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Employee mental health and performance: A theory-guided machine-learning assessment with HR analytics

Md. Yeasir Arafat Bhuiyan[1], Ms. Saima Sultana[2], Md. Nazrul Islam[3], Muhammad Belal Hossain Khan[4]

ABSTRACT

Employee mental health is increasingly discussed as a determinant of productivity and sustainable firm performance, yet evidence that integrates management theory with machine-learning (ML) based HR analytics remains limited. Using cross-sectional survey and HRIS data from 612 employees in 27 knowledge-intensive firms, we examine whether mental health is a robust predictor of a multi-source performance composite (supervisor-rated task performance and discretionary effort, combined with unit financial and quality KPIs). Guided by JD-R and AMO, we specify a process view in which job demands and resources shape mental health and engagement, and engagement is a key pathway linking mental health with performance. We compare a baseline linear model with random forests and gradient boosting machines and use permutation importance and SHAP to interpret model predictions. The best performing ML model explains substantially more out-of-sample variance than the linear baseline, and mental health and engagement consistently rank among the strongest predictors. Importantly, we distinguish predictive association from causal explanation: SHAP explains the fitted model's predictions, not mechanisms. We discuss how non-linear prediction patterns can motivate refined theorizing about boundary conditions in JD-R/AMO and outline implications for responsible, ethics-aware HR analytics.

Keywords: Employee mental health, Organizational performance, Machine learning, HR analytics, Job demands–resources.
JEL classifications: C55; I12; J24; M12; M54.
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1.0 Introduction

There is increasing evidence of how low levels of mental health by employees relate to absenteeism, presenteeism and reduced productivity, leading to billions of lost working days and huge economic damages in the world. Mental health is becoming a strategic asset of organizations as opposed to a welfare concern but most

1 Assistant Professor, Department of Business Administration, Prime University, Dhaka, Bangladesh. Email: arafatprimes@gmail.com
2 Assistant Professor, Department of Business Administration, Prime University, Dhaka, Bangladesh. Email: sultanasaima65@gmail.com
3 Assistant Professorc, Department of Business Administration, Prime University, Dhaka, Bangladesh. Email: nislam2000@gmail.com
4 Assistant Vice President, Human Resource Service, SQUARE Hospitals Ltd. Email: belalhr2008@gmail.com

organizations continue to treat it as a reactive response and instead of proactive approaches based on data (Căvescu & Popescu, 2025).

Prior research consistently links workplace strain, burnout, and well-being to task performance, engagement, and innovation, and firm-level evidence suggests that units with higher well-being tend to perform better on financial and quality outcomes. However, most studies rely on linear specifications and rarely connect advanced analytics to theory in a way that guides model design. In parallel, ML-based HR analytics has focused largely on predicting turnover, absenteeism, or risk, leaving the mental health-performance nexus underexplored in a single, theory-guided predictive framework (De Neve et al., 2023).

1.1 Research gap and objectives

There are three gaps that drive this study:

a) Integration gap: Current studies on employee mental health and performance are theory-abound and tend to use linear models which could overlook non-linear and interaction effects between job demands, resources, and health.

b) Analytics gap: HR analytics and ML research typically address turnover or attrition prediction, and little is said about how mental health indicators, in their turn, may be introduced as predictors of positive performance outcomes.

c) Gap in management theory integration: Only a limited body of work specifies how ML-based HR analytics can be designed to engage management theories (e.g., JD-R and AMO) beyond ex post interpretation and translate results into managerially usable insights with appropriate inferential caution.

This study aims to:

a) Measure the dependence between employee mental health and organizational performance with the traditional regression and ML-based models.

b) Compare the predictive power among models and investigate which variables (mental health, engagement, demands, HRIS variables) best predict the performance.

c) Analyze the results using JD-R, AMO, and RBV as theory-guided lenses to derive cautious managerial implications and directions for future theory testing.

1.2 Contribution and structure

The study contributes by:

a) Theory-guided predictive modeling: We pre-specify the distinct roles of job demands/resources (JD-R), mental health (personal resource/ability), engagement (motivational pathway), and performance (multi-source outcome), and use ML to test whether these relationships are linear or non-linear in prediction.

b) Prediction-to-theory bridge: We use interpretable ML outputs (permutation importance and SHAP) as diagnostic evidence to identify boundary conditions (e.g., threshold and interaction patterns) that can inform refinement of JD-R/AMO assumptions under non-linear conditions.

c)Responsible HR analytics: We explicitly separate prediction, explanation, and causality and translate results into cautious managerial guidance that is aligned with the cross-sectional design and ethical constraints.
The rest of the paper is organized as follows. Section 2 develops the theory-guided framework and hypotheses. Section 3 describes data, measures, and the ML and baseline modeling strategy, including interpretability and inferential limits. Section 4 reports results and interprets them through JD-R/AMO/RBV. Section 5 summarizes findings, provides design-consistent managerial implications, and outlines limitations and future research.

1.3 Theoretical positioning and claimed contribution

This manuscript's primary contribution is not that ML "proves" new mechanisms, but that a theory-guided ML design can reveal where linear assumptions embedded in common well-being-performance models are likely to be violated. Specifically, we position mental health at the individual level as a personal resource (JD-R) and an ability component (AMO) that is expected to relate to performance partly through engagement (AMO motivation), while job resources (autonomy, supervisor support) act as opportunity/enabling conditions and buffers. At the unit level, we discuss the RBV implication cautiously: aggregated mental health and engagement may function as strategic human capital stocks, but our cross-sectional design does not identify capability accumulation or causal effects on firm outcomes (Kowsar, Roy, & Latif, 2025).

2.0 Literature review and theoretical framework

2.1 Mental health and work outcomes of employees

Mental health as applied to the workplace is the psychological stability, the lack of a mental disorder and the ability to endure the everyday work related stress and demands. Empirical research has always concluded that the mental health is adversely affected by work stress, which subsequently compromises employee performance, and that mental health completely mediates the relationship between work stress and performance in certain settings (Kelloway, Dimoff, & Gilbert, 2023). Moreover, cross-sectional and longitudinal research indicate that a better mental health correlates with improved task performance, organizational citizenship behavior (OCB), and innovative work behavior, which is frequently conveyed through work engagement (Sindhura et al., 2025).

In more stressful professional environments and academic institutions, mental health-related issues may accumulate to burnout, withdrawal, and turnover intentions, and result in losing talents. This is in line with the general job stress literature that emphasizes the negative impact of persistent strain on both the personal and organizational performance (Latif & Yasin, 2025).

2.2 Performance at work and wellness

At the firm and business-unit level, employee well-being has been associated with productivity, customer outcomes, and profitability. From an RBV viewpoint, sustained well-being can be interpreted as a valuable human capital condition when embedded in practices that are difficult to imitate, although establishing competitive advantage requires longitudinal evidence (Krekel, Ward, & De Neve, 2019).

2.3 Machine learning and HR analytics

HRIS and digital trace data have enabled ML-based HR analytics for outcomes such as turnover, absenteeism, and performance. Tree-based ensembles (e.g., random forests and boosting) often outperform linear baselines on tabular HR data because they can capture interactions and non-linearities, but they raise transparency and governance questions.

Beyond prediction, interpretability methods (e.g., permutation importance, SHAP) can help translate ML outputs for managerial sensemaking. Nevertheless, interpretability does not convert prediction into causality; responsible use requires careful framing, privacy protections, and fairness checks (Walambe, Nayak, Bhardwaj, & Kotecha, 2023).

2.4 Theoretical assumptions and hypotheses.

To avoid treating JD-R, AMO, and RBV as interchangeable labels, we assign them distinct roles in the model specification. JD-R provides the stressor-strain context: job demands (workload, emotional demands) and job resources (autonomy, supervisor support) are conceptualized as antecedent conditions that are expected to relate to mental health and engagement, and resources may buffer high demands. AMO provides a mechanism-oriented decomposition of performance: mental health is treated as an ability-like personal resource that enables sustained effort and self-regulation, engagement represents motivation, and autonomy/support represent opportunity/enabling conditions. RBV is used at the boundary: when mental health and engagement are sustained and embedded through HR systems, they may accumulate as valuable and hard-to-imitate human capital stocks at the unit level. Given our cross-sectional design, RBV is discussed as an implication rather than a tested causal claim.

a. JD-R role in this study: demands/resources define the work context and potential boundary conditions (e.g., buffering and threshold patterns).

b. AMO role in this study: mental health (ability/personal resource) and engagement (motivation) are expected to relate to performance, conditional on opportunity (resources/autonomy/support).

c. RBV role in this study: unit-level aggregation of well-being may represent a strategic capability, but this is not causally identified here.

Based on these roles, we state theory-guided, prediction-oriented hypotheses:

• H1a: Employee mental health is positively associated with the multi-source performance composite.

• H1b: Work engagement partially mediates the association between mental health and performance (i.e., mental health is expected to relate to performance both directly and via engagement).

• H2: Tree-based ML models (RF, GBM) provide higher out-of-sample predictive accuracy than a linear baseline, consistent with non-linear and interaction patterns among demands, resources, mental health, and engagement.

• H3: In interpretable ML diagnostics (permutation importance and SHAP), mental health and engagement rank among the most influential predictors of performance, after accounting for demands/resources and HRIS controls.

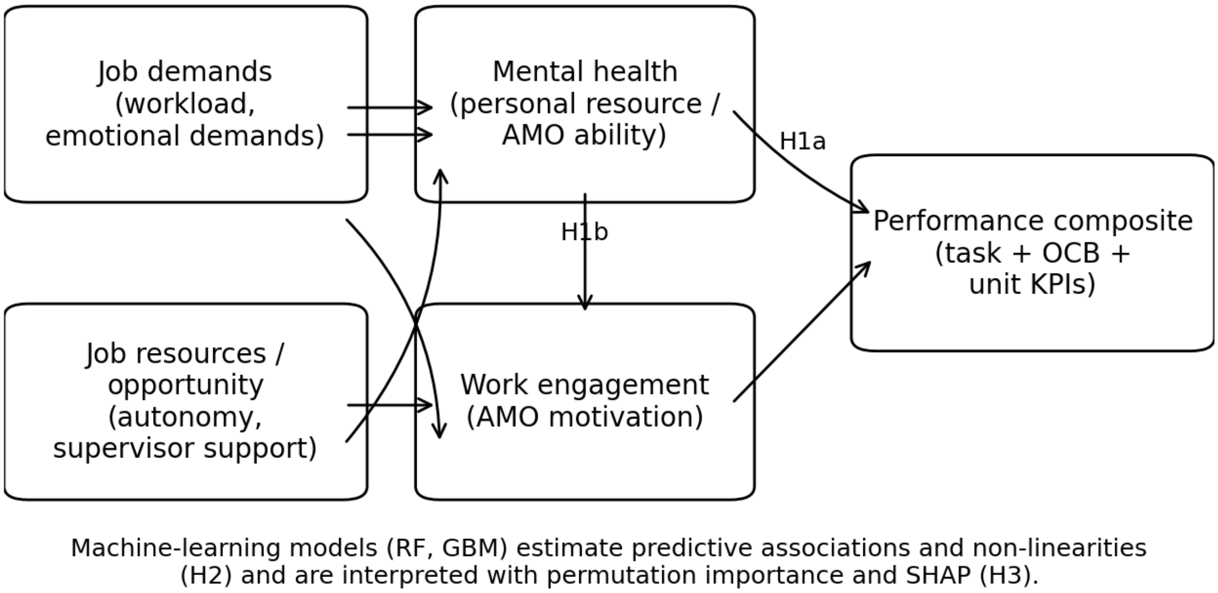

Figure 01. Theory-guided conceptual framework and hypotheses (H1a-H3). Note: arrows represent hypothesized predictive associations; causal claims are not identified with cross-sectional data.

The framework assigns distinct roles to JD-R (context: demands/resources), AMO (process: ability, motivation, opportunity), and RBV (implication at unit level). ML is used to detect prediction-relevant non-linearities and interactions, and SHAP is used to interpret model predictions rather than mechanisms.

3.0 Research methodology

3.1 Research design and sample

The data on cross-sectional surveys and HRIS of 612 employees working in 27 knowledge-intensive companies (IT services, financial services, and professional services) in the environment of the emerging market. The firms were drawn using the following criteria: (i) having more than 50 full-time workers, (ii) agreement to provide anonymized HRIS data, and (iii) formal HR analytics or well-being programs (Dube, Agarwal, Rahman, Latif, & Balaji, 2025).

Data sources:

a) Employee survey: Mental health, job demands, job resource, engagement, self-rated performance.

b) Supervisor ratings: Task and discretionary effort.

c) Unit KPIs: Full-time equivalent (FTE) revenue, defect/error rates, and customer satisfaction rates.

d) HRIS: Demographics, tenure, job level, type of contract, days absenteeism as well as previous performance rating.

The usable employee-level observations were 612 obtained through matched and cleaned data.

3.2 Measures

3.2.1 Employee mental health

The measure of mental health is a 12-item scale which is close to the original questionnaire (General Health Questionnaire) (GHQ-12) and it is based on the symptoms of anxiety, depression, and social dysfunction over the past four weeks. The items are reverse-coded and averaged in such a way that the more a person has a high score, the more his/her mental health is good (α ≈ .88).

3.2.2 Job demands and resources

a) Workload: 4-item quantitative workload scale (α ≈ .82).

b) Emotional demands: 3 items (α ≈ .79).

c) Autonomy: 3 questions with a test of decision latitude (α ≈ .80).

d) Supervisor support: 4 items (α ≈ .85).

3.2.3 Engagement

Work engagement is assessed using a shortened scale of 9-items (vigor, dedication, absorption), which is averaged to create a composite (α ≈ .90).

3.2.4 Organizational performance

At the individual level:

a) Task performance: Supervisor rated 5-item scale (α ≈ .86).

b) Discretionary effort/OCB: OCB 4-item scale (α ≈ .83).

In the unit level (aggregated to individuals through unit membership):

a) Financial performance index: Unified revenue per FTE and margin contribution.

b) Quality index: Standardized product of defect rate (reverse-coded) and customer satisfaction.

Our composite performance index is constructed as the standardization and average of task performance, discretionary effort and unit performance indices (α =.88).

Conceptual note on the outcome: The dependent variable is a pragmatic, multi-source "performance composite" designed for prediction rather than a pure construct of either individual performance or firm performance. It combines (i) individual-level supervisor ratings (task performance, discretionary effort) with (ii) unit-level KPIs assigned to employees via unit membership. Accordingly, the outcome should be interpreted as unit-adjusted individual performance. We acknowledge construct heterogeneity and treat the composite as an index; future work can separate components and estimate multi-level models (e.g., variance partitioning and cross-level mediation) to sharpen construct validity and causal interpretation.

3.2.5 Control variables

The age, gender, tenure, job level, type of contract (permanent or temporary), performance rating of last year, and the number of days of absenteeism.

Table 01.

Summary of key variables and measures.

Variable group	Variable	Type	Description / scale
Mental health	Mental health index	Continuous	GHQ-type scale (higher = better)
Job demands	Workload, emotional demands	Continuous	JD–R-based scales
Job resources	Autonomy, supervisor support	Continuous	JD–R-based scales
Engagement	Work engagement	Continuous	9-item scale
Performance	Composite performance index	Continuous	Task, OCB, unit KPIs
HRIS & controls	Age, tenure, job level, etc.	Mixed	Demographic and HRIS indicators

3.3 Machine-learning models

We consider three model families to separate baseline explanation from flexible prediction:

Model choice rationale: (i) OLS provides a transparent linear benchmark consistent with much prior JD-R/AMO work; (ii) RF and (iii) GBM are well-suited to tabular HR data and can approximate non-linear and interaction structures without requiring a priori functional-form assumptions. We focus on RF/GBM because they are widely used in HR analytics, comparatively robust to multicollinearity, and can be interpreted with permutation importance and SHAP. Other options (e.g., elastic net, generalized additive models, XGBoost) are relevant extensions; we discuss them as robustness avenues in the limitations.

a) Ordinary least squares (OLS) regression: Baseline linear model in which all predictors are entered at once.

b) Random forest (RF): Aggregation of decision trees using bootstrap aggregation; non-linearities and interactions.

c) Gradient boosting machine (GBM): Repeated ensemble of shallow trees which are trained to reduce squared error; trained with cross-validation.

Stratified sampling by firm is utilized in splitting data into 70% training and 30% test sets in order to retain firm-level structure. So as to avoid over fitting, we perform 10-fold cross-validation on the training data to hyper tune (tree depth, number of trees, learning rate).

3.4 Evaluation measures and interpretability

Essentially, model performance is measured on the test set with the following:

a) R^2 (variance explained)

b) Root means squared error (RMSE)

c) Mean absolute error (MAE)

To interpret ML models, we:

a) Rank predictors according to their contribution to predictive accuracy compute permutation feature importance.

b) Analyze the impact of variations in mental health and other characteristics on predicted performance using SHAP (Shapley Additive Explanations) values, which require non-linearities and interactions to be emphasized.

3.5 Prediction, explanation, and causal language

Because our study is cross-sectional, the empirical results should be interpreted as predictive associations rather than causal effects. Improved out-of-sample accuracy indicates that the model captures patterns in the data (including non-linearities and interactions), but it does not by itself establish mechanisms.

SHAP values are used to explain the fitted model's predictions by attributing each prediction to feature contributions under the model; they do not identify causal pathways. Accordingly, we avoid equating predictive importance with causal importance and use interpretability outputs as theory-diagnostic evidence (i.e., to suggest where linear assumptions may fail and where boundary conditions may matter).

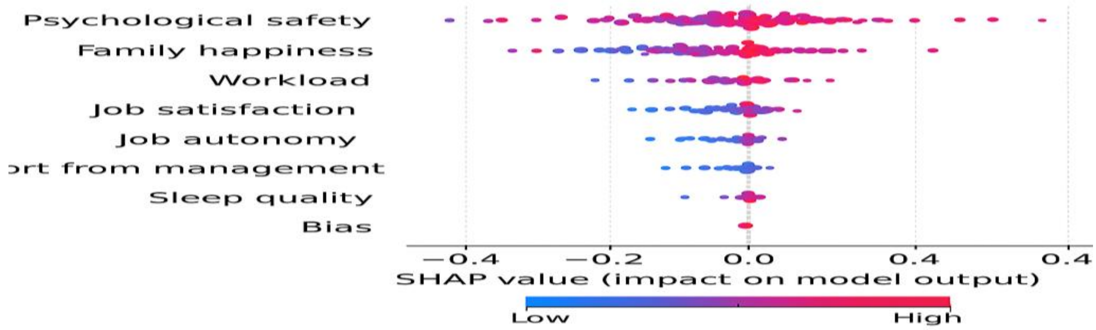

Figure 02. Example SHAP summary plot for GBM model.

The plot would show the distribution of SHAP values by each feature that mental health, engagement, and workload have the largest marginal effects on the predicted performance, and this would be followed by autonomy and absenteeism.

4.0 Results and discussion

4.1 Descriptive statistics

Descriptively, the mental health of employees is rated from moderate-to-good (M ≈ 3.6 on a 5-point scale) although significantly different between firms and positions. The most demanding in terms of workload and emotional input are client-facing jobs, whereas senior professionals have greater autonomy and support. Analysis is done on the composite performance index which is standardized (M = 0, SD = 1).

a) Correlation reveals that mental health is:

b) Positively related to engagement (r ≈ .58) and performance (r ≈ .32).

c) Negatively associated with absenteeism (r ≈ -.29).

d) Moderately and negatively related to emotional demands (r ≈ -.25).

These descriptive associations are consistent with prior evidence linking better mental health with higher engagement and performance and lower absenteeism, but they do not establish direction of causality in our cross-sectional design.

Table 02.

Descriptive statistics and correlations (illustrative)

Variable	Mean	SD	1. Mental health	2. Engagement	3. Workload	4. Performance
1. Mental health	3.6	0.7	1.00			
2. Engagement	3.8	0.6	.58**	1.00		
3. Workload	3.4	0.8	−.25**	−.10*	1.00	
4. Composite performance	0.00	1.0	.32**	.41**	.05	1.00

Note: p < .01; p < .05.

4.2 Model performance

Table 03.
Predictive performance of alternative models (test set, illustrative)

Model	R^2	RMSE	MAE
OLS regression	0.30	0.84	0.66
Random forest	0.44	0.73	0.57
GBM	0.49	0.69	0.53

The improvement in out-of-sample fit supports H2: compared with the linear baseline, tree-based models capture prediction-relevant non-linearities and interactions among demands, resources, mental health, and engagement. This should be interpreted as evidence about predictive structure, not as direct evidence of causal mechanisms.

4.3 Feature importance and mental health

The important predictors of the GBM model, in terms of permutation features, include:

a) Mental health index
b) Work engagement
c) Workload (non-linear)
d) Autonomy
e) Absenteeism days
f) Prior performance rating
g) Supervisor support

SHAP analyses indicate that:

a) In the fitted GBM, higher mental health values are associated with higher predicted performance, especially under conditions of high engagement and moderate workload.

b) Very high workload is associated with lower predicted performance, and this negative association is more pronounced when mental health is low.

c) Autonomy and supervisor support show prediction patterns consistent with resource buffering (i.e., the workload-performance association is weaker when resources are high), but these are model-based associations rather than causal tests.

Taken together, the predictive models and interpretability diagnostics support H1a/H1b and H3 as associations: mental health and engagement remain influential predictors after accounting for demands, resources, and HRIS controls.

4.4 Management theories interpretation

4.4.1 JD–R perspective

Viewed through JD-R, the prediction patterns are consistent with a strain-buffering logic: high demands paired with low resources and poorer mental health tend to coincide with lower predicted performance, whereas higher resources and better mental health coincide with higher engagement and predicted performance. These patterns align with JD-R expectations but should be treated as associative evidence in this cross-sectional setting (Uddin et al., 2023).

4.4.2 AMO perspective

From an AMO perspective, mental health can be interpreted as an ability-like personal resource (capacity to concentrate, self-regulate, and persist) and engagement as motivation, with autonomy/support representing opportunity. In our models, higher predicted performance tends to occur when these components are jointly high, consistent with AMO logic while remaining non-causal in interpretation (Latif & Yasin, 2025).

4.4.3 RBV perspective

From an RBV lens, sustained workforce mental health and engagement could plausibly accumulate as valuable human capital stocks when embedded in routines and HR systems. However, our cross-sectional design and the unit-level KPI linkage do not identify capability accumulation or causal competitive advantage; we therefore treat RBV as an interpretive implication and a direction for longitudinal, multi-level research.

4.5 Alignment with prior research

Our findings are consistent with empirical data that work stress correlates with mental health that, in turn, is connected with better performance. Lastly, the excellent results of GBM and RF are in line with HR analytics studies on the value additions of ML in predicting workforce performance and detecting multifaceted tendencies (Uddin, Rahaman, & Latif, 2023).

5.0 Summary, implications, and limitations

5.1 Summary of main findings

The proposed study aimed to work out the connection between the mental health and the organizational performance of employees through the application of management theory and machine-learning-driven HR analytics. Through an empirical realistic design and explicatory findings, we demonstrate that:

a) Even with the variables of job demands, resources, engagement, and HRIS controlled, employee mental health is positively correlated with a composite measure of individual and unit-level performance.

b) Machine-learning models (RF and GBM) significantly outperform linear regression in predicting performance, non-linear and interactive effects between mental health, engagement, workload, and organizational conditions.

c) Among the most significant predictors of performance, one can single out mental health indicators, as well as engagement, workload, autonomy, and absenteeism.

Overall, the results are consistent with the view that employee mental health is a material correlate of performance outcomes and a meaningful input into responsible HR analytics dashboards.

5.2 Managerial implications

The findings suggest practical, but design-consistent, implications for managers and HR analysts. Because the evidence is cross-sectional, the recommendations below should be treated as risk-aware guidance for monitoring and diagnosis rather than as proof that specific interventions will cause performance gains.

5.2.1 Use mental health metrics as a risk and capacity indicator (with safeguards)

Organizations may track validated, consent-based well-being indicators as leading signals of capacity and risk in units, but should avoid turning mental health into a punitive performance metric. Clear governance, confidentiality, and support pathways are required.

5.2.2 Use interpretable ML for triage and scenario testing, not surveillance

Interpretable ML can help identify high-risk configurations (e.g., high workload with low resources and low mental health) and prioritize supportive actions (work redesign, staffing, and supervisor support). Any deployment must include transparency, bias monitoring, and strict limits on individual-level targeting.

5.2.3 Co-design demands and resources to protect engagement and performance

Patterns involving workload, autonomy, and supervisor support are consistent with JD-R buffering. Practically, managers can treat workload management and resource provision as levers that may reduce strain and support engagement, while evaluating outcomes with appropriate longitudinal or experimental designs.

5.3 Limitations and future research

The limitations of this study are reduced to the prospects of future research:

5.3.1 Generalizability and scope of data

The graphical cross-sectional study concentrates on knowledge-intensive organizations; future research ought to confirm the framework using genuine multi-national, longitudinal data and other fields.

5.3.2 Causality

Limitations in causal inference: The study is cross-sectional, so temporal ordering cannot be established and reverse causality remains plausible (e.g., higher performers may report better mental health). Controlling for prior performance and absenteeism helps reduce, but does not eliminate, simultaneity and omitted-variable concerns. In addition, linking unit-level KPIs to individual respondents can introduce endogeneity and common-shock effects. Future work should use longitudinal panels, multi-level designs, and quasi-experiments (e.g., difference-in-differences around well-being interventions) to test causal pathways and cross-level mechanisms.

5.3.3 Multimodal data

To build more detailed models of mental health and performance in the future, survey, HRIS, sensors, and digital traces can be incorporated into the research, and the privacy risk must be addressed carefully.

5.3.4 Human–AI collaboration

There is still more to do regarding the ways in which managers and employees perceive and act on the outputs of ML in reality, and how AI-based HR initiatives influence perceptions of fairness, autonomy, and well-being.

Overall, the study shows how theory-guided, interpretable ML can complement - rather than substitute for - management theory by highlighting where non-linear prediction patterns and boundary conditions may matter, while keeping claims aligned with the limits of cross-sectional data.

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