally tested and therefore represent tentative environmental–economic variation rather than confirmed asymmetry. The study contributes by integrating human, AI-governance, and innovation capabilities and by operationalising EA as an organisational governance construct in an emerging-economy manufacturing context.

Introduction

Intensifying climate pressures and resource scarcity are encouraging manufacturing firms to shift from conventional production models toward lower-carbon and more circular alternatives. This transition is closely aligned with global priorities concerning sustainable industrialisation and responsible production under SDGs 9 and 12 and climate action under SDG 13. Recent manufacturing evidence associates green innovation and eco-technologies with stronger green productivity, while complementary organisational practices such as sustainability reporting and environmental management accounting are linked to sustainable competitive advantage

(Van *et al*., 2025; Wang *et al*., 2025). From the Natural Resource-Based View (NRBV), however, environmental technologies do not become strategically valuable through acquisition alone; their value depends on their integration with organisational knowledge, routines, governance arrangements, and managerial priorities (Hart, 1995; Hart & Dowell, 2011; Alkaraan *et al*., 2024). Consistent with this reasoning, Frau *et al*. (2022) show that digital technologies facilitate cleaner production through nature-driven agility, but that the resulting environmental benefits depend substantially on managers' commitment to environmental sustainability and stakeholder pressures. Digital and green technologies must therefore be embedded within broader organisational capability systems if they are to produce durable sustainability value.

Eco-innovation research has consequently expanded beyond technological adoption to recognise the role of organisational and human resource systems. Recruitment, training, appraisal, involvement, and reward practices aligned with environmental objectives—collectively referred to as green human resource management practices (GHRMPs)—can develop the knowledge, motivation, participation opportunities, and accountability needed to support environmental change. Empirical research associates coordinated GHRMPs with employee participation in environmental initiatives, environmentally responsible behaviour, sustainability-oriented organisational cultures, green innovation, and environmental performance (Ansari *et al*., 2021; Aftab *et al*., 2023; Teng & Wu, 2025; Bindeeba *et al*., 2025). Nevertheless, GHRMPs are frequently examined as direct predictors of employee or organisational outcomes, leaving further scope to explain how green HR architecture interacts with digital governance and innovation mechanisms to generate sustainability value.

Artificial intelligence has simultaneously become embedded in production planning, predictive maintenance, logistics, energy management, emissions monitoring, and sustainability-oriented decision-making. These applications can improve firms' ability to identify inefficient resource patterns and evaluate cleaner production alternatives (Sun *et al*., 2025). Their deployment also creates risks concerning algorithmic bias, privacy, data security, transparency, accountability, and insufficient human oversight. Ethical AI (EA) is therefore understood in this study as the organisational principles and governance practices through which firms seek to design, deploy, monitor, and use AI in accordance with fairness, transparency, privacy, accountability, safety, and sustainability considerations (Akbarighatar *et al*., 2026; Gidage & Bhide, 2025; Mura & Stehlíková, 2025; Papagiannidis *et al*., 2025).

Responsible-AI and sustainability research is growing rapidly, and the present study does not claim to originate either this literature or the broader relationship between organisational capabilities and sustainability. Its more bounded research gap concerns the limited empirical understanding of how green HR architecture, responsible AI governance, and green innovation may operate together within a manufacturing capability system. Existing responsible-AI research often emphasises principles, technical properties, or conceptual governance frameworks, while providing less evidence on how EA is organisationally connected with HR systems and sustainability-oriented innovation (Morley *et al*., 2021; Mäntymäki *et al*., 2022; Papagiannidis *et al*., 2025). Conversely, GHRM research increasingly examines employee green behaviour, environmental strategy, green innovation, and environmental performance but rarely incorporates responsible AI governance as an intermediate organisational mechanism (Aftab *et al*., 2023; Aftab & Veneziani, 2024; Gyensare *et al*., 2024; Bindeeba *et al*., 2025). The present study addresses this narrower intersection by examining GHRMPs, EA, green innovation performance (GIP), and two distinct sustainability outcomes within an integrated model.

The NRBV provides a capability-based explanation for these relationships. GHRMPs represent an upstream human and organisational capability that develops environmental competencies, incentives, participation mechanisms, and accountability expectations. EA represents a complementary governance capability that structures how AI-supported information and decisions are generated, monitored, and used. GIP subsequently represents the proximal conversion mechanism through which these upstream human and governance capabilities can become embodied in cleaner products, processes, and operational routines. This sequence shifts the theoretical emphasis from possessing isolated green or digital resources to coordinating complementary capabilities that convert those resources into organisational outcomes.

The NRBV logic also suggests that sustainability outcomes should not be treated as interchangeable or assumed to emerge uniformly. Green product and process innovations may be relatively closely associated with physical environmental improvements because they directly alter material consumption, energy use, emissions, recycling, and waste. Operational economic value, by contrast, depends on whether those environmental improvements are converted into measurable reductions in material, energy, and waste-disposal costs. Prior research similarly indicates that the contribution of green innovation to organisational performance can operate through interconnected sustainability mechanisms. Maldonado-Guzmán *et al*. (2023), for example, show that economic, environmental, and social sustainability dimensions strengthen the relationship between green innovation and firm performance in the automotive industry. This evidence supports a process-based interpretation in which innovation-related value may be transmitted through sustainability improvements rather than being understood solely as an immediate and uniform financial return.

Accordingly, this study introduces environmental–economic asymmetry as a provisional analytical possibility rather than a confirmed theoretical proposition. The same capability-conversion sequence may be associated differently with environmental improvement and operational resource-cost efficiency because the two outcomes represent distinct stages and forms of sustainability value realisation. Environmental effects may be more proximal to implemented green innovations, whereas operational economic effects require the additional conversion of resource efficiencies into cost reductions. Because the present study does not formally test differences between coefficient magnitudes, any observed variation is interpreted descriptively and as requiring further validation rather than as evidence of established asymmetry.

Thailand provides a theoretically informative setting because it combines the institutional and resource constraints of an emerging economy with a diversified, export-oriented manufacturing base embedded in regional and global value chains. Its manufacturers face a strategic challenge increasingly shared across economies: adopting digital technologies while reducing environmental impacts and maintaining cost competitiveness. Thailand's Bio-Circular-Green Economy strategy and Eco Factory programme further intensify pressures for technological upgrading, cleaner production, and stronger environmental governance (FTI, 2023).

Thailand therefore represents a useful bridge case. For developing economies, it illustrates how firms pursue digital and environmental upgrading under institutional and resource constraints. For developed economies, it provides insight into the governance and sustainability capabilities of suppliers operating within internationally connected production networks, where practices adopted in emerging-market facilities may influence multinational supply chains, responsible sourcing, and crossborder decarbonisation (OECD, 2026; World Bank, 2026). Evidence from Thailand can thus inform broader debates on how HR systems, responsible AI governance, and green innovation are aligned during the simultaneous digital and low-carbon transformation of manufacturing.

Grounded in the NRBV, this study tests a capability-conversion model in which GHRMPs are treated as a distal enabling capability associated with EA, EA as an intermediate governance capability associated with GIP, and GIP as the proximal mechanism associated with environmental performance and operational economic performance. The model also assesses whether GHRMPs retain direct associations with the two performance outcomes after EA and GIP are incorporated. Cross-sectional survey data from 422 supervisory, managerial, and executive respondents representing 422 medium-sized and large Thai manufacturing firms are analysed using two-stage partial least squares structural equation modelling.

The study makes three bounded contributions. First, it provides context-specific evidence for operationalising EA as an organisational governance construct and examining its connections with green HR architecture and green innovation. Second, it tests an integrated NRBV-based sequence connecting human, AI-governance, and innovation capabilities with dual sustainability outcomes, without claiming that the cross-sectional estimates establish universal or causal capability conversion. Third, it distinguishes environmental performance from operational economic performance and evaluates whether the estimated relationships display descriptive environmental–economic variation. These contributions refine the application of the NRBV to digitally enabled green manufacturing rather than claiming to redefine responsible-AI or sustainability research.

The remainder of the article is organised as follows. The Literature Review presents the NRBV-based theoretical framework and develops the hypotheses. The Research Methods section explains construct operationalisation, sampling and data collection, the analysis procedure, and the two-stage higher-order specification of GHRMPs. The Results section reports the common method variance assessment, sample characteristics, measurement- and structural-model evaluations, predictive assessment, and hypothesis tests. The Discussion interprets the findings, followed by the theoretical and practical implications, conclusions, limitations, and directions for future research.

Literature review

Theoretical framework: Natural resource-based view (NRBV)

The Natural Resource-Based View (NRBV) extends the Resource-Based View by recognising that environmental constraints and opportunities shape the strategic value of firm resources (Barney, 1991; Hart, 1995). Pollution prevention, product stewardship, and sustainable development can become sources of advantage when environmental knowledge, technologies, and organisational routines are embedded in valuable and difficult-to-imitate capability systems (Hart & Dowell, 2011). Recent research further emphasises that sustainability performance depends not simply on possessing environmental resources, but on coordinating human, digital, governance, and innovation capabilities (Alkaraan *et al*., 2024).

Within this study, GHRMPs represent an upstream human and organisational capability because green recruitment, training, involvement, performance management, and rewards develop the skills, motivation, participation opportunities, and accountability required to support environmental change. Their strategic value is expected to emerge through complementary mechanisms rather than through HR practices alone, consistent with recent evidence linking GHRM with green innovation and competitive advantage (Zhang *et al*., 2024; Usman *et al*., 2025). Ethical AI represents a complementary governance capability that translates fairness, transparency, privacy, accountability, and human oversight into organisational practices governing the design, deployment, and monitoring of AI systems (Papagiannidis *et al*., 2025).

Green innovation performance represents the proximal mechanism through which these upstream capabilities are associated with sustainability outcomes. Responsibly governed AI and green-oriented human capabilities may support cleaner products, processes, and operational routines, while implemented green innovations are associated with lower emissions, waste, and resource consumption and with reduced material, energy, and waste-disposal costs (Crocco *et al*., 2025; Rahman *et al*., 2026). Accordingly, the NRBV provides the theoretical basis for examining GHRMPs as a distal enabling capability, ethical AI as an intermediate governance capability, and green innovation as the mechanism associated with environmental and operational economic performance. Given the cross-sectional design, these relationships are interpreted as theory-consistent associations rather than confirmed causal effects.

Conceptual scope of ethical AI

Ethical AI, responsible AI governance, and digital ethics are related but should not be treated as interchangeable. Ethical AI concerns the extent to which normative principles are reflected in the design and organisational use of AI systems. In contrast, responsible AI governance encompasses the broader structural, relational, and procedural arrangements through which organisations allocate decision rights, define responsibilities, engage stakeholders, monitor AI systems, and manage risks across the AI lifecycle (Papagiannidis *et al*., 2025). Recent configurational evidence also indicates that responsible-AI principles are enacted through different combinations across organisational contexts rather than through one universally applicable set of practices (Akbarighatar *et al*., 2026). AI governance therefore provides the wider organisational architecture within which ethical AI practices may be implemented.

Digital ethics and digital responsibility have an even broader scope because they address the ethical and societal implications of data, algorithms, digital platforms, information systems, and digital transformation beyond AI alone (Recker *et al*., 2025). Accordingly, EA in this study is defined more narrowly as the organisational enactment of transparency, privacy protection, fairness, and accountability in the use of AI. These four dimensions correspond to the indicators retained in the final measurement model. Safety, security, regulatory compliance, sustainability, human oversight, formal governance structures, and lifecycle risk management remain relevant to responsible AI governance but are not comprehensively measured by the present EA construct. EA is therefore conceptualised as a focused ethical-practice capability embedded within, but not equivalent to, the broader system of organisational AI governance.

Hypothesis development

GHRMPs on Ethical AI

Green employee involvement, recruitment and selection, training and development, performance management, and compensation and rewards collectively create organisational conditions that may support ethical AI practices. An integrated GHRM system develops environmental competencies, strengthens employee participation, aligns incentives with sustainability objectives, and embeds accountability expectations within organisational routines. Recent evidence associates GHRM with organisational learning, employee environmental engagement, green innovation, and the development of sustainability-oriented capabilities (Chiarini & Bag, 2024; Zhang *et al*., 2024; Usman *et al*., 2025). These human and organisational resources may extend beyond conventional environmental activities by enabling employees and managers to scrutinise AI-supported decisions, recognise potential ethical consequences, and incorporate transparency, privacy, fairness, and accountability into AI use.

Nevertheless, the relationship is neither automatic nor well established empirically. GHRM initiatives may remain confined to environmental programmes, while responsibility for AI is assigned separately to IT, legal, compliance, or data-management functions. Meta-analytic evidence also shows that the effects of GHRM vary across industries, firm sizes, geographical settings, and implementation conditions, indicating that formal green HR practices do not uniformly become effective organisational capabilities (Bindeeba *et al*., 2025). Similarly, responsible AI requires coordinated structural, relational, and procedural arrangements rather than employee values or training alone, and ethical principles may be enacted through different organisational configurations (Papagiannidis *et al*., 2025; Akbarighatar *et al*., 2026). The proposed relationship is therefore theory-driven: GHRMPs should support EA when their competencies, participation mechanisms, incentives, and accountability systems are extended to AI-supported organisational activities.

H1: *GHRMPs are positively associated with EA.*

Ethical AI on green innovation performance

EA may support GIP by improving the organisational quality and legitimacy of AI-supported environmental decisions. Transparency can make algorithmically supported recommendations more understandable and traceable, privacy protection can encourage legitimate and responsible data use, fairness can reduce systematic distortions in decision criteria, and accountability can clarify responsibility for AI-supported outcomes. Recent manufacturing research indicates that AI literacy, green absorptive capacity, and green information systems strengthen firms' ability to identify environmental opportunities and translate digital knowledge into green product and process innovation (Cheng *et al*., 2025a). AI is also more strongly connected with green innovation and sustainability when combined with complementary green capabilities, intellectual capital, and knowledge-sharing processes (Crocco *et al*., 2025; Rahman *et al*., 2026).

However, ethical principles do not necessarily enhance innovation under all conditions. Transparency can conflict with technical complexity or proprietary knowledge, privacy requirements may constrain data availability, and accountability arrangements may become procedural rather than substantive. Responsible-AI practices also remain unevenly institutionalised, and recent evidence demonstrates that different combinations of principles can produce responsible outcomes across different organisational contexts (Akbarighatar *et al*., 2026). Governance controls that are fragmented, symbolic, or disproportionate may add administrative burden without improving the environmental direction of innovation, whereas coherent controls may reduce uncertainty and strengthen confidence in AI-supported experimentation (Papagiannidis *et al*., 2025). On balance, EA is expected to support GIP when ethical principles are translated into workable organisational practices rather than remaining aspirational statements.

H2: *EA is positively associated with GIP.*

Green innovation performance on sustainability performance

GIP captures implemented product and process innovations that reduce the environmental burden of organisational activities. Green product innovation may involve environmentally preferable materials, recyclable components, lower-impact product designs, and reduced lifecycle effects, whereas green process innovation may involve cleaner production, lower energy and material intensity, reduced emissions, and improved waste management. Because these innovations directly alter physical inputs, processes, and outputs, they are expected to be associated with improvements in resource consumption, recycling, emissions, and waste. Recent evidence links green innovation with stronger environmental performance and shows that AI-enabled green capabilities can facilitate the conversion of environmental knowledge into sustainability outcomes (Crocco *et al*., 2025; Cheng *et al*., 2025a; Rahman *et al*., 2026).

The evidence concerning economic outcomes is more conditional. Green innovation can reduce operating costs, but its benefits depend on innovation type, implementation quality, scale, complementary capabilities, and the period over which outcomes are assessed. Cheng *et al*. (2025b), for example, distinguish pollution-prevention innovation from pollution-control innovation and show that their environmental and financial consequences are not uniform. Pollution-prevention innovations were more consistently associated with future environmental and financial performance, whereas pollution-control innovations did not produce equivalent benefits. These findings suggest that environmental outcomes may be more proximal to green innovation, while economic outcomes depend on whether physical efficiencies are successfully converted into material, energy, and waste-disposal savings. Positive relationships with both outcomes are therefore expected, but their magnitudes are not assumed to be identical. Because the present study does not formally compare coefficient magnitudes, any observed difference is interpreted as tentative environmental–economic variation rather than confirmed asymmetry.

H3a: *GIP is positively associated with ENP*.

H3b: *GIP is positively associated with ECP*.

GHRMPs on sustainability performance

GHRMPs may be associated with ENP because they embed environmental objectives into recruitment, development, participation, appraisal, and reward systems. Green recruitment and training develop employees' environmental values and competencies, involvement mechanisms enable employees to identify operational problems and propose improvements, and performance-management and reward practices reinforce attention to environmental targets. Recent manufacturing evidence associates integrated GHRM systems with employee green behaviour, cleaner workplace practices, environmental engagement, and organisational environmental performance (Aftab & Veneziani, 2024; Chiarini & Bag, 2024; Dwumah *et al*., 2025). These practices may also support operational ECP by encouraging resource conservation, process discipline, and reductions in avoidable material, energy, and waste-management costs.

Nevertheless, empirical relationships between GHRM and firm-level performance are not uniformly direct or equally strong. Recent meta-analytic evidence identifies substantial variation across organisational and empirical settings and indicates that green innovation, organisational learning, employee participation, and other complementary mechanisms frequently transmit the performance implications of GHRM (Bindeeba *et al*., 2025). GHRM practices may also remain symbolic or disconnected from operational investment and production decisions, thereby limiting their direct influence on environmental or economic outcomes. Recent research accordingly emphasises mechanisms such as green organisational learning, responsible leadership, identity, and innovation through which GHRM becomes strategically consequential (Zhang *et al*., 2024; Usman *et al*., 2025). The direct relationships are therefore retained as plausible but contestable expectations whose strength may diminish once EA and GIP are included as more proximal mechanisms.

H4a: *GHRMPs are positively associated with ENP*.

H4b: *GHRMPs are positively associated with ECP*.

The indirect effect of GHRMPs on GIP through EA

The capability-conversion logic suggests that GHRMPs may contribute to GIP through an intervening ethical-practice capability. GHRMPs create upstream conditions by developing environmental competencies, participation opportunities, incentive alignment, and accountability expectations. These resources may increase organisational readiness to evaluate AI-supported decisions and incorporate ethical concerns into digital activities. EA can then organise these HR-based resources around transparent, privacy-protective, fair, and accountable AI use. Recent evidence shows that GHRM contributes to environmental learning and innovation through complementary organisational processes, while responsible AI governance depends on clear responsibilities, stakeholder relationships, and procedures for translating principles into practice (Usman *et al*., 2025; Bindeeba *et al*., 2025; Papagiannidis *et al*., 2025).

The proposed indirect association also responds to limitations in the existing evidence. Direct empirical research connecting GHRMPs with EA remains scarce, and green HR systems and AI governance may develop in separate organisational functions. Moreover, the practical enactment of responsible-AI principles varies across organisational configurations, suggesting that HR-based competencies produce innovation value only when converted into coherent ethical practices (Akbarighatar *et al*., 2026). Once enacted, EA may improve the credibility and organisational usability of AI-supported information, while AI literacy, absorptive capacity, and green information systems facilitate its application to green innovation (Cheng *et al*., 2025a). Thus, the innovation-related value of GHRMPs is expected to be transmitted partly through EA rather than arising solely from HR practices themselves.

H5a: *GHRMPs have a positive specific indirect effect on GIP through EA.*

The indirect effects of EA on sustainability performance through GIP

EA is unlikely to improve sustainability performance merely because ethical principles have been formally stated. Transparency, privacy, fairness, and accountability become environmentally consequential when they shape the identification, development, and implementation of cleaner products and processes. EA may improve the traceability and legitimacy of AI-supported environmental decisions, while GIP converts those decisions into changes in materials, energy use, production methods, emissions, and waste. Recent research indicates that AI-related capabilities contribute to sustainability through green innovation, green absorptive capacity, knowledge sharing, and complementary organisational capabilities rather than through technology adoption alone (Cheng *et al*., 2025a; Crocco *et al*., 2025; Rahman *et al*., 2026).

This mediated expectation is consistent with mixed evidence concerning both responsible AI and green innovation. Responsible-AI principles can remain aspirational, and their practical effects depend on organisational configuration and implementation quality (Papagiannidis *et al*., 2025; Akbarighatar *et al*., 2026). Likewise, different types of green innovation do not generate equivalent environmental and economic consequences; pollution-prevention innovation appears more capable of producing future performance benefits than pollution-control innovation in some settings (Cheng *et al*., 2025b). EA is therefore expected to influence ENP and operational ECP when it facilitates implemented green innovation, while the resulting environmental and economic associations may differ because economic gains require the further conversion of physical efficiencies into operational cost savings.

H5b: *EA has a positive specific indirect association with ENP through GIP*.

H5c: *EA has a positive specific indirect association with ECP through GIP*.

Serial indirect effects of GHRMPs on sustainability performance through EA and GIP

The complete capability-conversion argument positions GHRMPs, EA, and GIP as complementary but functionally distinct components. GHRMPs develop employees' environmental competencies, participation opportunities, incentives, and accountability expectations; EA applies transparency, privacy, fairness, and accountability to organisational AI use; and GIP embodies these upstream resources in implemented green products and processes. Recent evidence supports the importance of coordinated human, governance, and innovation capabilities: GHRM contributes to environmental performance through organisational and innovation mechanisms, responsible AI governance requires organisational structures and routines, and AI-enabled green capabilities support sustainability through green innovation and knowledge sharing (Aftab & Veneziani, 2024; Papagiannidis *et al*., 2025; Crocco *et al*., 2025; Rahman *et al*., 2026).

At the same time, each stage represents a possible point of capability-conversion failure. GHRMPs may remain symbolic, ethical principles may not be operationalised, and green innovations may not generate equivalent environmental and economic returns. Meta-analytic evidence shows heterogeneity in the GHRM–innovation relationship, configurational research shows that responsible-AI principles operate differently across organisations, and recent evidence demonstrates that the performance consequences of green innovation depend on innovation type (Bindeeba *et al*., 2025; Akbarighatar *et al*., 2026; Cheng *et al*., 2025b). These inconsistencies strengthen, rather than weaken, the rationale for testing the full sequence because they suggest that no individual capability is sufficient. The proposed serial pathways therefore examine whether GHRMPs are associated with sustainability outcomes when transmitted successively through EA and GIP.

H5d: *GHRMPs have a positive serial indirect association with ENP through EA and GIP*.

H5e: *GHRMPs have a positive serial indirect association with ECP through EA and GIP.*

All hypotheses are presented in Figure 1.

Empirical and methodological challenges in the existing literature

Despite growing evidence linking GHRMPs, digital technologies, green innovation, and sustainability performance, important empirical problems remain. The literature is fragmented, often examining green HR systems, AI-related capabilities, green innovation, and organisational performance separately rather than as an integrated capability-conversion process. Meta-analytic evidence indicates that the positive GHRM–green innovation relationship varies across industries, firm sizes, and study periods, while GHRM itself is inconsistently operationalised as either individual practices or an integrated bundle of recruitment, training, involvement, performance management, and rewards (Bindeeba *et al*., 2025). Sustainability outcomes are similarly heterogeneous: economic performance ranges from profitability and market indicators to operational savings, obscuring the distinction between broader financial outcomes and the resource-cost benefits of green innovation (Carballo-Penela *et al*., 2023). Responsible-AI research has also advanced from abstract principles toward organisational governance, yet the translation of transparency, privacy, fairness, accountability, safety, and human oversight into coherent, measurable practices remains underdeveloped (Mäntymäki *et al*., 2022; Papagiannidis *et al*., 2025). Evidence that these principles operate differently across organisational and institutional contexts further supports treating ethical AI as a multidimensional governance capability rather than a universal checklist (Akbarighatar *et al*., 2026).

Recurring methodological limitations reinforce these concerns. Much of the GHRM and green-innovation literature relies on cross-sectional, self-reported, and single-source data, restricting causal inference and raising concerns about common method variance, reverse relationships, and temporal ordering (Bindeeba *et al.*, 2025). Geographically concentrated samples, differing construct specifications, and varied analytical approaches also limit generalisability and comparability. Because GHRMPs, responsible AI governance, green innovation, and environmental performance are theoretically adjacent, careful assessment of dimensionality, collinearity, and discriminant validity is essential. These challenges informed the present design: GHRMPs are modelled as a reflective–formative higher-order construct comprising five HR dimensions; EA is operationalised through organisational governance practices; and environmental performance is distinguished from operational economic performance. Although the cross-sectional key-informant design cannot establish temporal causality, the study uses respondent-eligibility criteria, one observation per firm, procedural and statistical common-method controls, two-stage PLS-SEM, bootstrapped specific and serial indirect effects, and out-of-sample predictive assessment. The following section details these measurement, sampling, and analytical procedures.

Methods

Operationalization and measures

The study examines five focal constructs—GHRMP, EA, GIP, ENP, and ECP. All items were assessed using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Consistent with research conceptualising GHRM as a bundled organisational capability, GHRMP was specified as a second-order formative construct composed of five first-order reflective dimensions: green employee involvement (GEI), green recruitment and selection (GRS), green training and development (GTD), green performance management (GPM), and green compensation and rewards (GCR). The modelling procedure for this hierarchical construct is described in the Higher-Order Construct Specification and Estimation subsection, while the operational definitions and measurement items are presented in Table 1.

Table 1 presents the initial pool of measurement items administered in the questionnaire, whereas the final PLS-SEM specification contains the indicators retained after construct-scope clarification and measurement-model assessment. EA5 and GIP6 were excluded from the final measurement model because their outer loadings were below the recommended threshold of 0.70, indicating insufficient indicator reliability. Their removal did not materially reduce construct coverage: EA1–EA4 retain the core principles of transparency, privacy, fairness, and accountability, while the retained GIP indicators continue to capture both green product and process innovation. ECP4 and ECP5 were excluded during construct refinement because they measure broader accounting outcomes—return on investment and earnings per share—whereas the final ECP construct was deliberately defined as operational economic performance reflected in reductions in material, energy, and waste-disposal costs. The final measurement model therefore comprises EA1–EA4, GIP1–GIP5 and GIP7–GIP8, and ECP1–ECP3.

Sampling technique and data collection

A cross-sectional structured online questionnaire was administered to knowledgeable key informants from medium-sized manufacturing firms employing 50–200 employees and large manufacturing firms employing more than 200 employees in Thailand. The firm constituted the unit of analysis, while one eligible organisational representative provided information about each firm's GHRMPs, EA, GIP, ENP, and ECP. Respondents were required to be employed full-time, have at least one year of organisational tenure, and occupy a supervisory or higher-level position. Eligible positions included supervisor, manager, general manager, director, and president/owner, particularly in human resources, operations or production, IT or AI, sustainability, and general management. These eligibility requirements were intended to ensure that respondents possessed sufficient knowledge of the firm-level practices and outcomes examined in the study.

Potential respondents were accessed through industry-specific associations and professional networks. A purposive key-informant sampling approach was adopted because participation required knowledge of organisational human resource practices, AI use, green innovation, and sustainability outcomes. The questionnaire was administered through Google Forms, while invitations and follow-up communications were distributed through LINE, personal referrals, email invitations, and telephone outreach. These channels facilitated access to eligible supervisory, managerial, and executive respondents across different manufacturing activities and locations in Thailand.

Before full administration, the questionnaire was reviewed by academic experts and pilot-tested with managers from Thai manufacturing firms, resulting in minor refinements to its wording and presentation. Several procedural measures were implemented to reduce evaluation apprehension and potential common method bias. Participation was voluntary and confidential, respondents were informed that the findings would be reported only in aggregate, and the instructions emphasised that there were no objectively correct or socially preferred responses. Predictor and outcome measures were placed in separate questionnaire sections, and concise and neutral wording was used throughout.

Survey invitations were distributed to 800 eligible organisational contacts. A total of 481 completed questionnaires were received, corresponding to a gross completion rate of 60.1%. Following data screening, 59 questionnaires were excluded because of substantial missing information or evidence of inattentive responding. The final analytical sample therefore comprised 422 usable responses, yielding a usable response rate of 52.8% and a retention rate of 87.7% among completed questionnaires.

The firm was treated as the unit of analysis, and only one knowledgeable key informant was retained for each participating organisation. To ensure independence of observations, completed questionnaires were cross-checked against available survey-administration records and organisational-affiliation information to identify possible multiple submissions from the same firm. No duplicate firm-level observations remained in the final analytical dataset. Consequently, the 422 usable responses represented 422 distinct manufacturing firms.

The sampling frame was open to medium-sized and large firms from all manufacturing industries in Thailand. Based on the available recruitment information, the most commonly represented manufacturing groups were automotive, electronics, and food processing, although firms from other manufacturing activities were also represented. Geographically, participating firms were dispersed across Thailand, with notable representation from Bangkok, Samut Prakan, and Chonburi. Because detailed subsectoral and province-level frequencies were not retained in the final analytical dataset, these characteristics are reported as descriptive indicators of sample coverage rather than evidence of proportional sectoral or regional representation. Moreover, because purposive rather than probability sampling was used, the sample should not be interpreted as statistically representative of the entire Thai manufacturing population.

Potential non-response bias was assessed through an early–late respondent comparison, with later respondents treated as proxies for organisations that were initially less inclined to participate. The 422 usable responses were ordered according to questionnaire-completion timestamp. The first and final quartiles were classified as early and late respondents, respectively, resulting in 106 cases in each group; the middle 50% was excluded to maximise the temporal distinction between the comparison groups. Construct scores were calculated using the indicators retained in the final measurement model, and Welch's independent-samples t tests were used to compare GHRMPs, EA, GIP, ENP, and ECP across the two groups.

Analysis technique

PLS-SEM was applied to estimate the measurement and structural models using SmartPLS 4. A variance-based approach was appropriate given the study's predictive orientation, the presence of multiple latent variables connected through direct and indirect relationships, and the evolving theoretical development of greentech research (Hair *et al*., 2017).

Because the data were collected from one key informant through a single self-report questionnaire, potential common method variance was addressed using procedural remedies and multiple post hoc diagnostics. Procedurally, participation was voluntary and confidential, the findings were reported only in aggregate, neutral and concise item wording was used, and respondents were informed that there were no objectively correct or socially preferred answers. Predictor and outcome measures were also presented in separate questionnaire sections. Statistically, full-collinearity VIF values were examined for all latent constructs using the conservative threshold of 3.3 (Kock, 2015). As a supplementary diagnostic, a single-factor confirmatory measurement model was estimated using maximum likelihood, with all 38 indicators retained in the final measurement model constrained to load on one latent factor. The combined diagnostics were used to assess whether a dominant common method factor was evident. Nevertheless, because the study did not include a marker variable, temporal separation, multiple informants, or an explicitly modelled latent method factor, residual common method variance cannot be excluded.

The analysis followed a two-step procedure. First, the measurement model was evaluated using outer loadings, average variance extracted (AVE), Cronbach's alpha (CA), and composite reliability (CR). Indicators with loadings of at least 0.70 were retained where feasible, AVE values of 0.50 or higher indicated satisfactory convergent validity, and CA and CR values of at least 0.70 demonstrated adequate internal consistency (Hair *et al.*, 2017). Discriminant validity was examined using the Fornell–Larcker criterion, cross-loadings, and the heterotrait–monotrait ratio of correlations (HTMT) (Henseler *et al.*, 2015). HTMT inference was conducted using 10,000 bootstrap subsamples, one-tailed testing at α = .05, and bias-corrected bootstrap bounds. Construct distinctiveness was evaluated using both the stricter criterion that the upper bound remain below 0.90 and the original HTMT-inference criterion that the bootstrap interval should not include 1.00.

Second, the structural model was assessed using inner VIF values, coefficients of determination (R^2 and adjusted R^2), f^2 effect sizes, approximate model-fit indices, and the significance of the direct and indirect relationships. Inner VIF values below 3.3 indicated the absence of critical predictor collinearity, while f^2 values of 0.02, 0.15, and 0.35 were interpreted as small, medium, and large effects, respectively. Approximate model fit was examined using the standardised root mean square residual (SRMR), d_ULS, d_G, and the normed fit index (NFI). Statistical significance was evaluated using nonparametric bootstrapping with 10,000 subsamples, two-tailed testing at α = .05, and percentile-based 95% confidence intervals.

Out-of-sample predictive performance was assessed using PLSpredict with 10 folds and 10 repetitions. Predictive relevance was evaluated through Q^2predict values, and PLS-SEM prediction errors were compared with those of the indicator-average and linear-model benchmarks. CVPAT was additionally applied to determine whether the PLS-SEM model achieved significantly lower predictive loss than these benchmarks (Shmueli *et al.*, 2019; Liengaard *et al.*, 2021).

Specific indirect effects were assessed using nonparametric bootstrapping with 10,000 subsamples, two-tailed testing at α = .05, and percentile-based 95% confidence intervals. The structural model did not include direct paths from GHRMP to GIP or from EA to ENP and ECP because the theorised model focused on transmitting these relationships through EA and GIP, respectively. Consequently, H5a–H5c were evaluated as specific indirect-effect hypotheses. The results were not used to classify these relationships as full, partial, complementary, or competitive mediation because such classifications require estimation of the corresponding direct effects.

In addition to the component-specific indirect effects, the complete serial specific indirect effects of GHRMPs on ENP and ECP through EA and GIP were assessed using nonparametric bootstrapping with 10,000 subsamples, two-tailed testing at α = .05, and percentile-based 95% confidence intervals. A serial indirect effect was considered statistically significant when its confidence interval excluded zero. The corresponding total effects were also examined by combining the estimated direct and indirect relationships.

Given the cross-sectional, single-informant, and self-reported design, the estimated path coefficients and specific indirect effects are interpreted as theory-consistent statistical associations rather than causal relationships. The design does not establish temporal ordering among GHRMPs, EA, GIP, ENP, and ECP, and the possibility of reverse relationships cannot be excluded.

Higher-Order construct specification and estimation (Two-Stage PLS-SEM)

This study specifies GHRMP as a higher-order construct formed by five reflective lower-order dimensions: green employee involvement, green recruitment and selection, green training and development, green performance management, and green rewards and compensation. Conceptually, firms deploy these HR practices as a mutually reinforcing bundle that reflects an underlying "green HR architecture" rather than five isolated policies (Al-Swidi *et al*., 2021; Teng & Wu, 2025; Vázquez-Brust *et al*., 2023). A hierarchical specification therefore captures this integrated capability while avoiding long indicator lists and collinearity issues that arise when all items are estimated at a single level (Hair & Alamer, 2022; Sarstedt *et al*., 2019).

Stage 1 – estimation of lower-order components

In Stage 1, the five reflective GHRM dimensions—GEI, GRS, GTD, GPM, and GCR—were estimated together with EA, GIP, ENP, and ECP. Each reflective construct was assessed in terms of indicator reliability, internal consistency, convergent validity, and discriminant validity. After satisfactory measurement quality was established, latent-variable scores for the five GHRM dimensions were exported for use in the Stage-2 higher-order construct estimation.

Stage 2 – higher-order construct and structural model

In Stage 2, the latent-variable scores of the five GHRMP dimensions were re-imported as formative indicators of the higher-order construct. The reflective–formative specification was assessed by examining outer VIF values, formative outer weights, and their significance using 10,000-subsample bootstrapping, two-tailed testing, and percentile-based 95% confidence intervals. Outer VIF values below 5.0 indicated the absence of critical collinearity, with values close to or below 3.0 considered preferable. When a formative weight was nonsignificant, the corresponding outer loading and its significance were examined to assess the dimension's absolute contribution. Dimensions with meaningful and significant loadings were retained when theoretically necessary to preserve the content validity of GHRMP (Sarstedt *et al*., 2019; Hair & Alamer, 2022). The structural model then estimated the hypothesised direct and indirect relationships among GHRMP, EA, GIP, ENP, and ECP.

Results

Non-response bias assessment

Potential non-response bias was examined by comparing the first and final quartiles of respondents according to questionnaire-completion timestamp. As reported in Table 2, early respondents reported significantly higher GHRMP scores, $t(206.82) = 5.36$, $p < .001$, Hedges' $g = 0.73$, and EA scores, $t(200.60) = 4.59$, $p < .001$, Hedges' $g = 0.63$. No statistically significant early–late differences were identified for GIP, $p = .465$, ENP, $p = .840$, or ECP, $p = .058$, although the ECP difference approached the .05 significance level. Potential non-response bias therefore cannot be ruled out for GHRMPs and EA, whereas comparable differences were not evident for the innovation and performance outcomes. These findings are considered when interpreting the structural relationships, and the diagnostic does not conclusively represent organisations that declined to participate.

Common Method Variance (CMV)

Potential common method variance was evaluated using the procedural safeguards described above, full-collinearity VIFs, and a supplementary single-factor confirmatory measurement model. The full-collinearity VIF values ranged from 1.546 to 2.523 and remained below the conservative threshold of 3.3, indicating no critical common method inflation.

The single-factor model, in which all 38 retained indicators were constrained to load on one latent factor, exhibited poor fit: $\chi^2(665) = 3{,}869.24$, $p < .001$, CFI = .699, TLI = .682, RMSEA = .107, and SRMR = .084. Thus, one general factor did not adequately reproduce the covariance structure of the observed indicators. Considered together, the procedural remedies, full-collinearity VIF results, and poor fit of the single-factor model do not indicate that a dominant common method factor explains the data. These diagnostics cannot, however, eliminate method-related covariance; residual CMV remains possible because the research design relied on one respondent per firm and did not include a marker variable, temporal separation, multiple data sources, or a latent method factor.

Sample demographics

The final sample consisted of 422 respondents working in Thai manufacturing enterprises. Males represented 64.69%, consistent with the gender structure typical of production-intensive sectors. The age profile was mainly mid-career, with 43.60% aged 30–39 and 36.26% aged 40–49, indicating substantial organisational tenure and familiarity with operational realities. The group was also highly educated: 52.84% held a master's degree and 36.49% a bachelor's degree, implying strong capacity to interpret firm-level HR, AI, and sustainability initiatives. Regarding hierarchical position, managers (45.26%) and supervisors (31.75%) formed the largest segments, thus integrating both operational and strategic viewpoints on GHRM, EA, and GIP. With respect to organisational scale, 53.08% of respondents came from medium-sized firms and 46.92% from large firms, providing a balanced representation across manufacturing contexts. Detailed sample characteristics are presented in Table 3.

Validity and reliability assessment

The initial item pool was screened for conceptual alignment, indicator reliability, and measurement quality before the final measurement model was assessed. EA5 and GIP6 were removed because their standardised outer loadings were below the recommended threshold of 0.70, indicating insufficient indicator reliability. ECP4 and ECP5 were excluded to maintain the construct's focus on operational resource-cost performance rather than broader accounting returns. The final retained indicator set is reported consistently in Tables 4 and 7.

The measurement properties of the retained indicators were evaluated in terms of reliability and convergent and discriminant validity. All retained indicators exhibited standardised outer loadings above 0.70, indicating satisfactory indicator reliability (Hair *et al.*, 2017). As reported in Table 4, the AVE values for all constructs exceeded 0.50, while Cronbach's alpha and composite reliability values were above 0.70, confirming satisfactory convergent validity and internal consistency.

Discriminant validity was assessed using the Fornell–Larcker criterion, cross-loadings, and the HTMT. As shown in Table 5, the Fornell–Larcker criterion was satisfied for most construct pairs, but two exceptions were identified. The EA–GEI correlation (0.814) exceeded the square roots of AVE for EA (0.799) and GEI (0.806), while the GIP–ENP correlation (0.777) exceeded the square root of AVE for GIP (0.761). The criterion was therefore not fully satisfied, warranting further assessment using the more diagnostic HTMT procedure (Henseler *et al.*, 2015).

The HTMT results reported in Table 6 show that all point estimates were below 0.90, ranging from 0.487 to 0.881. For the construct pairs highlighted by the reviewer, the HTMT values were 0.844 for EA–GEI and 0.863 for GIP–ENP. Bias-corrected bootstrap inference based on 10,000 subsamples showed that none of the upper bounds reached 1.00, supporting construct distinctiveness under the original HTMT inference criterion. Nevertheless, the upper bounds for GIP–ENP (0.907), GPM–EA (0.920), GPM–GCR (0.909), and GPM–GEI (0.927) marginally exceeded the stricter 0.90 benchmark. The results therefore provide overall, although not unequivocal, support for discriminant validity.

Focusing specifically on the five GHRMP dimensions, the HTMT point estimates ranged from 0.720 to 0.881 and all remained below 0.90. Most bias-corrected upper bounds also remained below 0.90; however, the upper bounds for GPM–GCR (0.909) and GPM–GEI (0.927) marginally exceeded this stricter benchmark, although neither confidence interval included 1.00. The evidence therefore supports the empirical distinctiveness of the GHRMP dimensions overall, but not unequivocally. This interpretation is further supported by the cross-loadings reported in Table 7, as every indicator loaded most strongly on its intended dimension, and by the outer VIF values of 2.169–3.075 reported in Table 8, which indicate that the five lower-order components do not exhibit critical redundancy. Nevertheless, the two borderline HTMT relationships are acknowledged and interpreted cautiously.

The relatively high associations are theoretically plausible because the five dimensions form complementary elements of an integrated green HR architecture, but they remain functionally distinct. GRS concerns the acquisition of employees whose values and competencies fit environmental objectives; GTD concerns the development of environmental knowledge and skills; GPM concerns formal goal setting, appraisal, monitoring, and feedback; GCR concerns monetary and non-monetary reinforcement; and GEI concerns employee voice, communication, participation, and environmental problem solving. The higher GPM–GCR association reflects the practical connection between evaluating environmental performance and rewarding it, but performance control and incentive provision remain different HR functions. Similarly, GPM and GEI are related because performance expectations may encourage employee participation, yet GPM represents formal managerial control, whereas GEI represents employee voice and involvement. Retaining the five dimensions therefore preserves the content validity of the reflective–formative higher-order GHRMP construct rather than treating closely related but non-interchangeable practices as a single undifferentiated component.

Assessment of the Higher-Order GHRMP Construct

After establishing the reliability and validity of the five reflective lower-order dimensions, the formative measurement properties of the higher-order GHRMP construct were assessed. As reported in Table 8, the outer VIF values ranged from 2.169 to 3.075. All values were below 3.3 and substantially below the critical threshold of 5.0, indicating that the five dimensions did not exhibit problematic collinearity. Although the VIF values for green employee involvement and green compensation and rewards marginally exceeded the stricter benchmark of 3.0, they remained within acceptable limits.

The bootstrapping results indicated significant formative weights for green employee involvement (weight = 0.435, t = 5.993, $p < .001$, 95% CI [0.289, 0.572]), green recruitment and selection (weight = 0.171, t = 2.471, p = .013, 95% CI [0.042, 0.311]), and green compensation and rewards (weight = 0.266, t = 3.304, p = .001, 95% CI [0.108, 0.421]). Green employee involvement exhibited the largest formative weight and therefore made the strongest relative contribution to the higher-order GHRMP construct.

The formative weights of green training and development (weight = 0.131, t = 1.946, p = .052, 95% CI [−0.001, 0.261]) and green performance management (weight = 0.139, t = 1.894, p = .058, 95% CI [−0.004, 0.283]) did not reach statistical significance at the 5% level. Nevertheless, their outer loadings were substantial—0.830 and 0.846, respectively—and statistically significant at $p < .001$, demonstrating meaningful absolute contributions to GHRMP. Both dimensions were therefore retained because employee capability development and the alignment of performance systems with environmental objectives are theoretically indispensable to the content domain of a comprehensive green HR architecture. Overall, the results support the reflective–formative higher-order specification of GHRMP: three dimensions provide significant relative contributions, while the remaining two provide meaningful absolute contributions without introducing critical multicollinearity.

Structural model assessment

The inner VIF values ranged from 1.000 to 2.362, remaining below the conservative threshold of 3.3 and indicating that predictor collinearity did not materially affect the structural estimates. The model explained 71.6% of the variance in EA ($R^2 = 0.716$; adjusted $R^2 = 0.716$), 53.7% in GIP ($R^2 = 0.537$; adjusted $R^2 = 0.536$), 60.5% in ENP ($R^2 = 0.605$; adjusted $R^2 = 0.603$), and 49.7% in ECP ($R^2 = 0.497$; adjusted $R^2 = 0.495$). The close correspondence between the R^2 and adjusted R^2 values indicates that explanatory performance was not materially inflated by the number of predictors.

The f^2 results further clarify the substantive contribution of the structural relationships. GHRMP had a large effect on EA ($f^2 = 2.527$), and EA had a large effect on GIP ($f^2 = 1.160$). GIP also had large effects on ENP ($f^2 = 0.703$) and ECP ($f^2 = 0.493$). By contrast, the direct contributions of

GHRMP to ENP (f^2 = 0.002) and ECP (f^2 = 0.006) were negligible. These findings reinforce the interpretation of GHRMP as a distal enabling capability and GIP as the proximal mechanism associated with both sustainability outcomes.

The saturated-model SRMR was 0.062, whereas the estimated-model SRMR was 0.082. The latter is close to the conventional 0.08 guideline and should therefore be interpreted cautiously rather than as evidence of unequivocally strong model fit. The saturated/estimated values were 1.073/1.853 for d_ULS, 0.442/0.524 for d_G, and 0.837/0.816 for NFI. These approximate-fit measures were considered alongside the model's explanatory and predictive performance.

Out-of-sample predictive assessment

The model's out-of-sample predictive performance was assessed using PLSpredict with 10 folds and 10 repetitions. All construct-level Q^2predict values were positive—EA = 0.708, GIP = 0.550, ENP = 0.304, and ECP = 0.229—indicating predictive relevance relative to the indicator-average benchmark. CVPAT confirmed that PLS-SEM achieved significantly lower predictive loss than the indicator-average benchmark (average loss difference = −0.417, t = 11.211, $p < .001$). However, the comparison with the linear-model benchmark was non-significant (average loss difference = 0.007, t = 1.091, p = .276), and PLS-SEM produced lower RMSE values for only 4 of the 18 endogenous indicators.

Considered together with the effect-size results, these findings provide complementary robustness evidence. The principal capability-conversion relationships exhibited large f^2 values, whereas the direct contributions of GHRMPs to ENP and ECP were negligible. The model therefore demonstrates substantive explanatory importance and out-of-sample predictive relevance, but it does not exhibit superior predictive performance relative to the linear-model benchmark.

Hypothesis testing

The structural relationships were evaluated using 10,000 bootstrap subsamples, two-tailed testing at α = .05, and percentile-based 95% confidence intervals. As reported in Table 9, H1 is supported because GHRMPs have a strong positive effect on EA (β = 0.846, t = 52.731, $p < .001$, 95% CI [0.814, 0.877]). H2 is also supported, as EA positively affects GIP ($\beta = 0.733$, $t = 26.229$, $p < .001$, 95% CI [0.676, 0.785]). Both sustainability-performance hypotheses are supported. GIP has a significant positive effect on ENP (H3a: $\beta = 0.810$, $t = 16.572$, $p < .001$, 95% CI [0.704, 0.897]) and ECP (H3b: $\beta = 0.765$, $t = 15.837$, $p < .001$, 95% CI [0.663, 0.853]). By contrast, the direct effects of GHRMPs on ENP (H4a: $\beta = -0.043$, $t = 0.729$, $p = .466$, 95% CI [−0.147, 0.084]) and ECP (H4b: $\beta = -0.082$, $t = 1.434$, $p = .152$, 95% CI [−0.185, 0.041]) are nonsignificant. Accordingly, H4a and H4b are not supported.

Table 10 reports the component-specific and serial indirect effects. GHRMPs have a significant positive indirect effect on GIP through EA (H5a: $\beta = 0.620$, $t = 20.550$, $p < .001$, 95% CI [0.562, 0.679]). EA also has a significant positive indirect effect on ENP through GIP (H5b: $\beta = 0.593$, $t = 12.748$, $p < .001$, 95% CI [0.498, 0.682]) and a significant positive indirect effect on ECP through GIP (H5c: $\beta = 0.561$, $t = 12.856$, $p < .001$, 95% CI [0.473, 0.645]). Because the corresponding direct paths—GHRMP → GIP, EA → ENP, and EA → ECP—were not specified, these findings demonstrate significant indirect transmission through the proposed mechanisms but do not permit classification as full, partial, complementary, or competitive mediation.

The complete serial capability-conversion pathways were also tested directly. GHRMPs have a significant positive serial specific indirect effect on ENP through EA and GIP (H5d: $\beta = 0.502$, bootstrap SE = 0.042, $t = 12.057$, $p < .001$, 95% CI [0.419, 0.583]). The corresponding total effect of GHRMPs on ENP is also significant ($\beta = 0.460$, $t = 10.267$, $p < .001$, 95% CI [0.378, 0.553]). Because the direct GHRMP–ENP relationship is nonsignificant, the results indicate that the positive relationship between GHRMPs and environmental performance is transmitted through the sequential EA and GIP pathway. H5d is therefore supported.

GHRMPs likewise have a significant positive serial specific indirect effect on operational ECP through EA and GIP (H5e: $\beta = 0.475$, bootstrap SE = 0.040, $t = 11.747$, $p < .001$, 95% CI [0.396, 0.555]). The corresponding total effect is significant ($\beta = 0.393$, $t = 8.448$, $p < .001$, 95% CI [0.307, 0.490]), whereas the direct GHRMP–ECP relationship remains nonsignificant. This pattern indicates that the relationship between GHRMPs and operational economic performance is similarly transmitted through responsible AI governance and green innovation rather than operating directly. H5e is therefore supported.

Taken together, the two serial indirect effects provide direct empirical support for the proposed capability-conversion sequence. GHRMPs function as a distal enabling capability, EA as an intermediate governance capability, and GIP as the proximal mechanism associated with environmental improvement and operational resource-cost efficiency. The significant serial indirect effects, combined with the nonsignificant direct GHRMP–outcome relationships, are consistent with indirect-only serial transmission through EA and GIP. Given the cross-sectional design, however, these findings represent statistical indirect associations and should not be interpreted as definitive evidence of temporal causation.

Discussion

The findings support an indirect capability-conversion interpretation of the NRBV. The significant GHRMP–EA, EA–GIP, and GIP–performance relationships, together with the nonsignificant direct GHRMP–ENP and GHRMP–ECP paths, indicate that green HR architecture is unlikely to generate firm-level sustainability value independently. Rather, its contribution appears to depend on whether environmental competencies, incentives, participation, and accountability are translated into responsible governance routines and implemented green innovation. The significant serial indirect associations with ENP and ECP are therefore consistent with a coordinated capability system in which GHRMPs operate as a distal enabling capability, EA as an intermediate governance capability, and GIP as the proximal value-realisation mechanism (Hart & Dowell, 2011; Mady *et al*., 2023).

The strong GHRMP–EA relationship suggests that ethical AI has organisational and human-resource microfoundations. Principles such as transparency, privacy, fairness, and accountability may remain aspirational unless employees possess the knowledge, role clarity, incentives, and participation opportunities required to enact them. GHRMPs may support EA by embedding responsibility expectations into recruitment, training, appraisal, rewards, and employee involvement. This extends GHRM research beyond pro-environmental employee behaviour and complements responsible-AI research by identifying HR architecture as a potential organisational foundation for the practical enactment of ethical AI governance (Aftab *et al*., 2023; Vázquez-Brust *et al*., 2023; Mäntymäki *et al*., 2022; Papagiannidis *et al*., 2025).

The EA–GIP relationship further indicates that ethical governance need not function solely as a compliance constraint. Ethical practices that improve the traceability, legitimacy, and accountability of AI-supported decisions may reduce uncertainty surrounding data use and clarify responsibility for experimentation, thereby making AI-supported environmental initiatives more organisationally acceptable and usable. However, this relationship should not be interpreted as evidence that formal ethical principles automatically promote innovation. Fragmented, symbolic, or excessively procedural governance may instead increase administrative burdens without improving innovation quality. The positive association is therefore most plausibly linked to ethical practices that are integrated into organisational decision-making and innovation routines (Papagiannidis *et al*., 2025; Akbarighatar *et al*., 2026).

GIP was strongly associated with ENP ($\beta = 0.810$, $f^2 = 0.703$) and operational ECP ($\beta = 0.765$, $f^2 = 0.493$). The findings therefore do not suggest that green innovation fails to generate economic value. Rather, implemented green product and process innovations are associated with operational savings through lower material, energy, and waste-disposal costs. Because the final ECP construct captures resource-cost efficiency rather than profitability, return on investment, earnings per share, or market performance, the result supports an eco-efficiency interpretation rather than a general financial-performance claim (Zhang & Ma, 2021; Carballo-Penela *et al*., 2023; Cheng *et al*., 2025b).

The descriptively stronger GIP–ENP relationship is theoretically plausible because environmental outcomes are more proximal to implemented green innovation. Cleaner products and processes directly alter material consumption, energy use, emissions, recycling, and waste, whereas operational economic value requires these physical efficiencies to become sufficiently stable and substantial to produce observable savings. Upfront investment, process reconfiguration, employee learning, implementation scale, regulatory compliance, and delayed cost recovery may weaken or postpone broader financial benefits (Mady *et al*., 2023; Maldonado-Guzmán *et al*., 2023; Cheng *et al*., 2025b). Because the coefficient magnitudes were not formally compared and the cross-sectional design cannot distinguish short-term from long-term outcomes, this pattern represents tentative environmental–economic variation rather than confirmed asymmetry.

The unsupported H4a and H4b relationships are theoretically informative. GHRMPs develop competencies, incentives, accountability, and participation, but they do not directly modify production technologies, material inputs, energy intensity, emissions, or waste. Their direct contributions to ENP ($f^2 = 0.002$) and ECP ($f^2 = 0.006$) were negligible, whereas the serial indirect associations through EA and GIP remained significant. Green HR practices may also be implemented unevenly, remain symbolic, or be insufficiently connected with production investment and environmental strategy. Their performance implications therefore appear to depend on conversion through more proximal governance and innovation mechanisms rather than arising directly from HR practices themselves (Singh *et al.*, 2020; Aftab *et al.*, 2023; Aftab & Veneziani, 2024; Bindeeba *et al.*, 2025).

The effect-size and predictive analyses provide qualified robustness support for this interpretation. The principal capability-conversion relationships exhibited large f^2 values, all endogenous constructs produced positive Q^2predict values, and CVPAT indicated lower predictive loss than the indicator-average benchmark. However, the model did not significantly outperform the linear-model benchmark. The evidence therefore supports substantive explanatory importance and predictive relevance, but not superior predictive performance.

These conclusions should be bounded by the empirical context. The evidence concerns medium-sized and large Thai manufacturing firms operating under emerging-economy resource constraints, export-oriented supply-chain pressures, and national sustainability initiatives. The context-specific finding is that the proposed capability-conversion pattern is statistically supported in this setting. The more general theoretical implication is narrower: sustainability value may depend on complementarity among human, governance, and innovation capabilities, but the precise sequence and coefficient magnitudes should not be assumed to apply universally across countries or industries. Regulatory regimes, labour institutions, AI maturity, access to finance, energy prices, exchange-rate movements, and export demand may independently influence green investment and operational performance and were not explicitly modelled in this study (Hart & Dowell, 2011; FTI, 2023; OECD, 2026; World Bank, 2026).

Finally, the results do not establish temporal or causal ordering. All constructs were measured simultaneously using self-reported information from one key informant per firm, reverse relationships remain plausible, and potential non-response bias cannot be excluded for GHRMPs and EA. Longitudinal, multi-informant, cross-country, and externally validated studies are therefore needed to test whether the proposed capability sequence unfolds over time and whether its environmental and economic associations vary across regulatory, institutional, and macroeconomic conditions.

Implications

Theoretical implications

The findings refine the NRBV by shifting attention from resource possession to staged capability conversion. The nonsignificant direct GHRMP–performance relationships, together with the significant serial indirect associations through EA and GIP, suggest that green HR architecture is not sufficient to create sustainability value independently. Its value appears to depend on whether HR-based competencies, incentives, participation, and accountability are combined with governance routines and subsequently embodied in implemented green innovation. The NRBV should therefore account not only for capability complementarity but also for the sequence through which distal organisational resources become associated with proximal operational outcomes (Hart & Dowell, 2011; Mady *et al*., 2023).

The results also refine the NRBV assumption that coordinated environmental capabilities generate a unified form of sustainability value. Environmental and operational economic outcomes represent distinct stages of value realisation. Green innovation is relatively proximal to changes in energy use, materials, emissions, recycling, and waste, whereas operational economic value requires these physical improvements to be converted into stable material, energy, and waste-disposal savings. The descriptively different coefficients therefore suggest that capability conversion may vary according to outcome proximity, implementation costs, and the time required to realise value. Because the coefficient magnitudes were not formally compared, this constitutes tentative environmental–economic variation rather than confirmed asymmetry (Carballo-Penela *et al*., 2023; Maldonado-Guzmán *et al*., 2023).

Finally, the study extends the NRBV to digitally enabled sustainability by positioning EA as an intermediate governance capability. The strategic value of AI-related resources may depend not only on their technical sophistication but also on whether transparency, privacy, fairness, and accountability make AI-supported decisions organisationally legitimate and usable. In the Thai manufacturing context, the findings are consistent with EA linking human-resource architecture to green innovation, although the precise capability configuration may differ across institutional and industrial environments (Mäntymäki *et al*., 2022; Papagiannidis *et al*., 2025).

Practical implications

For resource-constrained manufacturers, implementation should follow a phased approach rather than requiring an immediate enterprise-wide governance system. In the short term, firms can prioritise one or two high-value applications, such as energy optimisation, predictive maintenance, emissions monitoring, or scrap reduction. Feasible practices include assigning an accountable project owner, defining basic human-review points, using simple data-quality and privacy checklists, providing focused training to existing employees, and documenting responsibility for AI-supported decisions. These relatively low-cost measures can connect GHRMPs, ethical safeguards, and green-innovation activity without requiring substantial new infrastructure (Mäntymäki *et al*., 2022; Papagiannidis *et al*., 2025).

As organisational capacity develops, firms can integrate these practices into HR and innovation systems. Medium-term actions include incorporating environmental and AI-governance responsibilities into job descriptions, training, appraisal, rewards, and employee-involvement mechanisms; introducing sustainability criteria into innovation stage gates; and monitoring leading indicators such as training completion, employee-generated green ideas, documented decision rights, and the proportion of AI projects converted into implemented innovations. Lagging indicators should then track material and energy productivity, emissions and waste reduction, and operational resource-cost savings. This distinction is important because enabling investments may not produce immediate firm-level outcomes (Aftab *et al*., 2023; Carballo-Penela *et al*., 2023).

Longer-term governance aspirations may include formal cross-functional oversight bodies, automated model monitoring, independent audits, integrated data infrastructure, and the scaling of successful green-AI applications across operations. Such investments should be sequenced according to firm size, AI maturity, financing capacity, regulatory exposure, and expected payback periods. Industry associations, technology partners, and public support programmes may help smaller or more resource-constrained firms access shared training, technical expertise, and governance templates. Because these specific practices were not directly measured, they should be treated as context-sensitive implementation options rather than universally validated prescriptions.

Conclusions

The findings are consistent with an indirect capability-conversion pattern linking GHRMPs, EA, GIP, and sustainability performance in Thai manufacturing. GHRMPs were strongly associated with EA, EA was positively associated with GIP, and GIP was positively associated with both environmental performance and operational resource-cost efficiency. By contrast, GHRMPs did not retain significant direct relationships with either performance outcome after EA and GIP were incorporated. The significant serial indirect associations therefore support an interpretation in which green HR architecture operates as a distal enabling capability, EA as an intermediate governance capability, and GIP as the proximal mechanism associated with sustainability value.

The study refines the NRBV by indicating that complementary capabilities may create differentiated forms of sustainability value through a staged conversion process rather than through uniform direct effects. However, this conclusion is bounded by the cross-sectional evidence from medium-sized and large Thai manufacturing firms and by the focused operationalisation of EA through transparency, privacy, fairness, and accountability. The findings therefore represent context-specific, theory-consistent associations rather than universal or causal evidence regarding the proposed capability sequence.

Limitations and future studies

This study has several limitations. First, all constructs were measured perceptually through one key informant per firm. Respondents' assessments may be affected by recall limitations, social-desirability tendencies, halo effects, or differences in their access to information about HR practices, AI governance, innovation, and performance. Perceived improvements in environmental and economic performance may also differ from verified organisational outcomes. Although procedural remedies, full-collinearity

VIF assessment, and a supplementary single-factor measurement-model test were applied, residual method-related covariance cannot be excluded.

Second, the purposive sample consisted of medium-sized and large manufacturing firms in Thailand. The relationships may differ in small firms, service organisations, other industries, or countries with different regulatory systems, labour institutions, technological maturity, financial resources, and stakeholder pressures. Moreover, detailed subsectoral and provincial frequencies were not retained, limiting assessment of proportional representativeness and sector-specific heterogeneity. Generalisation beyond the sampled Thai manufacturing context should therefore be undertaken cautiously.

Third, EA was operationalised narrowly through the four dimensions retained in the final measurement model: transparency, privacy, fairness, and accountability. This focused measure does not comprehensively capture the broader domain of responsible AI governance, including safety, security, technical robustness, human oversight, stakeholder participation, regulatory compliance, lifecycle monitoring, and formal governance structures. The estimated EA relationships should therefore be interpreted as applying to a focused ethical-practice capability rather than to the complete responsible-AI governance domain.

Future research should employ longitudinal, panel, or cross-lagged designs to test temporal ordering and should obtain data from multiple organisational respondents. Perceptual measures could be combined with objective indicators such as verified emissions, energy and material intensity, water use, waste and recycling rates, environmental violations, audited operating costs, and third-party ESG measures. Cross-country and cross-industry comparisons should examine whether regulatory stringency, AI maturity, access to finance, investment payback periods, and macroeconomic conditions alter the proposed relationships. Future studies should also develop and validate broader multidimensional measures of EA using organisational policies, audit records, model documentation, incident reports, human-oversight procedures, and technical assessments of AI fairness, security, and robustness.

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AI declaration statement

The authors declare that they got acquired, accept and apply General Artificial Intelligence Policy of the publisher.

The authors declare that they have not used AI tools for research process.

Compliance with ethical standards

This article does not contain any studies with human participants or animals performed by the authors. Extracting and inspecting publicly accessible files (scholarly sources) as evidence, before the research began no institutional ethics approval was required.

Data availability statement

All data generated or analyzed are included in the published article. The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation. The raw anonymized data can be provided by emailing the primary author.

Author contributions

All listed authors have made a substantial, direct and intellectual contribution to the work, and approved it for publication. The authors take full responsibility for the accuracy and the integrity of the source analysis.

Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Annex

Table 1. Initial measurement items and final retention status

Variable	Operationalization	Measurement Items	Source	Final status
Green recruitment and selection	It concerns attracting and selecting employees whose environmental beliefs and values fit the firm's green culture and strategies, by using environmental criteria and green employer branding in job advertisements and selection decisions	1. My company attracts green job candidates who use green criteria to select organizations 2. My company uses green employer branding to attract green employees 3. My company recruits employees who have green awareness 4. My company considers candidates' green a ttitudes in recruitment and selection	Shah and Soomro (2023)	GRS1–GRS4: Retained
Green training and development	It refers to training and development programmes in environmental management that enhance employees' environmental awareness, knowledge, skills and values, and strengthen their involvement in the organisation's environmental initiatives	1. My company develops training programs in environment management to increase environmental awareness, skills and expertise of employees 2. My company provides employees with green training to promote green values 3. Our firm has integrated training to create the emotional involvement of employees in environment management 4. My company provides employees with green training to develop employees' knowledge and skills required for green management	Shah and Soomro (2023)	GTD1–GTD4: Retained
Green Performance management	It captures the integration of environmental targets and indicators into performance standards, appraisal and feedback systems so that employees' performance is aligned with organisational sustainability goals	1. My company sets green targets, goals and responsibilities for managers and employees 2. My company uses green performance indicators in performance appraisals 3. My company considers employees' workplace green behaviors in promotion 4. In our firm, there are disbenefits in the performance management system for non- compliance or not meeting environment management goals	Shah and Soomro (2023)	GPM1–GPM4: Retained

Table 1. Continued

Variable	Operationalization	Measurement Items	Source	Final status
Green Compensation and Rewards	It denotes the use of monetary and non-monetary incentives (e.g. financial bonuses, green benefits, recognition and time off) that are explicitly tied to employees' workplace green behaviours and contributions to environmental management	1. My company relates employees' workplace green behaviors to rewards and compensation 2. Our firm makes green benefits (transport/travel) available rather than giving out pre-paid cards to purchase green products 3. In our firms, there are financial or tax incentives (bicycle loans, use of less polluting cars) 4. Our firm has recognition-based rewards in environment management for staff (public recognition, awards, paid vacations, time off, gift certificates)	Shah and Soomro (2023)	GCR1–GCR4: Retained
Green employee involvement	It encompasses HR practices and communication mechanisms that give employees opportunities to participate in the organisation's environmental management—through learning, sharing ideas and feedback, and taking part in green initiatives and problem-solving activities that support the firm's environmental goals	1. Our company has a clear developmental vision to guide the employees' actions in environment management 2. There is a mutual learning climate among employees for green behavior and awareness in my company 3. There are a number of formal or informal communication channels to spread green culture in our company In our firm, employees are involved in quality improvement and problem-solving on green issues 4. Our company offers practices for employees to participate in environment management, such as newsletters, suggestion schemes, problem-solving groups, low-carbon champions and green action teams	Shah and Soomro (2023)	Final model: GEI1–GEI4
Ethical AI	The extent to which a firm's AI systems are governed and operated in line with core ethical principles of transparency, privacy protection, fairness and accountability, and supported by clearly communicated organisational guidelines	1. AI systems used in my company are transparent in their operations 2. The AI technologies in my company respect the privacy of users and stakeholders. 3. The AI systems used in my company aim to ensure fairness in decision-making processes. 4. In my company, it is clear who is accountable for decisions supported by AI systems. 5. The ethical guidelines governing AI technologies in my company are clearly communicated to employees and other relevant users.	Koo *et al.* (2025)	EA1–EA4: Retained EA5: Excluded (outer loading < 0.70)

Table 1. Continued

Variable	Operationalization	Measurement Items	Source	Final status
Green Innovation Performance	The extent to which a firm has successfully developed and implemented green product and process innovations that reduce environmental impacts through energy saving, pollution prevention, waste recycling, green product design, and improvements in environmental management	1. The company chooses the materials of the product that produce the least amount of pollution for conducting the product development or design. 2. The company chooses the materials of their products that consume the least amount of energy and resources for conducting the product development or design. 3. The company uses the fewest amount of materials to comprise their products for conducting the product development or design. 4. The company would circumspectly evaluate whether their products are easy to recycle, reuse, and decompose for conducting the product development or design. 5. The manufacturing process of the company effectively reduces the emission of hazardous substances or wastes. 6. The manufacturing process of the company effectively recycles wastes and emission that can be treated and re-used. 7. The manufacturing process of the company effectively reduces the consumption of water, electricity, coal, or oil. 8. The manufacturing process of the company effectively reduces the use of raw materials	Chang and Chen (2013)	GIP1–GIP5: Retained GIP6: Excluded (outer loading < 0.70) GIP7–GIP8: Retained
Environmental Performance	It pertains to the capability to minimize the use of harmful waste in the SC and also it pertains to the knack of growing plants to lessened emissions	1. The efficiency of the consumption of raw materials has improved during the last 3 years 2. The resource consumption (thermal energy, electricity, water) has decreased (e.g. per unit of income, per unit of production) during the last 3 years. 3. The percentage of recycled materials has increased during the last 3 years. 4. The waste ratio (e.g. kg per unit of product, kg per employee per year) has decreased during the last 3 years.	Khan *et al.*, 2021, Umar *et al.*, 2022	ENP1–ENP4: Retained

Table 1. Continued

Variable	Operationalization	Measurement Items	Source	Final status
Economic Performance	It pertains to the ability to reduce costs from the production process, including material and components purchasing, energy and water consumption and waste discharge	1. The company has decreased in cost of materials purchased 2. The company has decreased in cost of energy consumption 3. The company has decreased in fee for waste discharge 4. The company has improved its return on investment 5. The company has improved its earnings per share	Umar *et al.*, 2022	ECP1–ECP3: Retained ECP4–ECP5: Excluded (outside the final operational economic-performance scope)

Note: Table 1 reports the initial questionnaire item pool and the final retention decisions. Tables 3 and 6 report only the indicators retained in the final measurement model. EA5 and GIP6 were excluded because their outer loadings were below 0.70. ECP4 and ECP5 were excluded to preserve the final ECP construct's focus on operational resource-cost performance rather than broader accounting returns.

Table 2. Early–late respondent comparison for potential non-response bias

Construct	Early respondents, n = 106, Mean (SD)	Late respondents, n = 106, Mean (SD)	Welch's t	p	Hedges' g
GHRMPs	5.970 (0.656)	5.514 (0.579)	5.364	< .001	0.734
EA	5.955 (0.870)	5.458 (0.698)	4.593	< .001	0.629
GIP	5.554 (0.871)	5.473 (0.731)	0.732	.465	0.100
ENP	5.458 (1.025)	5.432 (0.835)	0.202	.840	0.028
ECP	5.289 (1.081)	5.575 (1.105)	−1.906	.058	−0.261

Note: Early and late respondents represent the first and final quartiles based on questionnaire-completion timestamps. Positive Hedges' g values indicate higher scores among early respondents.

Table 3. Sample demographics

Measure	Category	Frequency	Percentage
Gender	Male	273	64.69%
	Female	149	35.31%
Age	20-29	51	12.09%
	30-39	184	43.60%
	40-49	153	36.26%
	≥50	34	8.06%
Education	High school and equivalent	14	3.32%
	Bachelor's degree	154	36.49%
	Master's degree	223	52.84%
	Doctoral degree	31	7.35%
Positions	Supervisor	134	31.75%
	Manager	191	45.26%
	General Manager	37	8.77%
	Director	41	9.72%
	President/Owner	19	4.50%
Firm size	50-100 employees	57	13.51%
	101-200 employees	167	39.57%
	200-500 employees	114	27.01%
	> 500 employees	84	19.91%

Table 4. Convergent validity and reliability

Constructs	Items	Outer loading	CA	CR	AVE
	EA1	0.780			
Ethical AI (EA)	EA2	0.812			
	EA3	0.781	0.812	0.876	0.639
	EA4	0.823			
	ECP1	0.820			
Economic Performance	ECP2	0.849	0.810	0.888	0.725
(ECP)	ECP3	0.884			
	ENP1	0.808			
Environmental Performance	ENP2	0.813	0.819	0.880	0.648
(ENP)	ENP3	0.809			
	ENP4	0.789			
	GCR1	0.764			
Green Rewards and	GCR2	0.876	0.849	0.899	0.690
Compensation (GCR)	GCR3	0.875			
	GCR4	0.802			
	GEI1	0.771			
	GEI2	0.837			
Green Employee	GEI3	0.789	0.820	0.881	0.650
Involvement (GEI)	GEI4	0.826			
	GIP1	0.822			
	GIP2	0.740			
	GIP3	0.762			
	GIP4	0.727			
Green Innovation	GIP5	0.797	0.878	0.906	0.579
Performance (GIP)	GIP7	0.701			
	GIP8	0.772			
	GPM1	0.820			
Green Performance and	GPM2	0.806	0.823	0.883	0.653
Management (GPM)	GPM3	0.818			
	GPM4	0.787			
Green Recruitment and	GRS1	0.722	0.812	0.877	0.642
Selection (GRS)	GRS2	0.862			
	GRS3	0.841			
	GRS4	0.773			
Green Training and	GTD1	0.824	0.856	0.902	0.698
Development (GTD)	GTD2	0.852			
	GTD3	0.836			
	GTD4	0.829			

Note: Table 3 reports the final retained indicators. EA5 and GIP6 were excluded following measurement-model assessment, whereas ECP4 and ECP5 were excluded to preserve the operational resource-cost scope of ECP. The item-treatment decisions are explained in the Operationalization and Measures section.

Table 5. Fornell-Larcker criterion

Constructs	EA	ECP	ENP	GCR	GEI	GIP	GPM	GRS	GTD
EA	**0.799**								
ECP	0.533	**0.851**							
ENP	0.597	0.756	**0.805**						
GCR	0.748	0.455	0.517	**0.831**					
GEI	0.814	0.451	0.509	0.773	**0.806**				
GIP	0.733	0.703	0.777	0.656	0.706	**0.761**			
GPM	0.714	0.405	0.503	0.720	0.727	0.672	**0.808**		
GRS	0.618	0.395	0.476	0.602	0.591	0.597	0.629	**0.801**	
GTD	0.680	0.451	0.476	0.684	0.688	0.634	0.708	0.704	**0.835**

Table 6. HTMT estimates and bias-corrected bootstrap bounds

Construct pair	HTMT	Bias-corrected 5% bound	Bias-corrected 95% upper bound	Assessment
ECP-EA	0.650	0.569	0.730	Supported
ENP-EA	0.726	0.659	0.792	Supported
ENP-ECP	0.828	0.789	0.870	Supported
GCR-EA	0.798	0.747	0.868	Supported
GCR-ECP	0.544	0.451	0.637	Supported
GCR-ENP	0.610	0.508	0.708	Supported
GEI-EA	0.844	0.759	0.881	Supported
GEI-ECP	0.551	0.461	0.644	Supported
GEI-ENP	0.615	0.514	0.711	Supported
GEI-GCR	0.826	0.781	0.870	Supported
GIP-EA	0.867	0.791	0.889	Supported
GIP-ECP	0.799	0.741	0.857	Supported
GIP-ENP	0.863	0.818	0.907	Borderline (UB > .90)
GIP-GCR	0.744	0.675	0.809	Supported
GIP-GEI	0.830	0.770	0.887	Supported
GPM-EA	0.867	0.814	0.920	Borderline (UB > .90)
GPM-ECP	0.492	0.402	0.584	Supported
GPM-ENP	0.609	0.519	0.697	Supported
GPM-GCR	0.857	0.803	0.909	Borderline (UB > .90)
GPM-GEI	0.881	0.832	0.927	Borderline (UB > .90)
GPM-GIP	0.784	0.722	0.841	Supported
GRS-EA	0.759	0.703	0.814	Supported

Table 6. Continued

Construct pair	HTMT	Bias-corrected 5% bound	Bias-corrected 95% upper bound	Assessment
GRS-ECP	0.487	0.403	0.575	Supported
GRS-ENP	0.585	0.518	0.654	Supported
GRS-GCR	0.723	0.655	0.789	Supported
GRS-GEI	0.720	0.658	0.779	Supported
GRS-GIP	0.694	0.636	0.752	Supported
GRS-GPM	0.764	0.705	0.821	Supported
GTD-EA	0.808	0.760	0.856	Supported
GTD-ECP	0.537	0.460	0.616	Supported
GTD-ENP	0.561	0.486	0.635	Supported
GTD-GCR	0.798	0.750	0.847	Supported
GTD-GEI	0.817	0.770	0.866	Supported
GTD-GIP	0.730	0.677	0.781	Supported
GTD-GPM	0.835	0.793	0.876	Supported
GTD-GRS	0.844	0.806	0.882	Supported

Note: HTMT inference was based on 10,000 bootstrap subsamples, a one-tailed test at alpha = .05, and bias-corrected bootstrap bounds. An upper bound below .90 supports discriminant validity under the stricter HTMT.90 criterion. "Borderline" denotes an upper bound above .90 but below 1.00; none of the upper bounds reached 1.00.

Table 7. Cross-loadings matrix

Items	EA	ECP	ENP	GCR	GEI	GIP	GPM	GRS	GTD
EA1	**0.780**	0.375	0.483	0.590	0.685	0.563	0.574	0.508	0.536
EA2	**0.812**	0.546	0.535	0.628	0.680	0.662	0.606	0.506	0.619
EA3	**0.781**	0.355	0.437	0.566	0.590	0.544	0.544	0.497	0.499
EA4	**0.823**	0.412	0.447	0.605	0.642	0.564	0.553	0.463	0.511
ECP1	0.482	**0.820**	0.649	0.407	0.406	0.617	0.384	0.355	0.413
ECP2	0.415	**0.849**	0.668	0.361	0.373	0.574	0.348	0.314	0.341
ECP3	0.461	**0.884**	0.615	0.392	0.371	0.602	0.300	0.337	0.394
ENP1	0.455	0.605	**0.808**	0.371	0.356	0.594	0.382	0.335	0.315
ENP2	0.477	0.561	**0.813**	0.411	0.404	0.599	0.416	0.419	0.397
ENP3	0.521	0.618	**0.809**	0.503	0.486	0.706	0.445	0.403	0.449
ENP4	0.464	0.653	**0.789**	0.362	0.380	0.589	0.371	0.372	0.361
GCR1	0.557	0.343	0.403	**0.764**	0.564	0.481	0.599	0.470	0.545
GCR2	0.688	0.482	0.532	**0.876**	0.683	0.643	0.645	0.576	0.669
GCR3	0.631	0.352	0.417	**0.875**	0.654	0.539	0.604	0.498	0.555
GCR4	0.602	0.323	0.354	**0.802**	0.663	0.503	0.542	0.448	0.494

Table 7. Continued

Items	EA	ECP	ENP	GCR	GEI	GIP	GPM	GRS	GTD
GEI1	0.637	0.334	0.385	0.718	**0.771**	0.540	0.574	0.456	0.548
GEI2	0.679	0.432	0.426	0.690	**0.837**	0.637	0.617	0.525	0.646
GEI3	0.607	0.338	0.397	0.527	**0.789**	0.524	0.566	0.408	0.492
GEI4	0.698	0.345	0.433	0.558	**0.826**	0.571	0.588	0.511	0.528
GIP1	0.642	0.581	0.617	0.603	0.648	**0.822**	0.587	0.512	0.571
GIP2	0.548	0.500	0.532	0.414	0.523	**0.740**	0.482	0.401	0.408
GIP3	0.561	0.473	0.555	0.493	0.526	**0.762**	0.514	0.478	0.478
GIP4	0.511	0.438	0.576	0.477	0.460	**0.727**	0.498	0.402	0.440
GIP5	0.592	0.528	0.543	0.524	0.598	**0.797**	0.549	0.478	0.553
GIP7	0.470	0.573	0.691	0.468	0.456	**0.701**	0.456	0.442	0.400
GIP8	0.571	0.628	0.615	0.503	0.536	**0.772**	0.489	0.460	0.512
GPM1	0.533	0.271	0.368	0.510	0.534	0.496	**0.820**	0.497	0.571
GPM2	0.542	0.334	0.430	0.571	0.555	0.544	**0.806**	0.514	0.515
GPM3	0.613	0.396	0.417	0.615	0.625	0.591	**0.818**	0.562	0.666
GPM4	0.608	0.300	0.409	0.618	0.624	0.533	**0.787**	0.458	0.527
GRS1	0.427	0.341	0.413	0.448	0.398	0.452	0.360	**0.722**	0.465
GRS2	0.541	0.405	0.421	0.522	0.519	0.533	0.504	**0862**	0.580
GRS3	0.510	0.216	0.344	0.469	0.479	0.445	0.570	**0.841**	0.548
GRS4	0.495	0.304	0.355	0.489	0.491	0.484	0.567	**0.773**	0.655
GTD1	0.538	0.362	0.382	0.560	0.536	0.541	0.532	0.666	**0.824**
GTD2	0.542	0.344	0.388	0.578	0.577	0.511	0.555	0.603	**0.852**
GTD3	0.552	0.370	0.364	0.545	0.577	0.475	0.613	0.519	**0.836**
GTD4	0.630	0.423	0.448	0.598	0.602	0.583	0.654	0.568	0.829

Table 8. Assessment of GHRMP as a reflective–formative higher-order construct

Formative dimension	Outer weight	Bootstrap SE	t-value	p-value	95% CI	Outer loading	VIF	Assessment
Green employee involvement	0.435	0.073	5.993	< .001	[0.289, 0.572]	0.932	3.075	Significant weight
Green recruitment and selection	0.171	0.069	2.471	0.013	[0.042, 0.311]	0.767	2.169	Significant weight
Green training and development	0.131	0.067	1.946	0.052	[-0.001, 0.261]	0.830	2.862	Retained: significant loading and content validity

Table 8. Continued

Formative dimension	Outer weight	Bootstrap SE	t-value	p-value	95% CI	Outer loading	VIF	Assessment
Green performance management	0.139	0.073	1.894	0.058	[-0.004, 0.283]	0.846	2.828	Retained: significant loading and content validity
Green rewards and compensation	0.266	0.081	3.304	0.001	[0.108, 0.421]	0.894	3.026	Significant weight

Note: Bootstrapping was conducted using 10,000 subsamples, two-tailed testing, and percentile-based 95% confidence intervals. The reported standard errors, t-values, p-values, and confidence intervals refer to the formative outer weights. Green training and development and green performance management were retained despite nonsignificant relative weights because their outer loadings were substantial and statistically significant at $p < .001$ and because both dimensions were required to preserve the content validity of GHRMP. ***p < .001.

Table 9. Summary of hypothesis testing (Direct effects)

Hypothesis	β	T-Value	Percentile Bootstrap 95% CI (B=10,000)		Decision
			Lower Bound	Upper Bound	
H1 (+) GHRMP → EA	0.846***	52.731	0.817	0.877	Supported
H2 (+) EA → GIP	0.733***	26.229	0.676	0.785	Supported
H3a (+) GIP → ENP	0.810***	16.572	0.704	0.897	Supported
H3b (+) GIP → ECP	0.765***	15.837	0.663	0.853	Supported
H4a (+) GHRMP → ENP	-0.043	0.729	-0.147	0.084	Not Supported
H4b (+) GHRMP → ECP	-0.082	1.434	-0.185	0.041	Not Supported

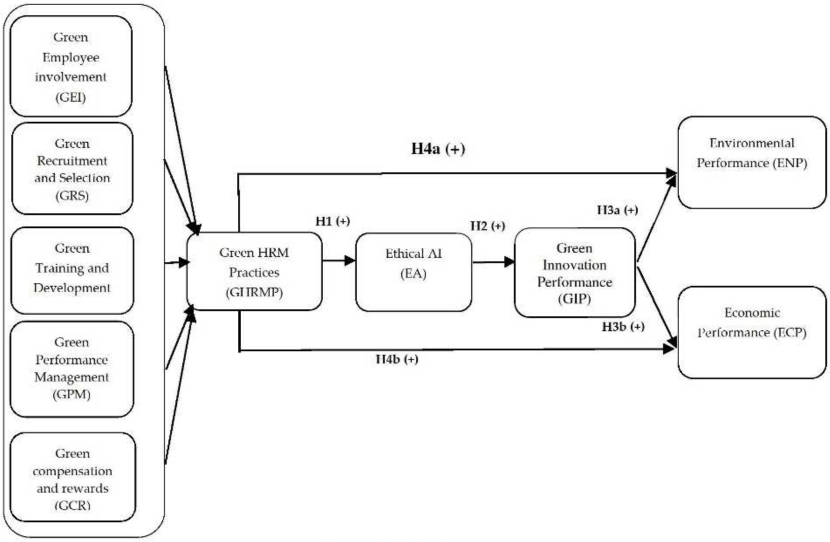
Note: B = 10,000 bootstrap subsamples; two-tailed tests; $\alpha = .05$; percentile-based 95% confidence intervals. The lower and upper bounds correspond to the 2.5th and 97.5th percentiles, respectively. ***p < .001; **p < .01; *p < .05.

Table 10. Assessment of specific and serial indirect associations

Hypothesis and indirect effect	β	t-value	p-value	95% CI	Corresponding direct path	Model-implied total effect	Interpretation
H5a: GHRMP → EA → GIP	0.620***	20.550	< .001	[0.562, 0.679]	GHRMP → GIP not specified	0.620	Significant specific indirect effect; mediation type not classified
H5b: EA → GIP → ENP	0.593***	12.748	< .001	[0.498, 0.682]	EA → ENP not specified	0.593	Significant specific indirect effect; mediation type not classified
H5c: EA → GIP → ECP	0.561***	12.856	< .001	[0.473, 0.645]	EA → ECP not specified	0.561	Significant specific indirect effect; mediation type not classified
H5d: GHRMP → EA → GIP → ENP	0.502***	12.057	< .001	[0.419, 0.583]	GHRMP → ENP: β = −0.043, p = .466	β = 0.460***; t = 10.267; p <.001; 95% CI [0.378, 0.553]	Significant serial specific indirect effect; consistent with an indirect-only serial pattern
H5e: GHRMP → EA → GIP → ECP	0.475***	11.747	< .001	[0.396, 0.555]	GHRMP → ECP: β = −0.082, p = .152	β = 0.393***; t = 8.448; p <.001; 95% CI [0.307, 0.490]	Significant serial specific indirect effect; consistent with an indirect-only serial pattern

Note: B = 10,000 bootstrap subsamples; two-tailed tests; α = .05; percentile-based 95% confidence intervals. For H5a–H5c, the corresponding direct paths were not specified; therefore, the model-implied total effects equal the specific indirect effects by construction, and mediation type is not classified. For H5d and H5e, the corresponding direct GHRMP–outcome paths were estimated but were nonsignificant, whereas the serial specific indirect effects were significant. These results are therefore consistent with indirect-only serial transmission through EA and GIP. ***p < .001; **p < .01; *p < .05.

Figure 1 Research framework



Specific and serial indirect associations:
H5a: GHRMP → EA → GIP;
H5b: EA → GIP → ENP;
H5c: EA → GIP → ECP;
H5d: GHRMP → EA → GIP → ENP;
H5e: GHRMP → EA → GIP → ECP.
Note: GEI, GRS, GTD, GPM, and GCR form the higher-order GHRMP construct. ENP and ECP were estimated as separate outcome constructs. H5a–H5e denote the specific and serial indirect associations tested in the model.