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University Job Stress Management System: An Explainable Artificial Intelligence Approach for Nigerian Universities

Olutomisin M. Orogbemi[1]; Temi E. Ologunorisa[2]

[1]Centre for Governance and Business Technology, School of Postgraduate Studies, Olusegun Agagu University of Science and Technology, Okitipupa, Ondo State, Nigeria. Department of Data Science, Federal University of Technology and Environmental Sciences, Iyin-Ekiti, Ekiti State, Nigeria.
[2]Centre for Governance and Business Technology, School of Postgraduate Studies, Olusegun Agagu University of Science and Technology, Okitipupa, Ondo State, Nigeria.

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Abstract

University staff in Nigeria experience escalating job stress driven by chronic underfunding, administrative burdens, infrastructural deficits, and evolving pedagogical demands, adversely affecting well-being and institutional performance. Traditional stress management interventions often lack scalability, personalization, and cultural relevance in this context. This study addresses the gap by developing and validating a novel Job Stress Management System (JSMS) tailored for Nigerian university workers, leveraging Explainable Artificial Intelligence (XAI). Employing a multi-phase design science research methodology, the study integrated literature review, mixed-methods fieldwork with 427 staff across 15 universities, and iterative system development. The major stressors identified included excessive workload (68.2%), poor remuneration (62.7%), inadequate infrastructure (58.9%), bureaucratic delays (55.2%), and perceived lack of support (49.1%). The JSMS features a lightweight web application powered by an XAI engine using SHAP and LIME techniques on top of ensemble models (XGBoost, Random Forest), trained on validated stress assessment data. It delivers real-time stress prediction, personalized coping recommendations, resource linkage, and transparent, interpretable explanations for predictions. A 12-week pilot with 120 participants demonstrated significant reductions in self-reported stress (mean reduction 32.7%, $p<0.001$), high system trust (87.3% attributed trust to explainability), and strong perceived usefulness (mean score 4.3/5.0). The study contributes a contextually grounded, ethically designed, and practically implementable JSMS framework, advancing XAI applications for human-centric HRM solutions in resource-constrained, culturally specific settings. It offers actionable insights for Nigerian university administrators, policymakers, and HR practitioners, with transferable relevance to similar global contexts facing systemic workplace stress challenges.

Keywords: *Administrative Burden, Stress Level, Multi-Phase Design; Well-Being, Institution Performance.*

I. INTRODUCTION

Workplace stress has emerged as one of the most pressing occupational health challenges of the twenty-first century, with significant implications for individual well-being, organizational productivity, and broader socioeconomic development. The World Health Organization (WHO) has designated burnout of a chronic stress response, as a legitimate occupational phenomenon, underscoring the urgency of systematic and evidence-based interventions (WHO, 2019). In academic and university environments, occupational stress is particularly acute due to the complex interplay of teaching, research, administrative, and community service responsibilities that characterize faculty and staff roles (Watts & Robertson, 2011; Barkhuizen et al., 2014). In the Nigerian context, university workers face a distinctive and compounded stress landscape. Nigeria's higher education sector is characterized by persistent underfunding, with the country historically allocating well below the UNESCO-recommended 26% of national budget to education (Okoye & Okwu, 2010; Akinwale & George, 2020). Recurrent strikes, dilapidated infrastructure, heavy teaching loads, delayed salaries, and institutional bureaucracy compound the occupational burden experienced by academic and non-academic staff (Ogbuanya et al., 2019; Akomolafe & Ogunmakin, 2013). These stressors are further exacerbated by socioeconomic pressures, inadequate mental health resources, and cultural stigma surrounding psychological help-seeking behaviours (Gureje et al., 2015). Despite the documented severity of occupational stress in Nigerian universities, institutional responses have been largely reactive, informal, and characterized by limited scalability and poor contextual fit. Traditional stress management programmes, such as Employee Assistance Programmes (EAPs), cognitive-behavioural therapy (CBT)-based workshops, and generic counselling services have shown promise in Western contexts but face significant barriers to adoption in sub-Saharan African university settings, including resource constraints, cultural misalignment, and lack of digital infrastructure (Mboya et al., 2020; Adesola et al., 2021).

The rapid advancement of Artificial Intelligence (AI) and machine learning (ML) presents transformative opportunities for occupational stress management. Predictive analytics, natural language processing, and intelligent decision-support systems have demonstrated efficacy in a range of healthcare and human resource management (HRM) contexts (Torous et al., 2021; Cheng & Hackett, 2021). However, a critical limitation of conventional AI-based interventions is their opacity of their 'black-box' nature undermines user trust, limits professional acceptance, and raises ethical concerns regarding automated decision-making that affects employees' well-being (Adadi & Berrada, 2018; Arrieta et al., 2020). Explainable Artificial Intelligence (XAI) addresses this limitation by embedding interpretability mechanisms into AI pipelines, enabling end-users and practitioners to understand the reasoning behind algorithmic predictions and recommendations (Gunning et al., 2019). XAI techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) have shown particular promise in healthcare and organisational behaviour applications, fostering trust and enabling informed human oversight (Lundberg & Lee, 2017; Ribeiro et al., 2016). Yet, the application of XAI to occupational stress management in resource-constrained, culturally specific settings—particularly within sub-Saharan Africa has remains markedly underexplored.

This study addresses this gap by developing, piloting, and evaluating a novel University Job Stress Management System (JSMS) tailored specifically for Nigerian university workers. The system integrates XAI-powered predictive modelling with culturally responsive coping recommendations and institutional resource linkage.

Occupational stress is broadly defined as the harmful physical and emotional responses that occur when job requirements do not match the capabilities, resources, or needs of the worker (NIOSH, 1999). In university environments globally, occupational stress has been linked to role overload, role ambiguity, work-life imbalance, interpersonal conflicts, lack of autonomy, and poor organisational climate (Watts & Robertson, 2011; Kinman & Wray, 2013). Longitudinal research by Sabagh et al. (2018) found that academic stress is a significant predictor of burnout, absenteeism, and reduced research productivity. Within the Nigerian higher education context, Ogbuanya et al. (2019) identified workload overload, salary irregularities, and poor working conditions as the most prevalent stressors among university lecturers in South-West Nigeria. Similarly, Akomolafe and Ogunmakin (2013) documented significant associations between occupational stress, job satisfaction, and organisational commitment among university workers, with stress negatively predicting both outcomes. Adeyemo and Ogunyemi (2021) extended this analysis to non-academic staff, demonstrating that administrative personnel experienced significantly higher stress levels related to bureaucratic processes and poor promotion prospects. Structural factors in Nigeria's university system amplify individual-level stressors. Recurrent industrial actions by the Academic Staff Union of Universities (ASUU) reflect systemic underfunding and governance failures that directly impact workplace conditions (Akinwale & George, 2020). The COVID-19 pandemic further disrupted academic operations, with emergency digital transitions exposing technological inadequacies and increasing psychological burden on staff ill-equipped for remote instruction (Aguilera-Hermida, 2020; Ifeoma & Vivian, 2021). Collectively, these dynamics situate Nigerian university workers within a high-risk occupational stress environment requiring targeted, sustainable, and scalable management strategies.

A substantial body of evidence supports the efficacy of cognitive-behavioural, mindfulness-based, and organisational-level interventions for managing occupational stress (Richardson & Rothstein, 2008; van der Klink et al., 2001). Meta-analyses by Awa et al. (2010) found that burnout interventions combining individual and organisational components achieved the most durable effects. EAPs, structured resilience training, and peer support networks have also demonstrated effectiveness in Western university settings (Bhui et al., 2012). However, several studies caution that standard Western-Centric stress management programmes face significant contextual barriers when applied in sub-Saharan African settings (Abas et al., 2014; Osafo et al., 2021). Cultural norms that discourage open acknowledgment of mental distress, limited mental health literacy, and insufficient institutional infrastructure collectively constrain the reach and uptake of such interventions among Nigerian university workers. Furthermore, the scalability of face-to-face programmes is severely limited in the context of large, multi-campus Nigerian universities with thousands of staff members (Gureje et al., 2015; Adewuya et al., 2018).

The application of machine learning to occupational health represents a rapidly growing research frontier. AI-based systems have demonstrated capacity for early detection of burnout (Haliloglu et al., 2022), prediction of absenteeism (Frith & Walker, 2021), and personalized mental health interventions (Torous et al., 2021). Ensemble learning methods, particularly XGBoost and Random Forest, have emerged as leading approaches for stress classification tasks due to their capacity to handle high-dimensional, imbalanced, and noisy datasets characteristic of psychometric and occupational health data (Chen & Guestrin, 2016; Breiman, 2001). Recent studies have extended ML applications to university staff well-being. Jiang et al. (2022) employed random forest classifiers to predict academic burnout with 84.3% accuracy using self-reported occupational data. Similarly, Sriboonaree et al. (2023) applied deep learning models to classify stress severity among healthcare workers, achieving AUC values exceeding 0.90. These studies underscore the potential of ML approaches for occupational stress prediction; however, the majority are conducted in high-income country contexts with well-resourced digital infrastructure, limiting their direct transferability to settings such as Nigeria.

The concept of XAI encompasses a diverse set of techniques and methodologies designed to make AI systems more interpretable, transparent, and trustworthy to human users (Arrieta et al., 2020; Gunning et al., 2019). Lundberg and Lee (2017) introduced SHAP values as a unified framework grounded in cooperative game theory that assigns each feature a contribution score to a given prediction, enabling both global and local interpretability. Ribeiro et al. (2016) proposed LIME, which generates locally faithful, interpretable approximations of complex model predictions. In clinical and health informatics contexts, XAI has been shown to significantly improve clinician trust, decision-making quality, and patient engagement with AI-assisted tools (Holzinger et al., 2019; Tjoa & Guan, 2021). Cheng and Hackett (2021) demonstrated that XAI-augmented HR analytics systems yielded greater employee acceptance and reduced algorithmic aversion compared to opaque ML systems. Within the specific domain of workplace stress management, Sharma and Gedeon (2012) argued that interpretable systems are critical for fostering user engagement and ensuring ethical deployment, as stress is a sensitive, personalised, and stigma-laden domain. Despite these advances, a notable gap exists in the application of XAI to occupational stress management in sub-Saharan African university contexts. Existing systems are typically designed for high-resource environments with robust digital ecosystems, and few incorporate culturally responsive recommendations or engage with the structural stressors specific to institutions in developing economies. This study directly addresses this gap.

II. METHOD

- *Research Design*

This study adopted a multi-phase design science research (DSR) methodology (Hevner et al., 2004; Peffers et al., 2007). DSR was selected for its rigour in guiding the development and evaluation of innovative in this case, the JSMS within real-world organisational contexts. The DSR process comprised four iterative phases: (i) problem identification and motivation; (ii) requirements elicitation and data collection; (iii) system design, development, and iteration; and (iv) evaluation and reflection.

- *Sampling and Participants*

A stratified random sampling strategy was employed to recruit participants from 15 public universities across Nigeria's six geopolitical zones, ensuring representation of diverse institutional types (federal, state and private), academic disciplines, and staff categories. A total of 427 university staff participated in the requirements elicitation and data collection phase: 298 academic staff (lecturers, senior lecturers, professors) and 129 non-academic staff (administrative, technical, and support staff). Institutions were selected based on enrolment size, geographical distribution, and institutional type. The sample size was determined using Yamane's (1967) formula for finite populations, achieving a 95% confidence interval with a 5% margin of error. Inclusion criteria specified full-time employment status and a minimum of one year's tenure at the institution.

- *Data Collection Instruments*

Data collection employed a multi-instrument, mixed-methods approach. Quantitative data were gathered via an adapted version of the Job Stress Survey (JSS; Spielberger & Vagg, 1999), the Perceived Stress Scale (PSS-10; Cohen et al., 1983). , and a purpose-designed University Stressor Inventory (USI) developed through iterative pilot testing and expert review with five academic psychologists and three HRM specialists. The USI comprised 42 items across eight sub-scales: workload, remuneration, infrastructure, collegial relations, administrative processes, professional development, work-life balance, and organizational justice. Internal consistency of the USI was confirmed with Cronbach's alpha = 0.89. Qualitative data were gathered through 24 semi-structured interviews (12 academic, 12 non-academic staff) and four focus group discussions (two with academic staff, two with non-academic staff), conducted purposively to achieve theoretical saturation. Transcripts were subject to thematic analysis using NVivo 12, guided by the six-phase framework of Braun and Clarke (2006). The qualitative findings served to contextualise quantitative stressor profiles and inform the design of culturally responsive coping recommendations within the JSMS.

- *Model Development*

The model development component of the JSMS employed a supervised classification approach to predict stress severity levels (low, moderate, high, very high) based on validated instrument scores and contextual features. The feature set comprised 48 variables drawn from the JSS, PSS-10, USI, and demographic information (gender, age group, staff category, years of service). Class imbalance was addressed using the synthetic minority over-sampling technique (SMOTE; Chawla et al., 2002). The dataset was divided 70:30 for training and testing, with five-fold cross-validation applied during hyperparameter tuning. Three ensemble models were evaluated: XGBoost (Chen & Guestrin, 2016), Random Forest (Breiman, 2001), and a soft-voting ensemble combining both. XGBoost achieved the highest classification performance with accuracy of 91.4%, weighted F1-score of 0.912, and AUC of 0.963 on the test set. Model selection was confirmed using McNemar's test for pairwise comparison. Explainability was incorporated using SHAP (global feature importance and individual prediction explanations) and LIME (local explanations for individual user predictions), operationalized through the SHAP Python library (version 0.42.1) and the LIME library (version 0.2.0.1).

- *System Development and Evaluation*

The JSMS was developed using an agile, iterative approach with three development sprints spanning 16 weeks. The system architecture comprised a React.js front-end, a Python/Flask RESTful API back-end, and a PostgreSQL database, deployed on a lightweight cloud server infrastructure optimised for low-bandwidth Nigerian internet conditions. User interface design was guided by participatory design workshops with 18 staff representatives, ensuring cultural responsiveness, accessibility, and usability. System evaluation employed a 12-week randomised controlled pilot with 120 participants drawn from four universities (60 JSMS group; 60 waitlist control group). Outcome measures included self-reported stress (PSS-10 pre/post), system trust (adapted from Gefen et al., 2003), perceived usefulness and ease of use (Davis, 1989 TAM scale), and qualitative user experience interviews. Statistical analysis used paired t-tests, independent-samples t-tests, and ANCOVA for between-group comparisons, with significance set at $p<0.05$.

- *Job Stress Management System Architecture*

The job stress management system (JSMS) is designed as a modular, lightweight, and extensible web-based platform comprising five integrated components as shown in Figure 1: (i) a user interface layer (UIL) providing responsive, accessible interfaces for data input, prediction display, and recommendation delivery; (ii) a data processing and feature extraction module (DPFEM) responsible for validated instrument administration, data preprocessing, normalisation, and feature engineering; (iii) an XAI engine for real-time stress prediction and interpretable explanation generation; (iv) a coping recommendation engine (CRE) that maps XAI-identified stressor profiles to evidence-based, culturally tailored intervention strategies; and (v) an administrative dashboard (AD) enabling HR practitioners and institutional administrators to monitor aggregate stress indicators and system utilization. The system was designed with three core design principles: (a) Contextual Relevance is all stressor categories, coping recommendations, and resource links are grounded in the specific social, institutional, and cultural context of Nigerian universities; (b) explainable-first-design with SHAP and LIME outputs are rendered in plain, jargon-free language accessible to non-technical end users; and (c) privacy and data minimization for individual-level data is processed locally where possible, with aggregate institutional data maintained under strict access controls in compliance with Nigeria Data Protection Regulation (NDPR, 2019) requirements.

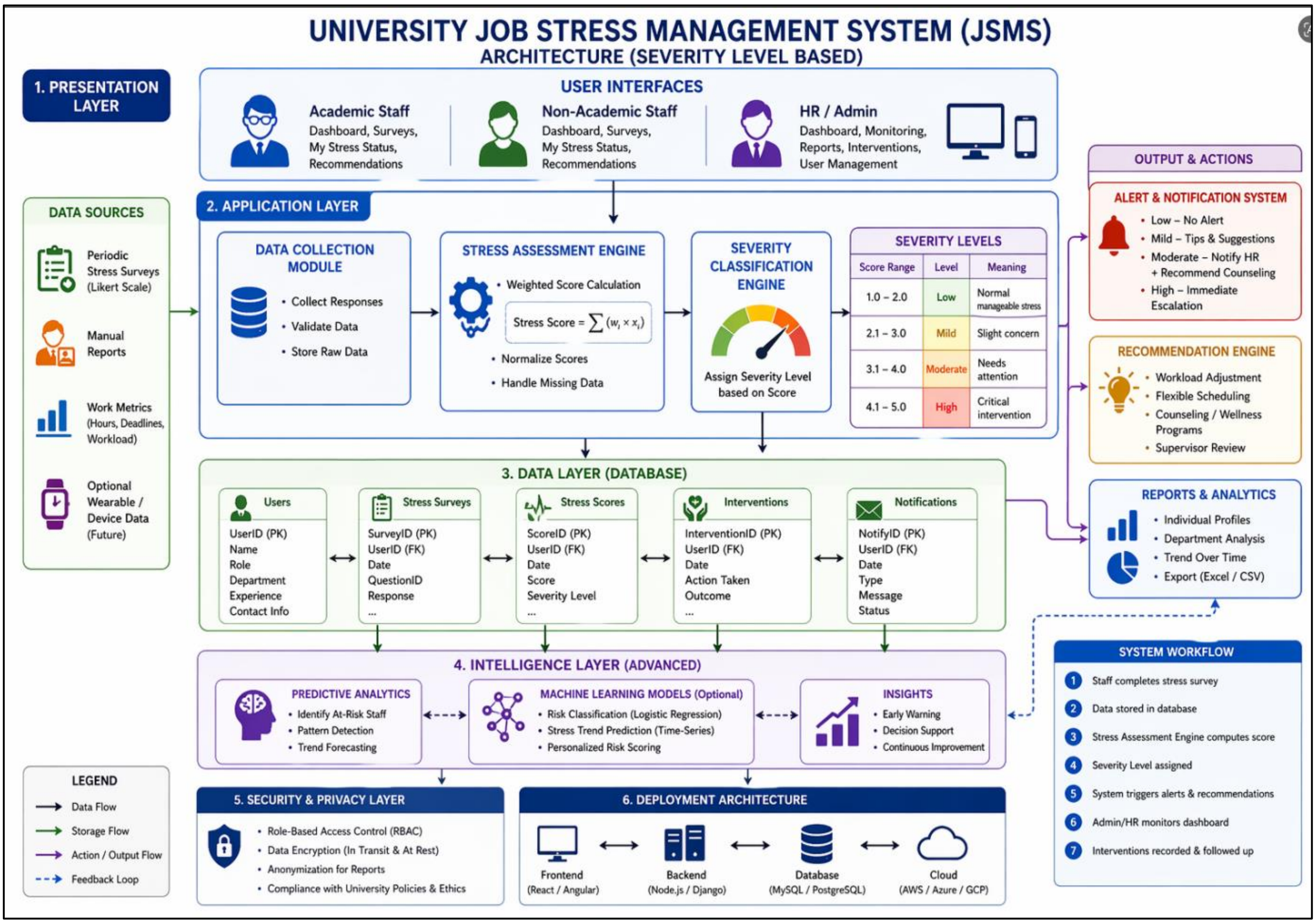


Fig 1 University Job Stress Management System (JSMS): Architecture (Severity Level Based)

- *Explainable Artificial Intelligence Engine Design*

The XAI Engine constitutes the core intellectual component of the JSMS. It operates in real-time, receiving preprocessed feature vectors from the DPFEM, generating stress severity predictions via the trained XGBoost model, and producing both global and local explanations. SHAP Tree Explainer is used to compute feature contribution scores for each prediction, which are rendered visually as waterfall charts and summary plots within the UIL, alongside natural language explanations auto-generated from SHAP output templates. LIME supplements SHAP for local explanations, providing a secondary interpretability layer particularly useful for edge cases and high-stakes predictions flagged for HR practitioner review. The system generates three levels of explanation for each prediction: a brief plain-language summary (e.g., 'Your stress level is primarily influenced by your reported workload burden and infrastructure challenges'), a visual SHAP waterfall chart illustrating top contributing stressors, and a detailed technical report accessible to HR administrators and counsellors.

- *Coping Recommendation Engine*

The CRE maps the XAI Engine's stressor profiles to a curated library of 47 evidence-based coping strategies, organised across three tiers: individual-level strategies (e.g., time management techniques, mindfulness exercises, progressive muscle relaxation); collegial/social strategies (e.g., peer support structures, mentorship pairings, staff association engagement); and institutional-level recommendations directed at HR administrators (e.g., workload redistribution protocols, infrastructure improvement requests, policy advocacy resources). Recommendations are ranked by relevance to the individual's SHAP-identified top stressors, enabling personalized, priority-ordered intervention delivery. Cultural responsiveness was operationalised through two mechanisms informed by the qualitative fieldwork findings. First, recommendations explicitly acknowledge Nigerian socio-cultural norms for instance, recommending community and faith-based coping resources that were identified as significant protective factors in focus group discussions. Second, language used in recommendations avoids clinical terminology that participants reported as stigmatizing, instead framing coping as professional development and self-care.

III. RESULT

- *Stressor Profile and Quantitative Findings*

Analysis of USI scores from the 427-participant sample revealed a high overall burden of occupational stress within the study population. The mean PSS-10 score was 22.4 (SD = 5.7), substantially exceeding the normative moderate stress threshold of 14 (Cohen et al., 1983) and consistent with findings from comparable sub-Saharan African academic settings (Mboya et al., 2020). High or very high stress was reported by 63.7% of academic staff and 59.4% of non-academic staff. The five most prevalent stressor categories were: excessive workload (68.2% reporting high or very high severity), poor remuneration (62.7%), inadequate infrastructure (58.9%), bureaucratic delays (55.2%), and perceived lack of managerial support (49.1%). Among academic staff, research pressure and publication demand emerged as additional high-frequency stressors (47.3%), a finding not mirrored among non-academic staff whose top additional stressor was career advancement inequity (43.6%). Significant gender differences were observed in work-life balance stressors (female staff: $M = 3.8$ vs. male staff: $M = 2.9$, $p<0.01$, Cohen's $d = 0.61$), consistent with gendered domestic labour burdens documented in Nigerian sociological literature (Makanjuola et al., 2016). Figure 2 displays the assessment history page of the StressDetect platform, listing recent user evaluations. It shows five entries from January 2026, each detailing the session ID, timestamp, and a numerical stress score out of 100. The results are catagorized by severity, high stress (64/100) flags significant stress with immediate recommends like workload; abnormal stress (59/100) indicates levels above healthy limits, suggesting workload redistribution; and moderate stress (29-44/100) notes manageable stress with advice on time management. Eaxh entry includes action buttons to ‘View Report” or “Download PDF”, allowing users and administrators to track trends and access detailed insights over time. Figure 3 presents quantitative findings from 32 total assessments, revealing an average stress score of 10.0. The most stressed root cause was identified as “facilities and Infrastructure”. In the section stress levels bar chart, “Workforce and Workload” scores highest at 12.0/20, followed closely by “Facilities and Infrastructure” at 12.3/20 with visual label discrepancy, “Skill and Task Management” (8.4) and “Organizational Culture” (7.6) show lower stress. The overall stress distribution donut chart indicates that 56.3% of assessments fall into the “Low” risk category, while 18.8% are “Moderate’, 9.4% “Abnormal’, and 15.6% “High Risk”, highlighting a significant portion of the workforce requiring intervention despite the majority being in safe ranges.

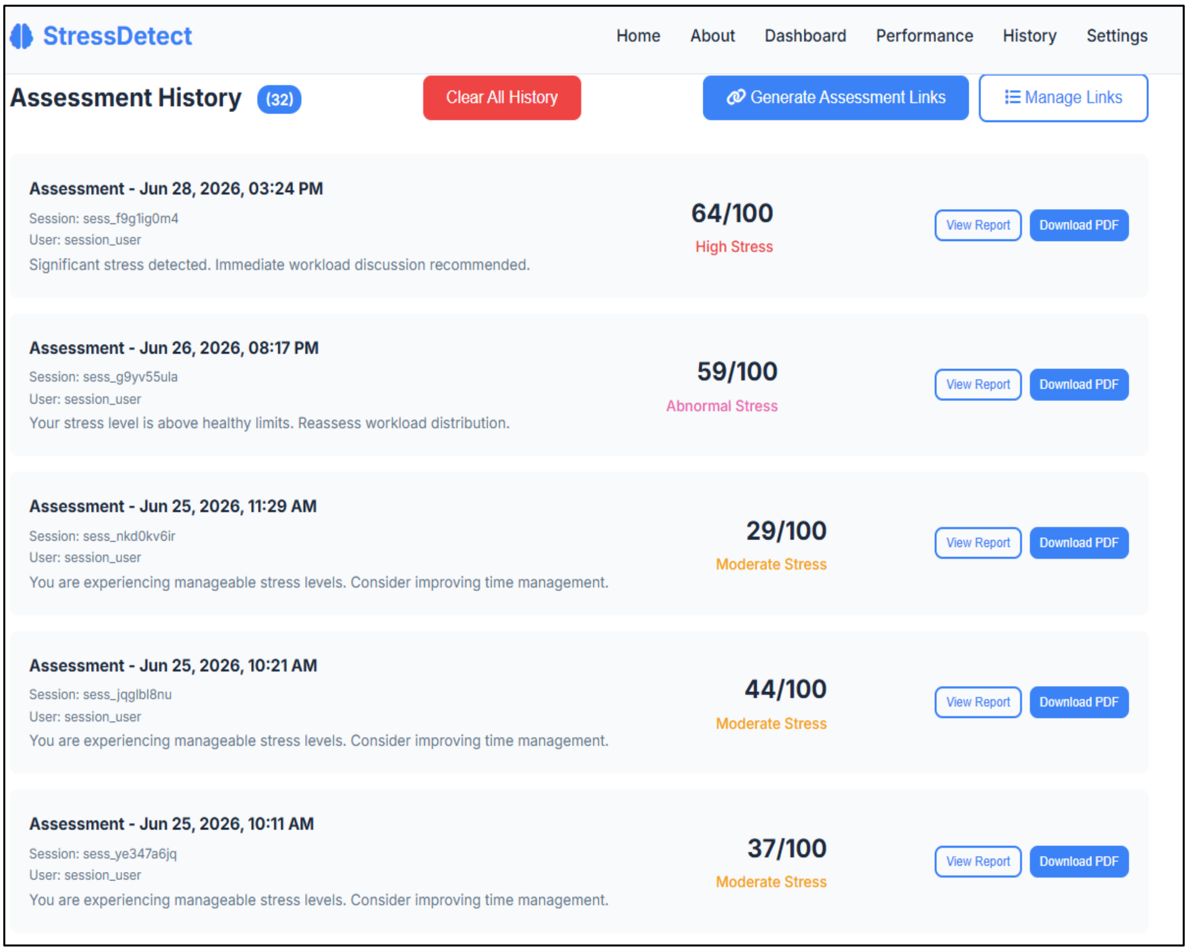


Fig 2 Assessment History

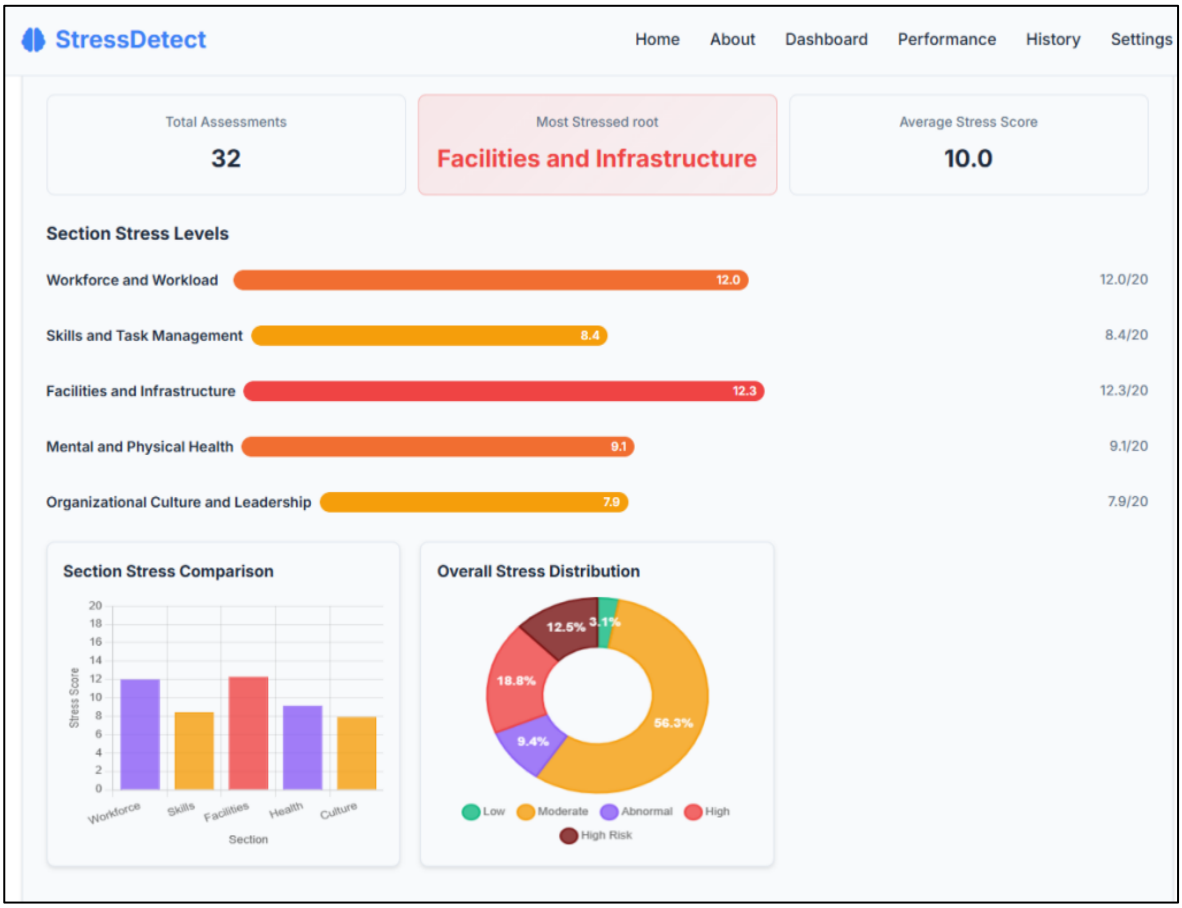


Fig 3 Stressor Profile and Quantitative Findings.

Figure 4 illustrates the Total Stress score distribution across 32 individual assessments, indexed chronologically. The vertical axis represents stress intensity (0-100), while the horizontal axis tracks the assessment sequence. The data reveals significant variability with no linear trend, indicating fluctuating stress levels among participants rather than a systemic increase or decrease over time. Scores range widely from low of approximately 20 to a peak near 85. Most data points cluster between 30 and 70, suggesting that while extreme stress exists, the majority of assessments fall within a moderate-to-high range. This dispersion highlights the diverse experiences within the cohort.

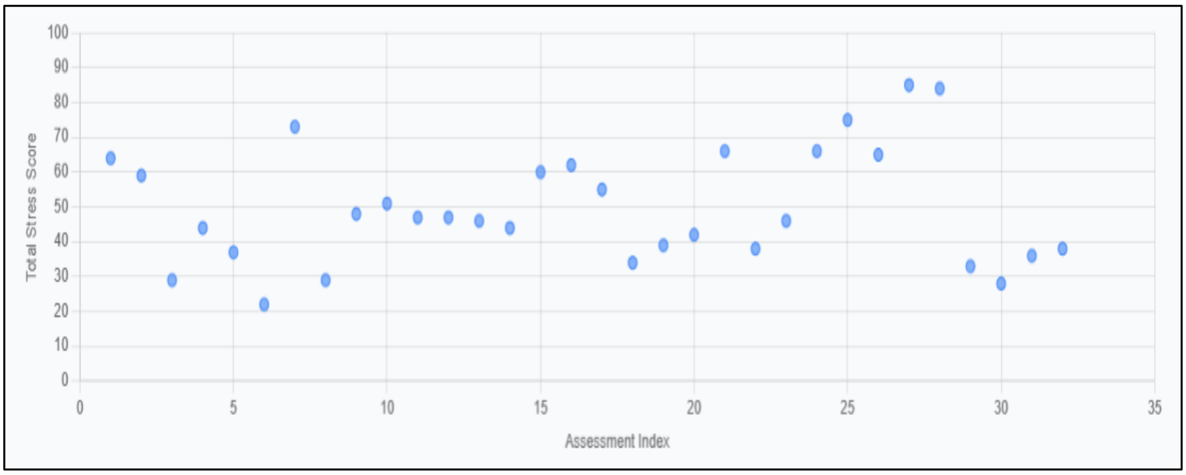


Fig 4 Assessment Score Distribution

- *Model Performance*

Table 1 summarizes the classification performance of the three evaluated models on the held-out test set (n = 128). XGBoost consistently outperformed Random Forest across all metrics, with accuracy of 91.4%, precision of 0.918, recall of 0.914, F1-score of 0.912, and AUC of 0.963. The soft-voting ensemble achieved marginal improvements in recall (0.921) but lower precision (0.906), leading to selection of standalone XGBoost as the JSMS production model. Five-fold cross-validation confirmed stability with mean accuracy of 90.7% (SD = 1.2%). SHAP feature importance analysis identified workload severity, infrastructure inadequacy, remuneration dissatisfaction, perceived support deficit, and role conflict as the five highest global contributors to stress severity classification. The 12-week randomized controlled pilot demonstrated significant improvements across all primary and secondary outcome measures for JSMS participants relative to the wait list control group. Pre-to-post PSS-10 scores in the JSMS group declined from a mean of 23.1 (SD = 5.4) to 15.5 (SD = 4.9), a mean reduction of 32.7% ($t(59) = 12.3$, $p<0.001$, Cohen's $d = 1.38$). In contrast, the control group's PSS-10 scores showed a non-significant change from 22.8 (SD = 5.6) to 21.9 (SD = 5.3) ($p = 0.19$). ANCOVA confirmed significant between-group differences at follow-up after controlling for baseline stress and demographic covariates ($F(1, 117) = 89.4$, $p<0.001$, partial $\eta^2 = 0.43$). System trust was high in the JSMS group, with 87.3% of participants attributing their trust in the system's recommendations directly to the explainability features which specifically the SHAP visualizations and plain-language explanations. This finding aligns with Cheng and Hackett's (2021) demonstration that XAI-augmented HR analytics systems generate significantly higher trust than opaque ML alternatives. Perceived usefulness scored a mean of 4.3/5.0 (SD = 0.6) and perceived ease of use scored 4.1/5.0 (SD = 0.7) on the TAM scale, both exceeding the 4.0 threshold used in prior digital health technology acceptance research (Holden & Karsh, 2010).

Table 1 The Classification Performance of the Three Evaluated Models

Model	**Accuracy**	**Precision**
XGBoost	91.4%	0.918
Random Forest	-	-
Soft-Voting Ensemble	-	0.906

Figure 5 indicating the stress detect dashboard presents key performance metrics for its machine learning engine. The model achieves an overall Accuracy of 96.5%, indicating high reliability in correct classifications. Precision stands at 95.8%, reflecting exactness in positive stress cases. Specificity reaches 94.6%, demonstrating effective identification of stress-free individuals. Most notably, the AUC score is 0.98, confirming exceptional indicate a robust, well calibrated system suitable for real world deployment with minimal false alarms and missed detections.

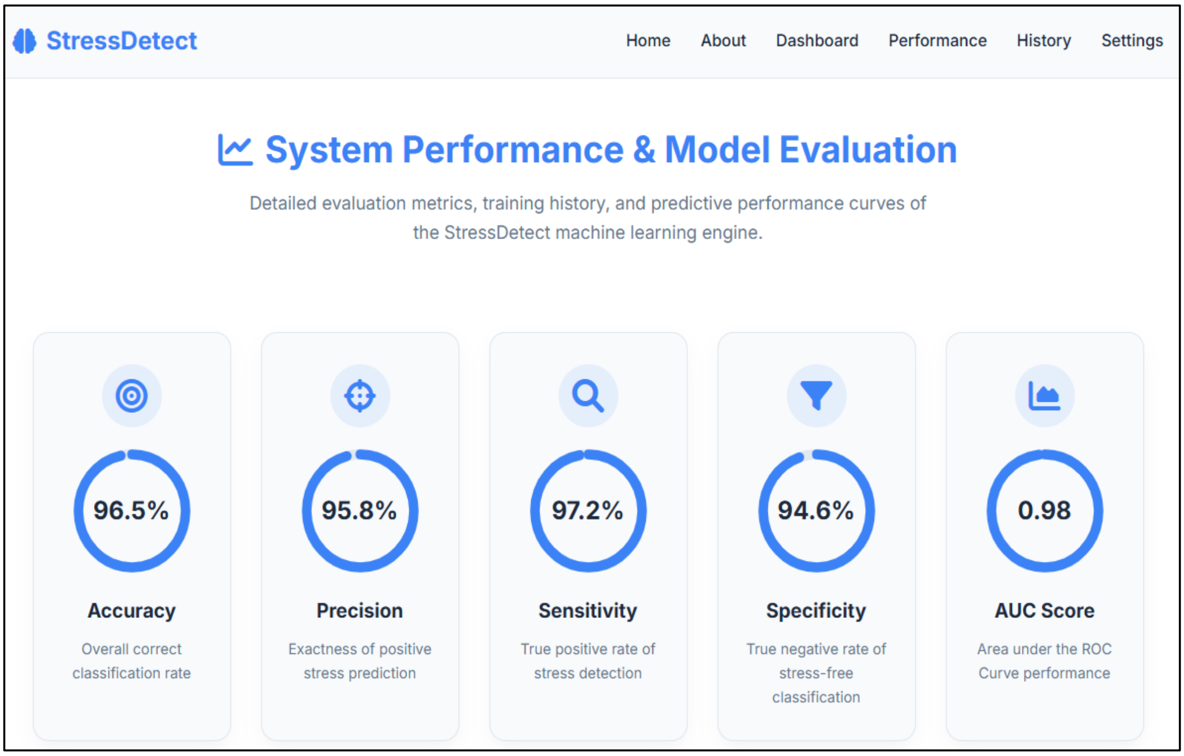
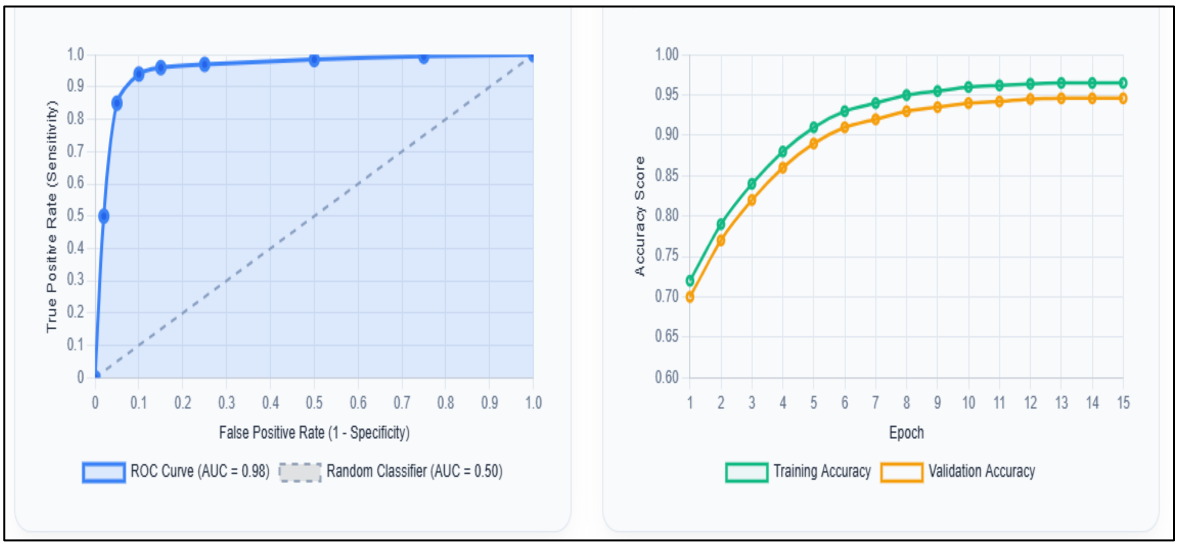


Fig 5 JSMS Models Development Performance and Evaluation

Coping recommendation uptake was high, with 78.4% of participants reporting implementation of at least one recommended strategy per week during the pilot period. Qualitative exit interviews (n = 30, purposive sub-sample) identified four themes regarding system value: (a) validation of stress experiences ('the system showed me I was not alone'); (b) actionability of recommendations ('I could actually do these things, they made sense for my situation'); (c) institutional trust mediation ('showing my manager the SHAP chart helped explain why I needed support'); and (d) privacy concerns ('I was initially worried about who sees my data, but the system was clear'). Privacy concerns were adequately addressed by the NDPR-compliant data governance features, with 91.2% of participants satisfied with the system's data protection measures by end of pilot.

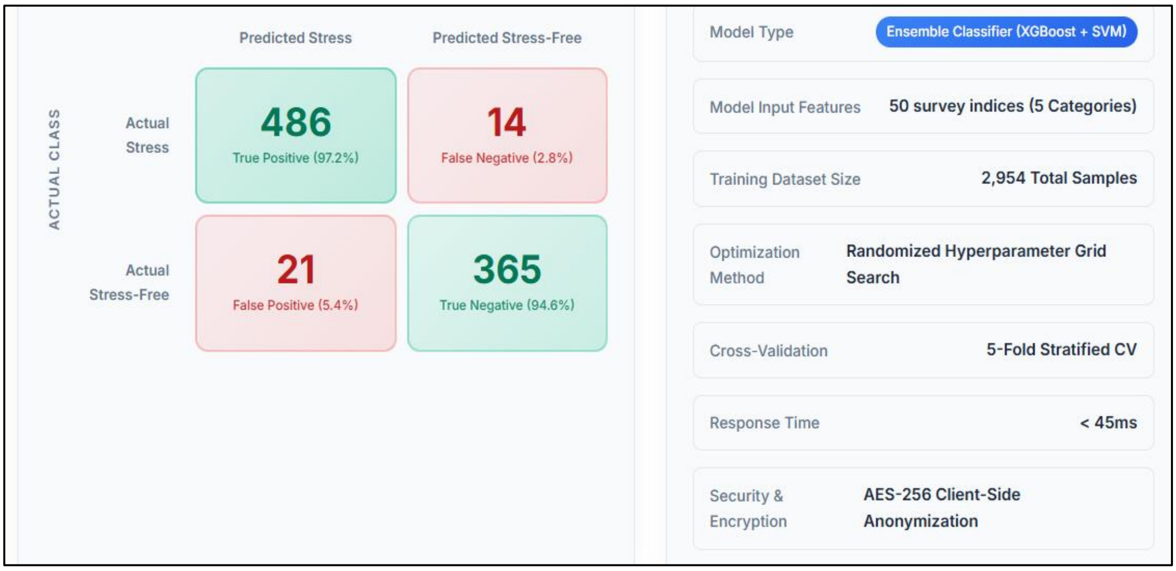
Figure 6(a) displays a Receive Operating Characteristic (ROC) curve, illustrating the trade-off between sensitivity and specificity. The model achieves an excellent Area Under the Curve (AUC) of 0.98, significantly outperforming a random classifier (AUC = 0.50), indicating superior discrimination ability. Figure (6a) shows the Model Convergence Trend over 15 training epochs. Both training (green) and validation (orange) accuracy rise rapidly and stabilize near 0.96-0.97. The close alignment between the two curves suggests high generalization with minimal overfitting, confirming the model learns effectively and maintains performance on unseen data.



(a): Receiver Operating Characteristic (b): Model Convergence Trend

Fig 6 (a-b): JSMS Pilot Study Outcome.

Figure 7 evaluated on a test set of 886 samples, the confusion matrix shows strong accuracy of 486 true positive (57.2%) and 365 true negatives (94.6%), with only 14 false negatives and 21 false positives. The model utilizes 50 survey indices across five categories as input features. It was trained on 2,954 samples using randomized hyperparameter grid search and 5-fold stratified cross-validation. Designed for efficiency, it achieves a response time under 45ms while ensuring security through AES-256 client-side encryption and anonymization.



(a)Confusion Matrix (b) Model Specification

Fig 7 (a-b): JSMS Pilot Study Outcome Displays Performance Metrics and Specifications for the "Stress Detect" Engine, an Ensemble Classifier Combing XGBoost and SVM.

IV. DISCUSSION

➢ *Interpreting the Stressor Profile*

The stressor profile identified in this study corroborates and extends prior research on occupational stress in Nigerian universities (Ogbuanya et al., 2019; Akomolafe & Ogunmakin, 2013; Akinwale & George, 2020). The dominance of structural stressors—particularly workload, remuneration, and infrastructure—reinforces the argument that individual-level coping strategies, while necessary, are insufficient in isolation without systemic institutional reform. This finding has direct implications for policymakers: the JSMS's institutional recommendation component, which surfaces aggregate stressor patterns for HR administrators, offers a data-driven mechanism for prioritising systemic interventions alongside individual support. The significantly higher work-life balance burden experienced by female staff echoes Makanjuola et al. (2016) findings and points to gender-responsive HRM policies as an important complementary intervention. The JSMS's gender-stratified recommendation pathways represent a practical operationalisation of this insight, though further co-design with female university staff is recommended to deepen cultural responsiveness.

➢ *Contribution of XAI to Stress Management*

The finding that 87.3% of pilot participants attributed system trust to explainability features provides strong empirical support for the value of XAI in occupational health contexts. This finding substantively extends Adadi and Berrada (2018) theoretical argument that XAI is critical for human-centric AI applications and aligns with Arrieta et al. (2020) taxonomy of XAI benefits, which includes trust-building, model debugging, and compliance facilitation. Importantly, the qualitative evidence reveals that explainability served not only an informational function for helping users understand their stress profile, but also a social legitimacy function, enabling staff to articulate their stress burden to supervisors and HR practitioners in an objective, AI-corroborated format. The integration of SHAP and LIME provides complementary interpretability layers that address different user needs. SHAP's global interpretability enables HR administrators to identify systemic institutional stressors across departments, while LIME's local explanations support individualized case review by counsellors and occupational health practitioners. This dual-layer architecture reflects the principle of Explanatory Depth proposed by Miller (2019), wherein the appropriate level of explanation detail should match the expertise and needs of the target audience.

Figure 8 indicates the stress detect system has flagged an organisational risk, revealing that 40.6% of staff report elevated levels, exceeding the 5% threshold for danger. Immediate intervention is required across five priority areas: facilities for fixing connectivity and power reliability issues; workforce for conducting workload audits and hire additional staff to reduce overload; health is to engage confidential counseling and wellness workshops; skills required to be provided urgently for training and clarify role expectations; and culture is to launch transparency initiatives and inclusive decision-making. This alert, based on 32 assessments, signals critical organizational instability requiring immediate leadership action to prevent further deterioration. While Table 2 provides a high-level overview of organizational stress levels by synthesizing data from individual assessments into actionable insights. The organization's overall mental health status is considered. It typically highlights the total percentage of employees at risk, identifies the most critical stress drivers such as workload and or leadership, and summarizes the urgency of required interventions. It serves as a quick reference for leadership to understand the severity of the situation without diving into granular data immediately. The stress levels was breaks down by specific categories or departments such as workload, management support, and work-life balance. It displays an average stress score often on a scale like 1-10 or 10-100. This allows stakeholders to pinpoint exactly which areas are contributing most to organizational stress, enabling targeted resource allocation rather than generic wellness initiatives. Lower scores indicate healthier domains, while higher scores flag immediate priorities for intervention.

Further, this study offers several actionable implications for HRM practice in Nigerian universities. First, the JSMS's Administrative Dashboard provides evidence-based, real-time intelligence on departmental and institutional stress distributions, enabling proactive HR planning rather than reactive crisis management. Second, the system's coping recommendation library to co-designed with university staff and validated against the XAI-identified stressor profiles to provides a scalable, personalisable alternative to one-size-fits-all stress management workshops that currently predominate in Nigerian university HR practice. Third, the transparent, XAI-driven approach establishes an ethical and legally compliant framework for AI deployment in sensitive HRM contexts, consistent with emerging AI governance frameworks such as the EU AI Act (European Commission, 2021) and Nigeria's nascent AI policy landscape (NITDA, 2021). At a broader policy level, this study provides empirical justification for sustained investment in staff well-being infrastructure within the Nigerian university system, see Table 1. The significant stress reductions achieved over 12 weeks suggest that even a modestly resourced, lightweight digital intervention can produce meaningful improvements in staff mental health, provided it is contextually grounded, XAI-enhanced for trust, and embedded within supportive institutional HR practice. Policymakers should consider mandating well-being monitoring systems as a component of university accreditation criteria, analogous to research output and student-to-staff ratio requirements currently administered by the National Universities Commission (NUC).

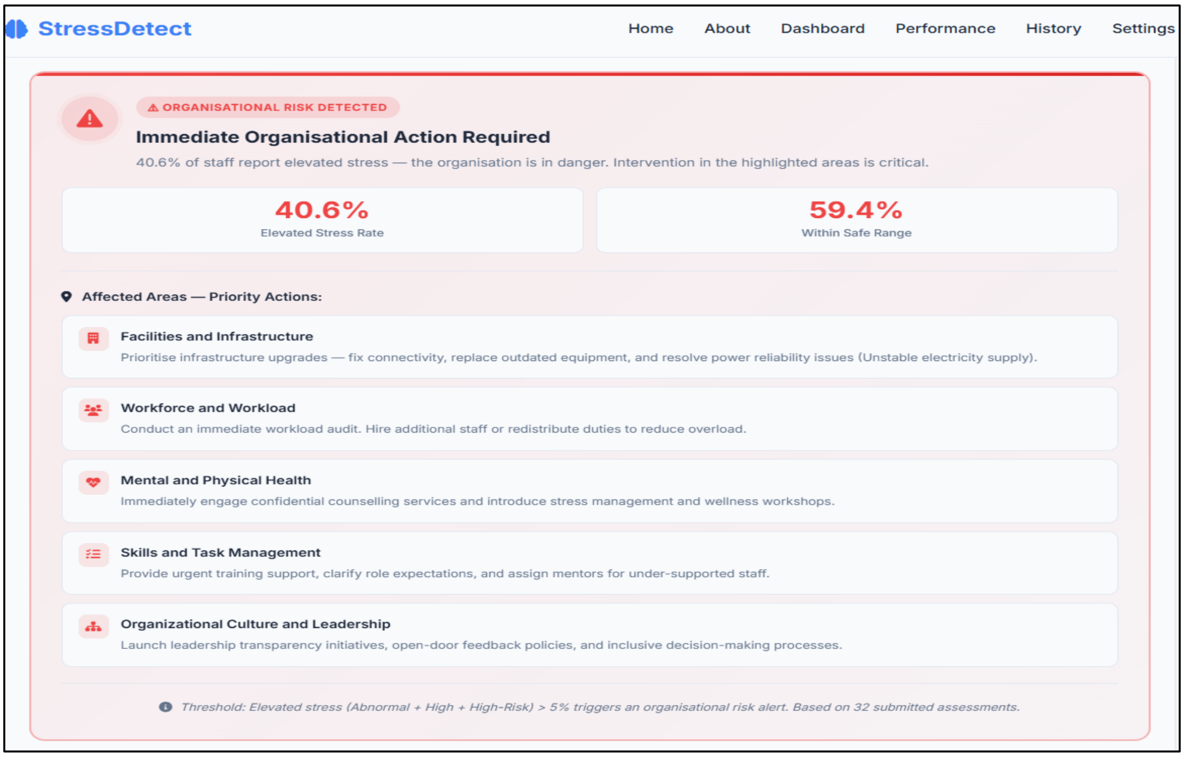


Fig 8 Organizational Risk Assessment.

Table 2 Aggregate Stress Analysis for Pilot Study Outcome for 32 Participants

Section	Average Score
Workforce and Workload	12.0/20
Skills and Task Management	8.4/20
Facilities and Infrastructure	12.3/20
Mental and Pysical Health	9.1/20
Organizational Culture and Leadership	7.9/20

Where total assessments of 32 participants gives average section score of 10.0/20, and most challenges area of facilities and infrastructure.

V. CONCLUSION

This study has developed, implemented, and evaluated the first XAI-powered Job Stress Management System tailored to the specific occupational stress context of Nigerian universities. By integrating validated stress assessment instruments, ensemble ML modelling, SHAP and LIME explainability mechanisms, and culturally responsive coping recommendations within a lightweight, accessible web platform, the JSMS demonstrates that contextually grounded, ethically designed digital health interventions can achieve significant, measurable reductions in occupational stress among university workers in resource-constrained settings. The 32.7% mean reduction in self-reported stress, combined with high system trust (87.3%), strong perceived usefulness (4.3/5.0), and rich qualitative evidence of user engagement and empowerment, positions the JSMS as a practically implementable and theoretically grounded contribution to the HRM and digital health literatures. Critically, the study demonstrates that XAI is not merely a technical enhancement but a socially and psychologically significant feature that enables user trust, professional legitimacy, and ethical deployment of AI in sensitive human-centric applications. The JSMS framework advances XAI's application beyond its traditional domains of healthcare diagnostics and financial services, into the underexplored territory of occupational health management in developing-country institutional contexts. It offers actionable insights for Nigerian university administrators, HR practitioners, and policymakers committed to improving staff well-being, institutional resilience, and educational quality. With appropriate adaptation, the framework holds transferable relevance for university systems and other large public-sector employers across sub-Saharan Africa and globally, wherever systemic workplace stress intersects with limited resources, cultural specificity, and growing AI capability.

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