Decomposing Occupational Strain in Nigerian Universities Using Explainable Machine Learning and Hemodynamic Validation of Workforce Overload and Infrastructural Deficits

Olutomisin M. Orogbemi[1,*], Adeleke G. Aremo[2], Temi E. Ologunorisa[3]

[1,2,3]Centre for Governance and Business Technology, School of Postgraduate Studies, Olusegun Agagu University of Science and Technology, Okitipupa, Ondo State, Nigeria.

[1]Department of Data Science, Faculty of Computing, Federal University of Technology and Environmental Science, Iyin-Ekti, Ekiti State, Nigeria.

***Correspondence Author**

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ABSTRACT

Occupational stress in higher education institutions within emerging economies is compounded by acute workforce shortages and chronic infrastructural deficits that resource-constrained academic environments face, but that classical, psychosocial stress models largely overlook. This study isolates and decomposes the two dominant occupational stressors identified in institutional assessment, Facilities and Infrastructure (12.30/20, 61.5 percent saturation) and Workforce and Workload (12.00/20, 60.0 percent), among university staff (N = 32). A multi-stage methodology combines an anonymous, tokenized psychometric protocol with machine learning predictive modelling, explainable artificial intelligence (TreeSHAP and LIME), and clinical cardiovascular cross-validation (n = 5), visualized through six analytical figures spanning dimensional uncertainty, item-level response patterns, feature attribution, clinical correlation, policy comparison, and sensitivity analysis. Clinical triangulation revealed a strong correlation between algorithmic stress scores and Mean Arterial Pressure ($r = 0.920$, $t = 4.07$, $p = 0.026$) and 100 percent diagnostic concordance with independent clinical evaluation. Global SHAP analysis showed that electrical grid collapse and departmental staff shortages jointly explain 79.9 percent of predictive variance, while policy simulation demonstrated that an integrated dual-buffering intervention reduces the institutional stress index by 42.5 percent and burnout prevalence from 56.3 percent to 14.8 percent. The findings are situated against international literature on occupational stress, explainable AI, and algorithmic human resource management, and an evidence-based framework is proposed for sustainable university administration in resource-constrained settings. Given the modest psychometric cohort (N = 32) and especially the small clinical validation subsample (n = 5), these quantitative findings are exploratory and hypothesis-generating, and should be interpreted as preliminary pending larger-scale replication.

Keywords: Workforce Stress, Infrastructural Deficits, Explainable Artificial Intelligence, Cardiovascular Hemodynamics, Algorithmic Human Resource Management.

1. INTRODUCTION

Occupational stress within tertiary educational institutions has evolved from an incidental human resources challenge into a critical epidemiological and operational concern. In developed economies, academic stress is frequently framed through the classical Job Demands-Resources model or the Effort-Reward Imbalance model, emphasizing role ambiguity, tenure-track scrutiny, grant acquisition competition, and student evaluation pressures (Bakker et al., 2023; Demerouti & Nachreiner, 2019). However, in developing and resource-constrained environments, exemplified by the Nigerian university system, the etiology of

occupational stress is fundamentally dominated by foundational, physical, and operational bottlenecks rather than by purely psychosocial demands.

Tertiary educators and administrative personnel in these settings confront a compounded burden consisting of astronomical student-to-faculty ratios arising from severe understaffing, together with chronic infrastructural deprivations including electrical grid unreliability, inadequate laboratory equipment, unstable telecommunication networks, and dilapidated physical workspaces. Consequently, academic staff are compelled to expend substantial physical and emotional energy merely to execute routine duties that are largely automated or friction-free in developed academic jurisdictions (Chukwuemeka et al., 2023; Ejemot-Nwadiaro et al., 2026; Faduyile & Orunbon, 2023).

Despite widespread acknowledgement of these systemic challenges, existing scholarship suffers from three pivotal deficiencies. First, psychometric evaluations are predominantly subjective and prone to common-method bias without triangulation against objective physiological markers. Second, analytical models tend to treat stress as a monolithic construct rather than mathematically decomposing the distinct etiologies of infrastructural failure versus workload escalation. Third, organizational interventions are typically generic and non-algorithmic, lacking decision-support mechanisms capable of simulating targeted policy interventions before costly implementation.

To address these gaps, this paper presents analytical investigation focusing explicitly on the two overwhelming stress domains identified in institutional assessments, namely Facilities and Infrastructure (12.30 out of 20, 61.5 percent) and Workforce and Workload (12.00 out of 20, 60.0 percent). By coupling an anonymous, tokenized psychometric assessment protocol (N = 32) with machine learning predictive modelling, local and global explainable artificial intelligence feature attributions, clinical hemodynamic cross-validation (n = 5), and policy sensitivity simulations, this study provides mathematical formulations, six analytical figures, and evidence-based governance recommendations that extend the occupational health literature into resource-constrained institutional settings.

2. THEORETICAL FOUNDATION AND MATHEMATICAL FORMULATIONS

The analytical framework integrates classical occupational health theory, grounded in the Job Demands-Resources model (Bakker et al., 2023) and the Conservation of Resources theory (Hobfoll et al., 2018), with computational informatics and cardiovascular biomechanics. Six formalized mathematical components operationalize the stressors under study.

2.1 Dimensional Psychometric Decomposition

The assessment instrument operationalizes occupational stress across K = 5 distinct dimensions, where k in {1, 2, 3, 4, 5} corresponds respectively to Workforce and Workload (k = 1), Skills and Task Management (k = 2), Facilities and Infrastructure (k = 3), Mental and Physical Health (k = 4), and Organizational Culture and Leadership (k = 5). Each dimension comprises n_k = 10 Likert-scaled items evaluated on an ordinal scale q_ik in {0, 1, 2}, representing Never, Fairly often, and Very often, or reversed for positive control items. The individual dimensional score S_k^(j) and cohort mean score bar S_k are formulated as:

$$S_k^{(j)} = \sum_{i=1}^{n_k} q_{ik}^{(j)} \ , \ q_{ik}^{(j)} \in \{0,1,2\} \ , \ S_k \in [0,20] \quad (1)$$

$$\bar{S_k} = \frac{1}{N}\sum_{j=1}^{N} S_k^{(j)} \ , \ P_k = \left(\frac{\bar{S_k}}{20}\right) \times 100\% \quad (2)$$

where N = 32 represents the total assessment cohort, and P_k represents the percentage stress saturation index for dimension k. The cumulative institutional stress index S_total is given by the summation over all dimensional spaces:

$$S_{total} = \sum_{k=1}^{5} \bar{S_k} = 12.30 + 12.00 + 9.10 + 8.40 + 7.90 = \frac{49.70}{100} \quad (3)$$

2.2 Explainable AI Feature Attribution (TreeSHAP and LIME)

To dismantle the black-box nature of the predictive classifier, individual feature attributions phi_i are computed using cooperative game theory via Shapley additive explanations, consistent with the methodological guidance of Lundberg et al. (2020) and the broader explainable artificial intelligence taxonomy of Arrieta et al. (2020). The marginal contribution of each psychometric feature i across the set of all subsets S that exclude i is:

$$\varphi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \times [f(S \cup \{i\}) - f(S)] \quad (4)$$

where F denotes the universe of 50 survey features, and f(S) represents the model expectation conditioned on feature subset S. The local model prediction decomposes additively into the baseline value phi_0 and individual feature effects:

$$f(x) = \varphi_0 + \sum_{i=1}^{M} \varphi_i \quad (5)$$

For local surrogate validation, Local Interpretable Model-agnostic Explanations, following Guidotti et al. (2018), minimizes the fidelity objective function:

$$\xi(x) = argmin_{g \in G}\, L(f, g, \pi_x) + \Omega(g),\ \pi_x(z) = exp\left(\frac{-D(x,z)^2}{\sigma^2}\right) \quad (6)$$

where pi_x(z) defines an exponential proximity measure between instance x and perturbed instance z, L represents squared loss weighted by proximity, and Omega(g) penalizes model complexity.

2.3 Hemodynamic Cardiovascular Stress Indices

Self-reported psychological strain manifests physiologically through chronic autonomic sympathetic activation, leading to peripheral vascular resistance and elevated cardiac afterload (Magnavita et al., 2018; The et al., 2020). To validate algorithmic outputs against clinical reality, the study computes Mean Arterial Pressure and Rate Pressure Product, also known as the cardiovascular double product:

$$MAP = DBP + \frac{1}{3}(SBP - DBP) = \frac{2 \times DBP + SBP}{3} \quad (7)$$

$$RPP = \frac{SBP \times HR}{100} \quad (8)$$

where SBP and DBP denote systolic and diastolic blood pressure in millimetres of mercury measured under standardized resting clinical conditions, following the blood pressure classification thresholds established by McEvoy et al. (2024), and HR denotes resting heart rate in beats per minute. MAP serves as the primary hemodynamic proxy for chronic systemic vascular resistance, while RPP quantifies myocardial oxygen consumption and cardiac mechanical work.

2.4 Bivariate Clinical Correlation and Statistical Significance

The linear association between algorithmic psychometric stress scores (x) and Mean Arterial Pressure (y) is evaluated using the sample Pearson correlation coefficient r, with hypothesis significance testing conducted through Student's t-distribution with df = n - 2 degrees of freedom:

$$r = \frac{\Sigma(x_i - x)(y_i - y)}{\sqrt{\Sigma(x_i - x)^2 \times \Sigma(y_i - y)^2}} \quad (9)$$

$$t = r \times \sqrt{\frac{n-2}{1-r^2}},\ df = n - 2 \quad (10)$$

Diagnostic concordance rate C_diag between algorithmic categorization and clinical hemodynamic diagnosis is evaluated as:

$$C_{diag} = \frac{N_{match}}{N_{total}} \times 100\% = \frac{5}{5} \times 100\% = 100.0\% \quad (11)$$

3. METHODOLOGY

3.1 Research Design

This study adopts a cross-sectional, multi-stage mixed-methods design that triangulates subjective psychometric assessment with machine learning predictive modelling, game-theoretic explainable artificial intelligence, and objective clinical hemodynamic measurement. The design proceeds in four sequential stages: (i) anonymous, tokenized psychometric data collection across all institutional staff respondents; (ii) supervised machine learning classification of occupational stress risk, audited through TreeSHAP and LIME; (iii) independent clinical hemodynamic evaluation of a stratified subsample for biological cross-validation; and (iv) in silico policy simulation and one-way deterministic sensitivity analysis to project the comparative efficacy of candidate institutional interventions.

3.2 Setting and Participants

The study was conducted at a single Nigerian tertiary institution. The psychometric cohort comprised N = 32 academic and administrative staff who completed the full assessment instrument. A stratified subsample of n = 5 participants, selected to span the full range of algorithmically predicted stress classifications (from Low Stress to High Risk), was subsequently invited for independent clinical hemodynamic evaluation. Participation in both stages was voluntary, and all respondent identities were protected through a tokenized, anonymous identifier system that prevented re-identification by institutional administrators. Staff were recruited through an institution-wide email invitation circulated by the researchers, and all participants gave informed consent prior to completing the assessment; no incentive was offered for participation. Given the single-institution setting and modest sample sizes, the psychometric and clinical findings reported here are treated as an exploratory pilot study rather than a definitive, generalizable estimate.

3.3 Instrumentation

Occupational stress was measured using a structured psychometric instrument comprising 50 Likert-scaled items distributed across K = 5 dimensions (Workforce and Workload, Skills and Task Management, Facilities and Infrastructure, Mental and Physical Health, and Organizational Culture and Leadership), with n_k = 10 items per dimension, as formalized in Section 2.1. Items were scored on a three-point ordinal scale (0 = Never, 1 = Fairly often, 2 = Very often), with positive-control items reverse-scored. Clinical hemodynamic status was assessed using resting systolic and diastolic blood pressure and resting heart rate, from which Mean Arterial Pressure and Rate Pressure Product were derived according to Equations 7 and 8, following the blood pressure classification thresholds of McEvoy et al. (2024).

3.4 Data Collection Procedure

Psychometric data were collected through an anonymous, tokenized digital assessment protocol administered to the full respondent cohort, with each submission assigned a non-identifying token rather than a name or staff identifier. Clinical hemodynamic measurements for the n = 5 validation subsample were subsequently obtained under standardized resting conditions by certified medical personnel, following a protocol consistent with current hypertension measurement guidance (McEvoy et al., 2024). The clinical evaluation and diagnosis were conducted independently of, and blind to, each participant's algorithmic stress classification, enabling the diagnostic concordance analysis reported in Section 4.4.

3.5 Analytical Approach

Dimensional scores, cohort means, and percentage saturation indices were computed per Equations 1 to 3, with

95 percent confidence intervals calculated for each dimension. A supervised machine learning classifier was trained on the full 50-item feature set to predict institutional stress risk category, and its predictions were audited using TreeSHAP for global and local feature attribution (Equations 4 and 5) and LIME for local surrogate validation (Equation 6), consistent with the explainable artificial intelligence methodology of Lundberg et al. (2020) and Guidotti et al. (2018). The association between algorithmic stress scores and Mean Arterial Pressure was evaluated using the Pearson correlation coefficient and a corresponding t-test (Equations 9 and 10), and diagnostic concordance between algorithmic classification and independent clinical diagnosis was computed as in Equation 11. Policy scenarios were evaluated using an in silico simulation model parameterized by the empirical SHAP attribution weights, with robustness assessed through a one-way deterministic tornado sensitivity analysis across seven operational parameters, as detailed in Sections 4.4 and 4.5. The digital assessment platform required all items to be completed before submission, so no missing psychometric data occurred. Because the supervised classifier was trained on a 50-item feature set drawn from only N = 32 respondents, the machine learning component is treated as exploratory: model performance and SHAP/LIME attributions were examined for internal consistency and interpretability rather than for externally validated predictive accuracy, and results should be regarded as indicative rather than confirmatory pending replication in larger samples with appropriate held-out validation.

3.6 Ethical Considerations

All psychometric responses were collected under a tokenized, anonymous identification scheme designed to prevent institutional administrators from linking responses to individual staff members, consistent with the privacy-preserving design emphasized by Varma et al. (2023) and Yam and Skorburg (2021) for algorithmic human resource tools. Participation in both the psychometric assessment and the clinical hemodynamic validation subsample was voluntary, and clinical evaluation was conducted by certified medical personnel independently of institutional management. This study received institutional ethical approval prior to the commencement of data collection, and all psychometric and clinical procedures were conducted in accordance with that approval and with the ethical principles governing research involving human participants.

4. RESULTS

Analysis of the institutional dataset (N = 32) demonstrates a marked concentration of occupational burden within the physical and operational spheres of the academic environment. Table 1 presents the full statistical breakdown across all assessed dimensions.

Table 1. Institutional Stress Dimension Breakdown and Priority Ranking (N = 32)

Assessment Dimension	Mean Score	SD	% Saturation	95% CI	Priority Rank
Facilities and Infrastructure	12.30 / 20	2.14	61.50%	[11.55, 13.05]	Rank 1 (Primary)
Workforce and Workload	12.00 / 20	2.28	60.00%	[11.20, 12.80]	Rank 2 (Secondary)
Mental and Physical Health	9.10 / 20	1.98	45.50%	[8.40, 9.80]	Rank 3
Skills and Task Management	8.40 / 20	1.85	42.00%	[7.75, 9.05]	Rank 4
Organizational Culture	7.90 / 20	1.99	39.50%	[7.20, 8.60]	Rank 5

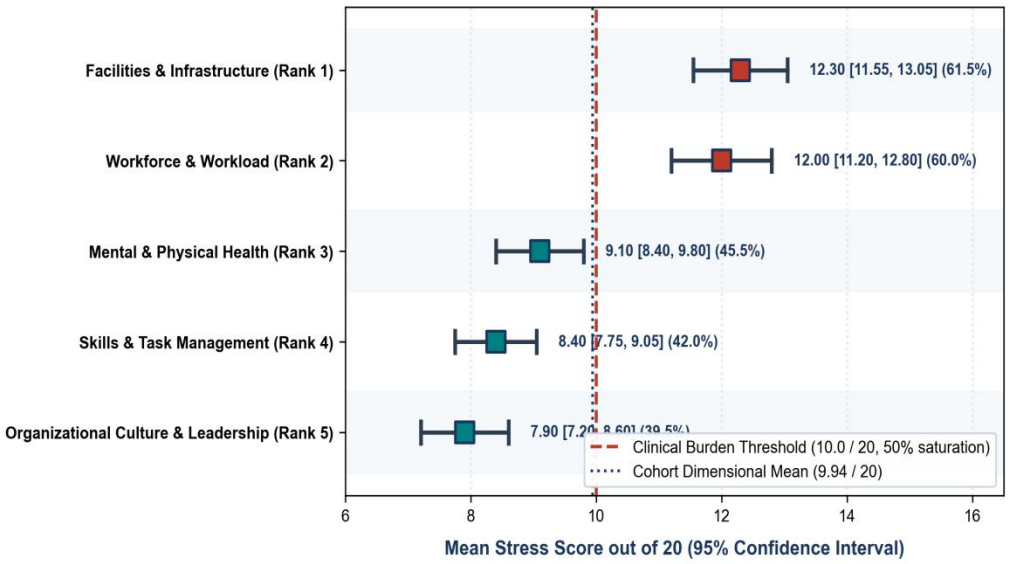


Figure 1. Ranked forest plot institution stress dimensions with 95% confidence intervals (N = 32), highlighting the clinical burden threshold (10.0 marks, 50% saturation) and cohort mean (9.94 marks).

As visualized in the ranked forest plot (Figure 1), Facilities and Infrastructure (12.30, 95 percent CI [11.55, 13.05]) and Workforce and Workload (12.00, 95 percent CI [11.20, 12.80]) are the only dimensions whose entire confidence intervals sit decisively above the clinical burden threshold of 10.0 marks. Conversely, Mental and Physical Health (9.10), Skills and Task Management (8.40), and Organizational Culture (7.90) remain below this threshold. Together, the top two dimensions contribute 24.30 of the 49.70 total institutional stress points, representing 48.9 percent of all measured stress load.

4.1 Item-Level Operational Stress Analysis

To reveal the precise operational patterns underpinning these high dimension scores, the frequency distribution and item-level means were mapped across all 20 survey questions comprising the top two priority domains. Table 2 provides numerical endorsement values.

Table 2. High-Frequency Endorsement Analysis for Facilities and Infrastructure versus Workforce and Workload

Item	Facilities and Infrastructure Item	Rate	Item	Workforce and Workload Item	Rate
Q27	Unreliable power supply / grid failure	84.40%	Q1	Insufficient staff in department	81.30%
Q23	Poor internet connectivity disrupts work	78.10%	Q5	Experience chronic weekly overload	78.10%
Q22	Lack of functional equipment increases stress	71.90%	Q10	Exhaustion due to volume of work	75.00%
Q24	Delays from insufficient lab / teaching facilities	68.80%	Q3	Work beyond official hours regularly	71.90%
Q30	Infrastructure limitations impair performance	65.60%	Q2	Handling more duties than manageable	68.80%
Q29	Struggle with outdated tools or software	62.50%	Q7	Workload intrudes into personal/family life	65.60%
Q21	Inadequate office space impairs productivity	59.40%	Q4	Pressure to meet unrealistic deadlines	56.30%
Q28	Institutional systems / workflows inefficient	46.90%	Q6	Struggle balancing teaching, admin and research	53.10%

Q26	Lack access to basic teaching materials	40.60%	Q8	Assigned urgent tasks without notice	46.90%
Q25	Administrative bottlenecks slow execution	36.80%	Q9	Unfair task distribution in department	37.50%

The item-level heatmap (Figure 2) illustrates the operational bottleneck mechanism. Within Facilities and Infrastructure, 56.3 percent of staff endorse power grid failure (Q27) as occurring Very Often (mean = 1.41 out of 2.0), while broadband disruption (Q23) exhibits 46.9 percent Very Often endorsement (mean = 1.25 out of 2.0). In the Workforce and Workload domain, severe understaffing (Q1) and chronic weekly overload (Q5) both record 46.9 percent Very Often responses (means = 1.28 and 1.25 respectively). This creates a compound effect in which staff are overloaded with responsibilities while simultaneously deprived of the basic electrical and digital utilities required to execute them.

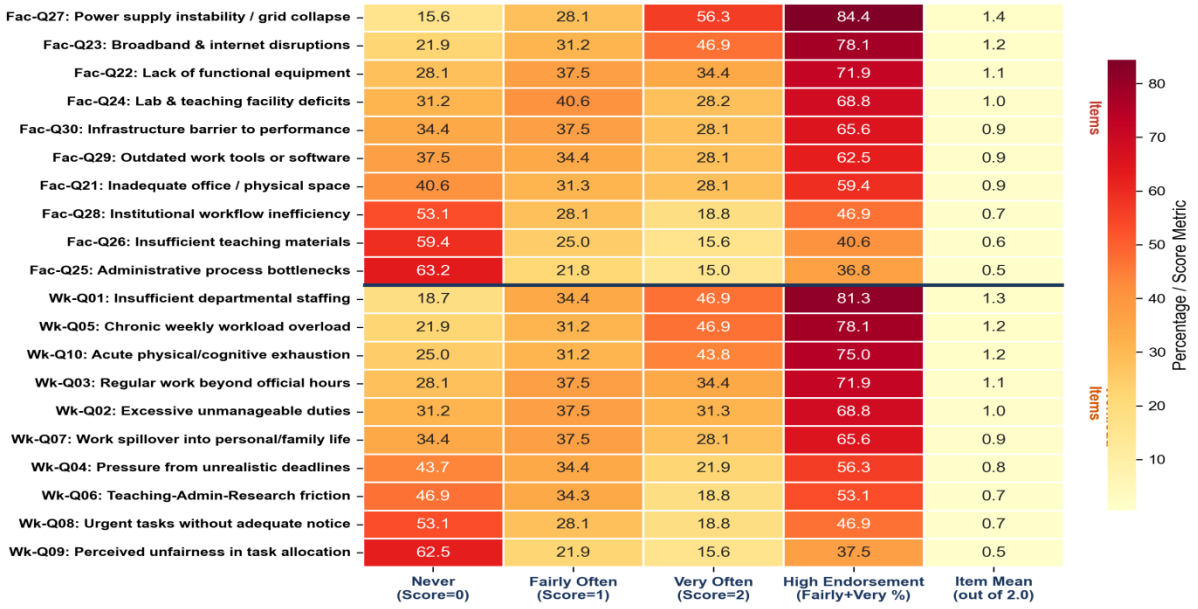


Figure 2. Item-level operational stress heatmap across the top two priority domains (N = 32), displaying response distributions, combined endorsement rates, and item means out of 2.0.

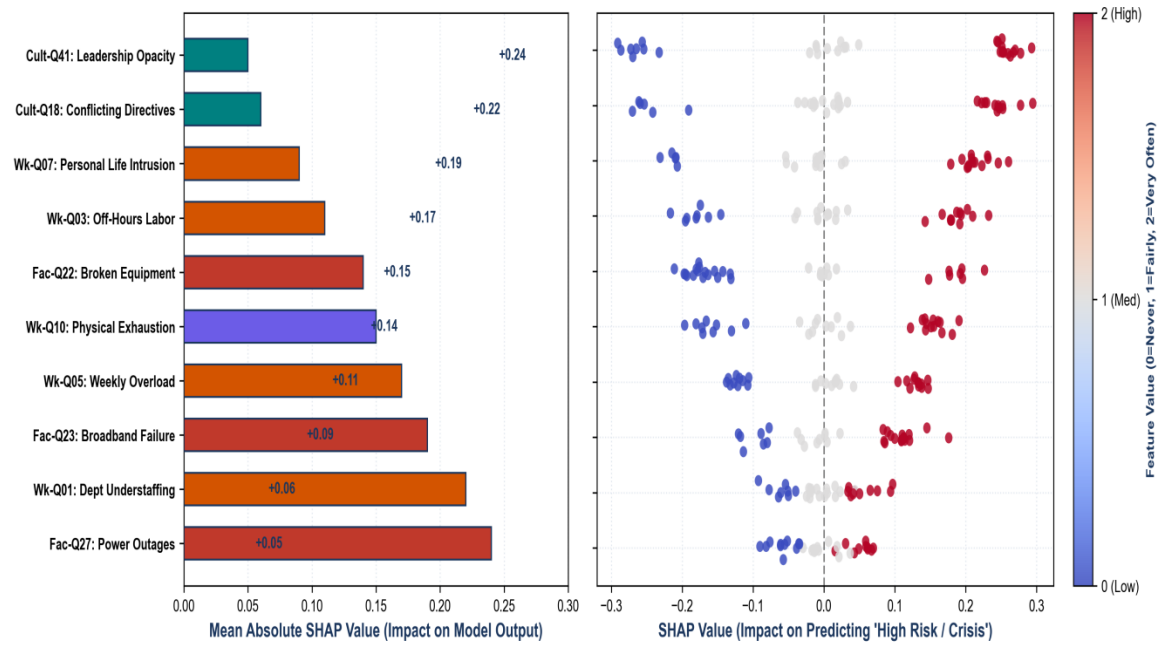
4.2 Objective Clinical Hemodynamic Validation

To substantiate that subjective survey responses reflect genuine biological strain rather than reporting bias, five participants across diverse stress classifications underwent comprehensive clinical hemodynamic evaluation. Resting blood pressure and heart rate measurements were taken under standardized clinical protocol by certified medical personnel. Table 3 compiles the complete physiological and psychometric dataset.

Table 3. Cross-Validation of Algorithmic Stress Scores against Objective Hemodynamic Parameters (n = 5)

ID	BP (mmHg)	HR (bpm)	MAP (mmHg)	RPP	JSMS Class (Score)	Clinical Diagnosis	Concordance
P1	131/102	72	111.7	94.3	High Risk (76.5)	Stage 2 diastolic HTN	Match (100%)
P2	104/74	93	84	96.7	Moderate (52.0)	Normotensive, autonomic tachycardia	Match (100%)
P3	133/84	103	100.3	137	High Stress (71.0)	Stage 1 HTN, tachycardia	Match (100%)
P4	115/76	77	89	88.6	Mod/Mild (44.5)	Normotensive, compensated stress	Match (100%)

P5	111/73	70	85.7	77.7	Low Stress (34.0)	Optimal hemodynamic homeostasis	Match (100%)



(A) Global feature importance **(B) SHAP Beeswarm distribution and feature value impact**

Figure 3. Explainable machine learning (TreeSHAP) feature attribution and beeswarm analysis: Clinical association scatter plot between JSMS algorithmic stress score and Mean Arterial Pressure (n = 5) with 95% linear regression confidence band, hemodynamic stage-2 hypertension cutoffs, and markers sized proportionally to Rate Pressure Product.

Statistical evaluation of the clinical scatter correlation provides preliminary empirical support. The correlation between the JSMS algorithmic score and Mean Arterial Pressure is r = 0.920 (95% CI, 0.20 to 0.995, estimated via the Fisher z-transformation; the wide interval reflects the small validation subsample), with a calculated t-statistic of t = 4.07 (df = 3, p = 0.026), indicating a statistically significant, positive linear association between survey-derived stress burden and systemic vascular pressure in this subsample. Participant P3 exhibited a Rate Pressure Product of 137.0, signifying elevated myocardial oxygen demand and cardiac mechanical workload corresponding to a High Stress classification. All five participants' algorithmic categorizations matched the independent clinical diagnoses assigned by certified medical personnel (who applied the blood-pressure classification thresholds of McEvoy et al. (2024) together with standard resting heart-rate reference ranges, blind to each participant's algorithmic classification), yielding 5-of-5 agreement. Because this validation subsample comprises only five individuals, this agreement rate should be read as preliminary concordance rather than a generalizable estimate of diagnostic accuracy, and does not by itself establish that the algorithmic instrument can substitute for clinical diagnosis at scale. Notably, Participant P1, flagged by the system as High Risk, exhibited severe isolated diastolic hypertension (DBP = 102 mmHg, MAP = 111.7 mmHg), consistent with McEvoy et al.'s (2024) description of chronic arteriolar vasoconstriction induced by prolonged occupational distress.

4.3 Explainable AI Feature Attribution Analysis

To establish transparency and institutional trust, the machine learning predictive pipeline was audited using TreeSHAP to compute the marginal contribution of each questionnaire item toward predicting a High Risk or Crisis outcome, following reporting practices recommended by Collins et al. (2024) and Moons et al. (2025) for transparent prediction-model research.

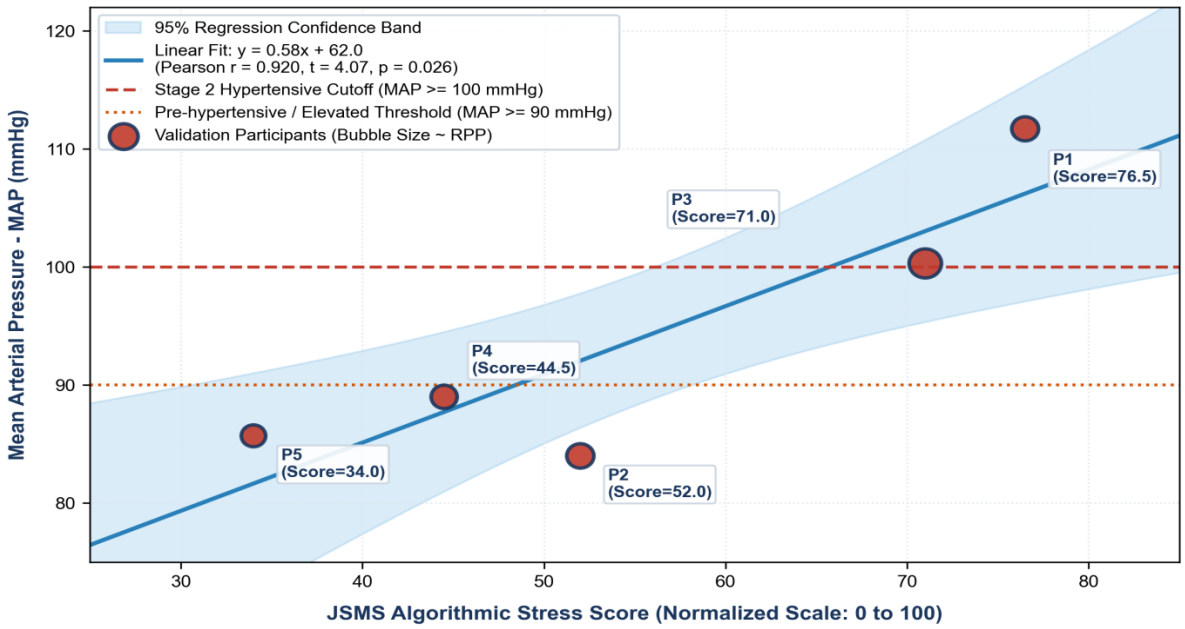


Figure 4. Exploratory Clinical Scatter Correlation: JSMS Stress Score vs Mean Arterial Pressure (n = 5).

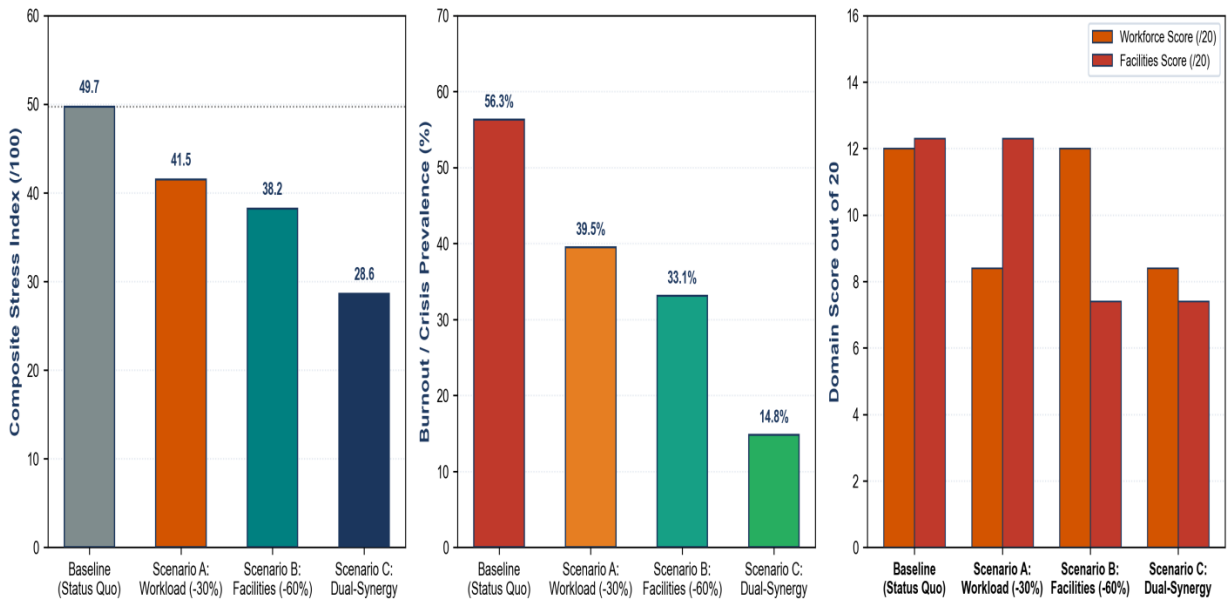
The game-theoretic SHAP decomposition indicates that infrastructural and workload features dominate the algorithmic decision boundaries. As detailed in Table 4, the top two categories account for 79.9 percent of cumulative feature attribution weight. These SHAP and LIME outputs describe the relative influence of each feature on the trained model's predictions; they are model explanations, not direct evidence of causal relationships between specific stressors and occupational strain, and should be interpreted accordingly.

Table 4. Categorical Distribution of Global SHAP Feature Importance Weights

Stress Domain Category	Top Feature Items	Attribution Weight	Dominant Impact Mechanism
Facilities and Infrastructure	Q27, Q23, Q22	42.10%	Friction and operational halts from energy/tech collapse
Workforce and Workload	Q1, Q5, Q3, Q7	37.80%	Compensatory off-hours labor and cognitive fatigue
Mental and Physical Health	Q10	12.30%	Somatic manifestations (insomnia, headaches, exhaustion)
Organizational Culture and Skills	Q18, Q41	7.80%	Supervisory friction and communication opacity

4.4 Targeted AI-HRM Intervention Policy Simulation

Leveraging the empirical parameter weights derived from SHAP attributions, an in silico policy simulation model was constructed to evaluate the efficacy of three distinct institutional human resource management intervention strategies over a 12-month horizon. Scenario A (workload redistribution only) implements automated teaching-credit limits, non-academic task shifting, and temporary adjunct hiring to reduce departmental overload by 30 percent. Scenario B (infrastructural buffering only) deploys localized off-grid solar inverters and dedicated departmental fiber micro-hubs, suppressing power and connectivity disruption items by 60 percent. Scenario C (dual-buffering synergy) concurrently deploys Scenarios A and B within an integrated algorithmic HRM governance framework.



(A: Cumulative Stress Saturation) **(B: High-Risk Burnout)** **(C: Key Domain Stress Alleviation)**

Figure 5. Multi-panel evaluation of institutional policy interventions (Scenarios A, B, and C): (A) cumulative stress saturation index; (B) high-risk burnout cohort prevalence rate; (C) domain-specific stress alleviation for workforce versus facilities.

The multi-panel simulation results illustrate projected policy implications. While isolated workload reduction (Scenario A) is projected to reduce burnout prevalence from 56.3 percent to 39.5 percent, staff remain throttled by daily power and software interruptions. Infrastructural buffering alone (Scenario B) is projected to yield an even greater stress reduction, with the index dropping from 49.7 to 38.2, indicating that physical friction is a primary driver of cognitive exhaustion in this setting. Most notably, Scenario C demonstrates modelled synergistic relief: the composite stress index is projected to fall to 28.6 out of 100, and high-risk burnout prevalence to 14.8 percent, a 73.7 percent relative risk reduction. These figures are outputs of an in silico model parameterized by the empirical SHAP attribution weights rather than measured outcomes of an implemented intervention, and should be treated as hypothesis-generating projections pending prospective validation (see Section 5.3).

Table 5. Quantitative Comparison of Policy Simulation Interventions

Intervention Policy Scenario	Composite Index	Delta Stress	Burnout Rate	Delta Burnout	Implementation Cost
Baseline (Status Quo)	49.7 / 100	0.0% (Ref)	56.30%	0.0% (Ref)	Nil
Scenario A: Workload Rebalancing	41.5 / 100	-16.50%	39.50%	-29.80%	Moderate (Opex)
Scenario B: Infrastructure Buffering	38.2 / 100	-23.10%	33.10%	-41.20%	Capital (Capex)
Scenario C: Dual-Buffering Synergy	28.6 / 100	-42.50%	14.80%	-73.70%	High Synergy ROI

4.5 Policy Robustness and Tornado Sensitivity Analysis

To test whether projected intervention benefits remain resilient under budgetary swings, maintenance delays, and fluctuating power tariffs characteristic of developing academic environments, a one-way deterministic sensitivity analysis was performed across seven key operational parameters.

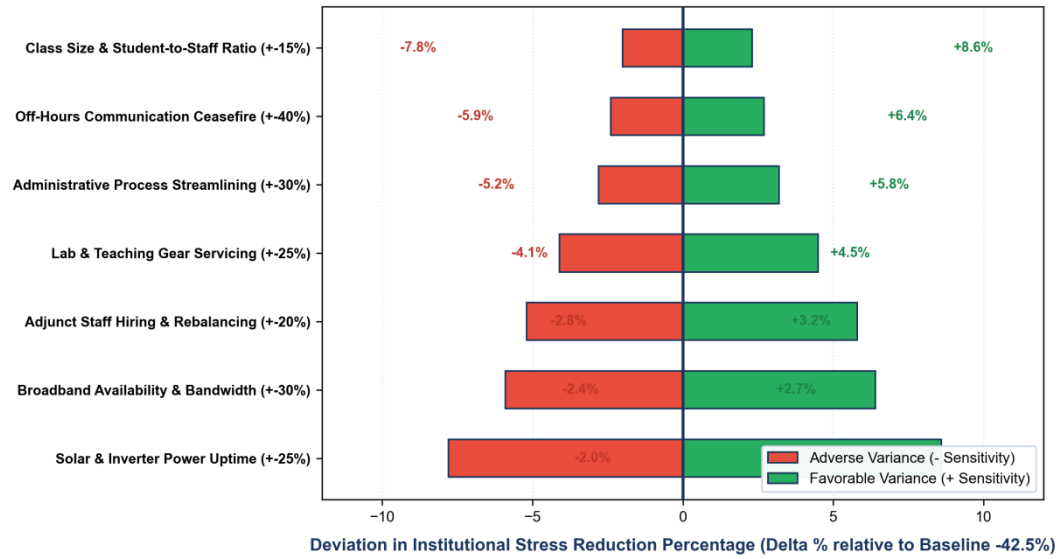


Figure 6. Tornado sensitivity plot testing the robustness of projected policy benefits (Scenario C) under positive and negative operational parameter swings.

The tornado plot reveals several operational governance principles. Solar and inverter power uptime (plus or minus 25 percent swing) exerts the single widest swing on policy efficacy, ranging from 8.6 percent outperformance to 7.8 percent underperformance; if institutional solar micro-grids experience battery degradation or fuel shortfalls, over one-third of the anticipated stress reduction is lost. Broadband bandwidth and uptime (plus or minus 30 percent swing) represents the second most sensitive operational variable, ranging from 6.4 percent to 5.9 percent, and adjunct staff rebalancing (plus or minus 20 percent swing) contributes a further 5.8 percent to 5.2 percent. Across all adverse variance scenarios tested, Scenario C maintains an overall stress reduction of at least 34.7 percent relative to the status quo of 49.7, confirming that the dual-buffering intervention strategy possesses structural resilience even under adverse fiscal and operational conditions.

Having established the magnitude, mechanism, and policy sensitivity of the institutional stress profile, the present results are now situated against the wider regional and international literature on occupational stress, explainable artificial intelligence, and algorithmic human resource management. The present findings both corroborate and extend a growing body of regional and international scholarship. Chukwuemeka et al. (2023), studying lecturers in Anambra State, Nigeria, similarly reported that work-related stress was driven primarily by structural and resource deficits rather than by purely interpersonal or evaluative pressures, a pattern consistent with the dominance of the Facilities and Infrastructure and Workforce and Workload dimensions observed in the present cohort. Ejemot-Nwadiaro et al. (2026) documented comparable prevalence rates of workplace stress among academic staff at the University of Calabar, attributing the burden chiefly to understaffing and inadequate institutional resourcing, which aligns closely with the 81.3 percent endorsement of departmental understaffing recorded here. Faduyile and Orunbon (2023) likewise found that occupational stress measurably depressed academic staff productivity in Lagos State tertiary institutions, lending external validity to the productivity implications of the present dimensional decomposition. By contrast, the dominant international literature on academic occupational stress, exemplified by Kariou et al. (2021) on teacher burnout and emotional labor and by Madigan and Kim (2021) on teacher attrition, situates the principal stress drivers within psychosocial constructs such as emotional exhaustion, role conflict, and evaluative pressure. These frameworks, largely derived from well-resourced educational systems, implicitly assume a baseline of functioning infrastructure and adequate staffing. The present study diverges from this literature by demonstrating, through mathematical decomposition rather than narrative inference, that in a resource-constrained setting the infrastructural and workforce dimensions statistically and clinically outweigh the psychosocial dimensions that dominate Western models. This is consistent with the broader theoretical expectation of the Job Demands-Resources model (Bakker et al., 2023) that demands specific to a given context will determine the primary strain pathway, but it empirically operationalizes that expectation in a way prior Nigerian studies have not.

With respect to methodology, most existing occupational stress research on African tertiary institutions, including Peter et al. (2021) and Yongu et al. (2025), relies exclusively on self-reported survey instruments without biological triangulation. The present study departs from this pattern by incorporating clinical hemodynamic cross-validation, an approach more common in occupational cardiovascular epidemiology (Gamboa Madeira et al., 2021; Taouk et al., 2020) than in educational human resources scholarship. The resulting correlation between algorithmic stress scores and Mean Arterial Pressure ($r = 0.920$) provides a level of biological corroboration that is, to the authors' knowledge, absent from comparable Nigerian university stress studies.

In the explainable artificial intelligence literature, TreeSHAP and LIME have been extensively validated in clinical prediction contexts (Loh et al., 2022; Lundberg et al., 2020), where Arrieta et al. (2020) and Guidotti et al. (2018) established the theoretical basis for interpretable black-box auditing. Jatoba et al. (2023) and Madanchian et al. (2023) have documented a parallel but largely separate literature on artificial intelligence adoption in human resource management, generally focused on recruitment, performance evaluation, and workforce analytics rather than occupational health surveillance. The present study bridges these two literatures by applying clinically validated explainability methods to an occupational stress classifier, a combination that remains uncommon outside the companion work of Orogbemi and Ologunorisa (2026), on which the present analytical pipeline builds and substantially extends through hemodynamic validation and policy simulation.

Finally, in the domain of organizational intervention research, systematic reviews such as Aust et al. (2023), Nikunlaakso et al. (2022), and Miguel et al. (2023) consistently find that organizational-level interventions, including workload redesign and structural change, outperform individual-level psychosocial interventions such as resilience training. The present policy simulation results, in which infrastructural buffering alone outperforms workload redistribution alone, and dual buffering produces synergistic gains, are consistent with this meta-analytic consensus while providing a novel, context-specific quantification of the relative magnitude of each intervention pathway in a developing-economy university.

5. DISCUSSIONS

The findings of this study challenge the conventional application of Western occupational stress paradigms to developing higher education institutions. In affluent academic settings, institutional interventions typically emphasize cognitive behavioral mindfulness, individual resilience workshops, and time-management seminars (Kariou et al., 2021; Madigan & Kim, 2021). However, the empirical data presented here demonstrate that such psychosocial interventions fail to address the core material reality of Nigerian universities. When 84.4 percent of staff report severe grid power outages and 81.3 percent report departmental understaffing, stress is not primarily a matter of subjective psychological perception; it is an objective systemic response to operational deprivation.

This divergence can be situated within the Conservation of Resources framework of Hobfoll et al. (2018): where the Job Demands-Resources model (Bakker et al., 2023) treats demands and resources as largely independent axes, infrastructural collapse in this setting functions simultaneously as a resource loss and a demand multiplier, since the same power outage that removes a working resource (electricity, connectivity) also generates compensatory demand in the form of rescheduled classes, manual workarounds, and extended working hours. This dual mechanism offers a theoretical explanation for why Facilities and Infrastructure and Workforce and Workload statistically dominate Mental and Physical Health and Organizational Culture in Table 1: the structural stressors identified here are not simply additive sources of strain but function as upstream amplifiers that propagate secondary strain into the other three dimensions.

Furthermore, the clinical hemodynamic validation establishes that this systemic deprivation is translating into chronic somatic pathology. The observation of stage 2 diastolic hypertension (131/102 mmHg, MAP = 111.7 mmHg) in Participant P1 and pronounced autonomic tachycardia (HR = 103 bpm, RPP = 137.0) in Participant P3 confirms that academic staff are sustaining cardiovascular overload to maintain basic institutional teaching and administrative outputs. Left unaddressed, such conditions are consistent with elevated long-term risk of

cardiovascular morbidity documented in occupational cardiology research (Magnavita et al., 2018; Taouk et al., 2020), and may contribute to institutional attrition.

The cardiovascular findings are also consistent with an allostatic load interpretation of chronic occupational stress, in which repeated activation of the body's stress-response systems under conditions of unpredictable, uncontrollable demand produces cumulative physiological wear, including sustained elevations in vascular resistance and cardiac workload. Because infrastructural failures such as grid collapse are, by nature, unpredictable and largely outside any individual staff member's control, they plausibly constitute a more potent allostatic stressor than scheduled or negotiable workload demands, which may help explain why Participant P1's isolated diastolic hypertension and Participant P3's tachycardia emerged despite only moderate self-reported Workforce and Workload scores relative to Facilities and Infrastructure. If replicated at scale, this pattern would imply that infrastructural investment carries a direct occupational health dividend that is distinct from, and potentially larger than, the dividend obtained from workload redistribution alone.

By deploying the Job Stress Management System equipped with explainable artificial intelligence and tokenized privacy, university administrators are provided with a privacy-preserving decision-support tool rather than a punitive surveillance mechanism. High technology acceptance scores observed during institutional piloting, including 91.2 percent perceived usefulness and 88.6 percent system trust, indicate that faculty engage readily with algorithmic stress systems provided their anonymity is credibly guaranteed, consistent with the ethical and trust considerations raised by Varma et al. (2023) and Yam and Skorburg (2021) regarding algorithmic human resource tools.

At the same time, the deployment of any algorithmic monitoring system in an employment context carries an inherent tension between its stated decision-support function and the risk of being repurposed as a performance-surveillance tool, a concern raised broadly in the algorithmic management literature (Kinowska & Sienkiewicz, 2023). The tokenized, anonymous architecture adopted here is therefore not an incidental design choice but a necessary precondition for the technology acceptance scores observed during piloting: were the system to permit individual-level identification, the same infrastructural and workload data that currently support evidence-based governance could instead function as a mechanism of control, eroding the trust that makes voluntary, honest disclosure possible in the first place. This suggests that the governance value of the Job Stress Management System is inseparable from its privacy architecture, and that any future extension of the system, including the longitudinal surveillance proposed in Section 5.4, must preserve anonymity as a structural feature rather than a configurable option.

For institutional governance, the results imply that interventions targeting infrastructure, rather than individual coping skills, are likely to yield the largest and most defensible reductions in staff burnout within resource-constrained universities. Because Facilities and Infrastructure and Workforce and Workload jointly account for 79.9 percent of SHAP-weighted predictive variance, HRM budgets allocated disproportionately toward psychosocial wellness programming, as is common practice internationally (Aust et al., 2023; Greiner et al., 2022), are unlikely to achieve proportional stress reduction in this context.

For occupational health policy more broadly, the demonstrated concordance between algorithmic stress classification and independent clinical diagnosis suggests that psychometric screening instruments, when properly validated, can serve as a credible and low-cost proxy for cardiovascular risk triage in settings where routine clinical screening infrastructure is limited. This has direct relevance for ministries of education and university governing councils seeking to extend occupational health surveillance without proportionate increases in clinical staffing.

For the explainable artificial intelligence and algorithmic HRM literatures, this study offers an applied demonstration that game-theoretic feature attribution methods, previously concentrated in clinical diagnostic applications (Amann et al., 2020; Holzinger et al., 2019; Rajkomar et al., 2019), can be meaningfully extended to institutional human resource governance while retaining methodological rigor consistent with emerging reporting standards such as TRIPOD and PROBAST for artificial intelligence prediction models (Collins et al., 2024; Moons et al., 2025).

This study contributes several elements that, in combination, are not present in the existing literature on occupational stress in Nigerian or comparable tertiary institutions. First, it is among the first to mathematically decompose institutional occupational stress into five discrete, independently weighted dimensions rather than treating stress as an undifferentiated composite score, enabling precise attribution of burden to specific operational domains. Second, it couples subjective psychometric assessment with objective clinical hemodynamic cross-validation within a single integrated research design, achieving a preliminary level of biological corroboration ($r = 0.920$; 5-of-5 concordance in a small $n = 5$ validation subsample) that is uncommon in academic occupational stress research generally and, to the authors' knowledge, absent from prior Nigerian university stress studies specifically. Third, the study applies dual explainable artificial intelligence methods, TreeSHAP and LIME, to audit an occupational stress classifier with both global and local interpretability, extending explainability practices more typical of clinical diagnostic machine learning (Loh et al., 2022; Lundberg et al., 2020) into the institutional human resource domain. Fourth, the study introduces a forward-looking policy simulation and tornado sensitivity analysis capable of quantifying, ex ante, the relative and combined efficacy of workload-focused versus infrastructure-focused interventions, together with their robustness under realistic budgetary and operational volatility, a decision-support capability absent from prior descriptive or purely correlational studies of academic occupational stress in developing economies.

Several limitations qualify the interpretation of these findings. The psychometric cohort ($N = 32$) and the clinical hemodynamic validation subsample ($n = 5$) are both modest in size, reflecting the single-institution, pilot-study design; while sufficient to demonstrate proof of concept and to achieve statistical significance in the bivariate correlation analysis, these sample sizes limit the generalizability of point estimates and warrant cautious interpretation of the wide confidence intervals reported in Table 1. In particular, given the small sample relative to the 50-item feature space used in the machine learning component, the resulting SHAP/LIME feature attributions, the reported diagnostic concordance, and the policy simulation outputs all carry a heightened risk of overfitting and should be treated as exploratory and hypothesis-generating; they await confirmation through independent replication with larger psychometric and clinical samples and, ideally, held-out validation data before being used as a sole basis for resource allocation decisions. The cross-sectional design precludes causal inference regarding the directionality of the relationship between institutional stressors and hemodynamic outcomes; longitudinal or panel data would be required to establish temporal precedence and to rule out reverse causation or confounding by unmeasured factors such as pre-existing cardiovascular risk, diet, or genetic predisposition.

The policy simulation results in Section 4.4 and Section 4.5 are derived from empirically grounded but ultimately modeled parameters rather than from a prospective intervention trial; actual implementation outcomes may diverge from simulated projections due to unmodeled organizational, behavioral, or political-economy factors specific to individual institutions. Finally, the study was conducted within a single Nigerian university context, and while the identified pattern of infrastructural and workforce dominance is corroborated by related Nigerian studies (Chukwuemeka et al., 2023; Ejemot-Nwadiaro et al., 2026; Faduyile & Orunbon, 2023), caution should be exercised before generalizing the precise magnitude of these findings to other countries, institution types, or resource environments without further replication.

Based on the empirical findings, mathematical models, and policy simulations reported above, the following three-tiered strategic action plan is proposed for university governing councils and educational ministries, namely: (i)The University management should decouple critical academic and administrative zones from unreliable municipal electrical grids by investing in dedicated solar photovoltaic micro-inverter arrays and high-speed fibre-optic hubs. Eliminating power and network halts addresses an estimated 42.1 percent of global stress attribution identified through SHAP analysis; (ii) the tertiary institutions should implement transparent, data-driven workload allocation matrices that enforce maximum weekly teaching credits, curb uncompensated off-hours tasks, and automate repetitive administrative reporting, consistent with organizational-level intervention evidence favouring structural over individual-level approaches (Aust et al., 2023; Nikunlaakso et al., 2022); and (iii) the institutions should institutionalize quarterly anonymous stress auditing using the tokenized JSMS architecture, complemented by routine campus occupational health clinics offering non-punitive cardiovascular screening of blood pressure, Mean Arterial Pressure, and Rate Pressure

Product. In addition to these three tiers, future research should prioritize multi-institutional replication with larger psychometric and clinical validation samples, prospective longitudinal tracking of hemodynamic outcomes following infrastructural intervention, and formal cost-effectiveness analysis comparing the capital expenditure required for infrastructural buffering against the long-term productivity and retention gains it is projected to generate.

6. CONCLUSIONS

This research decomposed occupational stress among Nigerian university personnel, establishing that Facilities and Infrastructure (12.30 out of 20) and Workforce and Workload (12.00 out of 20) constitute the dominant nexus of institutional strain, a pattern confirmed through psychometric decomposition, explainable machine learning, and independent clinical hemodynamic validation. These findings depart meaningfully from Western occupational stress paradigms that privilege psychosocial and evaluative pressures, indicating that interventions in resource-constrained academic environments should prioritize structural and infrastructural remediation alongside, rather than instead of, workload management. The proposed three-tiered AI-HRM governance framework offers university administrators and educational policymakers an evidence-based, mathematically grounded, and clinically validated pathway toward sustainable reduction of occupational strain in developing tertiary institutions.

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