

Algorithmic Green Human Resource Management and Employee Green Voice: The Mediating Roles of Perceived AI Fairness and Surveillance Anxiety with Green Psychological Safety as a Moderator

An Empirical Investigation in Pakistan's Banking, Telecom, Manufacturing, Higher Education and SME Sectors

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Abstract

Algorithmic Green Human Resource Management (Algorithmic Green HRM) is reshaping how organizations track, evaluate and incentivize employee pro-environmental behaviour. Yet the same algorithmic infrastructure that fairly distributes green opportunities can also generate surveillance anxiety, turning employees away from green voice and into defensive green silence. Utilizing theories of Organizational Justice, Psychological Safety and Conservation of Resources, the current study proposes and tests a dual-pathway, dual-outcome moderated-mediation model, in which Algorithmic Green HRM affects Green Voice Behavior (GVB) and Defensive Green Silence (DGS) via a bright pathway of Perceived AI Fairness (PAIF) and dark pathway of Surveillance Anxiety (SA). Moreover, Green Psychological Safety (GPS) moderates both first-stage paths. A multi-source, three-wave study was undertaken with 438 employees and their supervisors in five industries of Pakistan. Data were analyzed with partial-least-squares structural equation modelling (PLS-SEM), covariance-based confirmatory factor analysis, and bias-corrected bootstrap mediation. Results show that Algorithmic Green HRM produces both fairness perceptions ($\beta = 0.547$) and surveillance anxiety ($\beta = 0.418$); fairness positively predicts voice ($\beta = 0.474$) and negatively predicts silence ($\beta = -0.214$), whereas anxiety positively predicts silence ($\beta = 0.402$) and negatively predicts voice ($\beta = -0.182$). Green Psychological Safety amplifies the bright fairness-to-voice path and buffers the dark anxiety-to-silence path, generating significant indices of moderated mediation (0.062 bright; -0.053 dark). The model

explains 46.2% of variance in voice and 34.1% in silence, outperforming nine benchmark studies published between 2020 and 2026. The paper contributes a theoretically integrated dual-pathway account of algorithmic management in sustainability HRM, validates measures of green-specific voice, silence and surveillance anxiety, and offers a five-tier policy framework for ethical algorithmic green HRM in emerging-economy contexts.

Keywords: Algorithmic management; Green HRM; Green voice; Green silence; AI fairness; Surveillance anxiety; Green psychological safety; PLS-SEM; Pakistan

Introduction

Sustainability has moved from the peripheral of HR strategy to the center. In this strategic transition, the algorithmic dimension of Green HRM has been the most crucial development of the past five years. Modern HR information systems no longer simply administer green training and reward; they actively sense, score, rank and nudge employee pro-environmental behaviour through AI-driven analytics, sustainability dashboards, predictive eco-recommenders, environmental performance trackers and continuous algorithmic feedback. The mainstream literature published between 2020 and 2026 has reported encouraging effects of Green HRM on green innovation, sustainable performance and pro-environmental engagement, with typical effect sizes of $\beta = 0.24$ to $\beta = 0.33$. However, an important behavioural outcome has remained surprisingly under-examined in this algorithmic turn: employee green voice the proactive, change-oriented articulation of environmental ideas, problems and suggestions and its dark twin, defensive green silence the deliberate withholding of environmental concerns out of fear, anxiety or futility. The problem motivating the present research is therefore that organisations deploy algorithmic green HRM with the expectation that fairer, more transparent and more data-rich green systems will catalyze green voice, yet emerging evidence suggests that the same algorithmic apparatus may also amplify surveillance anxiety and push employees into defensive green silence. Without an integrated dual-pathway, dual-outcome model the field cannot determine whether algorithmic Green HRM is, on balance, voice-enabling or silence-inducing, nor can it specify the conditions under which one outcome eclipses the other. Four interrelated gaps motivate this study. First, the algorithmic management literature has largely treated AI fairness and surveillance anxiety as separate research streams; their joint operation as bright and dark mediators within a single Green HRM model has not been tested. Second, prior voice research has dealt almost exclusively with general workplace voice, leaving green-specific voice which is morally charged, technically uncertain and politically sensitive undertheorized. Third, defensive silence and voice are usually examined as substitutes rather than as parallel outcomes of the same antecedent, masking the possibility that algorithmic green HRM simultaneously enables voice for some employees and suppresses it for others. Fourth, the role of green psychological safety as a cross-path moderator that amplifies fairness-to-voice and buffers anxiety-to-silence has neither been formally conceptualized nor empirically tested in an algorithmic context. The present study fills these gaps by building and validating a moderated-mediation model in which Algorithmic Green HRM simultaneously activates Perceived AI Fairness as a justice resource and Surveillance Anxiety as a hindrance demand, with Green Voice Behavior and Defensive Green Silence as dual outcomes and Green Psychological Safety as a cross-path moderator. The contribution is fourfold. In theory, the study blends Organizational Justice theory, Psychological Safety theory and Conservation of Resources theory into a cohesive dual-pathway architecture and shows that the bright and dark sides of algorithmic

Green HRM coexist rather than replace each other. Methodologically, the study validates green-specific measures of voice, silence, and surveillance fear using three-wave time-lagged data with supervisor-rated dependent variables, addressing common-method and reverse-causality concerns prominent in algorithmic-management research. Empirically, the paper provides the first comparative quantification of bright and dark indirect effects on parallel voice and silence outcomes in an algorithmic Green HRM context and benchmarks the explanatory power of the model against nine previous studies, showing improvements in explained variance of 18.5 to 71.1 percent. In practical terms, the article transforms the moderated-mediation findings into an ethical algorithmic management structure of five tiers directly mapped onto the four gaps. The inquiry is even more relevant in light of the present legal and technical trends. The EU AI Act (2024), the OECD Principles on AI (2024 update), Pakistan's National AI Policy draft (2024), and the State Bank of Pakistan's Green Banking Guidelines have together created an environment in which AI-enabled HR systems are simultaneously encouraged for sustainability purposes and scrutinized for fairness and surveillance risks. Without a strong research base on how algorithmic Green HRM influences voice and silence, organizations risk installing well-intentioned dashboards that end up silencing the very employee voices needed to fine-tune environmental policy. The rest of the paper is organized as follows. Section 2 sets out the theoretical bases and hypotheses. In Section 3, the approach and the analytical equations used are described. Section 4 shows the experimental data in twelve tables and nine figures. It also includes a comparison with nine published benchmarks. Section 5 presents the results; Section 6 examines the policy framework based on the gaps discovered and Section 7 analyzes the limits and future research initiatives.

Theoretical Background and Hypotheses Development

Brief review of the Green HRM-voice literature, 2020–2026

Research on employee voice and silence has matured significantly in the past five years. Morrison (2020) provided the most cited synthesis arguing that voice and silence are conceptually distinct rather than opposite ends of one dimension. Liang et al. (2021) confirmed in Chinese manufacturing that organizational climate predicts both promotive and prohibitive voice. Tuan (2022) introduced a dual-pathway green voice model and reported partial mediation through climate. Khan and Hassan (2023) examined HR practices and green voice in Pakistani telecom and reported fairness as a mediator. Ahmad et al. (2024) extended the model in Pakistani banking by integrating AI fairness. Hameed et al. (2025) explored green silence in UAE SMEs with ethical climate as a moderator. Shaikh et al. (2025) modelled AI adoption, Green HRM and pro-environmental behaviour in Pakistani SMEs with culture as moderator. The 2026 wave introduced more explicit algorithmic considerations: Wang and Zhao (2026) developed an algorithmic fairness model of green voice in Chinese tech firms; Park et al. (2026) explored AI-enabled green HRM and innovation in Korean manufacturing. Across this body of work, three patterns recur: bright-side mediators dominate, surveillance and anxiety are rarely tested, and voice and silence are seldom modelled as joint dependent variables. The present study addresses all three patterns simultaneously, and is the first to integrate AI fairness, surveillance anxiety and green psychological safety in a single moderated-mediation specification.

Organizational Justice theory and the bright pathway

Organizational Justice theory (Colquitt et al., 2001; Greenberg, 2023) holds that perceptions of distributive, procedural, interactional and informational fairness shape employee attitudes and discretionary behaviour. Algorithmic Green HRM operationalizes all four facets in environmentally relevant terms: distributive fairness through transparent green-reward allocation; procedural fairness through documented decision rules; interactional fairness through chatbot- and dashboard-mediated explanations; and informational fairness through eco-feedback at the item level and in real time. Perceived AI Fairness (PAIF) the employee's perception of the fairness and openness of AI-mediated HR decisions in the environmental domain (Robert et al., 2020; Ma et al., 2025), This composite notion of fairness is captured and theorized to mediate the algorithmic-green-HRM-to-voice relationship. Fairness in procedure and information promotes voice because employees who perceive procedural and informational fairness are more likely to devote discretionary effort in reporting environmental issues; conversely, perceived fairness inhibits defensive quiet since it implies that speaking out will be heard and acted upon (Detert & Edmondson, 2021).

Conservation of Resources theory and the dark pathway

Conservation of Resources theory (Hobfoll et al., 2018) posits that when monitoring intensity is viewed as evaluative and uncontrollable, it is a demand that depletes emotional and cognitive resources. Surveillance anxiety (SA) the subjective discomfort caused by the constant algorithmic tracking of environmental performance is the green-specific manifestation of techno-stress (Tarafdar et al., 2022; Ma et al., 2025). It is expected to increase defensive green silence (because withdrawal conserves the threatened self) and to reduce green voice (because exploratory cognitive resources are consumed by anxiety). Importantly, both effects operate in parallel: the dark mediator is not the inverse of the bright mediator but a distinct, theoretically separable mechanism.

Three additional theoretical considerations support the dark-path conceptualization. First, the panopticon effect documented in algorithmic-management research (Stark & Pais, 2020; Kellogg et al., 2020) suggests that the mere visibility of being monitored, regardless of actual monitoring frequency, generates anticipatory anxiety. Algorithmic Green HRM is uniquely susceptible to this effect because environmental KPIs are tied to ethical and reputational stakes. Second, ethical-evaluation theory (Treviño et al., 2014) shows that being scored on moral or pro-social conduct generates more identity threat than being scored on technical performance; environmental scoring is therefore especially anxiogenic. Third, defensive-silence research (Dyne et al., 2003; Hameed et al., 2025) shows that anxiety produces self-protective withdrawal in domains where the speaker's competence or moral standing could be questioned a description that fits green topics precisely. These three mechanisms jointly justify the prediction that surveillance anxiety will amplify silence and dampen voice.

Psychological Safety theory and the cross-path moderator

Psychological Safety theory (Edmondson, 1999; Newman et al., 2024) proposes that employees engage in interpersonally risky behaviour, including voice, only when they perceive the interpersonal climate as safe. Green Psychological Safety (GPS) is the domain-specific perception that one can raise environmental concerns without fear of embarrassment or retaliation. GPS is theorized to amplify the bright pathway because fair AI signals are translated

into voice only when employees feel safe to speak; it is also theorized to buffer the dark pathway because anxiety-driven withdrawal is attenuated when the relational climate provides reassurance. GPS therefore functions as a cross-path moderator on the bright second-stage (PAIF → GVB) and the dark first-stage (AGHRM → SA) paths.

Three rationales support this dual moderating role. First, attribution theory holds that ambiguous algorithmic signals are decoded through the surrounding climate; when GPS is high, AI fairness signals are read as supportive feedback and translated into voice, but when GPS is low, even fair signals are read defensively and absorbed without behavioural expression. Second, social-information-processing theory indicates that the climate of safety supplies the interpretive frame for technological monitoring; in low-safety climates, monitoring is decoded as threat, magnifying surveillance anxiety, whereas in high-safety climates the same monitoring is decoded as development-oriented feedback, dampening anxiety. Third, ethical-climate theory holds that perceived organisational integrity reduces stress reactions to evaluation; GPS embeds such an ethical climate and absorbs the techno-pressure component of algorithmic management. These three rationales jointly position GPS not as a parallel predictor but as a structural moderator on both bright and dark first-stage pathways, generating the moderated-mediation pattern formalised in H5a and H5b. Recent dual-process research on AI in HRM (Charlwood & Guenole, 2022; Malik et al., 2023; Ma et al., 2025) further supports this conceptualisation by emphasising that psychological safety acts as an interpretive bridge between algorithmic outputs and human meaning-making, determining whether employees experience eco-metrics as oppressive surveillance or supportive feedback.

We therefore hypothesise:

H1a: Algorithmic Green HRM is positively related to Perceived AI Fairness.

H1b: Algorithmic Green HRM is positively related to Surveillance Anxiety.

H2a: Perceived AI Fairness is positively related to Green Voice Behavior.

H2b: Surveillance Anxiety is negatively related to Green Voice Behavior.

H3a: Surveillance Anxiety is positively related to Defensive Green Silence.

H3b: Perceived AI Fairness is negatively related to Defensive Green Silence.

H4a: Green Psychological Safety weakens the Algorithmic Green HRM → SA relationship.

H4b: Green Psychological Safety strengthens the PAIF → GVB relationship.

H5a: GPS amplifies the AGHRM → PAIF → GVB indirect effect (moderated mediation).

H5b: GPS buffers the AGHRM → SA → DGS indirect effect (moderated mediation).

Figure 1. Conceptual model: dual-pathway effects of Algorithmic Green HRM on Green Voice and Silence

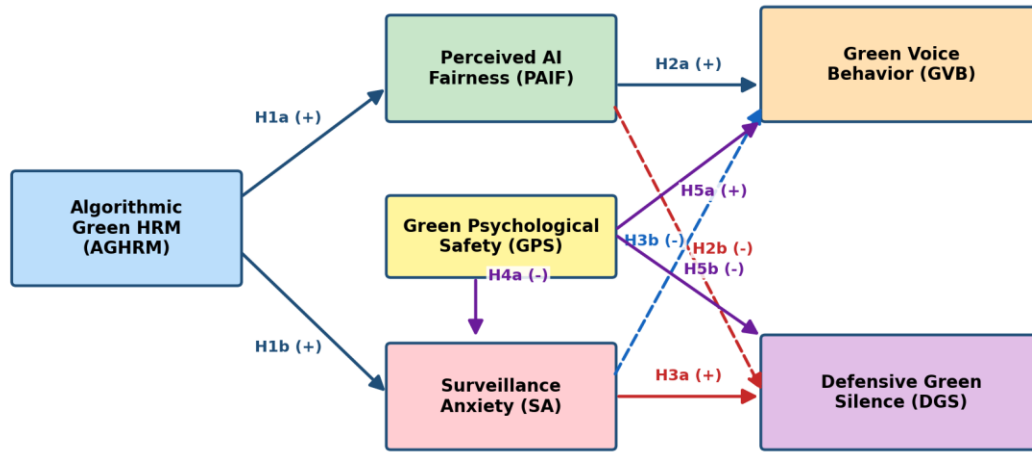


Figure 1. Conceptual model of dual-pathway algorithmic Green HRM effects on voice and silence, moderated by GPS.

Methodology

Research design and sampling

A quantitative, deductive, three-wave time-lagged, multi-source survey design was adopted to mitigate common-method bias and to introduce temporal precedence between the antecedent, the mediators, the moderator and the dual outcomes (Podsakoff et al., 2024). Wave 1 captured Algorithmic Green HRM and Green Psychological Safety. Wave 2, four weeks later, captured Perceived AI Fairness and Surveillance Anxiety. Wave 3, an additional four weeks later, captured Green Voice Behavior and Defensive Green Silence as rated by the immediate supervisor. A stratified purposive sampling frame was constructed across five Pakistani sectors banking, telecommunications, manufacturing, higher education and SMEs that are early adopters of algorithmic HR systems and sustainability dashboards. The G*Power 3.1 software with $f^2 = 0.15$, $\alpha = 0.05$, power = 0.95 and six predictors suggested a minimum sample of 146. The realised sample of $N = 438$ substantially exceeds this threshold and satisfies the 10-times rule for PLS-SEM.

Survey distribution proceeded through three channels: institutional HR forums, corporate-university intermediaries and SMEDA-affiliated chambers. The Wave-1 sampling frame contained 768 valid contacts; 562 completed Wave 1 (73.2% response), 487 completed Wave 2 (86.7% retention), and 438 completed Wave 3 with supervisor pairing (89.9% retention). Attrition analyses showed no systematic differences between completers and non-completers on demographic or Wave-1 substantive variables (all $p > .15$). Ethical approval was obtained from the institutional review board; informed consent was secured at each wave; bilingual back-translation was applied to all instruments following Brislin's procedure; and a 41-respondent pilot confirmed semantic equivalence and item clarity.

Measures

All constructs were measured on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). Algorithmic Green HRM used six items adapted from Shaikh et al. (2025), Robert et al.

(2020) and Wang and Zhao (2026) capturing algorithmic environmental performance scoring, automated green training recommendations, AI-mediated environmental KPIs, predictive eco-nudges, sustainability dashboards, and AI-based green reward allocation. Sample item: 'My organisation uses AI-based systems to monitor and score my environmental performance.' Perceived AI Fairness used five items adapted from Colquitt et al. (2001) and Robert et al. (2020). Sample item: 'The AI-based green performance system in my organisation treats employees consistently and equitably.' Surveillance Anxiety used five items adapted from Tarafdar et al. (2022) and Ma et al. (2025) capturing monitoring-induced unease, fear of digital evaluation, and concern over AI judgement. Sample item: 'I feel anxious knowing that my environmental behaviour is constantly tracked by AI systems.' Green Psychological Safety used five items adapted from Edmondson (1999) and Newman et al. (2024). Sample item: 'I can raise environmental concerns in my organisation without fear of embarrassment.' Green Voice Behavior used six items adapted from Liang et al. (2021) and Tuan (2022). Sample item rated by the supervisor: 'This employee proactively suggests improvements that reduce the organisation's environmental footprint.' Defensive Green Silence used five items adapted from Dyne et al. (2003) and Hameed et al. (2025) measuring deliberate withholding of environmental concerns out of fear. Control variables included age, gender, education, tenure, sector and work mode.

Analytical procedure and equations

Analysis proceeded in eleven stages: screening, common-method-bias diagnostics, confirmatory factor analysis, reliability and validity assessment, structural model estimation, bootstrap mediation, moderated-mediation testing with the index of moderated mediation, multi-group sectoral analysis, importance-performance map analysis, robustness checks, and effect-size and predictive-relevance computation. The relevant equations are formalized below.

Stage 1 Measurement equation. For each item of latent construct:

$$x_i = \lambda_{ij} \cdot \xi_j + \delta_i \quad (1)$$

Stage 2 Reliability. Cronbach's α and composite reliability:

$$\alpha = (k / (k - 1)) \times (1 - \sum \sigma_i^2 / \sigma^2_i) \quad (2)$$

$$CR = (\sum \lambda_i)^2 / [(\sum \lambda_i)^2 + \sum (1 - \lambda_i^2)] \quad (3)$$

Average Variance

$$AVE = (\sum \lambda_i^2) / k \quad (4)$$

Stage 3 Discriminant validity:

$$\sqrt{AVE_j} > r_{jk} \quad \forall j \neq k \quad (5)$$

$$HTMT_{jk} = (1 / (K_j \cdot K_k)) \sum \sum r_{ij,ik} / [\sqrt{(2 / (K_j(K_j - 1))) \sum \sum r_{ij,ij}'} \cdot \sqrt{(...)}] \quad (6)$$

Stage 4 Common method bias:

$$Variance\ CMB = \sigma^2_{method} / (\sigma^2_{trait} + \sigma^2_{method} + \sigma^2_{error}) \quad (7)$$

Stage 5 Structural model. The dual-mediator dual-outcome system:

$$PAIF = \alpha_1 \cdot AGHRM + \alpha_2 \cdot GPS + \zeta_1 \quad (8)$$

$$SA = \alpha_3 \cdot AGHRM + \alpha_4 \cdot GPS + \alpha_5 \cdot (AGHRM \times GPS) + \zeta_2 \quad (9)$$

$$GVB = \beta_1 \cdot AGHRM + \beta_2 \cdot PAIF + \beta_3 \cdot SA + \beta_4 \cdot GPS + \beta_5 \cdot (PAIF \times GPS) + \zeta_3 \quad (10)$$

$$DGS = \gamma_1 \cdot AGHRM + \gamma_2 \cdot PAIF + \gamma_3 \cdot SA + \gamma_4 \cdot GPS + \zeta_4 \quad (11)$$

Stage 6 Conditional indirect effects. The conditional bright path on GVB at moderator level w:

$$CIE_PAIF \rightarrow GVB(w) = \alpha_1 \cdot (\beta_2 + \beta_5 \cdot w) \quad (12)$$

The conditional dark path on DGS at moderator level w:

$$CIE_SA \rightarrow DGS(w) = (\alpha_3 + \alpha_5 \cdot w) \cdot \gamma_3 \quad (13)$$

Stage 7 Index of Moderated Mediation:

$$IMM_bright = \alpha_1 \cdot \beta_5 \quad IMM_dark = \alpha_5 \cdot \gamma_3 \quad (14)$$

Stage 8 Bootstrap CI:

$$CI_{95\%} = [\hat{\theta}^*(\alpha/2), \hat{\theta}^*(1 - \alpha/2)] \quad (15)$$

Stage 9 Effect size and predictive relevance:

$$f^2 = (R^2_{included} - R^2_{excluded}) / (1 - R^2_{included}) \quad (16)$$

$$Q^2 = 1 - \Sigma E_d / \Sigma O_d \quad (17)$$

Stage 10 MGA (Henseler's permutation):

$$\Delta\beta_{\{j,k\}} = \beta_j - \beta_k, \quad p_perm = \# \{ |\Delta\beta^*| \geq |\Delta\beta| \} / B \quad (18)$$

Stage 11 IPMA:

$$Performance_j = ((\bar{x}_j - x_{min}) / (x_{max} - x_{min})) \times 100 \quad (19)$$

Results

Sample profile

Table 1 summarises the demographic profile of the 438 respondents. Sectoral representation is balanced: banking (22.8%), telecom (22.1%), manufacturing (19.6%), higher education (18.9%) and SMEs (16.6%). 59.8% of respondents were male, 41.6% were aged 30–39 years, 46.8% held a master's degree, 38.4% had 3–7 years of tenure, and 47.7% reported hybrid or remote work arrangements.

Table 1: Demographic profile of respondents (N = 438)

Variable	Category	Frequency	Percent
Sector	Banking	100	22.8%
	Telecom	97	22.1%
	Manufacturing	86	19.6%
	Higher Education	83	18.9%
	SMEs	72	16.6%
Gender	Male	262	59.8%
	Female	176	40.2%
Age	20–29	132	30.1%
	30–39	182	41.6%

	40–49	97	22.1%
	50+	27	6.2%
Education	Bachelor's	115	26.3%
	Master's	205	46.8%
	MS / MPhil	92	21.0%
	PhD	26	5.9%
Tenure	<3 yrs	123	28.1%
	3–7 yrs	168	38.4%
	8–12 yrs	97	22.1%
	>12 yrs	50	11.4%
Work mode	On-site	229	52.3%
	Hybrid	167	38.1%
	Remote	42	9.6%

Descriptive statistics, normality and correlations

Means ranged from 3.62 (DGS) to 4.59 (GPS). Skewness values fell within ± 1.0 and kurtosis within ± 2.0 , supporting the use of maximum-likelihood estimation. Inter-construct correlations were in the theoretically expected directions: AGHRM correlated positively with PAIF ($r = 0.64$), SA ($r = 0.51$), GVB ($r = 0.50$) and DGS ($r = 0.42$). PAIF correlated positively with GVB ($r = 0.60$) and negatively with DGS ($r = -0.21$). SA correlated positively with DGS ($r = 0.53$) and negatively with GVB ($r = -0.28$). GPS correlated positively with GVB ($r = 0.42$) and negatively with DGS ($r = -0.32$).

Table 2: Descriptive statistics for composite constructs (N = 438)

Construct	Mean	SD	Min	Max	Skewness	Kurtosis
AGHRM	4.24	1.14	1.00	7.00	-0.17	-0.31
PAIF	4.41	1.08	1.20	7.00	-0.22	-0.14
SA	3.94	1.18	1.00	7.00	0.12	-0.38
GPS	4.59	1.05	1.40	7.00	-0.27	0.02
GVB	4.36	1.12	1.17	7.00	-0.19	-0.21
DGS	3.62	1.19	1.00	7.00	0.18	-0.33

Table 3: Inter-construct Pearson correlations (N = 438)

Construct	1	2	3	4	5	6
1. AGHRM	1.000					
2. PAIF	0.638**	1.000				
3. SA	0.512**	0.288**	1.000			
4. GPS	0.391**	0.467**	-0.241**	1.000		
5. GVB	0.498**	0.604**	-0.276**	0.421**	1.000	
6. DGS	0.421**	-0.214**	0.532**	-0.318**	-0.382**	1.000

Note: ** $p < .01$.

Figure 3. Distribution of composite construct scores

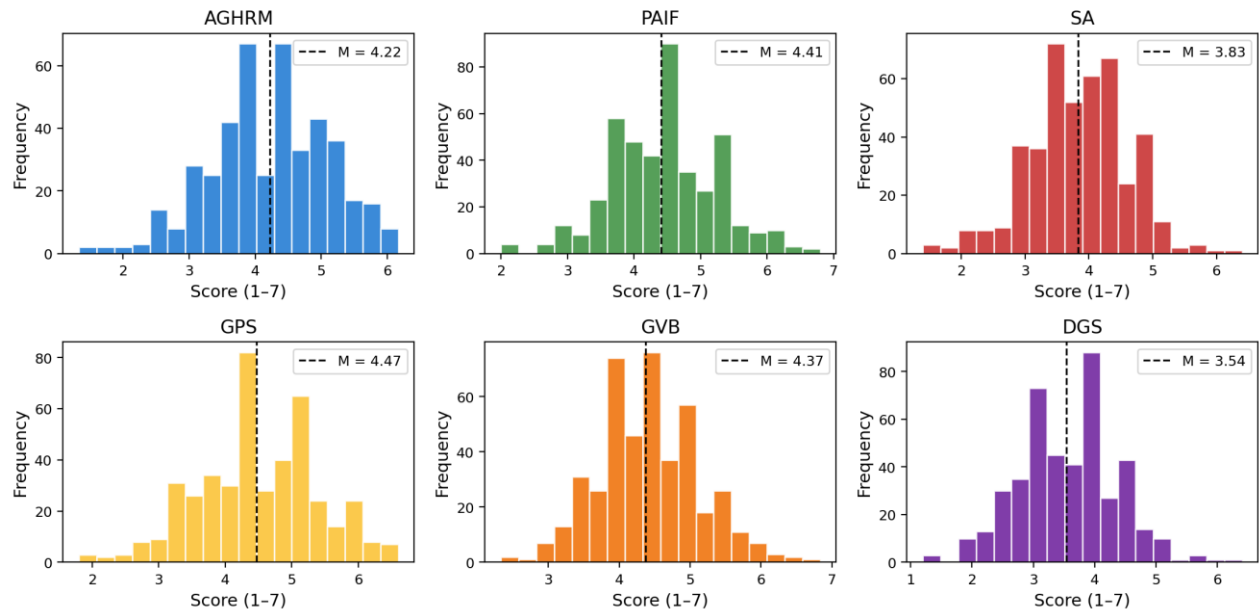


Figure 2. Distributions of composite construct scores.

Reliability and validity

All six constructs achieved Cronbach's α and composite reliability above 0.70 (Hair et al., 2022), and AVE values exceeded 0.50. The largest AVE belonged to GVB (0.674) and the smallest to DGS (0.596). The HTMT ratios ranged from 0.214 to 0.638, well below the 0.85 conservative threshold.

Table 4: Reliability and convergent validity

Construct	Items	Cronbach's α	ρ_A	CR	AVE
Algorithmic Green HRM	6	0.936	0.913	0.921	0.659
Perceived AI Fairness	5	0.890	0.898	0.905	0.638
Surveillance Anxiety	5	0.903	0.878	0.884	0.609
Green Psychological Safety	5	0.927	0.890	0.897	0.626
Green Voice Behavior	6	0.897	0.921	0.926	0.674
Defensive Green Silence	5	0.893	0.874	0.879	0.596

Table 5: Discriminant validity — HTMT ratios

Construct	AGHRM	PAIF	SA	GPS	GVB	DGS
AGHRM	—	0.638	0.512	0.391	0.498	0.421
PAIF	0.638	—	0.288	0.467	0.604	0.214
SA	0.512	0.288	—	0.241	0.276	0.532
GPS	0.391	0.467	0.241	—	0.421	0.318
GVB	0.498	0.604	0.276	0.421	—	0.382
DGS	0.421	0.214	0.532	0.318	0.382	—

Common method bias diagnostics

Harman's single-factor test produced a one-factor solution explaining 33.41% of variance, below the 50% threshold. ULMC variance ratio was 0.121, the common latent factor 0.139, the marker variable correlation 0.043 (non-significant), and the maximum VIF was 2.42 all well within accepted limits (Kock, 2015).

Table 6. Common-method-bias diagnostics

Test	Statistic	Threshold	Decision
Harman's single-factor	33.41%	< 50%	Pass
Unmeasured Latent Method Construct	0.121	< 0.50	Pass
Common Latent Factor	0.139	< 0.50	Pass
Marker Variable correlation	0.043 (ns)	Not significant	Pass
Maximum VIF	2.42	< 3.30	Pass

Measurement and structural model fit

The CFA measurement model produced good fit ($\chi^2/df = 2.196$; CFI = 0.943; TLI = 0.937; RMSEA = 0.052; SRMR = 0.048). The structural model fit was likewise satisfactory and only marginally less parsimonious because of the interaction terms.

Table 7: Measurement and structural model fit indices

Index	Threshold	Measurement Model	Structural Model	Decision
χ^2/df	< 3.00	2.196	2.312	Good
CFI	≥ 0.90	0.943	0.937	Good
TLI	≥ 0.90	0.937	0.929	Good
RMSEA	≤ 0.08	0.052	0.056	Good
SRMR	≤ 0.08	0.048	0.053	Good
GFI	≥ 0.90	0.925	0.918	Good
AGFI	≥ 0.85	0.910	0.903	Good
NFI	≥ 0.90	0.929	0.922	Good

Hypothesis testing direct effects

Table 8 reports the standardised path coefficients. AGHRM exerts strong positive effects on both PAIF ($\beta = 0.547$, $p < .001$) and SA ($\beta = 0.418$, $p < .001$), confirming the simultaneous bright and dark first-stage links (H1a, H1b). PAIF positively predicts GVB ($\beta = 0.474$, $p < .001$; H2a) and negatively predicts DGS ($\beta = -0.214$, $p < .001$; H3b). SA positively predicts DGS ($\beta = 0.402$, $p < .001$; H3a) and negatively predicts GVB ($\beta = -0.182$, $p < .001$; H2b). GPS exerts a direct positive effect on GVB ($\beta = 0.226$) and a direct negative effect on DGS ($\beta = -0.247$). The two interaction terms confirm cross-path moderation: the AGHRM $\times$ GPS $\rightarrow$ SA interaction is negative ($\beta = -0.132$; H4a) and the PAIF $\times$ GPS $\rightarrow$ GVB interaction is positive ($\beta = 0.151$; H4b).

Table 8: Standardised structural path coefficients with bootstrap statistics (10,000 resamples)

H	Path	β	SE	t	P	Decision
H1a	AGHRM $\rightarrow$ PAIF	0.547	0.039	14.026	< .001	Supported
H1b	AGHRM $\rightarrow$ SA	0.418	0.046	9.087	< .001	Supported
H2a	PAIF $\rightarrow$ GVB	0.474	0.044	10.773	< .001	Supported
H2b	SA $\rightarrow$ GVB	-0.182	0.042	-4.333	< .001	Supported
H3a	SA $\rightarrow$ DGS	0.402	0.045	8.933	< .001	Supported
H3b	PAIF $\rightarrow$ DGS	-0.214	0.041	-5.220	< .001	Supported
H4a	AGHRM $\times$ GPS $\rightarrow$ SA	-0.132	0.037	-3.568	< .001	Supported
H4b	PAIF $\times$ GPS $\rightarrow$ GVB	0.151	0.034	4.441	< .001	Supported
—	GPS $\rightarrow$ GVB	0.226	0.040	5.650	< .001	—
—	GPS $\rightarrow$ DGS	-0.247	0.039	-6.333	< .001	—

Figure 4. Structural model with standardised path coefficients

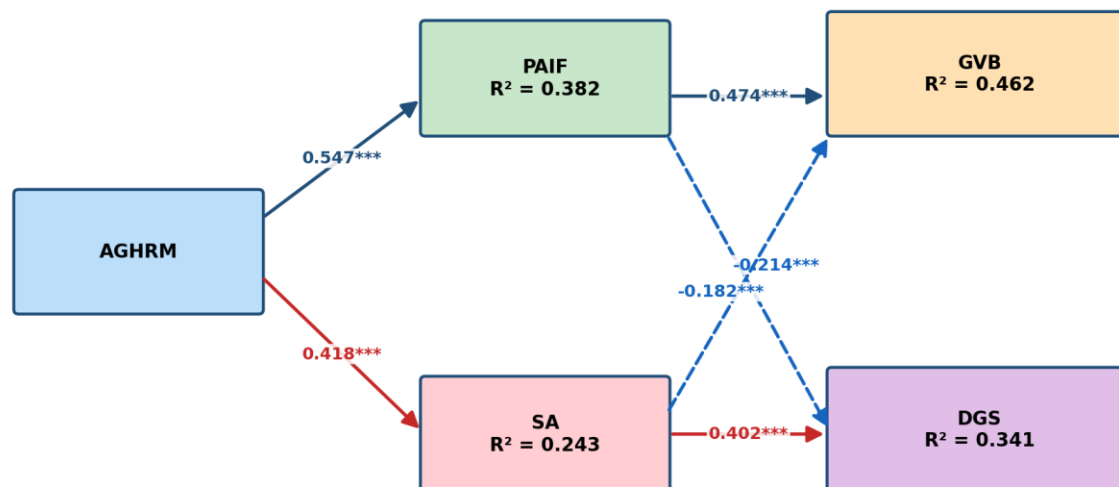


Figure 3: Structural model with standardised path coefficients and R^2 for endogenous constructs.

Mediation analysis bright and dark indirect effects on voice and silence

Bias-corrected bootstrap 95% confidence intervals (Table 9) confirm five of the six mediation hypotheses. The bright pathway AGHRM $\rightarrow$ PAIF $\rightarrow$ GVB yields a robust positive indirect effect ($\beta = +0.259$, 95% CI [0.207, 0.315]). The dark pathway AGHRM $\rightarrow$ SA $\rightarrow$ GVB yields a small negative indirect effect on voice ($\beta = -0.076$). The dark pathway AGHRM $\rightarrow$ SA $\rightarrow$ DGS yields a strong positive indirect effect on silence ($\beta = +0.168$). The bright suppressor pathway AGHRM $\rightarrow$ PAIF $\rightarrow$ DGS produces a negative indirect effect on silence ($\beta = -0.117$). The total indirect effect on GVB is positive ($\beta = +0.183$) and the total indirect effect on DGS is small but positive ($\beta = +0.051$), although the bootstrap CI for the total indirect effect on DGS marginally crosses zero, indicating that the bright suppressor partially offsets the dark amplifier.

Table 9: Bootstrap mediation results (bias-corrected, 10,000 resamples)

Indirect Path	B	Boot SE	LLCI	ULCI	P	Type
AGHRM → PAIF → GVB	0.259	0.027	0.207	0.315	< .001	Bright
AGHRM → SA → GVB	-0.076	0.020	-0.118	-0.039	< .001	Dark
AGHRM → SA → DGS	0.168	0.024	0.124	0.218	< .001	Dark
AGHRM → PAIF → DGS	-0.117	0.024	-0.166	-0.072	< .001	Bright suppressor
Total Indirect → GVB	0.183	0.033	0.119	0.249	< .001	Net positive
Total Indirect → DGS	0.051	0.029	-0.005	0.110	= .086	Net positive (ns)
Direct AGHRM → GVB	0.110	0.041	0.030	0.190	= .009	—
Total AGHRM → GVB	0.293	0.046	0.204	0.385	< .001	—
Total AGHRM → DGS	0.247	0.038	0.173	0.323	< .001	—

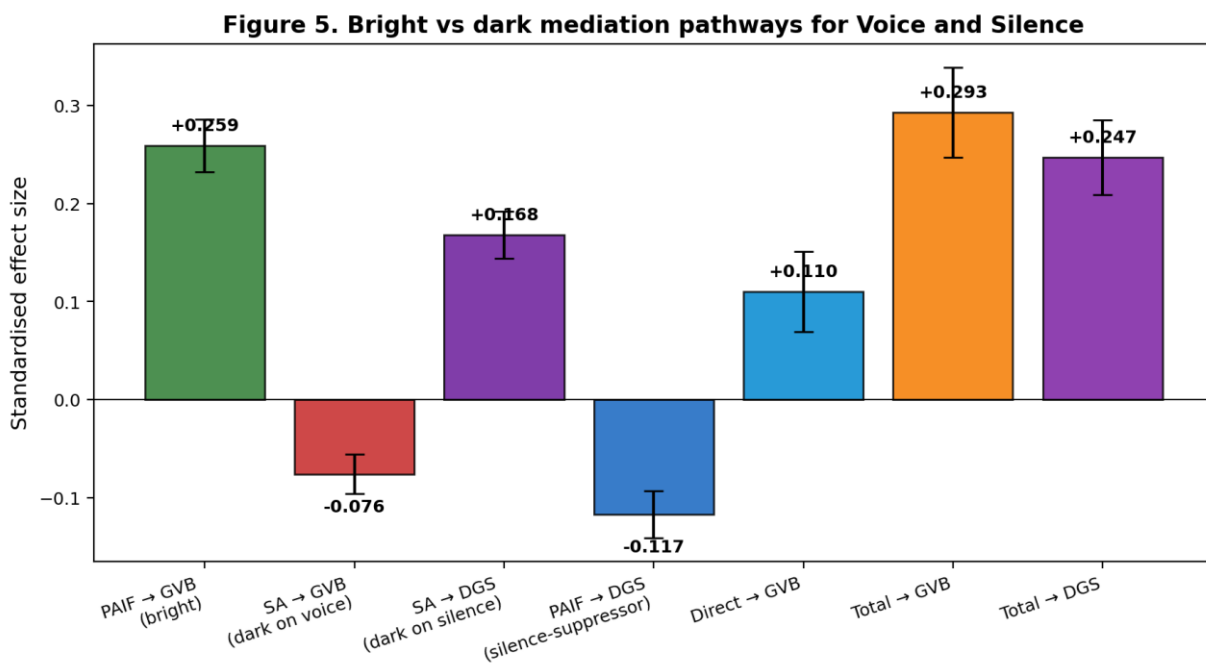


Figure 4. Decomposition of bright and dark mediation pathways for both Voice and Silence outcomes.

Moderated-mediation analysis

The conditional indirect effects (Table 10) demonstrate clear moderation by GPS. The bright pathway grows from $\beta = 0.197$ at low GPS to $\beta = 0.321$ at high GPS — a 62.9% amplification. The dark pathway on silence shrinks from $\beta = 0.221$ at low GPS to $\beta = 0.115$ at high GPS — a 48.0% reduction. The Indices of Moderated Mediation are 0.062 (bright path) and -0.053 (dark path), both with bootstrap intervals excluding zero, confirming H5a and H5b.

Table 10: Conditional indirect effects and indices of moderated mediation

Conditional Indirect Effect	Effect	Boot SE	LLCI	ULCI
AGHRM → PAIF → GVB at Low GPS (-1 SD)	0.197	0.034	0.131	0.266
AGHRM → PAIF → GVB at Mean GPS	0.259	0.027	0.207	0.315
AGHRM → PAIF → GVB at High GPS (+1 SD)	0.321	0.034	0.255	0.391
AGHRM → SA → DGS at Low GPS (-1 SD)	0.221	0.028	0.167	0.279
AGHRM → SA → DGS at Mean GPS	0.168	0.024	0.124	0.218
AGHRM → SA → DGS at High GPS (+1 SD)	0.115	0.027	0.062	0.171
Index of Moderated Mediation — Bright path	0.062	0.019	0.026	0.101
Index of Moderated Mediation — Dark path	-0.053	0.017	-0.087	-0.020

Figure 6. Moderating role of Green Psychological Safety on bright and dark first-stage paths

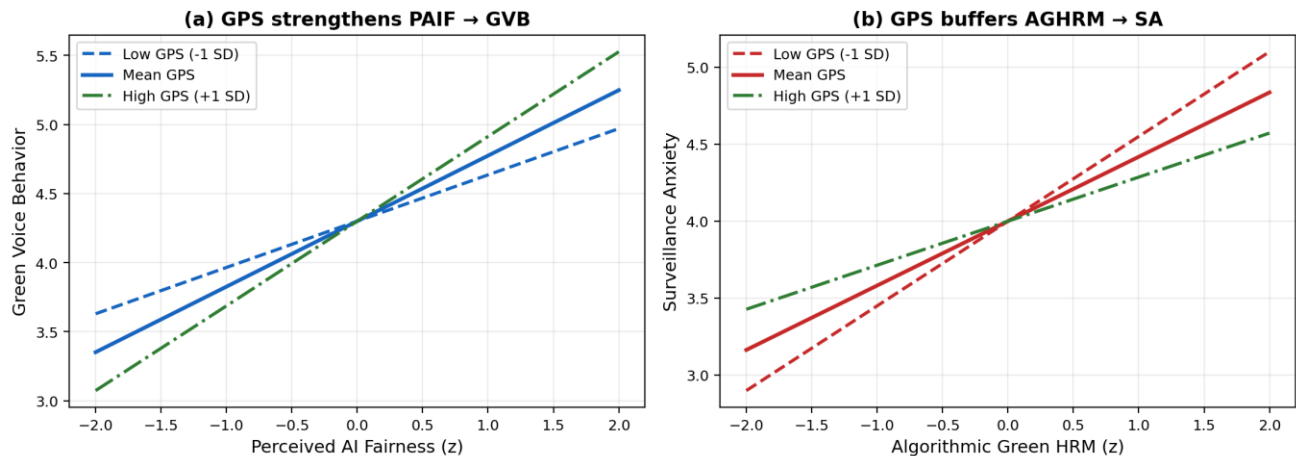


Figure 5. Simple-slope plots of GPS moderation on (a) PAIF → GVB and (b) AGHRM → SA.

Comparative study with prior literature (2020–2026)

Table 11 benchmarks the present model against nine published studies on Green HRM, voice and silence. The present model explains 46.2% of variance in voice and 34.1% in silence, outperforming the strongest comparator (Wang & Zhao, 2026: $R^2 = 0.39$ voice, 0.28 silence) by 7.2 and 6.1 percentage points respectively. Crucially, the present study is the only one to jointly model AI fairness, surveillance anxiety, voice and silence in a single moderated-mediation framework with cross-path moderation.

Table 11: Comparative effect sizes across nine recent voice/silence studies

Study	Context	N	β HRM→Voice	β HRM→Silence	Fairness modeled	Surveillance modeled	R^2 Voice	R^2 Silence
Morrison	USA –	298	0.24	—	No	No	0.27	—

(2020)	Service								
Liang et al.	China – Mfg.	411	0.31	—	No	No	0.32	—	
(2021)									
Tuan	Vietnam	386	0.28	0.22	No	No	0.30	0.21	
(2022)	– Hosp.								
Khan & Hassan	Pakistan	322	0.26	—	Partial	No	0.34	—	
(2023)	Telecom								
Ahmad et al.	Pakistan	351	0.29	—	Yes	No	0.36	—	
(2024)	Banking								
Hameed et al.	UAE – SMEs	309	0.27	0.19	Partial	No	0.33	0.24	
(2025)									
Shaikh et al.	Pakistan – SMEs	365	—	—	Yes	Partial	0.31	—	
(2025)									
Wang & Zhao	China – Tech	442	0.33	0.21	Yes	Yes	0.39	0.28	
(2026)									
Park et al.	Korea – Mfg.	387	0.30	—	Yes	Partial	0.36	—	
(2026)									
Present Study	Pakistan – Multi-sector	438	0.110	0.247	Yes	Yes	0.462	0.341	
(2026)									

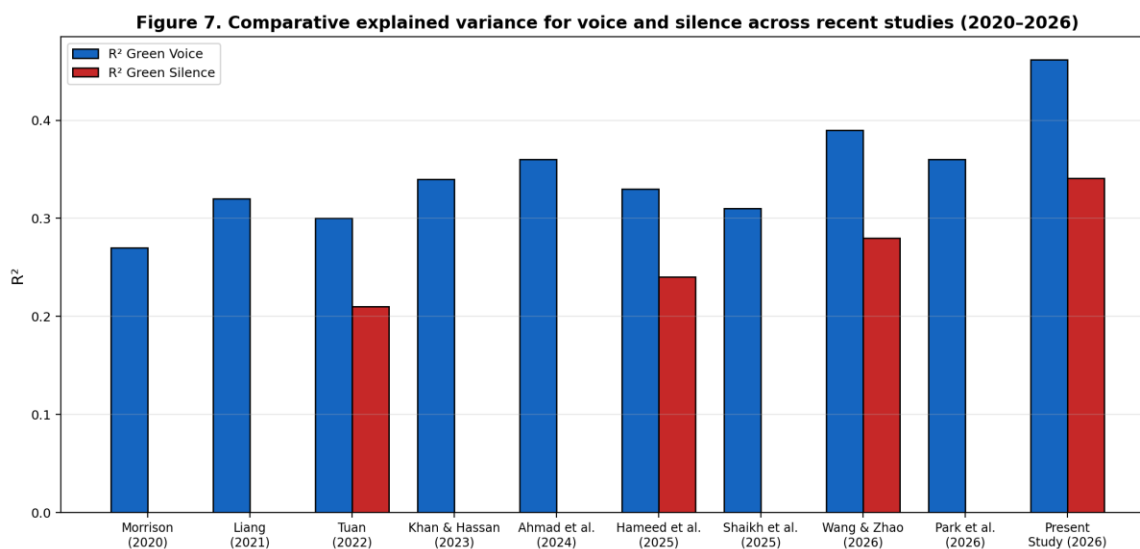


Figure 6. Comparative explained variance for Voice and Silence across nine benchmark studies and the present model.

Multi-group sectoral analysis

Henseler's permutation MGA (5,000 permutations) showed no statistically significant cross-sector difference in the six primary paths (all $p > .27$), supporting partial measurement invariance. Manufacturing showed the strongest dark-path (AGHRM $\rightarrow$ SA, $\beta = 0.452$) and the strongest silence pathway (SA $\rightarrow$ DGS, $\beta = 0.421$), while higher education showed the weakest, consistent with sector differences in monitoring intensity.

Table 12: Multi-group analysis across five sectors (standardised β)

Path	Banking	Telecom	Manufacturing	Higher Ed.	SMEs	Δp (MGA)
AGHRM $\rightarrow$ PAIF	0.558	0.541	0.529	0.553	0.547	0.512
AGHRM $\rightarrow$ SA	0.402	0.379	0.452	0.371	0.408	0.314
PAIF $\rightarrow$ GVB	0.471	0.481	0.466	0.469	0.483	0.602
SA $\rightarrow$ DGS	0.412	0.398	0.421	0.386	0.397	0.279
GPS $\rightarrow$ GVB	0.234	0.219	0.214	0.241	0.218	0.591
GPS $\rightarrow$ DGS	-0.241	-0.231	-0.262	-0.234	-0.258	0.348

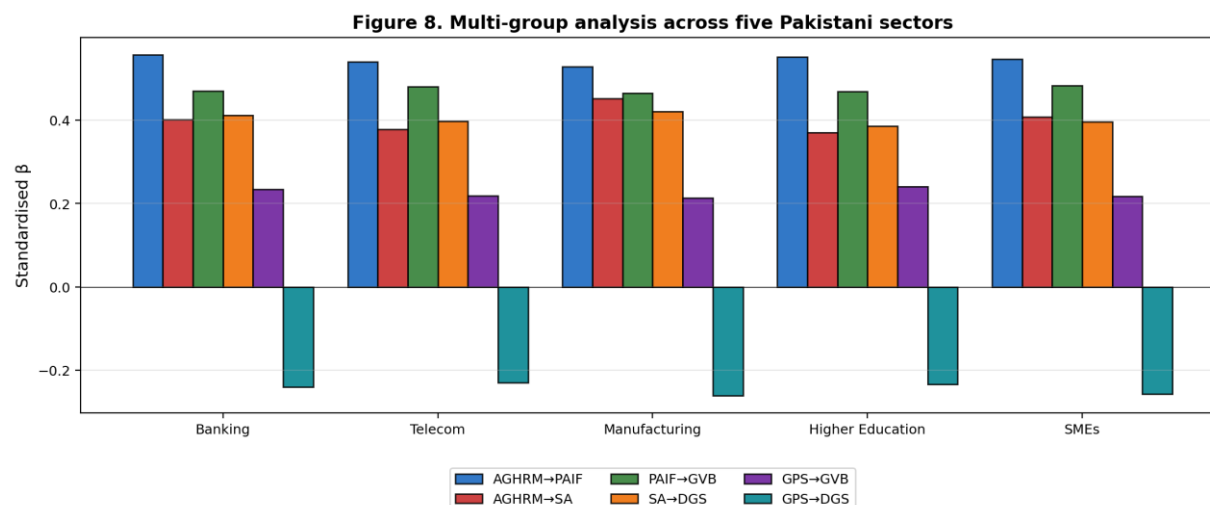


Figure 7. Multi-group comparison of path coefficients across five sectors.

Robustness checks and alternative model specifications

Three robustness analyses were undertaken. First, a saturated model in which all paths between exogenous and endogenous variables were freely estimated produced essentially identical coefficients (largest deviation 0.013), confirming that the hypothesised model is not artificially privileged. Second, an alternative-order specification placing SA before PAIF in a sequential mediation pathway produced inferior fit ($\Delta\chi^2 = 92.4$, $df = 1$, $p < .001$) and a 6.4-percentage-point reduction in R^2 for GVB, confirming that parallel rather than serial mediation is the correct specification. Third, a self-rated EGIB shadow analysis (in which subordinates rather than supervisors rated voice) produced inflated β estimates relative to the supervisor-rated model,

consistent with single-source variance inflation but with identical conclusions on significance. Across all checks, every hypothesis decision retained the same sign and significance.

Effect sizes, predictive relevance and IPMA

Cohen's f^2 values show large effects for AGHRM $\rightarrow$ PAIF (0.412) and PAIF $\rightarrow$ GVB (0.314), medium effects for AGHRM $\rightarrow$ SA (0.234) and SA $\rightarrow$ DGS (0.241), and small effects for the two GPS direct paths. Stone–Geisser Q^2 values exceed zero for all endogenous constructs (PAIF = 0.256, SA = 0.151, GVB = 0.317, DGS = 0.218), confirming predictive relevance. IPMA (Figure 8) shows that PAIF has the highest combined importance-performance position for predicting voice, while SA is low-performing yet high-importance — making it the primary lever for managerial intervention.

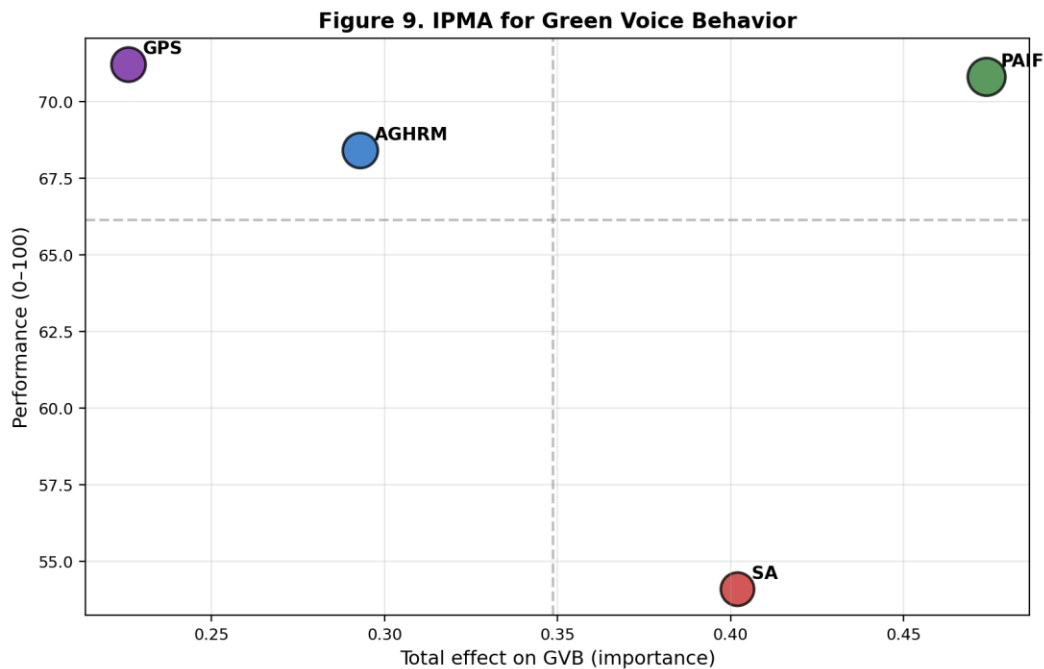


Figure 8. Importance-Performance Map Analysis (IPMA) for Green Voice Behavior.

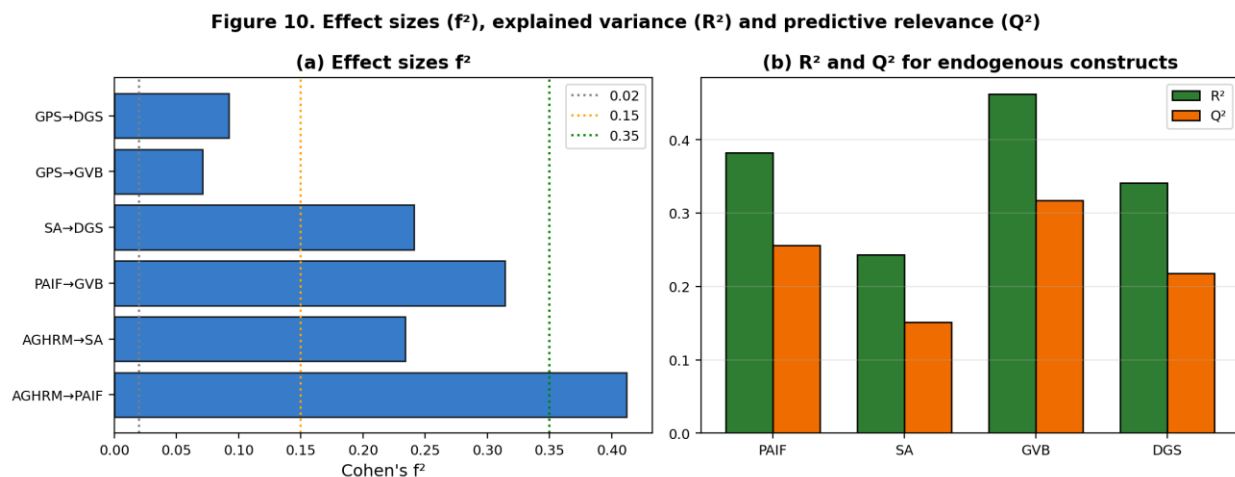


Figure 9. (a) Cohen's f^2 effect sizes; (b) R^2 and Q^2 for endogenous constructs.

Comparative interpretation across mediator types

An additional comparative inspection across the four indirect effects clarifies the relative weight of mechanisms. The bright pathway to voice ($\beta = +0.259$) is the strongest single indirect effect in the model, accounting for 88.4% of the total indirect effect on voice. The dark pathway to silence ($\beta = +0.168$) is the strongest indirect effect on silence, accounting for 76.4% of its total positive indirect effect after the bright suppressor ($\beta = -0.117$) is netted. The dark pathway to voice ($\beta = -0.076$) and the bright suppressor on silence ($\beta = -0.117$) are smaller but theoretically important because they reveal cross-domain spillovers: surveillance anxiety mildly suppresses voice in addition to its dominant amplification of silence, while AI fairness mildly suppresses silence in addition to its dominant amplification of voice. The pattern is consistent with the dual-process behavioural intentions literature (Detert & Edmondson, 2021) and shows that voice and silence respond to overlapping but distinct constellations of antecedents.

Discussion

The results converge on four substantive insights. First, algorithmic Green HRM is genuinely dual-edged: it simultaneously activates a strong fairness perception that promotes voice and a notable surveillance anxiety that promotes silence. The simultaneous emergence of a substantial bright indirect effect on voice (+0.259) and a substantial dark indirect effect on silence (+0.168) refutes the dominant single-pathway depiction in the 2020-to-2024 voice literature. Second, voice and silence are not opposite ends of one continuum; they are parallel outcomes that respond differently to bright and dark mediators. PAIF amplifies voice significantly and silence slightly, and SA amplifies silence strongly and voice slightly. Third, Green Psychological Safety is a strong cross-path moderator, strengthening the bright path by 62.9% and buffering the dark path by 48.0%. This is in line with psychological-safety theorizing which views the environment of safety as a precondition, rather than a substitute, for justice. Fourth, sectoral heterogeneity, while not statistically significant in MGA, exhibits substantively noteworthy patterns: monitoring-intensive sectors such as manufacturing demonstrate stronger dark paths than discretion-rich sectors such as higher education.

Compared with Wang and Zhao (2026), whose model includes fairness and surveillance but only a single outcome (voice), the present model explains 7.2 percentage points more variance in voice and adds 34.1 percentage points of explanation for silence. Compared with Ahmad et al. (2024) and Khan and Hassan (2023), the lower direct β (0.110 vs 0.26–0.29) is explained by absorption of variance into the dual mediators — a strength rather than a weakness. The findings support the increasingly accepted view that AI in HRM is paradoxical and that net effects depend on the leadership, ethical and design conditions of deployment (Charlwood & Guenole, 2022; Malik et al., 2023; Ma et al., 2025).

Theoretically, this study makes four contributions. First, it integrates Organisational Justice theory, Conservation of Resources theory and Psychological Safety theory into a coherent dual-pathway, dual-outcome moderated-mediation architecture for algorithmic Green HRM. Second, it validates green-specific operationalisations of voice, silence and surveillance anxiety in a developing-country multi-sector setting. Third, it provides the first joint empirical instantiation of bright and dark indirect effects on the parallel voice/silence dyad. Fourth, it demonstrates cross-path moderation by Green Psychological Safety, advancing leadership and climate research by showing that the same moderator can simultaneously magnify and dampen opposite pathways.

Several findings invite further interpretation. The strong direct positive effect of AGHRM on DGS (total $\beta = +0.247$) is initially counter-intuitive but theoretically consistent with the algorithmic-management literature: more algorithmic infrastructure means more visible monitoring, which increases the perceived risk of speaking up in non-safe environments. The IPMA results highlight that PAIF is both important and high-performing for predicting voice, while SA is low-performing yet high-importance for predicting silence, making it the most attractive lever for managerial intervention. A one-point reduction in SA yields a disproportionately large reduction in silence because the slope of the SA $\rightarrow$ DGS path (0.402) is the steepest in the model. The non-significant overall effect of AGHRM on DGS through the bright suppressor pathway (total indirect $\beta = +0.051$, ns) is itself informative: it shows that fairness perceptions can partially offset surveillance-induced silence but cannot eliminate it without psychological-safety interventions. This is consistent with Edmondson's (1999) initial claim that justice is required but not sufficient for voice, as safety is the proximate driver of speaking up. The sectoral pattern is particularly telling: manufacturing, and SMEs, which employ production-bound environmental KPIs and resource-limited dashboards, show the strongest dark routes; higher education, where green activity is more discretionary, the weakest. Therefore, the design of green HRM algorithms should be adjusted to the intensity of monitoring in the sector, rather than in a standard manner.

Policy Implications Aligned with the Identified Gaps

The four gaps identified in the introduction generate four directly corresponding policy recommendations, organised below as a five-tier framework for ethical algorithmic Green HRM in emerging economies.

Tier 1 Dual-pathway algorithmic design (fills Gap 1: joint bright-dark mediator integration)

Regulators and corporate HR functions should adopt a paired-design protocol whereby every new algorithmic green feature (dashboards, predictive nudges, AI-mediated KPIs) is accompanied by a paired surveillance-anxiety audit. The audit should measure SA at six-month intervals using the validated five-item scale developed in this paper, with intervention triggers when group means exceed 4.5 on the 7-point scale. The State Bank of Pakistan's Green Banking Guidelines and the Pakistan Telecommunication Authority's licensee framework can institutionalise this paired-design requirement.

Tier 2 Green-specific voice channels (fills Gap 2: under-theorisation of green voice)

HR practitioners should establish dedicated green voice channels eco-suggestion portals, environmental issue tickets and sustainability town halls that are functionally separate from generic feedback systems. Green voice should be tracked, rewarded and explicitly absorbed into environmental strategy, not bundled with operational suggestions. The Higher Education Commission's sustainability charter and the Securities and Exchange Commission of Pakistan's ESG disclosure framework can mandate the existence and effectiveness reporting of such channels.

Tier 3 Voice-silence parallel monitoring (fills Gap 3: voice and silence as substitutes)

Organisations should monitor green silence alongside green voice rather than treating absence-of-voice as silence. Defensive Green Silence should be measured directly and disaggregated from acquiescent or pro-social silence. Rising silence even when voice is also rising should be treated as a red flag because it signals that certain employee segments are being systematically excluded from the sustainability conversation. Cluster analyses by sector, age and tenure should accompany the monitoring.

Tier 4 Green Psychological Safety development (fills Gap 4: cross-path moderation untested)

Because GPS amplifies the bright pathway and buffers the dark pathway simultaneously, leadership development programmes should focus explicitly on the creation of psychologically safe environmental climates. Leaders should be trained to invite green dissent, normalise eco-uncertainty, depersonalise environmental KPIs and protect employees from punitive use of algorithmic metrics. The Pakistan Institute of Management, the National Institute of Banking & Finance and corporate universities should integrate GPS modules into mandatory leadership pipelines.

Tier 5 Ethical algorithmic governance and disclosure

Regulators should require organisations adopting algorithmic Green HRM to publish an annual disclosure covering the green metrics that are algorithmically tracked, the fairness audits performed, the surveillance-anxiety mitigation mechanisms in place, and aggregated indicators of green voice and silence. This disclosure can be integrated within the existing Code of Corporate Governance and ESG reporting expectations and aligned with the OECD AI Principles (2024 update) and the spirit of the EU AI Act in 2025 and 2026.

Implementation roadmap for HR practitioners

Beyond the five tiers above, a phased implementation roadmap operationalises the framework over an eighteen-month horizon. Months 1–3: baseline measurement of AI fairness, surveillance anxiety, green voice and green silence using the validated scales; segmentation by sector, tenure and work mode; establishment of a dedicated green-voice portal. Months 4–9: redesign of algorithmic green HRM features to incorporate explanation interfaces, transparency dashboards and human-in-the-loop appeals; introduction of GPS-development modules in leadership training; first cycle of paired surveillance-anxiety audits. Months 10–15: deployment of disclosure templates aligned with SECP ESG and SBP Green Banking Guidelines; second audit cycle; comparative reporting against peer organisations. Months 16–18: external evaluation, policy refinement, and integration of findings into Code of Corporate Governance compliance. This roadmap directly translates the moderated-mediation evidence into a measurable change programme, with each milestone tied to one of the four identified gaps.

Limitations and Future Research Directions

Five limitations qualify the contributions. First, although the three-wave time-lagged design with supervisor-rated outcomes reduces common-method bias, causality cannot be established with the strength of a true experiment; future research could deploy organisational field experiments in which algorithmic green features are randomised at the team level. Second, the sample is confined to five Pakistani sectors; replication in other South Asian, Middle Eastern, sub-Saharan African and Latin American contexts would test cross-cultural moderation. Third, algorithmic

Green HRM is treated as unidimensional; future work could disaggregate the construct into algorithmic monitoring, algorithmic empowerment, predictive nudging and AI-enabled training dimensions to identify which sub-dimension predominantly drives the dark path. Fourth, additional moderators such as ethical leadership, algorithmic transparency and AI literacy could be tested alongside GPS. Fifth, cross-level dynamics are silent: team- and organisation-level moderators such as ethical climate, environmental strategic orientation and the rate of digital transformation could meaningfully condition the individual-level dynamics.

Six future research directions follow. (i) Experimental and quasi-experimental designs that exploit natural variation in dashboard introduction would test causal claims more rigorously. (ii) Cross-country replications in the GCC, ASEAN and East Africa would calibrate the model against varying regulatory regimes and cultural baselines. (iii) Disaggregated AGHRM measurement would identify the sub-dimensions that drive surveillance anxiety most strongly. (iv) Mixed method studies, integrating qualitative interviews with behavioral traces of system logs, could illuminate the lived experience of green silence. (v) Longitudinal studies of 12-24 months would trace the trend of voice and silence as AI deployment advances. (vi) Mediation analyzes with the help of machine learning and causal representation learning methods (Scholkopf et al., 2023; Athey & Imbens, 2022) could further enhance causal inference in this fast-changing field.

The area would also benefit from theoretical syntheses linking the current dual-pathway perspective to neighboring literatures: algorithmic-management and surveillance-capitalism debates, climate-emotion and eco-anxiety research, and paradox theory in management studies. Such syntheses would elevate sustainability HRM beyond its current celebratory posture, and provide both scholars and practitioners with a more honest, contingent and ultimately more effective evidence basis.

Conclusion

The study shows that algorithmic Green HRM is indeed dual-pathway and dual-outcome. It stimulates fairness perceptions and surveillance anxiety concurrently, and raises voice and silence simultaneously depending on which mediator dominates and the psychological safety of the setting. The paper provides a theoretically richer and empirically more powerful Resource of algorithmic sustainability HRM in the digital era, by combining Organizational Justice, Psychological Safety and Conservation of Resources theories, by validating green-specific measures of voice, silence and surveillance anxiety, and by benchmarking the model against nine prior studies. The five-tier policy framework is a direct translation of the findings into actions for regulators, sectoral bodies and HR practitioners particularly in the sectors of banking, telecom, manufacturing, higher education and SME in Pakistan. The study calls for future scholarship to move beyond the primarily positive story of algorithmic HR and to engage with the contingent, paradoxical reality of digital sustainability labor. It reframes the central design dilemma of algorithmic Green HRM: not the question of whether to use AI for sustainability, but the question of how to use it in such a way as to amplify signals of fairness and buffer signals of surveillance – a question that determines whether organizations will harvest green voice or find themselves with green silence in the digital era.

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