

Partial Least Squares Modeling Green HRM, Mindfulness, Employee Innovation Behavior

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Abstract: This study examines associations among green human resource management (GHRM), green mindfulness, and employees' green innovation behavior (EGIB) in Jordanian manufacturing. Drawing on the Ability–Motivation–Opportunity (AMO) framework and the Attention-Based View, GHRM was modeled as a reflective–reflective higher-order construct and estimated using a two-stage partial least squares structural equation modeling (PLS-SEM) procedure. Cross-sectional survey data from 384 employees in medium-sized and large manufacturing firms were analyzed with 5,000-resample bootstrapping. GHRM was positively associated with EGIB ($\beta = .448$) and green mindfulness ($\beta = .613$), while green mindfulness was positively associated with EGIB ($\beta = .174$). The specific indirect association through green mindfulness was positive and statistically significant ($\beta = .107$, $p = .002$, bias-corrected 95% CI [.040, .176]), while the direct GHRM–EGIB association remained significant. All three AMO components were positively associated with both outcomes. The results are consistent with a complementary partial indirect-association pattern, but the cross-sectional, single-source design does not establish temporal or causal mediation. The study demonstrates how higher-order PLS-SEM and bootstrapped indirect-effect assessment can be used to examine integrated green HR systems and employee green innovation in an emerging-economy manufacturing context.

Keywords: Attention-Based View; Employees' Green Innovation Behavior; Green Human Resource Management; Green Mindfulness; Partial Least Squares Structural Equation Modeling.

1 Introduction

Manufacturing firms face persistent pressure to improve resource efficiency, reduce waste and emissions, and translate sustainability commitments into continuous operational improvement [1]. Technologies and formal environmental policies are necessary, but they do not independently generate the numerous small-scale, context-specific innovations required in production systems [2]. Employees are often the first organizational members to identify process inefficiencies, material losses, quality problems, and opportunities for cleaner work practices. Whether employees generate and implement environmentally beneficial ideas is therefore central to organizational green innovation [3].

Employees' green innovation behavior (EGIB) differs from routine pro-environmental behavior. Compliance with environmental rules and resource conservation are valuable, but novelty, initiative, advocacy, and implementation are necessary for innovation. Solving an environmental problem requires employees to identify a potential issue, consider a solution, secure approval, and implement an idea [4, 5]. This distinction matters because an organization can be compliant without also developing the kinds of employee-driven innovations that reduce environmental impact over time [6].

GHRM is an organizational pathway toward developing this behavioral capacity. Environmental priorities can be integrated into the employee lifecycle through recruitment, training, performance management, recognition, job design, health and safety support, and participation mechanisms [7, 8]. Recent reviews emphasize treating these practices as an integrated package rather than as isolated interventions [9, 10]. However, prior empirical research has focused more on general green behavior, commitment, or environmental performance than on innovation-oriented employee behavior [11–13]. Ongoing research on green innovative work behavior confirms the importance of separating novelty, advocacy, and implementation from routine sustainability behaviors [14].

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A second gap concerns process. While formal HR systems can signal that sustainability matters, employees must notice, understand, and reflect on those signals in their own work before new environmental solutions can emerge. Green mindfulness is defined as the conscious awareness of environmental implications, processing of environmental information, and reflection on sustainability in employees' work decisions [15–18]. The Attention-Based View holds that organizational structures shape organizational members' attention [19]; accordingly, green mindfulness may function as a cognitive process linking GHRM and EGIB.

This study addresses these gaps in Jordanian manufacturing by treating GHRM as a higher-order AMO system and examining both the overall system and its ability-, motivation-, and opportunity-enhancing components. It then tests whether a statistically significant indirect association between GHRM and EGIB operates through green mindfulness. The contribution is threefold: it integrates an HR-system perspective with an attention mechanism, differentiates green innovation from routine environmental behavior, and provides evidence from an emerging-economy manufacturing setting that remains underrepresented in the literature.

2 Theoretical Background and Hypotheses

2.1 GHRM as an AMO-based higher-order system

The AMO framework holds that employees' actions can be explained by whether they have the capacity to act, are willing to act, and have the opportunity to act [20, 21]. In environmental management, ability-enhancing GHRM involves green recruitment, selection, training, and development; motivation-enhancing GHRM involves environmental appraisal, feedback, recognition, and reward; and opportunity-enhancing GHRM involves supportive job design, environmental responsibilities, safe participation, and avenues for employee involvement [7, 9].

These practices are best treated as an integrated system rather than as independent interventions. Ability without opportunity can leave knowledge unused; opportunity without ability can produce weak participation; and rewards without ability can produce low-quality ideas. A higher-order specification preserves this systemic logic while still allowing the three AMO pathways to be examined individually [27].

2.2 GHRM and employees' green innovation behavior

GHRM can legitimize and support green innovation as part of employees' work. Recruitment and training develop environmental knowledge and problem-solving skills. Rewards and appraisal communicate that green ideas matter. Job design and participative structures create discretion and access to implementation channels. Because innovation is often discretionary, unpredictable, and can extend beyond officially assigned tasks [23, 24], these mechanisms are especially important for EGIB.

At the component level, ability-enhancing practices should increase employees' capacity to identify environmental inefficiencies and generate practical solutions. Motivation-enhancing practices should increase persistence in promoting and implementing ideas, particularly when innovation entails effort or interpersonal risk. Opportunity-enhancing practices should enable employees to voice ideas, experiment safely, and participate in cross-functional environmental improvement.

H1: *GHRM is positively associated with employees' green innovation behavior.*

H1a–H1c: *Ability-, motivation-, and opportunity-enhancing GHRM are each positively associated with employees' green innovation behavior.*

2.3 GHRM and green mindfulness

The Attention-Based View argues that organizational arrangements distribute attention by making some issues more visible, legitimate, and repeatedly encountered than others [19]. Green HR practices provide recurring environmental cues through selection criteria, training content, performance conversations, rewards, safety procedures, and job responsibilities. Such cues can make environmental consequences more cognitively accessible and encourage employees to monitor how everyday activities affect the natural environment.

Ability-enhancing practices provide the knowledge needed to interpret environmental cues. Motivation-enhancing practices communicate that attention to environmental consequences is valued. Opportunity-enhancing practices expose employees to environmental responsibilities and problem-solving situations. Accordingly, GHRM should relate not only to action but also to the attentional process that precedes action.

H2: *GHRM is positively associated with green mindfulness.*

H2a–H2c: *Ability-, motivation-, and opportunity-enhancing GHRM are each positively associated with green mindfulness.*

2.4 Green mindfulness and green innovation behavior

Mindful attention can help employees detect environmental risks, question habitual routines, connect operational decisions to ecological consequences, and consider alternative ways of working. These cognitive activities are closely related to the idea-generation stage of innovation. Continued reflection may also strengthen the rationale employees use when promoting ideas and help them adapt proposed solutions during implementation [17, 25].

Green mindfulness is therefore expected to increase the likelihood that environmental information becomes innovation-oriented behavior rather than remaining a general attitude.

H3: *Green mindfulness is positively associated with employees' green innovation behavior.*

2.5 Green mindfulness as an indirect attention pathway

GHRM can be associated with EGIB through both a direct AMO route and an indirect attention route. The direct route reflects the capability, motivation, and opportunity supplied by HR practices. The indirect route reflects the extent to which the same practices focus employees' attention on environmental consequences and make environmental problems and improvement possibilities more salient. Because HR practices may also relate to innovation through non-cognitive mechanisms such as incentives, role expectations, and participation opportunities, the indirect pathway through green mindfulness is expected to coexist with a positive direct association.

H4: *A positive indirect association between GHRM and employees' green innovation behavior operates through green mindfulness.*

3 Materials and Methods

3.1 Design, context, sampling, and achieved sample

The study used an explanatory, quantitative, cross-sectional survey design. Data were collected during June and July 2026 from employees working in medium and large private manufacturing firms in Jordan. The population covered major industrial subsectors, including food, chemicals, pharmaceuticals, plastics, construction materials, and mining-related industries, with organizational locations concentrated in Amman, Zarqa, and Irbid.

Eligible firms were classified by manufacturing subsector, size, and location. Firms were selected within strata, and replacement firms were drawn from the same stratum when access was refused or unavailable. Within participating firms, employees were randomly selected when complete rosters were available; otherwise, human-resource-assisted lists of eligible operational, supervisory, and managerial employees were used. Because access was organization-facilitated, the achieved sample should not be interpreted as a fully self-weighting national probability sample. A power analysis based on four predictors, $\alpha = .05$, power = .90, and $f^2 = .05$ indicated a conservative minimum of 313 cases. The final analytical sample comprised 384 respondents: 54.2% operators/staff ($n = 208$), 31.0% supervisors ($n = 119$), and 14.8% managers ($n = 57$); 57.3% worked in medium-sized firms ($n = 220$) and 42.7% in large firms ($n = 164$). The subsector distribution was food processing ($n = 88$), chemicals ($n = 52$), pharmaceuticals ($n = 38$), plastics ($n = 61$), construction materials ($n = 59$), mining and related industries ($n = 57$), and other manufacturing subsectors ($n = 29$).

All 384 questionnaires issued after organizational access and participant identification were returned and retained, corresponding to a 100% achieved return among issued questionnaires (384/384). This figure should not be interpreted as a population- or firm-level response rate, because firms or individuals who were not reached, who declined access before distribution, or who were not selected fall outside the denominator. No item-level responses were missing and no imputation was required. No complete straight-lining cases or multivariate outliers under the study criterion ($p < .001$) were identified. Two aggregate overall-GHRM standardized scores with $|z| > 3.00$ were inspected and retained because their response patterns were judged plausible. The final analytical sample therefore remained 384 cases.

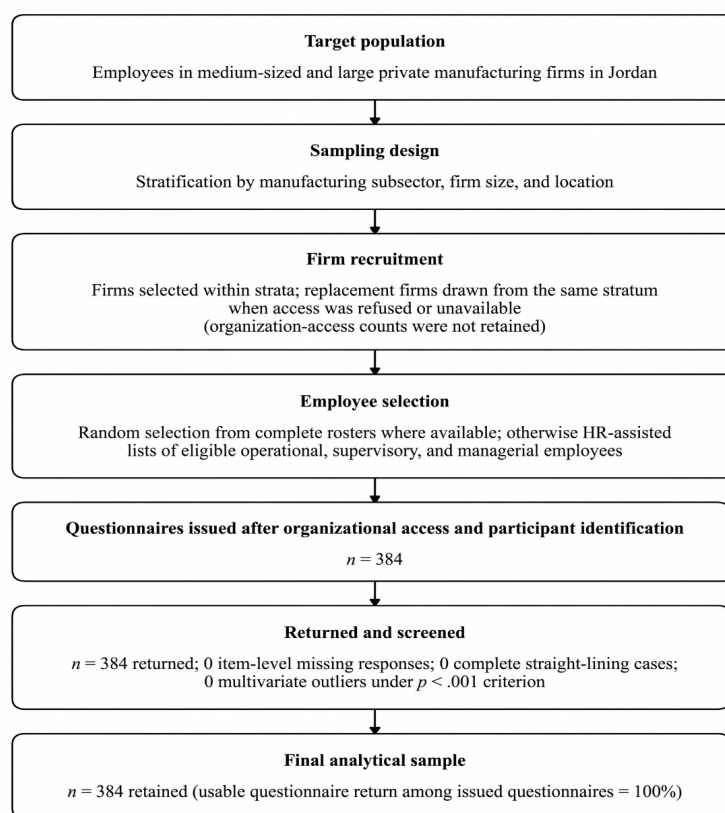


Fig. 1: Sampling and data-collection flow. Organization-access counts were not retained and are therefore not reported in the diagram.

3.2 Measures

All substantive items used five-point agreement scales. The instrument was available in English and Arabic and underwent translation and back-translation, expert review by three specialists, content-validity assessment, pretesting, and pilot testing. Pilot internal-consistency coefficients ranged from .87 to .93 across the substantive scales. These procedures support linguistic and content adequacy but do not eliminate the need to evaluate construct validity in the main sample.

GHRM was measured with 18 items adapted primarily from [8]. Six items represented ability-enhancing GHRM (green recruitment/selection and training/development), six represented motivation-enhancing GHRM (performance management and compensation/rewards), and six represented opportunity-enhancing GHRM (green health and safety and green job design/analysis). The three components formed a reflective–reflective higher-order construct using a two-stage approach.

Green mindfulness was measured with six items adapted from [15] and [18], capturing environmental awareness, attentive processing, and reflective consideration in work. EGIB was measured with six green-contextualized items based on the innovative-behavior tradition of [26] and [30], covering idea generation, promotion, and implementation. The reflective–reflective higher-order specification was theory-driven. Ability, motivation, and opportunity-enhancing GHRM were conceptualized as correlated reflective manifestations of an integrated green HR system rather than as independent formative ingredients. At the higher-order stage, the component loadings were .741, .718, and .698, respectively, and all three component weights were positive and statistically significant ($p < .001$). Collinearity was low in the component model: inner VIFs for the focal component paths ranged from 1.130 to 1.629, and outer-model VIFs ranged from 1.540 to 1.906. A conventional redundancy analysis requiring an independently measured global criterion was not conducted, because no separate global GHRM criterion item was collected in the survey and such a criterion

cannot be reconstructed post hoc. Convergent validity of the reflective specification was therefore evaluated using indicator loadings, reliability, AVE, discriminant validity, and the higher-order component loadings.

3.3 Analytical procedure

SPSS 26 was used for screening and descriptive analysis, and SmartPLS 4 was used for PLS-SEM. The reflective measurement models were evaluated using outer loadings, Cronbach's alpha, ρ_A , composite reliability, average variance extracted (AVE), heterotrait–monotrait ratios (HTMT), the Fornell–Larcker criterion, and variance inflation factors. The reflective–reflective higher-order GHRM construct was estimated using a two-stage procedure in which latent-variable scores for the three AMO components were used at the higher-order stage [27, 28]. Model-fit indices were treated as supplementary rather than as stand-alone acceptance criteria [29, 30].

Structural paths were evaluated using two-tailed bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals. Structural collinearity was assessed with inner VIFs, explanatory power with R^2 and adjusted R^2 , and local contribution with f^2 . The GHRM → green mindfulness → EGIB pathway was evaluated from the specific indirect association and its bootstrap confidence interval. Because the design is cross-sectional, the terms indirect effect and indirect association are used as statistical descriptions and are not interpreted as evidence of temporal or causal mediation. Procedural remedies were supplemented by common-method diagnostics: the first unrotated factor explained 25.32% of variance, and full-collinearity VIFs were below 3.3; these diagnostics reduce but do not eliminate common-method concerns [32–34].

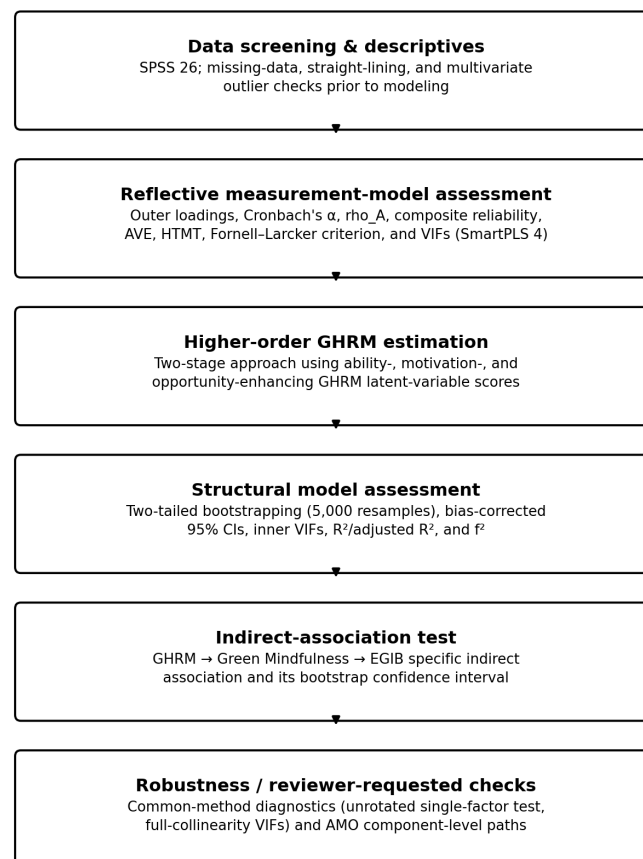


Fig. 2: Analytical procedure used for the focal model and the reviewer-requested robustness extensions.

3.4 Statistical equations

To make the reporting fully transparent, this subsection states the formal definitions of the statistics reported in Section 4 and used in the robustness analyses in Section 3.5.

Cronbach's alpha:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum \sigma_i^2}{\sigma_t^2} \right) \quad (1)$$

where k is the number of items, σ_i^2 is the variance of item i , and σ_t^2 is the variance of the summed scale.

Composite reliability:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum (1 - \lambda_i^2)} \quad (2)$$

where λ_i is the standardized outer loading of indicator i .

Average variance extracted:

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (3)$$

where n is the number of indicators loading on the construct.

Heterotrait–monotrait ratio of correlations:

$$HTMT_{ij} = \frac{\text{mean}(\text{heterotrait correlations}_{ij})}{\sqrt{\text{mean}(\text{monotrait correlations}_i) \times \text{mean}(\text{monotrait correlations}_j)}} \quad (4)$$

computed between the indicators of constructs i and j ; values below .85 (conservative) support discriminant validity.

Variance inflation factor:

$$VIF_i = \frac{1}{1 - R_i^2} \quad (5)$$

where R_i^2 is the R^2 obtained when predictor i is regressed on all other predictors in the same block.

Coefficient of determination and adjusted R^2 :

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}, \quad R_{\text{adj}}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \quad (6)$$

where n is the sample size and p is the number of predictors of the endogenous construct.

Effect size f^2 :

$$f^2 = \frac{R_{\text{included}}^2 - R_{\text{excluded}}^2}{1 - R_{\text{included}}^2} \quad (7)$$

comparing the R^2 of the endogenous construct with and without the focal predictor; conventional benchmarks are .02 (small), .15 (medium), and .35 (large).

Bias-corrected bootstrap confidence interval:

$$z_0 = \Phi^{-1}[\text{proportion of } \beta_b^* < \hat{\beta}], \quad CI = [\Phi(2z_0 + z_{\alpha/2}), \Phi(2z_0 + z_{1-\alpha/2})] \quad (8)$$

computed from the empirical distribution across $B = 5,000$ bootstrap resamples $\beta_1^*, \dots, \beta_B^*$, following the standard bias-corrected (BC) bootstrap procedure.

Out-of-sample predictive relevance (Q^2_{predict}):

$$Q^2 = 1 - \frac{\sum (Y_{\text{obs}} - Y_{\text{pred}})^2}{\sum (Y_{\text{obs}} - \bar{Y}_{\text{train}})^2} \quad (9)$$

computed for each holdout fold, where $\bar{Y}_{\text{train}}$ is the training-fold mean used as the naïve benchmark; $Q^2 > 0$ indicates predictive relevance relative to that benchmark.

Gaussian-copula endogeneity term:

$$GC(X) = \Phi^{-1}[F(X)], \quad Y = \beta_0 + \beta_1 X + \beta_2 \cdot GC(X) + \varepsilon \quad (10)$$

where $F(x)$ is the empirical distribution of the suspected endogenous regressor X , (required to be non-normal) and the copula term $GC(X)$ is entered as an additional predictor following [37]. A statistically significant β_2 indicates that the regressor's disturbance is correlated with the structural error term, consistent with endogeneity; a non-significant β_2 — as obtained for green mindfulness in Table 7 — provides no evidence of material endogeneity.

3.5 Reviewer-requested robustness and predictive analyses

To assess out-of-sample prediction, a repeated 10-fold PLS-based holdout procedure was conducted on the original item-level data following the logic of PLSpredict [35]. Ten repetitions of 10-fold cross-validation were used. In each training fold, Q19–Q24 was predicted from Q1–Q18 and Q25–Q30 was predicted from Q1–Q24 using partial least squares regression. Q^2_{predict} was calculated relative to a training-mean naive benchmark, and RMSE and MAE were compared with a multivariate linear-model benchmark estimated on the same training folds. This analysis is reported as a transparent post-hoc predictive robustness assessment rather than as a native SmartPLS PLSpredict export.

Endogeneity was examined with a Gaussian-copula robustness diagnostic using the archived SmartPLS latent-variable scores [37]. The non-normality precondition was evaluated before constructing copula terms. The higher-order GHRM score did not depart significantly from normality (Shapiro–Wilk $p = .275$), whereas the green-mindfulness latent score did ($p = .001$). Accordingly, the copula term was estimated for green mindfulness in the EGIB equation; 5,000 case-resampling bootstrap draws were used for the copula coefficient confidence interval.

For practical interpretation, a construct-level importance–performance analysis was calculated for EGIB using archived SmartPLS total effects as importance and the original five-point construct means rescaled to 0–100 as performance [36]. Results are explicitly labeled as a construct-level importance–performance analysis rather than as a native SmartPLS IPMA export.

The reviewer also requested MICOM and multi-group analysis by firm size, organizational level, and manufacturing subsector. The final de-identified item-level analytical file retains Q1–Q35 but not the case-level profile-to-response linkage needed to assign each respondent to a subgroup. Only aggregate group frequencies were preserved (medium $n = 220$, large $n = 164$; operator/staff $n = 208$, supervisor $n = 119$, manager $n = 57$; seven subsector categories). Because compositional invariance and group-specific path differences cannot be reconstructed validly from aggregate frequencies, MICOM/MGA was not estimated and no subgroup values were imputed. This limitation is reported transparently rather than by creating synthetic group assignments.

4 Results

4.1 Measurement model

Indicator loadings ranged from .717 to .793. Cronbach’s alpha, ρ_A , and composite reliability exceeded .70, and all AVE values exceeded .50. Outer-model VIFs ranged from 1.540 to 1.906. The estimated AMO model had SRMR = .050; NFI = .846 is reported descriptively and was not used as a sole decision rule. The higher-order GHRM component loadings were .741 for ability, .718 for motivation, and .698 for opportunity; the corresponding weights were .484, .466, and .440, respectively, and all were significant at $p < .001$. The full HTMT matrix is reported in Supplementary Table S1 rather than only as a range.

Table 1: Construct operationalization

Construct	Role and operationalization	Items
GHRM	Reflective–reflective higher-order construct: ability-, motivation-, and opportunity-enhancing components	18
Green mindfulness	Reflective attentional construct in the indirect pathway: environmental awareness, attention, and reflection	6
EGIB	Reflective outcome: green idea generation, promotion, and implementation	6

Table 2: Reliability and convergent validity

Construct	Cronbach’s α	ρ_A	Composite reliability	AVE
Ability-enhancing GHRM	.837	.839	.880	.550
Motivation-enhancing GHRM	.865	.866	.899	.596
Opportunity-enhancing GHRM	.862	.864	.897	.592
Green Mindfulness	.857	.857	.893	.582
Employees’ Green Innovation Behavior	.849	.849	.888	.569

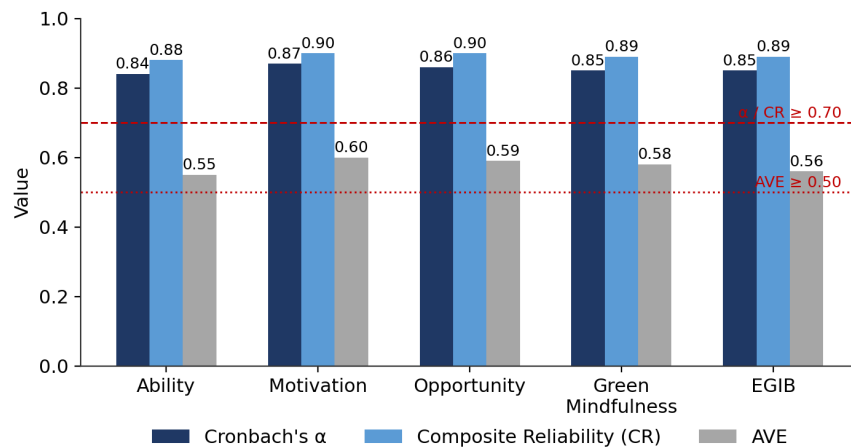


Fig. 3: Reliability and convergent validity by construct, with the $\alpha/CR \geq .70$ and $AVE \geq .50$ reference lines.

Table 3: Full HTMT matrix

Construct	Ability	Motivation	Opportunity	Green Mindfulness	EGIB
Ability	—	.333	.331	.538	.482
Motivation	.333	—	.303	.484	.497
Opportunity	.331	.303	—	.512	.435
Green Mindfulness	.538	.484	.512	—	.526
EGIB	.482	.497	.435	.526	—

Note. All HTMT values are below the conservative .85 threshold. Values are rounded to three decimals from the archived SmartPLS output.

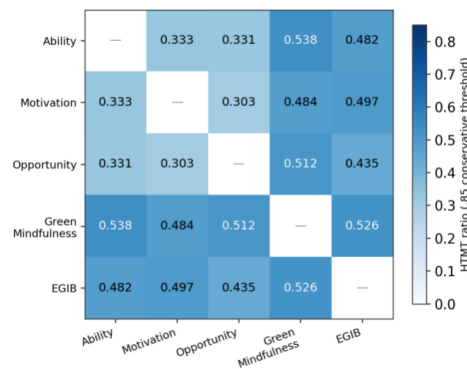


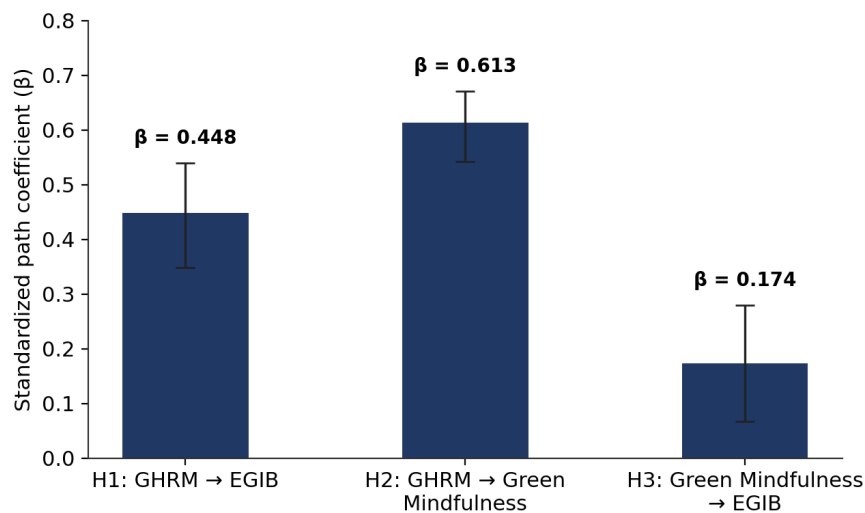
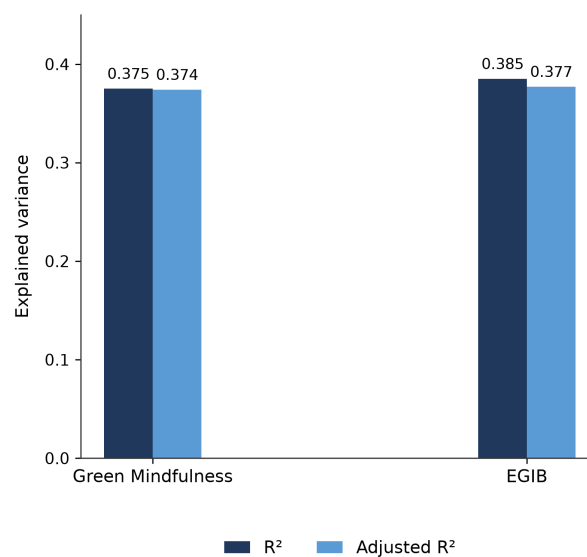
Fig. 4: Full HTMT matrix, shaded by ratio (darker cells indicate a higher heterotrait–monotrait ratio).

4.2 Structural relationships

The model explained 37.5% of the variance in green mindfulness ($R^2 = .375$; adjusted $R^2 = .374$) and 38.5% of the variance in EGIB ($R^2 = .385$; adjusted $R^2 = .377$). GHRM had a large local association with green mindfulness ($f^2 = .600$) and a medium direct association with EGIB ($f^2 = .202$). The green mindfulness–EGIB contribution was small ($f^2 = .030$) but statistically significant. All principal bootstrap confidence intervals excluded zero.

Table 4: Principal structural paths with effect sizes and bias-corrected confidence intervals

Hyp.	Path	β	SE	t	p	f^2	BC 95% CI
H1	GHRM $\rightarrow$ EGIB	.448	.049	9.102	< .001	.202	[.348, .540]
H2	GHRM $\rightarrow$ Green mindfulness	.613	.033	18.617	< .001	.600	[.542, .671]
H3	Green mindfulness $\rightarrow$ EGIB	.174	.054	3.241	.001	.030	[.067, .280]

**Fig. 5:** Principal structural paths (H1–H3) with bias-corrected 95% confidence intervals.**Fig. 6:** Explained variance (R^2 and adjusted R^2) in green mindfulness and EGIB.

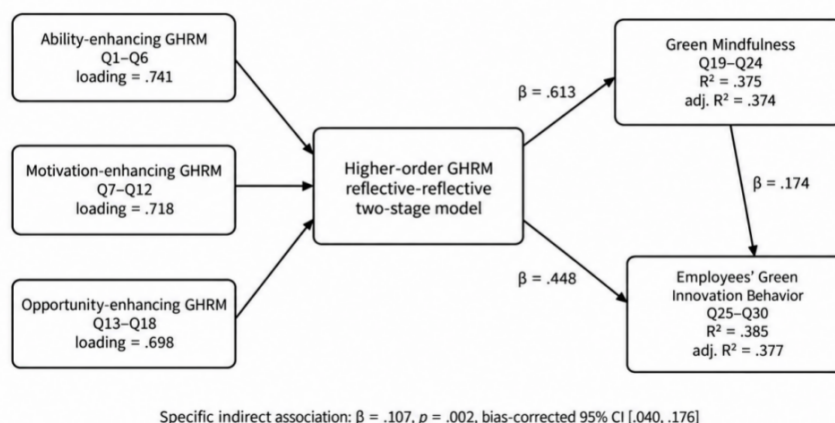


Fig. 7: Higher-order GHRM, green mindfulness, and EGIB model with standardized path coefficients and explained variance.

4.3 AMO-component results

All six component-level associations were positive and statistically significant. Motivation-enhancing GHRM had the strongest direct association with EGIB ($\beta = .245$), followed by ability-enhancing GHRM ($\beta = .221$) and opportunity-enhancing GHRM ($\beta = .155$). Ability-enhancing GHRM had the strongest association with green mindfulness ($\beta = .306$), followed by opportunity-enhancing GHRM ($\beta = .291$) and motivation-enhancing GHRM ($\beta = .255$). Bias-corrected confidence intervals for all six paths excluded zero.

Table 5: AMO-component associations with effect sizes and bias-corrected confidence intervals

Path	β	SE	t	p	f^2	BC 95% CI
Ability-enhancing GHRM → EGIB	.221	.044	5.024	< .001	.062	[.131, .302]
Motivation-enhancing GHRM → EGIB	.245	.049	5.023	< .001	.079	[.144, .337]
Opportunity-enhancing GHRM → EGIB	.155	.043	3.617	< .001	.031	[.069, .238]
Ability-enhancing GHRM → Green mindfulness	.306	.040	7.583	< .001	.131	[.223, .381]
Motivation-enhancing GHRM → Green mindfulness	.255	.041	6.226	< .001	.092	[.170, .330]
Opportunity-enhancing GHRM → Green mindfulness	.291	.040	7.286	< .001	.120	[.211, .368]

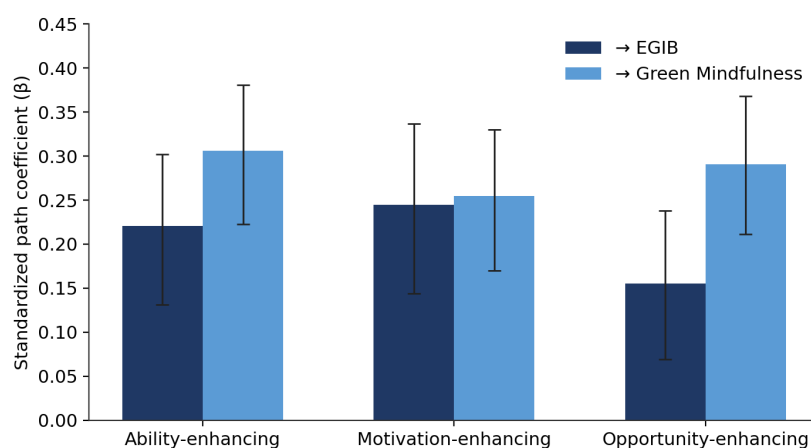


Fig. 8: AMO-component associations with EGIB and green mindfulness, with bias-corrected 95% confidence intervals.

Table 6: Direct, indirect, and total associations

Association	β	t	p	BC 95% CI	Interpretation
Direct: GHRM $\rightarrow$ EGIB	.448	9.102	< .001	[.348, .540]	Positive direct association
Specific indirect: GHRM $\rightarrow$ GM $\rightarrow$ EGIB	.107	3.094	.002	[.040, .176]	Positive indirect association
Total association	.555	15.108	< .001	[.474, .620]	Positive total association

4.4 Indirect association through green mindfulness

The specific indirect association from GHRM to EGIB through green mindfulness was positive and statistically significant ($\beta = .107$, $p = .002$, bias-corrected 95% CI [.040, .176]). The direct GHRM–EGIB association remained positive and significant after green mindfulness was included ($\beta = .448$, $p < .001$), and the direct and indirect coefficients had the same sign. Statistically, this pattern is consistent with a complementary partial indirect association. The indirect coefficient represented 19.2% of the total association, reported descriptively rather than as a strict criterion. Given the cross-sectional design, this result is not interpreted as temporal or causal mediation.

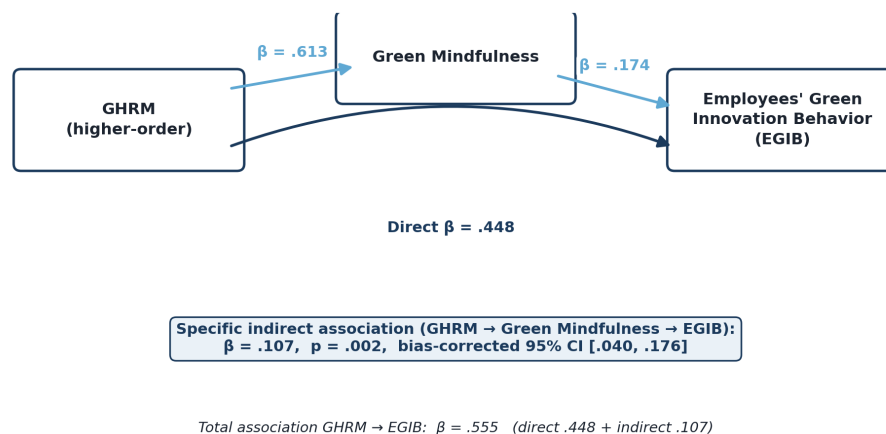


Fig. 9: Mediation diagram for the GHRM $\rightarrow$ green mindfulness $\rightarrow$ EGIB pathway, showing the direct ($\beta = .448$), specific indirect ($\beta = .107$), and total ($\beta = .555$) standardized associations reported in Table 6.

4.5 Reviewer-requested robustness results

The repeated 10-fold predictive assessment produced positive Q^2_{predict} values for every endogenous indicator. Values ranged from .177 to .220 for green-mindfulness indicators and from .127 to .175 for EGIB indicators. PLS-based RMSE and MAE were lower than the corresponding linear-model benchmark for all 12 indicators, although the margins were modest. This pattern indicates positive but moderate out-of-sample predictive relevance rather than strong predictive dominance.

The Gaussian-copula diagnostic did not indicate material endogeneity of green mindfulness in the EGIB equation. The copula coefficient was .212, with a 5,000-resample bootstrap $p = .664$ and 95% CI [−.653, .983]. The GHRM coefficient in the robustness regression remained positive and close to the PLS-SEM estimate ($\beta = .453$; bootstrap 95% CI [.353, .552]). Because the GHRM latent score did not meet the required non-normality condition, a copula term was not forced for GHRM.

The construct-level importance–performance analysis identified overall GHRM as the largest predictor-level importance for EGIB (total effect = .555; performance = 59.8/100), followed by green mindfulness (importance = .174; performance = 59.9/100). At the AMO-component level, motivation-enhancing GHRM had the highest total importance (.288) but the lowest performance (58.8), followed by ability-enhancing GHRM (.273; 59.7) and opportunity-enhancing GHRM (.204; 61.0). The component pattern therefore identifies motivation-enhancing practices as the clearest improvement priority when both importance and current performance are considered.

Table 7: Repeated 10-fold predictive assessment

Target	Indicator	Q^2_{predict}	RMSE (PLS)	MAE (PLS)	RMSE (LM)	MAE (LM)
Green Mindfulness	Q19	.220	.934	.762	.948	.779
Green Mindfulness	Q20	.208	.922	.755	.933	.763
Green Mindfulness	Q21	.177	1.003	.823	1.018	.838
Green Mindfulness	Q22	.204	.966	.769	.978	.777
Green Mindfulness	Q23	.184	1.011	.813	1.029	.828
Green Mindfulness	Q24	.220	.962	.787	.977	.792
EGIB	Q25	.136	.996	.803	1.003	.816
EGIB	Q26	.145	.966	.793	.981	.801
EGIB	Q27	.135	.998	.803	1.004	.808
EGIB	Q28	.127	1.050	.859	1.057	.860
EGIB	Q29	.175	.948	.773	.962	.783
EGIB	Q30	.159	.968	.782	.978	.784

Note. Ten repetitions of 10-fold cross-validation were conducted. Q^2_{predict} is relative to a training-mean naive benchmark. PLS and LM columns report holdout prediction errors from models estimated only on the corresponding training folds. This is a PLS-based holdout assessment following PLSpredict logic, not a native SmartPLS PLSpredict export.

Table 8: Gaussian-copula endogeneity robustness check

Term	Coefficient	Bootstrap p	95% Bootstrap CI	Interpretation
GHRM	.453	< .001	[.353, .552]	Stable positive association
Green-mindfulness copula	.212	.664	[−.653, .983]	No evidence of endogeneity

Note. The copula term was constructed only for green mindfulness because its archived latent score was non-normal (Shapiro–Wilk $p = .001$); the higher-order GHRM latent score did not meet the non-normality precondition ($p = .275$). The diagnostic uses archived SmartPLS latent-variable scores and 5,000 case-resampling bootstrap draws.

Table 9: Construct-level importance–performance analysis for EGIB

Level	Construct	Importance (total effect)	Performance (0–100)
Higher-order	Overall GHRM	.555	59.8
Higher-order	Green mindfulness	.174	59.9
AMO component	Ability-enhancing GHRM	.273	59.7
AMO component	Motivation-enhancing GHRM	.288	58.8
AMO component	Opportunity-enhancing GHRM	.204	61.0

Note. Importance values are total effects from the archived SmartPLS results. Performance is based on original construct means rescaled from the theoretical 1–5 scale to 0–100. Values are reported as a transparent construct-level importance–performance analysis rather than a native SmartPLS IPMA export.

MICOM and MGA were not estimated because the preserved de-identified analytical file does not contain respondent-level firm-size, job-level, or subsector labels linked to Q1–Q35. Aggregate frequencies confirm that the achieved sample contained medium and large firms, three job levels, and seven subsector categories, but these totals cannot support valid case assignment, permutation-based compositional invariance, or group-specific path estimation. No subgroup result was synthesized or inferred from the aggregate counts.

5 Discussion

The findings imply that an integrated green HR system is related to employee green innovation, rather than only to environmental compliance. This extends prior GHRM research into a more demanding behavioral goal: the generation, promotion, and adoption of new environmental ideas. In manufacturing, where workers routinely engage with production processes and resource flows, HR systems can make sustainability a supported part of everyday work.

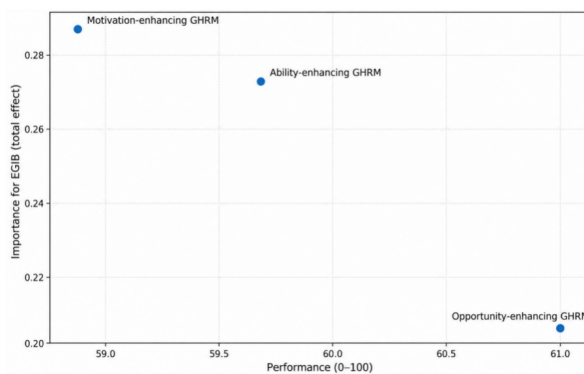


Fig. 10: Component-level importance–performance map for EGIB (AMO components only).

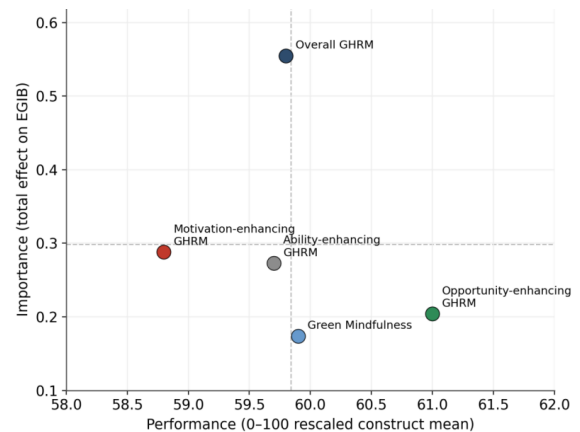


Fig. 11: Extended importance–performance quadrant map for EGIB, adding overall GHRM and green mindfulness with mean reference lines.

The component results complement the AMO explanation. The practices most directly associated with EGIB were motivational in nature. Green innovation is voluntary and involves employees proposing changes, breaking routines, and seeking support, which may make appraisal, feedback, recognition, and credible rewards especially salient. However, the positive associations for ability and opportunity indicate that motivation alone is not sufficient: technical and environmental competence is necessary to generate useful ideas, and organizational access and discretion are necessary to implement them.

The component most strongly associated with green mindfulness was ability-enhancing GHRM. Environmentally oriented training and recruitment can build knowledge structures that help employees notice and interpret environmental cues. Opportunity-enhancing practices were a close second, suggesting that environmental responsibilities and participation create repeated occasions for attention. Motivation-enhancing practices were also positively associated with mindfulness, consistent with the idea that appraisal and recognition communicate what deserves attention.

The indirect-association result is the study's principal theoretical contribution. GHRM was strongly associated with green mindfulness, and green mindfulness was positively associated with EGIB. This pattern is consistent with the proposition that formal HR practices relate to innovation partly by shaping what employees notice and reflect on while working. Integrating the Attention-Based View with employee-level sustainability behavior complements the AMO framework's focus on capability, motivation, and opportunity. The significant indirect coefficient should nevertheless be interpreted as a statistical pathway within a cross-sectional model rather than as evidence of a time-ordered mediating mechanism.

The reviewer-requested robustness analyses are broadly consistent with the explanatory results. All endogenous indicators had positive Q^2_{predict} values, and the PLS-based holdout errors were slightly lower than the linear-model benchmark, indicating modest predictive relevance. The Gaussian-copula term for green mindfulness was not significant, providing no evidence that endogeneity of the attention construct materially drives the EGIB equation. The importance–performance analysis further suggests that motivation-enhancing GHRM is a particularly actionable component, because it combines the highest AMO-level importance with the lowest current performance.

The Jordanian setting expands the empirical scope of GHRM studies. The model was applied in medium and large manufacturing companies in an emerging economy, where formal environmental systems and resource constraints may differ from more commonly studied settings. The findings should not be regarded as universally invariant, but they point to a system–cognition interaction that plausibly extends beyond samples drawn from high-income and East Asian contexts.

6 Theoretical and Practical Implications

6.1 Theoretical implications

The study offers a higher-order AMO modeling of GHRM while preserving interpretation at the component level, which avoids both the conceptual fragmentation of isolated-practice approaches and the loss of mechanism inherent in undifferentiated composites.

Second, the study distinguishes green mindfulness as a disposition from green mindfulness as an organizationally shaped attention process. Training, appraisal, reward, safety, and role design are mechanisms through which GHRM can repeatedly direct attention to environmental consequences.

Third, the study differentiates general pro-environmental behavior from green innovative behavior. The significant associations indicate that green HR systems and environmental attention are relevant to idea generation, promotion, and implementation behaviors that require more initiative and change orientation than routine compliance. Because the design is cross-sectional, these relationships should be treated as associations rather than as directional causal effects.

6.2 Practical implications

Manufacturing companies should design coordinated AMO packages rather than isolated interventions. Recruitment and job descriptions should state environmental expectations explicitly. Training should be role-specific and address waste, energy, process risk, and problem solving. Managers can build green mindfulness through simple recurring practices: environmental reflection in meetings, process walks focused on environmental loss, post-incident reviews, and questions that link operational decisions to environmental impact. Such practices should be tied to functioning decision channels; otherwise they risk producing awareness without action.

The component pattern implies a need for balance. While motivational practices show the strongest direct association with EGIB, opportunity practices are particularly important for building environmental attention, and ability practices are particularly important for implementation. A credible system should integrate all three rather than relying solely on reward or training.

7 Limitations and Future Research

The cross-sectional design does not establish temporal precedence or causality. Future longitudinal or multiwave studies should measure GHRM first, green mindfulness at a later point, and supervisor-rated EGIB subsequently. Experience-sampling designs could also examine whether environmental cues are followed by mindful attention and idea generation within specific work periods. All focal constructs were self-reported; future multisource studies should combine employee perceptions of GHRM with supervisor ratings, implemented-idea counts, or objective environmental-improvement measures. The available common-method diagnostics did not indicate a dominant factor, but they cannot establish the absence of method bias.

The analysis was conducted at the individual level, and unique firm identifiers were not retained in the analytical dataset. Future multilevel studies should preserve organizational identifiers and evaluate within-firm agreement, ICC values, and cross-level relationships before making firm-level claims. The reviewer-requested prediction, endogeneity, and importance–performance analyses were conducted as post-hoc robustness extensions and are not described as preregistered. MICOM/MGA could not be estimated validly, because the preserved de-identified Q1–Q35 file no longer contains the case-level profile-to-response linkage; aggregate group frequencies cannot be used to reconstruct respondent group membership. Future studies should preserve a de-identified group key specifically for measurement-invariance and subgroup analyses.

GHRM was operationalized through three AMO components formed directly from 18 indicators. Future research may compare this parsimonious specification with alternative hierarchical models. A separate global GHRM criterion item was not collected, so a post-hoc redundancy analysis based on an independent global criterion is not available. The reflective–reflective specification is instead supported by the theoretical measurement logic and by the observed reliability, AVE, HTMT, component loadings, and low collinearity.

8 Conclusion

Green HRM is positively associated with employees' green innovation behavior and with green mindfulness, and green mindfulness is positively associated with EGIB. The statistically significant indirect GHRM–green mindfulness–EGIB pathway suggests that an integrated green HR architecture and employee environmental attention are meaningfully linked in Jordanian manufacturing. The higher-order AMO specification further shows that ability-, motivation-, and opportunity-enhancing components each contribute to the focal relationships. Because the evidence is cross-sectional, the results support an indirect association rather than a causal mediation claim. Organizations seeking employee-driven environmental innovation should integrate HR architecture with practices that help employees notice, interpret, and act on environmental improvement opportunities.

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Declarations

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Data availability: De-identified data, the codebook, and analysis files may be made available from the corresponding author on reasonable request, subject to participant consent, organizational agreements, institutional policy, and data-protection requirements.

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