

The Impact of Higher-Order Partial Least Squares on Green HRM and Green Innovation

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Abstract: This study evaluates the association between green human resource management (GHRM) and employees' green innovation behavior (EGIB), and tests organizational environmental culture (OEC) as a moderator, using the reflective–reflective higher-order GHRM construct and two-stage partial least squares structural equation modeling. Cross-sectional responses from 384 employees in medium-sized and large Jordanian manufacturing firms were analyzed using 5,000-resample bootstrapping. The three AMO components loaded on higher-order GHRM at .741 (ability), .718 (motivation), and .698 (opportunity); its composite reliability was .762 and AVE .517. GHRM was positively associated with EGIB ($\beta = .448$, $p < .001$), whereas the OEC main association ($\beta = .012$, $p = .839$) and OEC $\times$ GHRM interaction ($\beta = .099$, $p = .101$, bias-corrected 95% CI $[-.003, .218]$, $f^2 = .010$) were not statistically significant. The fitted GHRM–EGIB slope increased from .349 at low OEC to .547 at high OEC; these point estimates do not establish a reliable difference in slopes. Archival common-method diagnostics found no dominant unrotated factor (25.32% of variance), but same-source and cross-sectional limitations remain. Fixed-score supplementary sensitivity checks are separated from the native Smart PLS inference. The results distinguish a positive green HR system association from an unconfirmed cultural amplification effect; neither absence of moderation nor causality can be established from these data.

Keywords: Ability–Motivation–Opportunity; Employees' Green Innovation Behavior; Green Human Resource Management; Higher-Order PLS-SEM; Organizational Environmental Culture.

1. Introduction

Employees' green innovation behavior (EGIB) comprises the generation, advocacy, and implementation of new ideas that improve environmental outcomes. It goes beyond routine adherence to environmental procedures because it requires novelty, initiative, and effort to secure support for change [1, 2, 3]. Employees working close to production systems may recognize avoidable material losses, energy inefficiencies, and opportunities to redesign practices.

Green human resource management (GHRM) can support these activities through an integrated set of recruitment and training practices, environmental appraisal and rewards, and opportunities for participation and safe experimentation. These ability-, motivation-, and opportunity-enhancing mechanisms should be considered as a system rather than isolated initiatives [4, 5, 6]. Whether environmental culture adds to the GHRM–EGIB association is a distinct question. Organizational environmental culture (OEC) refers here to employees' perceptions of shared environmental values, leadership priorities, peer support, encouragement, and norms of implementation. When informal norms confirm formal HR practices, employees may see green ideas as credible and safe to propose [7, 8, 9, and 10]. Yet culture may also overlap with the signals that a mature green HR system already provides, or operate at particular stages of innovation rather than as a uniform amplifier of the overall association [11].

The boundary-condition proposition is not guaranteed. Formal green HR systems may already communicate environmental expectations through clear training, incentives, role design, and participation channels, making cultural signals partly redundant. Furthermore, OEC may be consequential at particular stages—idea promotion, managerial approval, or implementation—rather than as a constant multiplier of the broad GHRM–EGIB association. These alternative mechanisms make the interaction test informative even when its interval includes zero [11].

This study asks whether perceived OEC changes the strength of the association between an integrated GHRM system and EGIB among employees in Jordanian manufacturing. The study distinguishes statistical evidence of an interaction from fitted differences in conditional coefficients and does not treat an unsupported interaction as proof that contextual effects are absent.

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2. Theoretical Background and Hypotheses

2.1 Green HRM as an AMO-based system

The AMO framework indicates that employees' behavior is driven by skills, desire and chance [12, 13]. Green recruitment and training can build environmental capabilities; appraisal and rewards can enhance motivation; and green job design, safe participation and employee involvement provide opportunities for action [4, 5, and 14]. The green HR literature suggests that these practices should be treated as a system and not as separate practices [6, 15].

GHRM is defined as a reflective–reflective higher-order construct consisting of three lower-order constructs: ability, motivation and opportunity. This system-specific specification continues to retain their complementary HR logic: training without involvement will generate unused knowledge, incentives without capability will generate weak ideas, and opportunities without motivational support will not sustain innovation. The three AMO scores are reflective measures of overall GHRM – not causal paths to be interpreted in that sense [16].

2.2 Employees' green innovation behavior

For EGIB, it is not just about following the rules but also creating, pushing and developing new environmentally friendly concepts. The difference is based on stages of innovative work behavior as defined by [1, 2].

GHRM is expected to be positively associated with EGIB as green training can enhance problem solving abilities, environmental appraisal and rewards can motivate employees and participative job design can provide opportunities to implement ideas. Previous studies have provided a connection between GHRM and employee green behavior, and green innovative behavior [17, 3, 18, and 19].

H1: Green Human Resource Management is positively associated with Employees' Green Innovation Behavior.

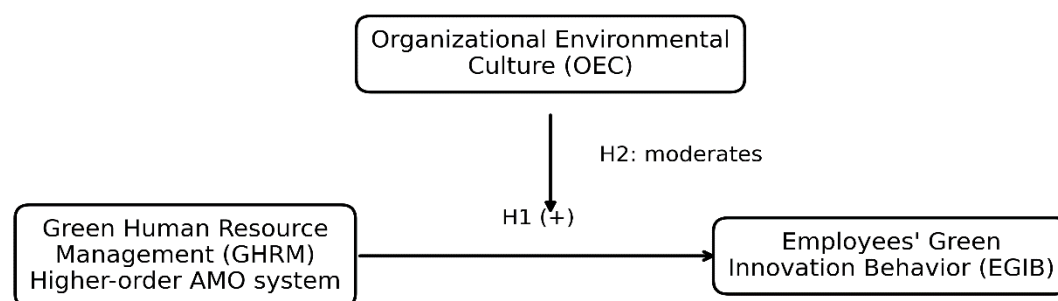
2.3 Organizational environmental culture as a boundary condition

OEC measures employee perceptions that environmental responsibility is embedded in shared values, managerial priorities, peer expectations, encouragement, and implementation norms [20, 9]. This is an individual-level perception of culture, not an aggregated organization-level score.

Social Learning Theory suggests that employees interpret and reinforce environmental norms by observing leaders and peers [21]. When cultural norms affirm formal HR signals, employees may view proposing or implementing green ideas as more legitimate and supported. Research links GHRM with the development of green organizational culture and downstream outcomes [8, 22, and 23]. The complementary-signals account therefore suggests a positive $OEC \times GHRM$ interaction. Yet AMO itself describes employee resources and participation, not a necessary environmental-culture moderator; the interaction hypothesis draws additionally on social learning and signal-consistency reasoning.

An opposing signal-redundancy account predicts little additional moderation if formal HR practices already provide sufficiently clear instructions, incentives, and opportunities. A stage-specificity account predicts that culture may influence idea endorsement or implementation more than the aggregate innovation scores. Finally, GHRM may help shape OEC, which may then relate to EGIB through a sequential indirect pathway rather than through an interaction [8, 22, 11, and 24]. The cross-sectional data here do not establish the temporal ordering required testing that mechanism causally. We nevertheless test the theoretically motivated amplification proposition:

H2: Organizational Environmental Culture positively moderates the GHRM–EGIB association, such that the association is stronger at higher levels of OEC.



AMO logic explains the GHRM–EGIB association; OEC is tested as a contextual boundary condition.

Fig. 1: Conceptual model of GHRM, OEC, and employee green innovation behavior.

3. Materials and Methods

3.1 Design, context, and sample

The study used an explanatory, quantitative, cross-sectional survey design. Data were collected in June and July 2026 from employees working in medium-sized and large private manufacturing firms in Jordan. The sectoral coverage included food, chemicals, pharmaceuticals, plastics, construction materials, and mining-related industries, with respondents located primarily in Amman, Zarqa, and Irbid. The individual employee was the unit of analysis.

The final analytical sample comprised 384 valid respondents. Medium-sized firms accounted for 57.3% of the sample and large firms for 42.7%. Operators or staff represented 54.2% of respondents, supervisors 31.0%, and managers 14.8%. All 384 questionnaires distributed to the achieved participant group were returned and retained after screening. No item-level missing responses, complete straight-lining cases, or multivariate outliers under the study criterion were identified. Because organizational access preceded employee distribution, the 100% achieved return rate should not be interpreted as eliminating possible access or selection bias.

3.2 Measures

All substantive indicators used a five-point Likert-type agreement scale from 1 = Strongly disagree to 5 = Strongly agree. The questionnaire was available in English and Arabic and underwent translation/back-translation, expert review, pretesting, and pilot testing before main data collection.

GHRM was measured by 18 indicators adapted primarily from Tang et al [5]: ability-enhancing Q1–Q6, motivation-enhancing Q7–Q12, and opportunity-enhancing Q13–Q18. In stage one, each six-item component was estimated reflectively; in stage two, the three component scores served as reflective indicators of higher-order GHRM (disjoint two-stage procedure). This approach aligns estimation with the actual AMO-based questionnaire and avoids reusing all 18 items in a repeated-indicators higher-order block [16].

EGIB was measured with six green-contextualized indicators based on the innovative behavior scale lineage of [1], supported by the staged logic of Yuan and Woodman [2]. Items captured employee involvement in green idea generation, promotion, sharing, and implementation.

OEC was measured reflectively with five indicators (Q31–Q35) adapted from organizational environmental culture and green work-climate literature, including [7,9] and [31]. The indicators represented environmental values, leadership emphasis, employee encouragement, peer support, and organization-wide environmental commitment. OEC was operationalized as an individual-level perception of organizational culture rather than an aggregated firm-level construct.

Table 1: Construct operationalization

Construct	Role and operationalization	Items
GHRM	Reflective–reflective higher-order AMO system: ability-, motivation-, and opportunity-enhancing components	18
OEC	Reflective moderator: shared environmental values, leadership emphasis, encouragement, peer support, and organization-wide commitment	5
EGIB	Reflective outcome: green idea generation, promotion, and implementation	6

3.3 Analytical procedure and reporting scope

SPSS 26 was used for screening and descriptive analysis and SmartPLS 4 for PLS-SEM. Following reflective measurement guidance [25, 26], the study examined outer loadings, alpha, rho_A, composite reliability, AVE, HTMT, and collinearity. The disjoint two-stage reflective–reflective GHRM model used the three first-stage AMO scores as its higher-order indicators, whose standardized loadings and weights are reported separately. Overall GHRM's square root of AVE is compared with its correlations with EGIB and OEC under the Fornell–Larcker criterion [27, 28, 29]. Structural paths use two-tailed 5,000-resample SmartPLS bootstrapping with bias-corrected 95% intervals. The supplementary fixed-score calculations described below do NOT replace the software's bootstrap estimates.

The primary moderation test is the continuous latent interaction $OEC \times GHRM \rightarrow EGIB$ from the broader original model. A non-significant interaction is not proof of no effect, and conditional simple-slope significance does not establish a significant difference between slopes. To address reviewer requests, a supplementary fixed-score, case-resampling bootstrap was conducted on the archived stage-two indicator data ($n = 384$; 5,000 draws; seed 20260923). Archived outer weights were applied to the standardized indicators to reconstruct stage-two GHRM, green mindfulness, EGIB, and OEC scores; the EGIB regression retained GHRM, green mindfulness, OEC, $GHRM \times OEC$ and $green\ mindfulness \times OEC$. This reconstruction reproduced the focal main coefficient to three decimals and the interaction to approximately three decimals; however, weights

were held fixed, whereas Smart PLS re-estimates its model during native bootstrapping. Supplementary conditional intervals are therefore labeled fixed-score approximations, not original/native bias-corrected SmartPLS intervals. A Johnson–Neyman-style exploration tests whether the conditional GHRM slope differs from zero; it does not test whether the interaction differs from zero. Item-deletion checks use alternative equal-weighted OEC score definitions with other construct scores fixed; they are diagnostic and are not a full Smart PLS measurement re-estimation.

This paper reports the GHRM–EGIB association and OEC moderation from the broader doctoral structural model; green mindfulness remains included as a covariate and a separate interaction where specified. The companion article addresses the mindfulness indirect association. Main paths are original Smart PLS estimates rather than results from a post-hoc three-variable refit. Archival single-factor and full-collinearity results from the same doctoral sample are used as method-bias screens; neither test rules out common-source bias [29, 30, 31].

3.4 Common method bias and supplementary analysis boundaries

The doctoral sample's archived unrotated single-factor assessment explained 25.32% of total item variance. Full-collinearity VIFs were 1.029–1.914 (principal) and 1.030–1.662 (AMO), below the screening threshold of 3.3. Harman and VIF screens have limited diagnostic specificity; they do not rule out shared respondent biases. [31] note that common method variance may attenuate interaction estimates. No marker variable or CFA marker was collected, and no marker-based statistic is claimed here.

4. Results

4.1 Measurement model

The AMO lower-order components had alpha .837–.865, composite reliability .880–.899 and AVE .550–.596. Higher-order GHRM used three AMO stage-two indicators, with loadings .741 (ability), .718 (motivation), and .698 (opportunity), and weights .484, .466 and .440; each weight and loading was positive and significant ($p < .001$). The higher-order composite reliability .762 and AVE .517 follow from those three standardized loadings. The square root of its AVE (.719) exceeded correlations with EGIB (.561) and OEC (.137) reconstructed from the preserved stage-two score data. The corresponding square roots of AVE were .754 for EGIB and .750 for OEC; OEC–EGIB correlation was .108 in the original Fornell–Larcker table. These values satisfy the reported pairwise Fornell–Larcker comparisons for the focal higher-order construct. Higher-order validity is not established by AVE alone: theoretical coherence, HTMT and correlations must also be considered.

Table 2a: Second-stage reflective higher-order GHRM measurement (original archived results)

AMO component	Loading	Outer weight	t (loading)	p (loading)	BC 95% CI (loading)
Ability	.741	.484	18.129	< .001	[.655, .816]
Motivation	.718	.466	15.774	< .001	[.618, .798]
Opportunity	.698	.440	14.766	< .001	[.600, .784]

Note. Original thesis stage-two export; all corresponding outer weights were also $p < .001$. HOC CR .762; AVE .517; $\sqrt{\text{AVE}}$.719. The native HOC stage-two measurement used AMO component scores.

Table 2b: Focal Fornell–Larcker comparison for higher-order GHRM (archived-score correlations)

Construct / comparison	Value	Interpretation
$\sqrt{\text{AVE}}$: higher-order GHRM	.719	Exceeds its correlations with both comparison constructs
GHRM–EGIB correlation	.561	< .719 and < EGIB $\sqrt{\text{AVE}}$.754
GHRM–OEC correlation	.137	< .719 and < OEC $\sqrt{\text{AVE}}$.750
OEC–EGIB correlation	.108	< .750 and < .754

Note. Values involving reconstructed higher-order GHRM are Pearson correlations from preserved stage-two scores; the OEC–EGIB entry is from the original thesis Fornell–Larcker table. This is an explicit pairwise focal comparison, not an unreported native HTMT matrix.

OEC had $\alpha = .836$, $\rho_A = .920$, CR = .864 and AVE = .563. The ρ_A –alpha difference is .084. Alpha assumes a more restrictive form of indicator equivalence, whereas ρ_A uses information from the estimated construct-score model; they need not coincide when indicator contributions differ. Here, Q33 has a positive loading but a small negative outer weight, and Q34 has a positive loading with a weight that is not statistically significant. These patterns may reflect heterogeneous or overlapping indicator contributions, but do not establish a unique cause of the ρ_A –alpha gap. We therefore interpret the gap cautiously and do not claim that a reliability threshold by itself settles item quality. The reflective indicator loadings remain the primary item-level evidence; outer weights are reported for transparency, not applied as formative-item deletion

criteria. Q33 (.593) and Q34 (.693) are retained for content coverage because the full OEC block retains acceptable alpha, composite reliability and AVE; alternative scoring checks below examine sensitivity without claiming native measurement re-estimation.

Table 2: Reliability and convergent validity of focal constructs

Construct	Cronbach's α	rho 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
Higher-order GHRM	—	—	.762	.517
Organizational Environmental Culture	.836	.920	.864	.563
Employees' Green Innovation Behavior	.849	.849	.888	.569

Table 3: Reflective OEC indicator loadings and archived outer-weight diagnostics (weights not primary reflective reliability tests)

Indicator	Standardized loading	Decision	Outer weight	Weight p
Q31	.822	Acceptable	.334	.086
Q32	.885	Acceptable	.530	.130
Q33	.593	Retained; construct criteria met	-.035	.916
Q34	.693	Retained; content coverage	.212	.311
Q35	.724	Acceptable	.179	.395

4.2 Direct association and moderation test

The native higher-order Smart PLS result supported H1: GHRM-EGIB $\beta = .448$, SE = .049, $t = 9.102$, $p < .001$, bias-corrected 95% CI [.348, .540], $f^2 = .202$. OEC's main association was $\beta = .012$, SE = .057, $t = .204$, $p = .839$. H2 was not supported: OEC $\times$ GHRM $\beta = .099$, SE = .060, $t = 1.642$, $p = .101$, bias-corrected 95% CI [-.003, .218], $f^2 = .010$. This local f^2 is conventionally negligible; the 95% interval also leaves room for a small positive interaction and so is not proof of a zero-population effect.

The original OEC $\rightarrow$ EGIB bias-corrected 95% interval [-.202, .070] in Table 4 was verified against the preserved Smart PLS bootstrap export (unrounded [-.201969, .070375]). The distinct original percentile interval was [-.142, .114]; their difference reflects the bootstrap correction and empirical distribution, not a transcription error. Neither interval supports a significant OEC main effect. The fitted high-minus-low conditional slope contrast is .198 ($= 2 \times .099$), but its inferential uncertainty is determined by the interaction, not by comparing separately significant simple slopes. Given the original SE = .060, a normal-approximation 80%-power sensitivity benchmark for a two-sided $\alpha = .05$ test would require an interaction near $|\beta| \approx (1.96 + .84) \times .060 = .168$ if precision stayed constant. This is an illustrative detestability calculation—not an observed/post-hoc power estimate—and suggests the study is not decisive about interactions as small as .099. An improved prospective power analysis would need an explicit target interaction, measurement model, and simulation assumptions.

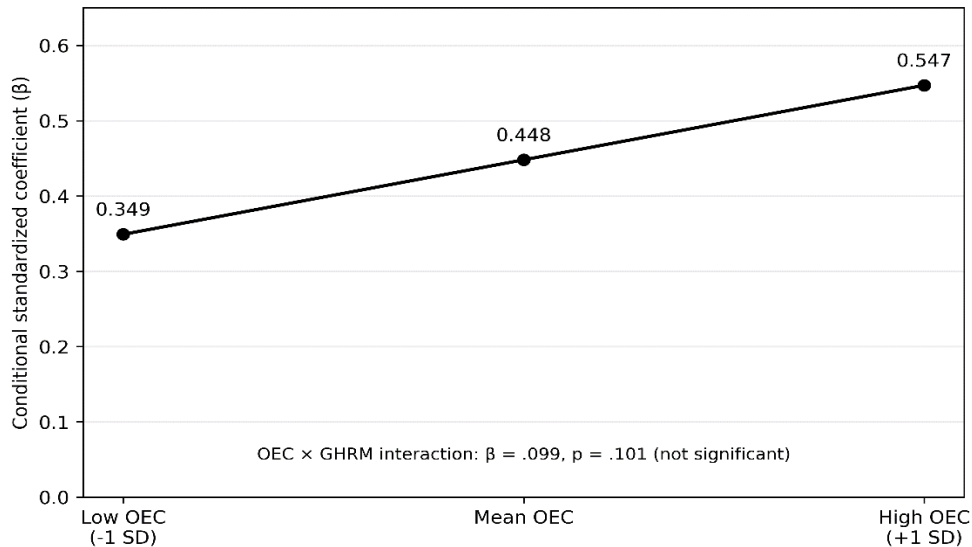
Table 4: Focal structural path results

Hypothesis / path	β	SE	t	p	Bias-corrected 95% CI	Decision
H1: GHRM $\rightarrow$ EGIB	.448	.049	9.102	< .001	[.348, .540]	Supported
OEC $\rightarrow$ EGIB	.012	.057	.204	.839	[-.202, .070]	Not significant
H2: OEC $\times$ GHRM $\rightarrow$ EGIB	.099	.060	1.642	.101	[-.003, .218]	Not supported

The original fitted GHRM-EGIB slopes were .349 at OEC -1 SD, .448 at the mean, and .547 at +1 SD. The preserved native Smart PLS export contains the bias-corrected intervals for the mean and high levels, but not the low-OEC interval. A supplementary 5,000-draw fixed-score case bootstrap estimated the low-OEC slope as .349 with a bias-corrected 95% CI [.218, .490]; under that auxiliary model its slope is above zero. This interval is conditional on measurement weights being fixed and is not a native Smart PLS bootstrap result. The original interaction test remains non-significant, so significance of an individual conditional slope cannot demonstrate that OEC significantly changes the slope. The exploratory Johnson-Neyman-style normal-approximation band for the auxiliary slope is above zero for OEC values greater than approximately -2.20 standardized units. This is a region in which GHRM's fitted slope differs from zero, not a region of statistically demonstrated moderation; the threshold is near the low end of the observed OEC score range (approximately -2.53 to 1.87 SD).

Table 5: Conditional GHRM–EGIB coefficients by OEC (native values; *auxiliary fixed-score bias-corrected CI)

OEC level	Conditional β	Inference	95% CI
Low (–1 SD)	.349	Fixed-score $p < .001^*$	[.218, .490]*
Mean	.448	Native $p < .001$	[.348, .540]
High (+1 SD)	.547	Native $p < .001$	[.400, .692]

**Fig. 2:** Conditional GHRM–EGIB coefficients at low, mean, and high OEC. The interaction itself was not statistically significant.

4.3 Supplementary sensitivity and inferential caveats

Using the archived stage-two indicator data, a 5,000-case-resample fixed-score bootstrap (seed 20260923) produced the auxiliary low-OEC slope .349 and bias-corrected 95% CI [.218, .490]. The original complete-model estimate was reproduced to rounding, but resampled weights were not re-estimated. Importantly, this auxiliary fixed-score bootstrap gives an interaction interval [.005, .191] for the original weighted OEC score, while the original native Smart PLS bias-corrected interaction interval is [–.003, .218] and $p = .101$. The differing inferential procedures and handling of estimated measurement scores mean that the auxiliary fixed-score confidence interval cannot replace primary Smart PLS inference. We retain the native non-significant interaction decision. The exploratory Johnson–Neyman-style zero-slope boundary is similarly conditional on fixed scores and is not evidence that moderation occurs. Item-deletion checks using alternative equally weighted OEC scores are reported below as descriptive scoring sensitivity, not re-estimated native PLS-SEM tests.

Table 6: Alternative OEC scoring sensitivity: fixed-score point estimates and auxiliary bias-corrected 95% intervals (5,000 draws)

OEC score definition	GHRM $\rightarrow$ EGIB β	OEC $\rightarrow$ EGIB β	OEC $\times$ GHRM β	Auxiliary BC 95% CI for interaction
Original weighted OEC score	.448	.012	.099	[.005, .191]*
All five OEC items; equal weight	.453	–.005	.091	[–.010, .194]
Four items, excluding Q33	.448	–.002	.079	[–.015, .174]
Four items, excluding Q34	.455	.007	.102	[–.001, .209]
Three items, excluding Q33 and Q34	.450	.014	.087	[–.009, .183]

Note. Original weighted OEC uses archived native outer weights; alternative OEC scores use equal weights on standardized included indicators, while other construct scores and the regression specification remain fixed. The full-sample point estimates are similar across variants; fixed-score BC intervals for reduced scores contain zero, so the apparent interaction is sensitive to both scoring and uncertainty assumptions. The original weighted-score auxiliary interval [.005, .191] differs from native Smart PLS [–.003, .218] and must NOT replace its non-significant interaction test. None of these rows is a native leave-one-item-out Smart PLS re-estimation; confirm with separately bootstrapped complete-model reruns if that level of sensitivity is required.

4.4 Independent full-score re-estimation with the author-confirmed respondent dataset

The corresponding author confirmed that the supplied workbook named “Simulated_Training_Data_GHRM_EGIB_n384(5).xlsx” contains the 384 actual study responses despite its filename. We used it on that author-provided basis. All 384 unique records had valid 1–5 responses for Q1–Q35 and no missing item values. The 17 raw columns Q19–Q35 matched the archived original Smart PLS stage-two respondent export in all 6,528 compared cells and row positions. This correspondence supports the match between the submitted workbook and the archived analysis file but cannot independently establish how the original fieldwork was conducted or verify individual participant provenance.

As an independent robustness analysis, we also resampled respondents 5,000 times (seed 20260923) and re-estimated all first-component scores (PC1) from standardized ability Q1–Q6, motivation Q7–Q12, opportunity Q13–Q18, green mindfulness Q19–Q24, EGIB Q25–Q30, and each OEC item block in every draw. A second-stage PC1 of the three AMO scores represented overall GHRM. Within each draw we refitted the same broad EGIB equation containing GHRM, green mindfulness, OEC, $\text{GHRM} \times \text{OEC}$, and $\text{green mindfulness} \times \text{OEC}$. Each of the two product scores was standardized; to express a conditional GHRM slope for a one-SD increase in OEC we accounted for product-score standardization. Reflective item weights and construct scores therefore changed with each bootstrap sample, unlike the fixed-score supplementary checks in Section 4.3. This is a PCA-based two-stage composite-score sensitivity estimator, not a rerun of the native Smart PLS PLS-SEM algorithm; the estimates are not substituted into the original tables or presented as Smart PLS output.

Table 7: Independent full-score re-estimation sensitivity (author-confirmed 384 responses, 5,000 bootstrap draws; bias-corrected 95% intervals)

OEC indicators	OEC alpha	GHRM direct β	Interaction β	BC 95% CI: interaction	Low OEC slope β	BC 95% CI: low
Q31–Q35	0.836	0.448	0.098	[−0.003, 0.198]	0.350	[0.216, 0.484]
Exclude Q33	0.809	0.443	0.086	[−0.007, 0.178]	0.357	[0.227, 0.489]
Exclude Q34	0.810	0.451	0.108	[0.005, 0.214]	0.342	[0.207, 0.482]
Exclude Q33 & Q34	0.773	0.445	0.095	[−0.001, 0.191]	0.350	[0.219, 0.485]

Note. The OEC alpha values were computed from the original observed indicators for each item set. All model-specific BC intervals use case-bootstrap re-estimation of the PCA-based measurement scores and the complete broad structural regression. The low-OEC slope is the fitted GHRM slope at one standardized OEC unit below the mean. This auxiliary approach estimates a different score model from the archived native Smart PLS PLS-SEM. It is therefore not a native reflective-indicator deletion test, and its intervals do not replace the original interaction $\beta = .099$, $p = .101$ and BC 95% CI [−.003, .218].

The independent full-score estimator produced interaction $\beta = .098$ and BC 95% CI [−.003, .198] with all five OEC indicators and low-OEC $\beta = .350$, BC 95% CI [.216, .484]. Dropping Q33 produced $\beta = .086$, CI [−.007, .178]; dropping Q34 produced $\beta = .108$, CI [.005, .214]; and dropping both produced $\beta = .095$, CI [−.001, .191]. The estimates were positive and of similar magnitude, but the marginal Q34-deletion interval excluded zero in this exploratory score model, whereas other intervals and the primary native test included zero. Such model-dependent inference cautions against treating the interaction as established. The native Q33 and Q34 loadings and the original non-significant moderation conclusion remain unchanged.

5. Discussion

5.1 Green HR systems and employee green innovation

Overall GHRM was positively related to employees’ green innovation, beyond routine green compliance. The association is consistent with the AMO account: environmental training provides capability, appraisal and rewards support motivation, and participation opportunities make ideas actionable [6, 5].

The cross-sectional design supports statistical association, not a causal impact claim.

This is especially pertinent in manufacturing as employee innovation is related to their operational knowledge. Laborers can detect resource losses, inefficiencies in the processes, waste, and constraints to implementation that may not be apparent at a higher-level management. GHRM can transform the identification and communication in relation to such improvement opportunities into legitimate work and not an option of sustainability activity.

5.2 Why OEC did not significantly moderate the direct relationship

The evidence did not establish the hypothesized OEC amplification of the direct GHRM–EGIB association. A non-significant interaction with a negligible local f^2 is compatible with weak or absent moderation, but also with an undetected small positive interaction within the original bootstrap interval. We therefore refrain from describing the relation as definitively unchanged

across cultures or describing the conditional coefficient contrast as statistically demonstrated reinforcement.

Signal redundancy offers one possible mechanism: green recruitment, training, appraisal, rewards, safety procedures and participation already deliver salient environmental instructions that a wider culture need not repeat. Stage specificity offers another: environmental norms might matter at the socially risky stages of proposing, endorsing, or implementing an idea, rather than uniformly across an aggregate EGIB outcome. Both arguments were introduced before H2 to specify competing expectations; neither was directly tested as a separate mechanism here [11].

Another untested possibility is that GHRM helps shape perceived OEC, which may transmit an association to EGIB rather than alter the GHRM slope. Roscoe et al. [8] link green HRM with green culture, and Fang et al. [22] describe possible indirect routes through green culture or innovation. Temporal ordering, a specified mediator model and appropriate uncertainty analysis would be required to assess such an alternative. The present OEC main coefficient and interaction are not evidence for or against the proposed mediated chain.

Recent evidence from Zhou et al. [19] shows that perceived organizational innovation support can positively moderate the GHRM–green innovative behavior relationship. The contrast with the present no significant OEC interaction is informative because organizational innovation support is more proximal to idea generation and implementation than broad environmental culture. A specific support climate may therefore be more likely than a broad cultural construct to change the strength of the direct HRM–innovation link.

5.3 Interpreting the conditional coefficient pattern

The fitted coefficients rose from .349 at low OEC to .547 at high OEC, a difference of .198 on the model's standardized coefficient scale. That range may matter operationally if replicated, but its uncertainty follows the original non-significant interaction ($\beta = .099$, $p = .101$, 95% CI $[-.003, .218]$); describing the contrast as a reliable cultural reinforcement would be incorrect. Supplementary fixed-score conditional and item-scoring checks add robustness context but are not evidence overturning the original PLS-SEM moderation decision.

6. Theoretical and Practical Implications

6.1 Theoretical implications

First, the model distinguishes an integrated AMO-based direct association from an unconfirmed cultural amplification proposition. The AMO framework itself supplies no necessary moderator prediction; Social Learning Theory and cultural signal-consistency motivate the additional contextual proposition. The null interaction test, with nontrivial uncertainty, should guide future precision-focused tests rather than be treated as a universal boundary-condition verdict.

Second, formal and informal environmental systems may overlap in their cues, or culture may operate at narrower behavioral stages or along an indirect pathway. Distinguishing signal redundancy, stage specificity, and $\text{GHRM} \rightarrow \text{OEC} \rightarrow \text{EGIB}$ as separate prospective mechanisms requires longitudinal or multiage designs and distinct outcome stages.

Third, the finding helps to distinguish between the broad and more proximal forms of support. This is in contrast to recent moderation studies on organizational innovation support [19], which highlights the importance of differentiating values/norms from direct resources, encouragement, implementation support, and psychological safety for innovation.

6.2 Practical implications

Building culture should not be a replacement for good green HR systems. It is necessary to design and implement recruitment, training, performance criteria, recognition, job responsibilities and avenues for employee participation in a clear manner. The direct GHRM–EGIB relationship was positive at all observed OEC levels, indicating that formal HR structure can offer a relatively solid basis to support employee green innovation.

In the meantime, the lack of significance for the interaction cannot be used as an excuse to ignore the importance of environmental culture. Legitimacy, peer behavior, leadership continuity and the institutionalization of environmental priorities can still be influenced by culture. Managers need to therefore reconcile cultural messages with HR systems and refrain from assuming that general messages of corporate "green" commitment will reinforce the positive effects of green HR practices.

A sensible progression for Jordanian manufacturing companies would be to first make sure that environmental responsibilities are part of the HR architecture and then evaluate the cultural level of support that is behaviorally closest: for instance, does the supervisor respond to ideas, are peers willing to experiment, do employees have materials to test environmental improvements?

7. Limitations and Future Research

The cross-sectional single-source design cannot establish causal or temporal relations. Common-method screens from the original doctoral analysis found that the first unroasted factor explained 25.32% of variance; full-collinearity VIFs ranged 1.029–1.914 in the principal model and 1.030–1.662 in the AMO model. These are useful diagnostics, not proof against method bias. Common method variance can attenuate estimated interactions under some conditions, so the non-significant interaction might reflect both substantive and methodological uncertainty [31,32]. Q33 and Q34 were retained for content, although Q33's low loading and the ρ_A -alpha gap warrant independent replication and a native model re-estimated without each item. The supplementary fixed-score sensitivity analyses use archived scores and cannot substitute for re-estimating the complete measurement and structural model. The auxiliary low-slope interval and J-N-style boundary condition on fixed weights, rather than on native Smart PLS re-estimation, should be interpreted accordingly. The original export contained no native low-OEC conditional CI and no preplanned interaction-power simulation. Unique firm identifiers were not retained, so OEC could not be aggregated at firm level; future studies should preserve clustering information and use multiwave and multisource indicators, supervisor ratings, objective innovation outcomes, and separately specified culture-mediation models. The fixed-score bootstrap interval for the original weighted interaction excludes zero, unlike the native Smart PLS interval; this sensitivity to inferential method is an additional reason not to infer reliable moderation from the auxiliary analyses. The author-confirmed raw dataset permitted additional complete score re-estimation under an independently specified PCA-composite method (Section 4.4); the exploratory Q34-exclusion interval highlights that indicator choice and estimation method affect marginal inference, without changing the archived Smart PLS result.

8. Conclusion

The study examined whether perceived OEC moderates the association between an integrated GHRM system and employee green innovation behavior in Jordanian manufacturing. Overall GHRM was positively associated with EGIB, while the OEC main association and $OEC \times GHRM$ interaction were not statistically significant. The conditional coefficients' fitted positive gradient is not reliable moderation evidence, and the original CI does not exclude small positive moderation. Two-stage higher-order reporting, verified OEC confidence bounds, common-method diagnostics, and explicitly labeled auxiliary sensitivity assessments improve transparency without changing the primary statistical inference. Further studies should separately test cultural mediation and stage-specific moderation with prospectively adequate precision. Independently re-estimated composite-score checks on the author-confirmed responses yielded similar interaction point estimates but slightly model-dependent uncertainty; no confirmatory conclusion is drawn from these exploratory variants.

Supplementary computational transparency

The archived native Smart PLS export M1 contains the unrounded original coefficient, bootstrap SE, p-value and distinct percentile and bias-corrected confidence intervals for the OEC main path and interaction; the table reports the bias-corrected bounds as originally exported. The auxiliary fixed-score calculations used the preserved respondent-level stage-two items and AMO scores (384 records), archived outer weights, 5,000 case-resampling draws, and seed 20260923. In each auxiliary draw the regression was refitted while previously estimated measurement weights remained fixed. Conditional slope at standardized $OEC = m$ was evaluated from $\beta_{GHRM} + m \times \beta_{interaction}$; for the interaction term standardized as a product, its product-scale normalization was accounted for. Percentile/bias-corrected intervals were calculated from the case-bootstrap distribution. The alternative-OEC analyses replaced only the moderator score definition, retaining the original covariates GHRM, green mindfulness, OEC, $GHRM \times OEC$, and $green\ mindfulness \times OEC$. This supplemental procedure does not recreate native Smart PLS iterative re-estimation, native uncertainty, or a stand-alone three-construct model. For the independently re-estimated Section 4.4 models, PC1 measurement weights were recomputed within each bootstrap draw from the 35 raw item responses; this procedure differs from both the Section 4.3 fixed-score bootstrap and native PLS-SEM. The workbook filename includes "Simulated", but the corresponding author identified its content as the real survey responses. The case-matched archived SmartPLS Q19–Q35 item values provide an internal consistency check, not external fieldwork verification.

Declarations

Ethics and consent. Formal organizational permission and voluntary informed consent were documented in the doctoral study. Participation was voluntary, questionnaire responses were anonymous, and data were handled confidentially. The supplied study materials did not include a separate institutional ethics approval number.

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

Competing interests. No competing interests were reported in the supplied study materials.

Funding. No study-specific external grant was reported in the supplied study materials.

Dataset-use transparency. This manuscript reports the GHRM–EGIB direct relationship and Organizational Environmental Culture moderation analysis from a broader doctoral dataset. A companion manuscript uses the same sample to examine Green Mindfulness as an attentional mediating mechanism. The focal hypotheses, theoretical contribution, tables, figures, and discussion are intentionally separated. The focal moderation coefficients reported here were estimated within the broader doctoral structural model; no new post hoc three-variable model was generated for this manuscript.

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