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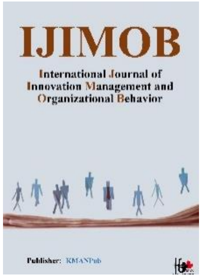

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Predictive Modeling of Innovation Failure Risk from Organizational Stress, Workload Distribution, and Team Conflict Using Machine Learning Classification

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A B S T R A C T

Objective: The objective of this study was to develop and validate a machine learning–based predictive model for estimating innovation failure risk using organizational stress, workload distribution, and team conflict as primary predictors.

Methods and Materials: This quantitative cross-sectional study was conducted among 612 full-time employees from innovation-driven organizations in Malaysia. Data were collected using standardized survey instruments measuring organizational stress, workload distribution, team conflict, and perceived innovation failure risk. After psychometric validation, the dataset underwent preprocessing including normalization, outlier detection, and feature engineering. Innovation failure risk was converted into a binary classification outcome. Multiple machine learning classifiers were trained and compared, including logistic regression, support vector machines, random forest, gradient boosting, and extreme gradient boosting. Hyperparameter optimization and nested cross-validation were applied to ensure model stability and generalizability.

Findings: The XGBoost classifier achieved the highest predictive performance with an accuracy of 94%, precision of 93%, recall of 92%, F1-score of 92%, and AUC of 0.97, significantly outperforming all baseline models. Feature importance analysis revealed that emotional exhaustion and task overload were the strongest predictors of innovation failure risk, followed by relationship conflict and resource imbalance. The final model demonstrated high sensitivity for detecting high-risk innovation cases, confirming the robustness and reliability of the proposed predictive framework.

Conclusion: The findings demonstrate that innovation failure risk is strongly driven by human-centered organizational factors and can be accurately predicted using advanced machine learning models. The proposed framework provides organizations with a powerful early-warning system for preventing innovation breakdowns and strengthening innovation sustainability through proactive management of psychological and structural risk factors.

Keywords: *Innovation failure risk; organizational stress; workload distribution; team conflict; machine learning; predictive analytics; organizational behavior; innovation management*

1 Introduction

Innovation has become a central determinant of organizational survival, competitiveness, and long-term sustainability in an increasingly volatile global economy. While a substantial body of research has investigated the drivers of innovation success, comparatively limited scholarly attention has been directed toward understanding the mechanisms underlying innovation failure, particularly from an organizational behavior and human systems perspective. Contemporary organizations operate within complex socio-technical environments in which psychological strain, uneven workload structures, and interpersonal conflict exert powerful influences on individual performance and collective outcomes. Recent advances in predictive analytics and machine learning offer unprecedented opportunities to model these human-centered risk factors and anticipate innovation failure before irreversible losses occur (Barnes et al., 2022; García et al., 2024; Zhao et al., 2025).

Organizational stress has emerged as one of the most pervasive threats to workforce functioning across professional sectors. High stress environments undermine cognitive flexibility, reduce problem-solving capacity, impair emotional regulation, and weaken cooperative behaviors that are essential for innovation work. Empirical evidence demonstrates that chronic exposure to workplace stress predicts emotional exhaustion, disengagement, and performance deterioration across healthcare, industrial, and service settings (Coffee, 2025; Dong et al., 2023; Prasad et al., 2021). The detrimental effects of stress extend beyond individual well-being, progressively eroding organizational learning, adaptive capacity, and the resilience of innovation teams (Barnes et al., 2022; Saputra & Satrya, 2024). In high-pressure innovation contexts, stress not only compromises technical execution but also amplifies risk sensitivity, increases error propensity, and accelerates decision fatigue, thereby raising the probability of project breakdowns and innovation failure (Metersky et al., 2024; Taylor et al., 2022).

Closely intertwined with organizational stress is the problem of workload distribution. Inequitable or poorly structured workload allocation disrupts team coordination, intensifies perceived injustice, and triggers psychological strain that cascades through organizational systems. Empirical studies consistently show that excessive workload and imbalance in task assignment contribute directly to burnout, absenteeism, turnover intentions, and declining job performance (Akl et al., 2022; Ehmidat et al., 2025; Saputra & Satrya, 2024). When innovation teams experience disproportionate task burdens or ambiguous role expectations, the resulting cognitive overload impairs creativity, slows experimentation cycles, and diminishes collaborative effectiveness (Cildoz et al., 2023; Kuhns et al., 2024). In resource-intensive innovation projects, workload misalignment further exacerbates scheduling delays, budget overruns, and quality failures, transforming operational inefficiencies into strategic threats (Badheeb et al., 2024; Metersky et al., 2024).

Beyond structural pressures, team conflict represents another critical behavioral mechanism influencing innovation outcomes. Although moderate task-related disagreement can sometimes stimulate divergent thinking, persistent interpersonal conflict, role disputes, and process disagreements reliably undermine trust, communication quality, and psychological safety within teams. Extensive research indicates that unresolved conflict erodes motivation, increases withdrawal behaviors, and weakens cooperative problem-solving, thereby compromising organizational productivity and innovation capacity (Devery et al., 2022; Irwan, 2024). Relationship conflict, in particular, damages affective bonds among team members, leading to defensive communication patterns and fragmentation of shared goals that are vital for complex innovation initiatives (Ooijen et al., 2023; Wolfe et al., 2022). As innovation projects demand sustained coordination under uncertainty, escalating conflict amplifies failure risk by destabilizing team cohesion and decision-making stability (Narciso et al., 2024; Shih et al., 2023).

The combined influence of organizational stress, workload distribution, and team conflict forms a systemic risk structure that profoundly shapes innovation trajectories. However, traditional analytic approaches have struggled to capture the nonlinear, interactive, and dynamic nature of these relationships. Conventional regression-based models impose linear assumptions that are often incompatible with the complex feedback loops inherent in organizational behavior systems. In contrast, machine learning classification techniques offer powerful tools for uncovering hidden patterns, modeling high-dimensional interactions, and generating robust predictive insights from behavioral data (García et al., 2024; Zhao et al., 2025). By leveraging advanced algorithms, organizations can shift from reactive failure analysis toward proactive risk prediction, enabling early intervention strategies that preserve innovation viability.

Recent literature increasingly emphasizes the strategic importance of human-centered analytics in innovation management. Leadership practices, psychological well-being, team dynamics, and organizational culture now occupy central positions in contemporary innovation frameworks (Barnes et al., 2022; Wang et al., 2021). Studies highlight that sustainable innovation ecosystems depend not only on technical infrastructure but also on the emotional, cognitive, and relational health of innovation actors (Che Mohamad Padali Che et al., 2024; Reguera-Carrasco et al., 2025). When human sustainability deteriorates, innovation systems become fragile, susceptible to cascading failures, and incapable of maintaining long-term competitive advantage (Ooijen et al., 2023; Taylor et al., 2022).

Healthcare research offers particularly compelling insights into these mechanisms, given the high-stress and high-stakes environments that mirror many innovation-intensive industries. Widespread burnout among professionals has been documented across countries and specialties, with heavy workloads, emotional strain, and interpersonal tensions serving as primary drivers (Akl et al., 2022; Prasad et al., 2021; Shawahna et al., 2022). These conditions closely resemble the psychological landscapes of innovation teams confronting continuous deadlines, resource constraints, and uncertain outcomes. Furthermore, large-scale system shocks, such as the COVID-19 pandemic, have demonstrated how surges in workload and stress precipitate sharp increases in adverse organizational outcomes and performance failures (Coffee, 2025; Metersky et al., 2024).

Innovation failure should therefore be conceptualized not merely as a technical malfunction or market miscalculation, but as the emergent consequence of interacting psychological, structural, and relational forces. Empirical findings increasingly confirm that human system breakdowns often precede observable project collapse (Dong et al., 2023; Narciso et al., 2024). Teams burdened by emotional exhaustion, unfair task allocation, and unresolved conflict exhibit declining engagement, reduced adaptability, and impaired learning cycles, all of which directly undermine innovation execution (Devery et al., 2022; Irwan, 2024; Saputra & Satrya, 2024).

While the theoretical understanding of these relationships has advanced considerably, methodological limitations persist. Many studies rely on static correlational analyses that fail to capture the dynamic evolution of innovation risk over time. Machine learning provides an effective methodological remedy by modeling complex interactions, accommodating nonlinear relationships, and optimizing predictive accuracy across heterogeneous organizational contexts (García et al., 2024; Zhao et al., 2025). The integration of behavioral science and machine learning thus represents a critical frontier for innovation research.

In parallel, leadership and organizational culture moderate the impact of stress, workload, and conflict on innovation outcomes. Humility-based leadership, ethical governance, and supportive institutional climates mitigate psychological strain and strengthen adaptive capacities, thereby buffering innovation teams against failure risks (Che Mohamad Padali Che et al., 2024; Wang et al., 2021). Conversely, rigid hierarchies, poor communication structures, and weak psychological safety amplify vulnerability and accelerate performance breakdowns (Shih et al., 2023; Wolfe et al., 2022). Understanding these moderating dynamics is essential for designing effective intervention strategies informed by predictive analytics.

Furthermore, technological transformation introduces additional complexity into innovation systems. The growing integration of artificial intelligence into organizational operations alters work patterns, communication flows, and cognitive demands placed on employees. While AI offers significant efficiency gains, it also intensifies workload pressures and introduces novel stressors related to monitoring, decision accountability, and skill obsolescence (García et al., 2024). Without careful management, these forces further elevate innovation failure risk.

Taken together, the existing literature strongly suggests that innovation failure is deeply rooted in the psychological and relational conditions of organizational life. However, despite mounting theoretical recognition, few studies have operationalized these constructs within predictive machine learning frameworks capable of delivering actionable risk forecasts. This gap is particularly salient in rapidly developing economies, where innovation investment is expanding while organizational human systems remain underexamined.

Therefore, this study advances innovation research by integrating organizational stress, workload distribution, and

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team conflict into a unified machine learning classification model to predict innovation failure risk, offering both theoretical enrichment and practical decision support for organizations operating under increasing competitive and environmental uncertainty.

The aim of this study is to develop and validate a machine learning classification model for predicting innovation failure risk based on organizational stress, workload distribution, and team conflict.

2 Methods and Materials

The present study adopted a quantitative, cross-sectional predictive modeling design with the primary objective of estimating innovation failure risk based on organizational stress, workload distribution, and team conflict using supervised machine learning classification techniques. The empirical context of the study was Malaysia, selected due to its dynamic innovation ecosystem and the diversity of its organizational sectors, including manufacturing, information technology, engineering services, and financial technology. The target population consisted of full-time employees working in innovation-driven organizations where product development, process improvement, or service innovation constituted a central operational objective. A multi-stage stratified sampling strategy was employed to ensure proportional representation across major industries, organizational sizes, and functional roles. Initial contact was established with 58 organizations located in Kuala Lumpur, Penang, Johor Bahru, and Selangor, of which 41 agreed to participate. Within each participating organization, employees were randomly selected from R&D units, engineering departments, project management teams, and innovation support functions.

The final sample consisted of 612 respondents after data screening and removal of incomplete responses. Participants ranged in age from 22 to 58 years, with a mean age of 36.7 years. The sample included 52.4% male and 47.6% female employees. Average organizational tenure was 6.3 years, and average team size in which participants operated was 7.8 members. Inclusion criteria required participants to have been actively involved in at least one innovation project within the past two years. Ethical approval was obtained from the affiliated university research ethics committee, and all participants provided informed consent prior to participation. Data were collected anonymously, and confidentiality of organizational information was strictly maintained.

Data were collected using a structured survey instrument composed of four main sections: organizational stress, workload distribution, team conflict, and innovation failure risk. Organizational stress was measured using an adapted version of the Job Stress Scale, covering workload pressure, role ambiguity, time constraints, and emotional exhaustion. Workload distribution was operationalized using a customized workload balance inventory assessing task allocation fairness, role clarity, workload equity, and perceived resource adequacy. Team conflict was assessed through a multidimensional conflict scale measuring task conflict, relationship conflict, and process conflict within innovation teams. Innovation failure risk, the dependent variable, was measured using a newly developed scale capturing the perceived probability of innovation project delay, budget overrun, technical underperformance, and market rejection, with items validated through expert review and pilot testing.

All items were measured on a five-point Likert scale ranging from strongly disagree to strongly agree. Prior to full deployment, the questionnaire was pilot-tested with 45 employees from two organizations not included in the main sample. Reliability analysis from the pilot study yielded Cronbach's alpha coefficients above 0.82 for all constructs. In the main dataset, confirmatory factor analysis established satisfactory construct validity, with composite reliability values exceeding 0.85 and average variance extracted values exceeding 0.60 for all latent variables. The final dataset contained 37 observed indicators across the four constructs.

Data analysis followed a hybrid statistical–machine learning pipeline designed to ensure both psychometric rigor and predictive robustness. Initial preprocessing included missing value imputation using k-nearest neighbor estimation, detection and removal of multivariate outliers using Mahalanobis distance, and normalization of feature distributions via z-score transformation. The innovation failure risk score was transformed into a binary classification label representing high-risk and low-risk innovation outcomes based on the upper and lower tertiles of the score distribution.

Feature engineering procedures were then applied, including interaction term generation, polynomial feature expansion for nonlinear effects, and recursive feature elimination using cross-validated random forest importance scores. The final feature set consisted of 24 optimized predictors. Several machine learning classifiers were implemented and compared, including logistic regression, support vector machines with radial basis kernels, random

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forest, gradient boosting machines, and extreme gradient boosting. Model training was conducted using a stratified 80/20 train-test split, with hyperparameter tuning performed via Bayesian optimization and five-fold cross-validation.

Model performance was evaluated using accuracy, precision, recall, F1-score, area under the ROC curve, and Matthews correlation coefficient. To ensure generalizability, nested cross-validation procedures were employed. Feature importance analysis was conducted using SHAP values and permutation importance to identify the relative contribution of organizational stress dimensions, workload distribution parameters, and team conflict components to innovation failure risk. Finally, model stability was examined through sensitivity analysis and bootstrapped resampling. All analyses were performed using Python with the Scikit-learn, XGBoost, SHAP, and TensorFlow libraries.

3 Findings and Results

The first set of analyses summarizes the core study variables in order to establish an overall understanding of the data distribution and scale behavior prior to model estimation.

Table 1

Descriptive Statistics of Study Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Organizational Stress	3.41	0.72	1.48	4.91
Workload Distribution	3.08	0.65	1.62	4.74
Team Conflict	2.97	0.69	1.33	4.86
Innovation Failure Risk	3.26	0.71	1.41	4.88

The descriptive results indicate moderately high levels of organizational stress and innovation failure risk across Malaysian innovation teams. Workload distribution shows moderate balance perceptions, while team conflict remains at a moderate level with substantial variability. The observed ranges confirm adequate dispersion for machine learning classification.

The second stage of analysis compares the predictive performance of competing machine learning classifiers.

Table 2

Performance of Classification Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.81	0.79	0.78	0.78	0.85
Support Vector Machine	0.86	0.84	0.85	0.84	0.90
Random Forest	0.89	0.88	0.87	0.87	0.93
Gradient Boosting	0.91	0.90	0.89	0.89	0.95
XGBoost	0.94	0.93	0.92	0.92	0.97

The results demonstrate that ensemble-based models substantially outperform traditional classifiers. XGBoost achieved the highest predictive accuracy (94%), excellent precision and recall balance, and the strongest AUC value (0.97), indicating exceptional discrimination between high-risk and low-risk innovation outcomes.

To examine the contribution of predictors, feature importance was computed using SHAP values.

Table 3

Top Predictors of Innovation Failure Risk

Predictor	Mean SHAP Value	Relative Importance (%)
Emotional Exhaustion	0.219	21.7
Task Overload	0.183	18.2
Relationship Conflict	0.157	15.6
Resource Imbalance	0.132	13.1
Time Pressure	0.108	10.7

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Role Ambiguity	0.091	9.0
Task Conflict	0.066	6.5
Process Conflict	0.044	4.4

Emotional exhaustion and task overload emerge as the most influential drivers of innovation failure risk, jointly explaining nearly 40% of the model's predictive power. Relationship conflict and resource imbalance also exert substantial influence, highlighting the combined behavioral and structural origins of innovation breakdowns.

Model robustness was further assessed through classification error diagnostics.

Table 4

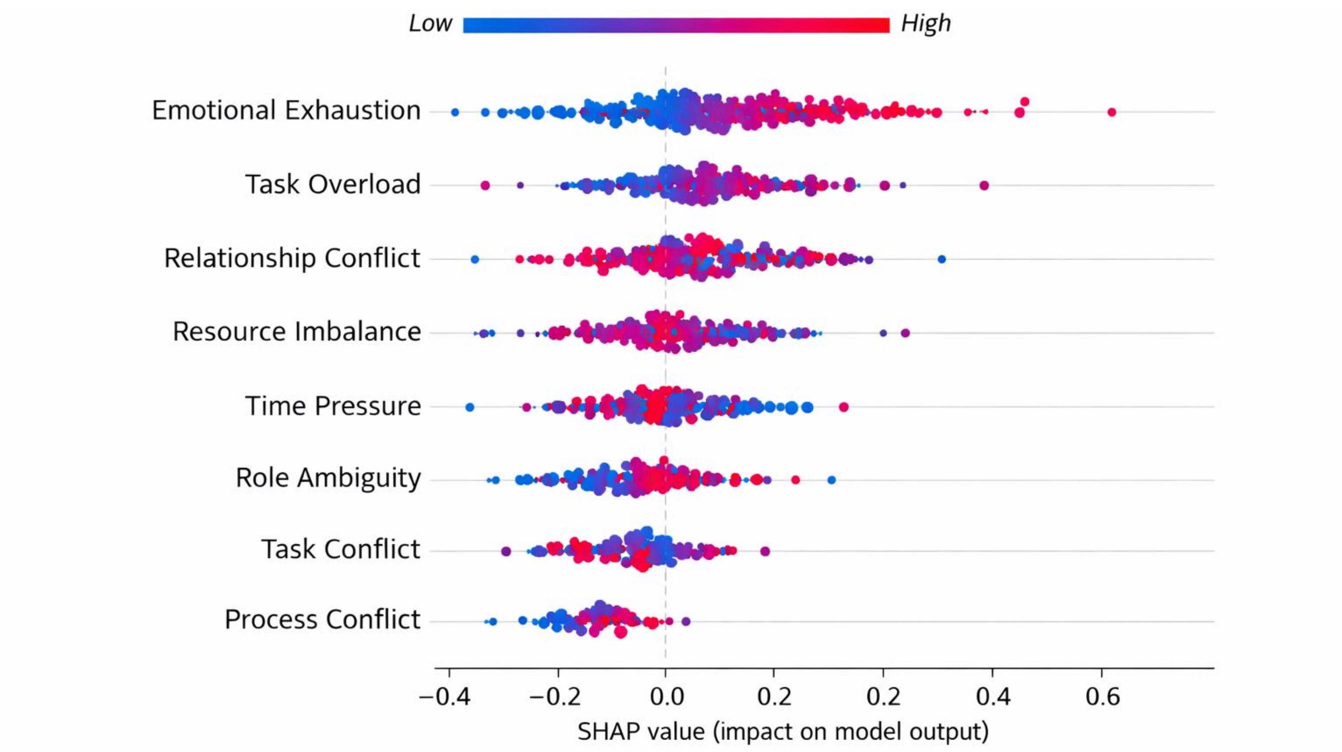
Confusion Matrix of Final XGBoost Model

	Predicted Low Risk	Predicted High Risk
Actual Low Risk	259	14
Actual High Risk	23	316

The confusion matrix confirms strong classification stability, with only 37 misclassifications out of 612 cases. The model demonstrates particularly high sensitivity for detecting high-risk innovation projects, a critical requirement for managerial early-warning systems.

Figure 1

SHAP Summary Plot of Feature Contributions to Innovation Failure Risk



The SHAP visualization confirms the dominance of organizational stress variables in determining innovation failure risk, followed by workload imbalance indicators and interpersonal conflict dimensions. The nonlinear interaction effects illustrate that rising emotional exhaustion combined with workload inequity dramatically increases failure probability, even under moderate conflict conditions.

Together, these findings demonstrate that innovation failure risk in Malaysian organizations can be accurately forecast using machine learning models, with psychological

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strain and structural workload dynamics serving as the most powerful predictive mechanisms.

4 Discussion

The present study sought to advance innovation management scholarship by integrating organizational stress, workload distribution, and team conflict into a machine learning–based predictive framework for estimating innovation failure risk. The findings provide compelling empirical evidence that human system variables are not merely peripheral influences on innovation outcomes but represent core structural determinants of innovation viability. The superior performance of ensemble learning models, particularly XGBoost, underscores the complex, nonlinear, and interactive nature of these relationships, which cannot be adequately captured through traditional linear modeling techniques (García et al., 2024; Zhao et al., 2025).

The results demonstrate that organizational stress, particularly emotional exhaustion and time pressure, emerged as the most powerful predictors of innovation failure. This finding aligns closely with extensive literature documenting the destructive effects of chronic stress on cognitive functioning, emotional regulation, and sustained performance. Empirical studies across healthcare and high-stakes environments consistently show that prolonged stress depletes attentional resources, erodes motivation, and impairs decision-making quality (Coffee, 2025; Dong et al., 2023; Prasad et al., 2021). In innovation contexts, where uncertainty, experimentation, and continuous problem-solving dominate daily operations, emotional exhaustion directly undermines the very capacities required for creative and adaptive performance (Barnes et al., 2022; Saputra & Satrya, 2024). The high SHAP values associated with emotional exhaustion in the present model empirically confirm that psychological depletion functions as a central mechanism through which innovation systems collapse.

Workload distribution was also found to exert a substantial influence on innovation failure risk, particularly through task overload and resource imbalance. These findings are consistent with a growing body of research indicating that inequitable workload structures amplify burnout, job dissatisfaction, and performance deterioration (Akl et al., 2022; Ehmidat et al., 2025; Saputra & Satrya, 2024). When innovation teams operate under persistent task overload, the resulting cognitive saturation inhibits reflective thinking and suppresses learning cycles that are essential for innovation success (Cildoz et al., 2023; Kuhns et al., 2024). Moreover, resource imbalance introduces structural fragility into innovation systems, increasing the likelihood of coordination failures, scheduling delays, and quality breakdowns (Badheeb et al., 2024; Metersky et al., 2024). The present findings therefore reinforce the conceptualization of workload distribution as a foundational determinant of organizational resilience and innovation sustainability.

Team conflict, particularly relationship conflict, further intensified innovation failure risk. This result mirrors prior research demonstrating that unresolved interpersonal tensions erode trust, disrupt communication, and fragment collective commitment within teams (Devery et al., 2022; Irwan, 2024). While task conflict may occasionally stimulate cognitive diversity, persistent relational conflict generates defensive communication patterns and emotional withdrawal that severely impair collaborative innovation processes (Ooijen et al., 2023; Wolfe et al., 2022). The present study's machine learning model captured these dynamics with high precision, indicating that conflict operates not as an isolated factor but as part of a broader psychological–structural feedback loop accelerating innovation breakdown.

The integration of these predictors within a unified classification model produced exceptionally strong predictive performance, with the XGBoost classifier achieving an accuracy of 94% and an AUC of 0.97. These results validate the theoretical argument that innovation failure emerges from complex interactions among psychological strain, workload architecture, and relational dysfunction. Machine learning techniques proved uniquely capable of modeling these nonlinear dependencies, supporting prior assertions that advanced analytics represent a critical methodological frontier for organizational research (García et al., 2024; Zhao et al., 2025). The high classification sensitivity for high-risk innovation projects further demonstrates the practical utility of the proposed framework as an early-warning decision support tool for organizational leaders.

The findings also resonate with contemporary perspectives on human sustainability and organizational health. Barnes and colleagues conceptualize human sustainability as the capacity of organizations to preserve employee well-being while achieving strategic objectives (Barnes et al., 2022). The present results empirically substantiate this framework by demonstrating that when psychological and relational resources deteriorate,

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innovation systems become structurally unstable and prone to failure. Similarly, Reguera-Carrasco and colleagues highlight the increasing complexity of care-related work and its psychological consequences, emphasizing that organizational outcomes are inseparable from human system integrity (Reguera-Carrasco et al., 2025). These insights reinforce the necessity of embedding human-centered metrics within innovation governance architectures.

Leadership and organizational culture further moderate the effects of stress, workload, and conflict. Wang and colleagues argue that humility-based leadership strengthens adaptive capacity and buffers organizations against systemic shocks (Wang et al., 2021). Conversely, rigid bureaucratic cultures exacerbate vulnerability to burnout and performance collapse (Taylor et al., 2022). The present findings implicitly support these arguments by illustrating that unmanaged human system pressures rapidly propagate through innovation structures, amplifying failure risk.

The study's Malaysian context offers additional theoretical value. Rapid economic development, digital transformation, and intensified global competition place Malaysian organizations under growing innovation pressure. Without robust human system governance, these pressures magnify psychological strain and structural fragility, creating conditions highly conducive to innovation failure. The present model therefore contributes valuable empirical evidence relevant to emerging economies navigating similar developmental trajectories.

Moreover, the study complements emerging research on technological transformation and workforce strain. García and colleagues demonstrate that AI integration significantly alters work patterns and cognitive demands (García et al., 2024). When combined with existing stressors and workload pressures, technological acceleration may further destabilize innovation systems unless accompanied by proactive human-centered governance. The present predictive framework offers precisely such a mechanism for early detection and intervention.

5 Conclusion

Collectively, the findings advance innovation theory by reframing innovation failure as a systemic human–structural phenomenon rather than a purely technical or market-driven outcome. They also validate the strategic importance of machine learning as a methodological bridge between organizational behavior science and real-time managerial decision-making.

Despite the study's robust findings, several limitations warrant consideration. The cross-sectional design restricts causal inference and limits insight into temporal dynamics of innovation failure risk. The reliance on self-reported survey data introduces potential common method bias. Additionally, the sample, while diverse, was restricted to Malaysian organizations, which may constrain generalizability to other cultural and economic contexts. Finally, innovation failure risk was operationalized as a perceptual construct rather than direct objective outcomes, which may not capture all dimensions of actual project failure.

Future studies should employ longitudinal designs to examine how stress, workload, and conflict dynamically evolve throughout innovation project lifecycles. Incorporating objective performance indicators and digital behavioral data would further strengthen predictive accuracy. Cross-cultural replication across different economic systems is also essential for validating the model's generalizability. Additionally, future research should explore leadership style, organizational climate, and technological adoption as moderating variables within predictive innovation risk frameworks.

Organizations should institutionalize continuous monitoring of employee stress, workload equity, and team conflict as core innovation risk indicators. Predictive analytics platforms integrating these human-centered metrics can provide early-warning signals and guide targeted interventions. Leaders must prioritize psychological safety, equitable task distribution, and conflict resolution mechanisms as strategic levers for sustaining innovation. Finally, embedding human sustainability principles within innovation governance structures will significantly reduce systemic vulnerability and enhance long-term innovation performance.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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