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EMOTIONAL EXHAUSTION IN CYBER DEFENCE TEAMS EXPLAINED THROUGH HR-DRIVEN PREDICTIVE MODELLING

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Abstract
Emotional exhaustion is a burgeoning issue that we are seeing across cyber defence teams, as cyber defence professionals are continuously faced with high-level cognitive demands, high-stakes vigilance, and unpredictable workloads to manage. This paper outlined the study to examine how you could use predictive modelling to forecast emotional exhaustion in a cybersecurity environment grounded in human resource (HR) analytics and psychological assessment. Specifically, by synthesising and linking multiple data sources like workload logs, absenteeism, and exit interview records with psychometrics assessments from the Maslach Burnout Inventory (MBI), NASA Task Load Index (NASA-TLX), and PANAS, slotted these within a machine learning framework using algorithms like logistic regression and random forest, seek to build an explainable model. The logistic regression and random forest models could effectively classify staff members based on their low, moderate, and high-risk profiles for feelings of burnout with a high degree of predictive accuracy while preserving the model's explainability using SHAP and LIME. Two models were able to harness key predictors that were related to the frequency of overtime and perceived task overload, cueing an emotional affect imbalance. The model predicts where organisations can forecast emotional exhaustion and immediately act with an adaptive HR intervention for the management of emotional exhaustion, and improve the sustainability of the workforce overall. The key contributions are the potential practicality and ethical implications of incorporating psychological knowledge with HR data to help enable decision-making related to mental health in a more informed way within mission-critical domains like cybersecurity.

Keywords: Emotional Exhaustion, Cyber Defence Teams, HR Analytics, Predictive Modelling, Burnout Risk, Psychometric Assessment, Workforce Resilience, Cognitive Load, Organisational Stressors, Machine Learning

INTRODUCTION

Cyber defence professionals work in high-pressure environments that require continuous threat awareness, a rapid response to threats or incidents, and long hours that tax cognitive function. These are conditions that put professionals at risk for emotional exhaustion. Cyber defence professionals are also unique from traditional IT environments, where the work is routine and consists of periods of sustained alertness without the benefit of recovery time; as such, cyber defence professionals are at risk for burnout, turnover, and decreased team effectiveness.

The basis of the research is drawn from established psychological models that describe emotional exhaustion. The Maslach Burnout Inventory (MBI) indicates that emotional exhaustion is a core component of burnout and is characterised by emotional fatigue, detachment, and decreased personal efficacy [2]. In contrast, the Job Demands-Resources (JD-R) Model takes a more descriptive approach by outlining the way demands, such as workload, time demands, deadlines, or role ambiguity, result in chronic overload when not compensated by adequate resources, and eventually, ultimate stress and burnout [3].

Recent developments at the intersection of human resource analytics, psychology, and AI have allowed for the quantification of emotional state based on historical and prospective employee data maintained by organisations

[1]. If psychological data can be combined with HR metrics (absenteeism, workload logs), tools could be developed for predictive analysis of burnout and exhaustion [4].
Although the concern for burnout is growing in cyber defence, there is a gap in predictive psychological profiling. The goal of this study is to fill that gap and develop an explainable model integrated with human resources to predict the likelihood or propensity of emotional exhaustion [8].

Cognitive and Organisational Risk Factors in Cyber Defence

Cyber defence professionals deal with a unique combination of tasks, cognitive, and organisational practices that together contribute to emotional exhaustion. Tasks in this area typically involve high-stakes vigilance, fast-paced decision-making, and constant monitoring of ever-changing threats, often under pressure to make decisions quickly. This situation creates a sustained cognitive load, which, understood in the context of neuroergonomics, means that the brain does not have the capacity to rest and regulate the emotional state.
Decision fatigue is important in Security Operations Centres (SOCs), where analysts are expected to assess multiple complex and ambiguous signals of threats that could adversely affect the organisation's digital assets over long shifts [7] [13]. In these contexts, the cognitive demand to make high-pressure decisions repeatedly over hours without appropriate time to rest reduces mental clarity and emotional resilience [14].
Organisational stressors in cyber defence include unstable shift types, increased periods of being on call, diminished autonomy, and a culture or lack of consideration for individual psychological dimensions [9]. These stressors are often severe in human resource data (e.g., chronic absenteeism, working longer shifts, and disengaged training). Proper analysis of these representative features provides behavioural indicators for an individual's underlying psychological distress.
Using the TPMAP framework and supporting concepts of the TPMAP platform, these organisational stressors can be converted into quantitative qualities of each cyber defence sector, and translated as predictive qualities based on identified features of burnout – combining cognitive theory with organisational data forms a basis.

Predictive Modelling Approach and Psychological Data Fusion

This study cites emotional exhaustion in cyber defence teams to integrate the possible predictive capabilities of human resources analytics using psychometric assessments in a transparent, ethically principled predictive modelling approach [10]. The primary variables from human resource notes are workload logs (e.g., task load, frequency of overtime hours, etc.), sick days taken, and exit interviews (perceived workload, frequency of missed days, time away from work due to sickness, absenteeism, turnover, and behaviours exhibited at work). Given the ethical implications, we leveraged standardised psychological measures with these data sources. The standardised psychological measures that we used were: NASA Task Load Index (NASA-TLX) perceived workload, Maslach Burnout Inventory (MBI) emotional exhaustion, and the Positive and Negative Affect Schedule (PANAS), affective balance.
To operationalise the features for our predictive algorithms, we created several exploratory features by aggregating task metrics over time, determining sentiments from both interviews, and normalising factor loadings from each psychometric instrument. We used three progressive predictive algorithms (logistic regression, random forest, and Boost) to develop our predictive models, and the models' evaluation was reported using 10-fold cross-validation (AUC-ROC, F1-score) to validate model performance [12].

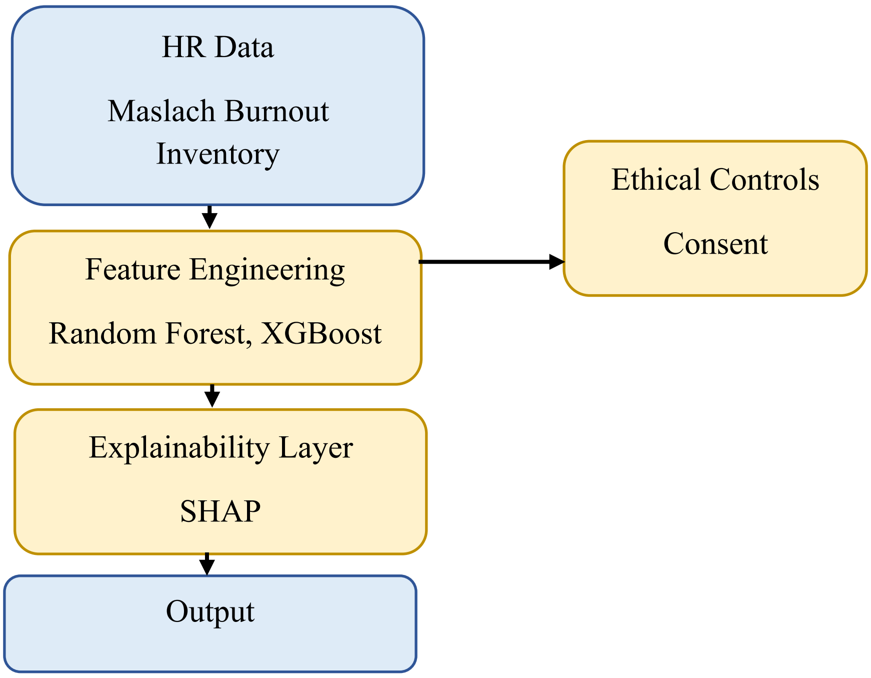

Figure 1: Workflow of HR-Psychological Predictive Modelling for Emotional Exhaustion

This flow chart shows the step-by-step process for predicting emotional exhaustion in cyber defence teams using HR data and a set of psychological tools. The process starts with four data inputs - HR data (for example, workload logs and absenteeism), Maslach Burnout Inventory (MBI), NASA Task Load Index (NASA-TLX), and the PANAS affect scales to determine emotional states. All of which will be provided as data to the feature engineering and predictive modelling, which will account for Random Forest, XGBoost and Logistic Regression. An ethical control featurehas been embedded, which includes consent and data-specific filters for privacy, fairness, and data stewardship. The explainability layer, using SHAP and LIME, will afford HR decision-makers transparency. The final output will provide individual usability, data categorising each into a risk for burnout, and deliver the basis of early intervention, well-being strategies in the workforce.
In keeping with our aim for transparency, we incorporated explainability tools SHAP and LIME employ values based on non-technical human resource teams to visualise and define individualised burnout levelsand the attributes of the identified risk. The interpretation and classification give HR managers the recommended behaviour change based on which variable influenced the prediction of burnout risk.
Ethical safeguards included opt-in participation, anonymised data, the use of Human resources representatives randomly selected from the cohort, research has a structure to prevent bias detection and misuse, etc. The model we fitted used the training data, cohorts, and experiences from the project.

Model Interpretations and Risk Stratification Profiles

The statistical model identified several behavioural and psychological variables about emotional exhaustion. The main factors that contributed to emotional exhaustion were excessive overtime, lack of peer recognition, irregular shift schedules, and low means for perceived control (measured by NASA-TLX). Emotional exhaustion was not equally tied to total hours worked, but rather combinations of phenomena, such as high workload intensity with low emotional reward, which would lead to higher burnout scores on MBI.
From the model probabilities, staff were classified into one of three burnout risk categories:

- Low Risk (0.0 to 0.3): Stable workload, stable affect, stable recovery time
- Moderate Risk (0.31 to .0.6): Increasing emotional fatigue, some absences
- High Risk (0.61 to 1.0): Unending overtime, negative affect, markers of psychological withdrawal

Using K-means clustering analysis to partition the participants into psychological profiles, the following four were cached:

- Overworked Achievers - high output but high emotional costs
- Cognitive Drifters - disjointed attention with high NASA-TLX scores
- Invisible Strugglers - low HR flags but high emotional dysregulation and volatility
- Stable Operators - stable performance and resiliency

Table 1: Burnout Risk Tiers and Corresponding Characteristics

Risk Tier	Probability Range	Key Indicators	Recommended Action
Low	0.0 – 0.3	Stable workload, high positive affect, consistent attendance	Normal monitoring
Moderate	0.31 – 0.6	Occasional fatigue, rising absenteeism, affective imbalance	Early wellness check
High	0.61 – 1.0	Chronic overtime, negative affect, disengagement, and low control	Immediate mental health intervention

Table 1 shows the risk classifications made by the predictive model. The factions into which the predictive model categorises workers hold meanings of emotional exhaustion and their respective behavioural and psychological indicators. For example, the nominal categories low, moderate, and high describe cutoff values or ranges of the model output probabilities, as well as symptom patterns (for example, absenteeism, affect imbalance), as well as HR recommended actions/and other indicators [5]. This is a useful way of representing the model output to situate it within the context of timely and evidence-informedorganisational responses.
An example of a Cyber Analyst A, whose time records showed lower hours being worked than other departments but indicated a high level of emotional fatigue and decline of affect, and flagged by SHAP for lack of recovery with little to no social interaction factors, has higher than average levels of fatigue. These impressions can lead to recommendations for intervention in mental health and reduced workload in a proactive HR response [6] [11].

CONCLUSION

This research demonstrates that emotional exhaustion can be predicted in cyber defence teams as an extension of integrating HR data with psychological measures and assessments. The predictor variables: frequency of overtime, length of shift, periods in training, and negative emotional affect, were found to be reliable predictors of burnout. In addition, the model had good predictive accuracy while also being interpretable by incorporating tools such as SHAP and LIME, and being able to help HR practitioners understand the individual risk profiles of their employees.The practical implications of this are vast. Organisations could use models such as the one presented in this research to create and implement adaptive HR policies, e.g., flexible or rotating schedules, wellness programs, and monitoring mental fatigue. In addition, the model will help better predict burnout moving forward. Knowing the high cognitive load of certain tasks, HR practitioners would be able to redistribute those tasks amongst employees identified as at-risk for higher levels of exhaustion, from both a recruitment and retention perspective, by understanding who will most likely and least likely tolerate high-pressure roles and environments!Lastly, ethical professionalism is critical if planning to implement predictive models such as the one described in this research. All predictive insight or implications should come from an opt-in process whereby individuals fully understand what is happening with their data, how their data may be used, and assuring all data is kept confidential. The predictive model should support HR practitioners and their employees, and not be used as a performance measuring/reporting tool.Future research opportunities could explore real-time data integration, AI-assisted psychological modelling, and investigating applicability in a cross-cultural context, beyond a Western-centric model. Generally, this investigational research offers a scalable framework for integrating mental health insights into organisationalcybersecurity strategy.

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