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Assessing the predictive influence of organizational culture on employee burnout within health systems: Insights and strategic implications

Teray Johnson[1*] and **Sameh Shamroukh**[2]

[1]Department of Data Analytics, Faculty of Data Analytics, Harrisburg University of Science and Technology, Harrisburg, Pennsylvania, United States of America

[2]Department of Information Technology and Decision Sciences, G. Brint Ryan College of Business, University of North Texas, Denton, Texas, United States of America

Abstract

Organizational culture (OC) affects every workplace, yet few studies have explored the relationship between OC and burnout using machine learning methods, which could provide new insights. This exploratory study employed a random forest algorithm to examine the relationship between OC and burnout among employees in health systems, aiming to determine whether OC can predict employee burnout. A 57-question survey assessing perceptions of OC and burnout was administered to employees across various health systems in the United States, yielding 67 responses. These survey results were used to train and test the random forest model. The findings indicated that several aspects of OC, such as job interference with home life, are predictive of burnout. Based on these preliminary results, employers should be aware of their organization's culture and actively work to improve it to alleviate employee burnout. Leaders should implement strategies, such as allowing flexible work schedules to promote work-life balance and providing employees with the necessary resources to excel in their roles. The model also highlights the significant impact of OC on burnout, suggesting that a variety of burnout symptoms may signal the need for improvements in OC. This study serves as a starting point for future research to further explore how OC predicts burnout, while emphasizing the importance of cultivating a positive OC.

Keywords: Burnout; Health systems; Employees; Organizational culture; COVID-19 pandemic; Random forest; Machine learning

***Corresponding author:**
Teray Johnson
(tjohnson1@harrisburgu.edu)

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1. Introduction

Organizational culture (OC) plays a crucial role in shaping workplaces around the globe. It encompasses the unique values, beliefs, and assumptions that consciously and subconsciously guide how employees behave and interact within an organization. These cultural elements are cultivated both by leaders – managers, executives, and decision-makers – and individual contributors who collectively define and sustain the workplace environment. OC is not merely a theoretical concept; it is a practical and impactful driver of organizational life, influencing employee behavior, team dynamics, performance outcomes, and customer experiences. A well-defined and positive OC creates a foundation for excellence, enabling employees to thrive and organizations to achieve their goals. OC is particularly critical in industries such as healthcare, where the stakes are high, and both patient-facing and non-patient-facing roles are essential to overall system performance. A strong, supportive OC can foster an environment where employees feel motivated, engaged, and equipped to perform at their best. Conversely, a negative or misaligned OC can lead to adverse outcomes, including reduced employee morale, high turnover, and diminished organizational effectiveness. Among these challenges, employee burnout stands out as a significant issue that has garnered increasing attention in recent years.

Burnout is a multidimensional phenomenon characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment. Exhaustion manifests as a sense of physical and emotional depletion, leaving employees feeling drained and unable to meet work demands. Depersonalization involves a sense of detachment, where employees may view clients, customers, or coworkers as objects rather than individuals. Finally, reduced personal accomplishment leads to diminished job performance and a weakened ability to solve problems effectively. These symptoms collectively impair employee well-being, productivity, and the overall health of an organization.

The coronavirus disease 2019 (COVID-19) pandemic has exacerbated burnout rates across industries, particularly within healthcare systems, which faced unprecedented challenges. While much of the existing research on burnout has focused on patient-facing roles such as nurses and physicians, non-patient-facing employees – those in administrative, technical, and support roles – also experienced significant stressors during the pandemic. These employees often dealt with increased workloads, rapid organizational changes, and the psychological toll of supporting frontline workers. Despite their critical role in maintaining the functioning of health systems, non-patient-facing employees remain understudied in the context of burnout and its relationship with OC.

Research has shown that OC influences burnout rates by shaping the environment in which employees work. For example, a culture that emphasizes work-life balance, provides social support, and aligns with employees' values can mitigate burnout, whereas a toxic culture can exacerbate it. Previous studies have begun to explore these dynamics, with one notable study employing decision trees and Bayesian analysis to predict burnout based on OC factors. While these findings provided valuable insights, the scope of prior research has been limited by its focus on specific methodologies and populations – such as patient-facing employees – and by a lack of investigation into the unique challenges posed by the COVID-19 pandemic.

To address these gaps, this study investigates the relationship between OC and burnout among health systems employees during the pandemic, focusing on non-patient-facing roles. By employing a random forest algorithm – a robust machine learning (ML) technique capable of handling complex and nonlinear relationships – this research aims to uncover which specific elements of OC are most predictive of burnout. In addition, it seeks to determine whether findings from earlier studies using decision tree and Bayesian methods hold true when tested with this advanced analytical approach.

The exploratory study leveraged data collected from a 57-question survey that assessed employees' perceptions of OC and their experiences with burnout. This survey captured a broad range of factors, including work-life balance, social support, alignment of values, and other organizational dynamics. By analyzing these data with a random forest model, the research aims to provide a nuanced understanding of how OC influences burnout and identify actionable insights that organizations can use to improve employee well-being and performance. Ultimately, this study underscores the strategic importance of fostering a healthy OC within organizations, particularly in high-stakes and high-stress environments like healthcare. By addressing burnout through targeted cultural interventions, organizations can enhance employee satisfaction, reduce turnover, and improve both individual and organizational outcomes. The findings of this research have the potential to inform policies and practices that support the development of resilient and supportive workplace cultures, benefiting employees and organizations alike.

2. Literature review

2.1. OC and its impact

OC encompasses shared values, norms, and practices that shape the behaviors and attitudes of members within an organization.[1] Schein's[1] model emphasizes the layered nature of culture, ranging from visible artifacts to deeply embedded assumptions, all of which influence how organizations operate and respond to challenges. Hofstede[2] complements this understanding by exploring cultural dimensions such as power distance and individualism-collectivism, which affect communication, decision-making, and employee interactions. A strong, positive OC fosters employee engagement, well-being, and productivity, while a toxic culture can breed dissatisfaction and disengagement. By aligning culture with organizational goals and employee needs, organizations can create a supportive environment that enhances both individual and collective performance.

2.1.1. Understanding of burnout and its dimensions

Burnout, as defined by Maslach and Leiter,[3] is a psychological syndrome resulting from prolonged exposure to work-related stressors. It manifests in three core dimensions: (i) emotional exhaustion, which reflects feelings of being overextended and depleted; (ii) depersonalization, characterized by cynicism and detachment from work; and (iii) reduced personal accomplishment, where individuals perceive their contributions as ineffective or insufficient. Burnout is prevalent across various industries and significantly impacts both individual well-being and organizational outcomes. Schaufeli *et al.*[4] highlight that burnout diminishes job satisfaction and contributes to turnover, absenteeism, and decreased productivity. Addressing these dimensions is essential to fostering a sustainable workforce and mitigating the long-term consequences of workplace stress.

2.1.2. Challenges in health systems

In health systems, particularly in non-patient-facing roles, OC and burnout intersect to create unique challenges. While much attention has been directed toward clinical roles, support staff and administrative teams face high workloads, role ambiguity, and limited recognition, all of which contribute to burnout.[5] These roles often operate behind the scenes, yet they are critical to the functionality and efficiency of healthcare systems. Tawfik *et al.*[5] emphasize the interplay between safety culture, work-life balance, and burnout, underscoring the need for organizational interventions that address these interconnected factors. Non-clinical staff often experience emotional exhaustion and reduced accomplishment due to the high-pressure environment, yet they receive less focus in research and policy initiatives.

2.1.3. Integration of culture and burnout mitigation

A robust OC that prioritizes employee well-being can mitigate burnout, particularly in high-stress environments such as health systems. Cameron and Quinn[6] suggest using the Competing Values Framework to diagnose and transform OC, fostering a balance between flexibility, stability, and a focus on both internal and external dynamics. By creating an inclusive culture that values the contributions of all employees, organizations can address emotional exhaustion and promote a sense of accomplishment. Interventions such as clear communication of roles, recognition programs, and resources for work-life balance are critical in reducing burnout among non-patient-facing staff. Aligning these efforts with the organization's cultural strengths can help create a resilient workforce and a more effective health system.

2.2. OC and burnout: Empirical evidence

Empirical studies have consistently highlighted the intricate relationship between OC and burnout, emphasizing how cultural factors can either exacerbate or alleviate stress. Schaufeli and Bakker,[7] through their Job Demands-Resources (JD-R) theory, illustrate that high job demands, when combined with insufficient resources, significantly contribute to burnout. Cultural elements such as managerial support, recognition, and resource allocation are critical buffers against these stressors. Conversely, a lack of these resources in an unsupportive culture amplifies burnout, manifesting in emotional exhaustion and disengagement. Their findings underscore the importance of cultivating a culture that balances demand with available resources to enhance employee well-being and engagement.

2.2.1. The role of work-life balance

Work-life balance, a key component of OC, has been shown to significantly influence burnout levels. Maslach and Leiter[8] identified "areas of worklife," including workload, control, reward, community, fairness, and values, as cultural dimensions that impact burnout. Organizations that prioritize work-life balance create a supportive environment where employees can manage both professional and personal demands, thus reducing emotional exhaustion and fostering job satisfaction. Conversely, cultures that promote excessive workloads and neglect work-life integration are prone to higher burnout rates. This research suggests that embedding work-life balance into organizational practices is a strategic approach to mitigate burnout and enhance workforce resilience.

2.2.2. Managerial support and organizational justice

Managerial support and perceptions of organizational justice are pivotal cultural factors influencing burnout. Alarcon conducted a meta-analysis linking burnout to job demands, resources, and attitudes, revealing that supportive leadership and fair treatment are critical in buffering against burnout.[9] When employees perceive their managers as approachable and their contributions as fairly recognized, they are less likely to experience depersonalization and reduced personal accomplishment. Conversely, environments characterized by perceived injustices or a lack of support from leadership tend to have higher burnout prevalence. These findings highlight the necessity of leadership training and transparent policies to foster a culture of equity and support.

2.2.3. Cultural interventions for burnout prevention

Organizations must align their cultural strategies with evidence-based interventions to effectively address burnout. Schaufeli and Bakker's[7] JD-R model suggests that organizations can proactively mitigate burnout by enhancing resources such as employee autonomy, recognition programs, and peer support networks. Policies that reinforce work-life balance, managerial engagement, and fair practices can shift cultural norms and reduce job-related stress. As Maslach and Leiter emphasize, aligning OC and employee values is crucial for creating an environment where employees feel supported and valued, leading to sustainable engagement and reduced burnout.[8] These findings underscore that the critical role culture plays in shaping employee experiences and organizational outcomes.

2.3. The role of ML in burnout prediction

ML has emerged as a powerful tool in organizational behavior research, offering novel approaches to predict and manage employee burnout. Chatterjee *et al.*[10] demonstrated how ML algorithms, such as random forests and support vector machines (SVM), can effectively analyze large datasets to identify patterns linked to employee well-being. These methods enable organizations to predict burnout by examining diverse variables, including workload, work-life balance, and psychological factors. By leveraging these predictive models, organizations can implement targeted interventions, making ML a valuable asset in proactive burnout management strategies.

2.3.1. Multidimensional data analysis with random forests

One key strength of ML techniques, like random forests, is their ability to handle complex and multidimensional data, such as survey responses. Random forests, an ensemble learning method, excel at capturing nonlinear relationships and interactions between variables. Bhardwaj *et al.*[11] highlight how this algorithm can analyze factors such as job demands, workplace support, and employee engagement, offering granular insights into burnout predictors. In addition, the interpretability of feature importance in random forests helps organizations pinpoint critical drivers of burnout, enabling data-driven decision-making. This adaptability makes random forests particularly suitable for the multifaceted nature of burnout research.

2.3.2. Advancements in behavioral data analysis

The application of ML extends beyond traditional survey data to include behavioral data collected through digital platforms and mobile devices. Ang *et al.*[12] discussed the potential of ML techniques for analyzing behavioral patterns, such as communication frequency, screen time, and mobility, which serve as indirect indicators of stress and burnout. These data-driven approaches enhance predictive accuracy and broaden the scope of burnout research by integrating passive data collection. By incorporating behavioral insights, ML models can offer a more comprehensive understanding of burnout, particularly in dynamic and technology-driven work environments.

2.3.3. Application expansion in mental health

ML's role in burnout prediction aligns with its broader applications in mental health research. Shatte *et al.*[13] underscore how algorithms like neural networks, and SVMs have been employed to predict mental health outcomes, including stress and anxiety. These approaches parallel their use in organizational settings, where burnout serves as a critical indicator of employee mental health. The flexibility and scalability of ML models make them ideal for addressing complex phenomena like burnout, paving the way for more personalized and effective interventions. As organizations continue to integrate ML into their practices, these tools hold promise for transforming burnout management and fostering healthier workplace cultures.

2.4. Survey-based studies on OC and burnout

Survey methodologies are instrumental in assessing OC and burnout, providing a structured approach to understanding complex workplace dynamics. Podsakoff *et al.*[14] emphasize the importance of mitigating common method biases in behavioral research to ensure the accuracy and reliability of survey findings. These biases, including social desirability and common rater effects, can distort results and hinder meaningful interpretations. Strategies such as separating data collection points and ensuring anonymity can help reduce these biases. When designed rigorously, surveys can yield valuable insights into the interplay between OC and burnout, enabling the implementation of targeted interventions.

2.4.1. Reliability and validity in survey instruments

Ensuring the reliability and validity of survey instruments is critical for effective survey design and interpretation. DeVellis and Thorpe[15] highlight the role of reliability metrics, such as Cronbach's alpha, in assessing the internal consistency of survey tools. This metric ensures that items within a scale measure the same underlying construct, such as burnout or OC. Validity, on the other hand, focuses on whether the survey accurately measures the intended concept. For instance, scales such as the Maslach Burnout Inventory (MBI) and the OC Assessment Instrument have undergone extensive validation, making them reliable tools for exploring burnout and cultural dynamics in organizations.

2.4.2. Thematic analysis in survey data

In addition to quantitative approaches, qualitative methods such as thematic analysis offer valuable insights into survey data. Braun and Clarke[16] described thematic analysis as a systematic approach to identifying, analyzing, and reporting patterns within qualitative data. This method is particularly useful for interpreting open-ended survey responses, providing a deeper understanding of employees' perceptions of OC and burnout. By complementing quantitative data with qualitative insights, researchers can capture nuanced perspectives, enhancing the overall richness and applicability of survey findings.

2.4.3. Use of established frameworks in survey analysis

Previous studies have successfully utilized standardized frameworks such as the MBI and the OC Assessment Instrument to examine OC and burnout. These instruments provide a robust foundation for comparative analysis across different organizational contexts. Podsakoff *et al.*[14] suggest integrating established frameworks with tailored questions to address specific research objectives while maintaining methodological rigor. For instance, combining the MBI with customized items on job demands and work-life balance can provide comprehensive insights into the factors driving burnout. This integrative approach enables organizations to effectively utilize survey data, informing strategies to foster a healthier and more productive workplace.

2.5. Organizational cultural interventions to mitigate burnout

Proactive strategies to address OC and reduce burnout are critical for fostering employee well-being. Bakker and Demerouti[17] emphasize the role of the JD-R model in identifying workplace factors that contribute to burnout and engagement. Organizations can intervene by balancing job demands with adequate resources. For example, offering flexible scheduling and workload management helps employees manage stress and maintain productivity. Leadership styles also play a pivotal role; adopting transformational leadership practices that focus on employee development and recognition can positively influence workplace culture and reduce burnout.

2.5.1. Intervention strategies for mental health

Dewa *et al.*[18] highlight employer best practices for addressing mental health issues, including burnout. Their case study suggests that creating a supportive work environment, providing access to mental health resources, and promoting employee recognition are effective strategies. Interventions such as wellness programs, team-building activities, and training managers to identify early signs of burnout have shown promise in improving workplace well-being. In addition, fostering open communication channels and destigmatizing mental health discussions can encourage employees to seek help, further enhancing organizational support systems.

2.5.2. Research gaps and opportunities

Despite significant advancements, gaps remain in the understanding of burnout and OC. For instance, while the JD-R model provides a robust framework for examining burnout, limited research has utilized advanced technologies like ML to analyze workplace culture comprehensively. Sonnentag and Frese[19] note the importance of dynamic organizational environments; however, most studies rely on cross-sectional designs, which limit their ability to establish causality. Longitudinal studies are needed to explore the evolving relationship between cultural factors and burnout over time, enabling a more nuanced understanding of their interplay.

2.5.3. Future directions in burnout research

Future research should leverage emerging technologies and interdisciplinary approaches to deepen insights into burnout and workplace culture. ML methods, for example, can analyze large, multidimensional datasets to uncover patterns and predictors of burnout not easily identified through traditional analyses. Furthermore, integrating qualitative and quantitative methods, such as thematic analysis with predictive modeling, can provide a comprehensive understanding of employee experiences. Expanding research to diverse industries and non-traditional roles will also help generalize findings, ensuring interventions are inclusive and applicable across varied organizational contexts.

2.6. OC as a predictor of burnout outcomes

OC reviews the values that employees understand and adhere to.[20] Previous research on nurses has found that aspects of OC, such as person-environment fit, social support, and value alignment, can predict retention, a consequence of burnout.[21] The authors' research demonstrated that ML techniques, such as decision trees, can be used to predict burnout consequences.[21] OC has also been shown to influence performance, which can be impacted by burnout.[22] However, previous research has focused primarily on nurses, with little attention given to non-patient-facing employees.

2.7. Burnout prediction

Linear and logistic regression models can be used to predict and diagnose burnout based on survey results.[23,24] Indicators such as exhaustion, cognitive performance issues, and lack of enjoyment in one's work are predictors of burnout.[23] Similarly to OC, low performance also predicts burnout. Highly neurotic individuals are more likely to experience burnout than those with high self-efficacy.

Additional ML techniques, such as k-means clustering, cluster analysis, and multitask learning, have been employed to classify and predict burnout.[25-27] These studies demonstrate the potential of ML techniques to predict behavioral issues like burnout using survey data. However, these studies do not focus on employees in health systems.

2.8. OC, burnout, and ML

Survey results have been used to predict components of burnout using aspects of OC, such as partial least squares regression and ordinary least squares regression.[22,28] The social environment has been identified as influencing work engagement, which is the opposite of burnout.[29] Engagement is comprised of vigor, dedication, and absorption.[30] Job quality, which involves work conditions valued by employees, also influences burnout and overall employee well-being. Creating a culture that fosters feedback, autonomy, work-life balance, a positive climate, and open communication also influences engagement and, consequently, reduces burnout.[31]

While numerous studies have identified predictors and influencers of burnout, it remains unclear whether these influencers can be used to predict burnout using ML techniques. For example, although a decision tree model has shown that OC can predict burnout, more advanced and complex techniques, such as random forest models, have not been employed to demonstrate the same results.[32] This research builds on previous work by investigating how ML, specifically a more complex and advanced random forest model, can be applied to predict burnout among non-patient-facing employees in health systems.[32] Based on existing literature regarding the prediction of burnout using OC and ML techniques, the research question is: Can a random forest ML model predict burnout among non-patient-facing employees in health systems?

Previous literature has established a relationship between OC and burnout. The dependent variables and independent variables described in prior research were utilized in this study's random forest model.[32] It was hypothesized that whether employees perceive their organization's culture as positive will predict several burnout symptoms, including emotional exhaustion after work, job home-life interference, irritability, anxiety, depersonalization, mood swings, and overall burnout. Further information on the hypotheses can be found in the literature.[32]

2.9. Gaps in existing literature

The existing literature on the relationship between OC and burnout highlights several unexplored or underexplored areas:

(i) Integration of ML in burnout studies
While burnout is a well-researched topic, few studies employ ML methods to analyze the relationship between OC and burnout. Traditional statistical methods dominate the field, leaving a gap in the application of advanced techniques such as random forests, neural networks, or ensemble methods for deeper and more nuanced insights.

(ii) Non-patient-facing health system employees
Most research on burnout focuses on patient-facing roles in healthcare, such as doctors and nurses, due to their high-stress environments. However, there is limited literature addressing burnout among non-patient-facing employees in health systems, despite their critical roles in organizational functioning.

(iii) OC as a predictor
Although many studies acknowledge that OC affects employee well-being, few quantitatively evaluate which specific cultural factors (e.g., communication, leadership style, and work-life balance) most significantly predict burnout. There is a gap in identifying and ranking these predictors using robust models.

(iv) Dynamic and contextual nature of burnout
Existing research often treats burnout as a static outcome rather than a dynamic process. Limited exploration of how changes in OC over time influence burnout leaves a gap in understanding the temporal and adaptive aspects of these relationships.

(v) Interdisciplinary approaches
Research on burnout and OC is often conducted in isolation, either focusing on psychological aspects or management theories. There is a need for interdisciplinary approaches that integrate psychological, sociological, and computational perspectives to study these complex interactions.

(vi) Generalizability across industries and cultures
Much of the current literature is geographically or culturally specific, with a strong focus on Western organizational practices. There is a need for studies that explore the cross-cultural applicability of findings and consider how the impact of OC on burnout may vary across industries and regions.

3. Data and methods

3.1. Setting, measurement, and study design

This cross-sectional and exploratory study was approved by the Harrisburg University of Science and Technology Institutional Review Board (20221026). To construct a random forest model, the optimal sample size was determined to be 570, as the model requires ten times the number of features (57) in the dataset.

A 57-item Likert scale survey, validated and reliable for measuring OC and burnout, developed by Kovner *et al.*[33,34] was used for data collection. Detailed information regarding the instrument's validated and reliability can be found in Kovner *et al.*'s[33,34] studies and in a previous study based on the same dataset.[32] The scale was modified to collect demographic information, such as the geographic location of the health system. Additional details about the survey's constructs for OC and burnout can be found in prior research[32] Information on the online distribution of the survey and the data collection period is also available in previous studies.

3.2. Participants

All employees who worked for a health system (defined as organizations with more than one owner and at least one hospital and physician practice) were eligible to participate. Further details about the number of organizations contacted and the target participants are provided in earlier research.[32]

3.3. Analysis

The random forest model was created, and data were summarized using R, a statistical analysis software. Since all survey questions were mandatory to answer, no missing data needed to be addressed. The data were divided into two categories: OC and burnout responses. Two random forest models were constructed using the OC and burnout question responses.

4. Results

A total of 67 responses were received from health system employees. Although the sample size was small alleviated, this limitation was addressed by a previous study, which employed Bayesian analysis to corroborate the predictive power of OC on burnout. Moreover, this exploratory study presented preliminary findings and methods that underscore the need for further research. Detailed demographic information is provided in Tables A1-A3 in the Appendix and is explained in depth in prior research.[32]

Each random forest regression model was created by splitting the survey data into 70% training data and 30% test data. The models created 500 trees. In Model 1, where question C30 served as the DV and was measured with questions B1, B5, B6, B7, B8, B9, B10, B11, B12, B15, and B17, the model explained 6% of the variance. At each split, three variables were tested based on the lowest mean squared error (MSE). Model 1 reached approximately 1% error after 500 trees, as shown in Table 1. The lowest MSE was achieved with 27 trees. The lack of improvement in performance after 27 trees indicates diminishing returns, suggesting that a higher number of trees is not optimal for Model 1 and does not provide additional information. In addition, the out-of-bag (OOB) score of 1.25 indicates that approximately one out of the data left out of training was correctly predicted. A lower OOB score reflects better performance, which aligns with the low MSE results.

Table 2 displays the variable importance and the contribution of each variable to node purity, illustrating how much each variable helps reduce impurity across the trees of the random forest model. Variable B17 (callousness toward others) demonstrated the highest predictive power, making it the most important variable for accurate predictions, while B12 (feeling at wit's end) exhibited the least predictive power, thus being less important for the

Table 1. Best performances of Models 1 and 2

Parameter	Model 1	Model 2
RMSE	0.97	1.06
OOB error	1.25	1.06
Accuracy (SD)	58% (19%)	47% (21%)
Kappa (SD)	0.33 (0.3)	0.19 (0.34)
Precision–Question C30	0.38	0.43
Recall–Question C30	0.5	0.6
F1 score	0.43	0.5

Abbreviations: OOB: Out-of-bag; RMSE: Root mean square error; SD: Standard deviation.

Table 2. Variable of importance of Model 1

Importance	Variable	Increase in node purity
1.	B17	6.22
2.	B15	4.76
3.	B7	4.32
4.	B1	3.73
5.	B11	3.71
6.	B9	2.70
7.	B10	2.68
8.	B5	2.52
9.	B8	2.45
10.	B12	2.44

accuracy of predictions. Due to its high node purity score, B17 effectively split Model 1, reducing error in C30 scores. In contrast, B12, which showed a lower node purity score, contributed less to reducing error in the model. B12 had fewer splits and a smaller reduction in impurity compared to B17. The high node purity score for B17 was attributed to a moderate negative correlation of -0.33 with C30. Conversely, the low node purity score for B12 reflected a weak negative correlation of -0.19 with C30, suggesting that B12 does not significantly explain variability in C30.

A multidimensional scaling plot (MDS), shown in Figure 1, was created to visualize clusters of participants in a lower-dimensional space for easier interpretation. The MDS was generated using the proximity matrix from Model 1. The axes represent the two dimensions used to construct the plot but do not correspond to specific variables or observations. Data points that are close together represent participants who scored similarly on the survey. The MDS revealed that participants who rated their OC positively were clustered with burnout symptoms, such as emotional exhaustion after work, job-home life interference, irritability, anxiety, mood swings, feeling on-edge, fatigue upon waking, feeling at wits' end, depersonalization, and callousness. In addition, the plots revealed that most participants scored similarly for these variables. However, three outliers were identified, indicating that these participants rated their organizations and burnout differently from the other participants. The separation of data points demonstrates that Model 1 is accurately classifying the participants and their scores.

In Model 2, where question C30 served as the DV and was measured by questions B2, B3, B4, B13, B14, B16, and B18, two variables were tested at each split, with MSE used

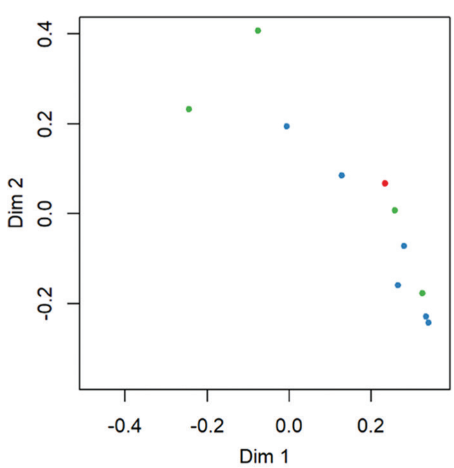

Figure 1. Multidimensional scaling plot for Model 1
Abbreviation: Dim: Dimension.

as the splitting criterion. This model explained 17% of the variance. Model 2 exhibited an error of approximately 1% after reaching 500 trees, as shown in Table 1. However, the lowest MSE was achieved with 23 trees. The OOB score of 1.25 indicates that approximately 1 out of the 30% of the test data, which was left out, was correctly predicted. The low OOB score aligns with the low MSE.

Similar to Model 1, a higher number of trees resulted in diminished performance due to the lack of additional information provided beyond 23 trees. The variable of importance is displayed in Table 3. B4 (retaking one's current job) demonstrated the most predictive power, proving to be the most important for accurate predictions and critical for Model 2's performance. In contrast, B2 (understanding patients' feelings) exhibited the least predictive power, being less important for accurate predictions and the least critical for the model's performance. Moreover, because B4 had the highest node purity score, it effectively split the model to predict scores and reduced error in the target variable C30. B2, on the other hand, had fewer splits and smaller decreases in impurity compared to B4. B4's high purity score was a result of a moderate positive correlation (0.5) between B14 and C30, whereas B2's lower purity score reflected a lower positive correlation (0.4) between B2 and C30. Although B4's high node purity score indicates its strong predictive power, it does not explain variability in C30 because it lacks a clear relationship with the target variable.

The MDS plot revealed that most participants scored differently from each other on questions related to understanding patients' and visitors' feelings, retaking one's current job, feeling stimulated when working with colleagues, effectively handling problems, feeling relaxed while managing emotional problems, and feeling exhilarated when working with and talking to patients. Several outlying participants were identified, as evidenced by data points that were not clustered. The separation of data points suggests that Model 2 is accurately classifying the data.

Table 3. Variable of importance of Model 2

Importance	Variable	Increase in node purity
1.	B4	12.81
2.	B16	9.65
3.	B13	7.13
4.	B18	6.83
5.	B14	6.65
6.	B3	4.34
7.	B2	3.43

To further assess model performance, we calculated cross-validation results, the area under the receiver operating characteristic (AUC-ROC) curves, recall, precision, and F1 scores. The models were tuned using 10-fold cross-validation, and performance was evaluated based on the number of splits in each model. Model 1's cross-validation results showed 58% accuracy and a Cohen's kappa of 34%, with two features randomly selected at each split in the decision tree. As the number of splits increased, performance worsened. At six features, accuracy and Cohen's kappa decreased to 55% and 32%, respectively. At 11 features, the accuracy dropped further to 52%, with a Cohen's kappa of 25%, as shown in Table 1. Notably, with two randomly selected features, the standard deviation of accuracy was small (19%), suggesting consistent performance across folds. The standard deviation of Cohen's kappa was also low (0.33%), indicating consistent agreement between observed and predicted scores. Despite the high accuracy at two randomly selected features, the low Cohen's kappa suggests only fair agreement between observed and predicted scores.

Similar to Model 1, Model 2 showed the best accuracy and Cohen's kappa with two randomly selected features. At two features, the model achieved 47% accuracy and a kappa of 0.19. With four features, accuracy decreased to 40%, with a kappa of 11%. At 11 features, the model showed 45% accuracy and a kappa of 17%. However, the standard deviations for both accuracy and kappa across all feature selections (2, 4, and 11) were low, indicating consistent model performance across folds and across observed and predicted values. Despite these findings, Model 1 outperformed Model 2 in terms of accuracy and kappa.

Model 1's AUC-ROC curve revealed an AUC of 0.57, indicating some predictive power, with the model correctly identifying positive and negative cases of score 5 approximately 57% of the time. However, the model demonstrated limited discriminatory power, as the AUC is relatively low, suggesting poor differentiation between classes. Given that the dataset involved a Likert scale, with many participants selecting 5 for question C30, the dataset may be imbalanced, which could explain the low AUC. The ROC curve's position above the diagonal line indicates performance slightly better than random, though the curve was not close to the top-left corner of the graph, which would indicate high sensitivity. The recall, precision, and F1 score for predicting scores of 5 were 0.5, 0.38, and 0.43, respectively, reflecting somewhat adequate performance but also indicating room for improvement in correctly identifying true positives and true negatives.

As shown in Figure 2, Model 2's AUC-ROC curve revealed an AUC of 0.6, suggesting relatively weak discriminatory power. The model correctly identified responses of 5 for the question regarding employees' perceptions of their organization's culture approximately 60% of the time, as illustrated in Figure 3. Model 2 showed weak discriminatory power, though its AUC, as shown in Figure 4, was slightly higher than that of Model 1, indicating somewhat better classification performance. The ROC curve, positioned above the diagonal line, reflects performance better than random, but it was still not close to the top-left corner, which would indicate high sensitivity and correct identification of positive perceptions of OC. The curve's position farther to the right suggests a higher false-positive rate, indicating that more scores that are not 5 are classified as 5. In addition, the recall of 0.6 for scores of 5 demonstrates that the model predicts 60% of true positives of score 5 correctly, while the precision of 0.43 means that 60% of the instances classified as positive are truly positive. The F1 score for Model 2's ability to correctly predict scores of 5 is 0.5, indicating somewhat adequate performance with room for improvement.

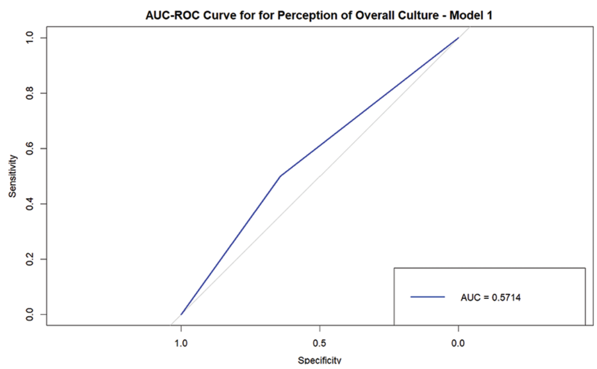

Figure 2. Area under (AUC) the receiver operating characteristic (ROC) curve for Model 1

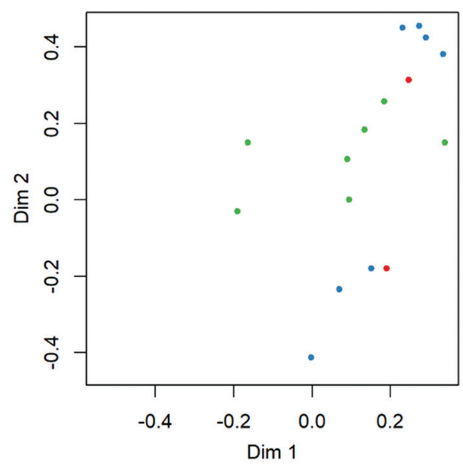

Figure 3. Multidimensional scaling plot for Model 2
Abbreviation: Dim: Dimension.

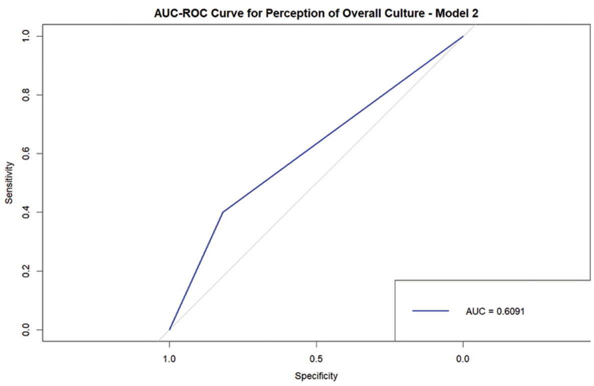

Figure 4. Area under (AUC) the receiver operating characteristic (ROC) curve for Model 2

5. Discussion

The analysis and model results demonstrate that employees' beliefs about OC predict and affect burnout symptoms. In Model 1, depersonalizing others – by feeling callous toward them and treating them as impersonal objects – was the most powerful predictor of other burnout symptoms and perceptions of overall OC. These findings align with several studies that emphasize the importance of depersonalization in predicting burnout and the impact of workplace factors on burnout.[35-37] However, this study highlights the significance of OC when predicting other burnout symptoms. One study also emphasizes the importance of physical characteristics, such as age, sex, and prior medical history (e.g., painkiller dependence), in predicting burnout.[38] Therefore, if an individual notices callousness toward others in themselves or their coworkers, it may be an indication of burnout symptoms linked to an OC that employees perceive negatively.

In addition, Model 1 reveals that feeling fatigued when waking in the morning has strong predictive power and may signal a negatively perceived OC. This finding aligns with another study showing that OC and fatigue are related and can impact turnover intentions.[39] For example, a volatile culture – where organizational elements such as rules and leadership continuously change – can lead to employee fatigue.[40] Further research is needed to identify specific aspects of OC that contribute to burnout symptoms, like fatigue.

On the other hand, feeling at the wits' end showed the least predictive power. Several studies have highlighted the importance of cultivating an OC where colleagues and supervisors support each other and where supervisors demonstrate empathy toward employees. However, feeling at the wits' end is a more individualized experience and a symptom of burnout, which may explain why it does not strongly predict perceptions of OC. Leaders should focus on a range of burnout symptoms, not just one, before determining whether their employees are burned out and respond by implementing additional safeguards, such as more flexible work schedules. This study suggests that feeling at the wits' end has a smaller impact on perceptions of OC compared to other variables. Further research is needed to quantify the impact of all variables included in the model on perceptions of OC.

Model 1's MDS plot in Figure 1 demonstrates a negative correlation between positive perceptions of OC and burnout symptoms. The more positively employees perceive their OC, the less likely they are to exhibit burnout symptoms, which aligns with findings in the literature.[37,41,42]

Model 2 shows that several engagement and personalization characteristics – such as feeling stimulated when working with colleagues and exhilarated when working with or talking to patients – are the most powerful predictors. Employees who are engaged in their work are less likely to experience burnout.[43,44] Models 1 and 2 underscore the importance of recognizing whether employees empathize with patients and coworkers, as this can predict burnout and whether OC is perceived positively.

Moreover, Model 2 demonstrates that the likelihood of an employee wanting to take their current job again holds significant predictive power. Turnover intention is important in recognizing burnout and indicating whether OC is positively perceived. Previous research has found similar results, showing that OC is related to turnover intention.[45-47] However, this study further illustrates how perceptions of OC can predict turnover intent.

Although depersonalizing others by treating them as impersonal objects and being callous toward them was identified as the most significant predictor of burnout using OC, another aspect of personalization – understanding visitors' feelings – was found to be the least important. This finding contrasts with those of previous studies. Empathizing with visitors, with whom non-patient-facing employees may have limited interact, may not be as crucial in predicting burnout as the way employees interact with coworkers and patients. Further research is needed to explore why empathizing with visitors is less important in predicting burnout than other depersonalization factors.

Model 2's MDS plot in Figure 3 reveals a positive correlation between perceptions of OC and burnout-related questions. The more positively employees perceive their OC, the more likely they are to be protected against burnout symptoms such as depersonalization. For example, employees who view their OC positively are more likely to understand visitors' feelings and feel stimulated when working with colleagues. This finding aligns with several studies showing that OC influences burnout symptoms, including depersonalization.[48-50] However, our approach is innovative in its ability to use a complex data model to predict burnout based on OC. The aforementioned studies did not employ a random forest model to predict burnout scores among non-patient-facing and patient-facing employees, highlighting the novelty of using a random forest algorithm for this purpose. Moreover, the models' strong performance, despite the small sample size, suggests that this approach can be expanded to predict burnout using OC and potentially other factors such as workload. The model's ability to predict burnout based on OC is supported by a previous study that used a decision tree model and Bayesian analysis on the same dataset.[32] The Bayesian analysis, which, like a random forest model, is suitable for small datasets, corroborates the results of this study.

The AUC-ROC curves for Models 1 and 2 demonstrate that the model classified, with some accuracy, whether employees perceived their organization's culture positively. Furthermore, the model suggests that burnout symptoms are more likely to be linked to perceptions of OC. This finding indicates to leaders that, if employees exhibit burnout symptoms, they may also perceive the OC as negative. Leaders could use the model's identification of specific burnout symptoms – such as depersonalization, as indicated by callousness toward others – to evaluate perceptions of OC. For instance, if leaders recognize that their employees are treating others harshly and exhibiting other burnout symptoms identified by the model (e.g., viewing others as impersonal objects), they could begin to foster a more positive OC. Strategies could include providing employees with the necessary equipment and resources to succeed, as well as offering flexible work schedules to promote work-life balance and reduce burnout symptoms.

While this exploratory study introduced a novel random forest method for predicting burnout using OC, it has several limitations. One notable limitation is the small sample size. Although a previous study's Bayesian analysis on the same dataset supports the results of the random forest model, other ML methods suited for small sample sizes, such as SVMs, could be explored in future studies.[32] Nonetheless, this exploratory study provides a framework and methodology for demonstrating how OC influences burnout. Moreover, this study was cross-sectional, meaning causality could not be established. It was also conducted solely in the United States. To determine the generalizability of the results, the study could be replicated in other countries.

The small dataset may have led to model overfitting, meaning it might have learned patterns specific to the training data rather than those applicable to more generalizable data. The model could have overreacted to small variations in the data, such as outliers or the responses of a few respondents who rated their OC as positive with a "1." Moreover, the small dataset may not have captured the complex, diverse perspectives of employees across different health systems, such as those who viewed their OC negatively but did not exhibit significant burnout symptoms. As a result, the model may not have fully learned all the relationships between the features, potentially performing poorly on unseen data due to noise specific to the small dataset. Future studies should incorporate larger datasets with a broader representation of various roles within health systems to improve generalizability, reduce bias, and prevent overfitting.

6. Conclusions and policy implications

This random forest model demonstrates that perceptions of OC can be used to predict specific burnout symptoms, such as engagement with others and empathy. The model also reveals that the more positively employees perceive their organization's culture, the less likely they are to exhibit burnout symptoms. Previous studies have quantified the effects of OC on burnout,[50,51] and this model further highlights that OC influences burnout more significantly than internal factors, such as resilience and self-care. If employees begin to display burnout symptoms, leaders could assess and improve the OC to mitigate these effects. Therefore, it is crucial for leaders in health systems to cultivate an OC where colleagues and employees are supported, workloads are manageable, and the resources needed to perform the job effectively and efficiently are provided.[52-55] As a result, perceptions of OC will improve, and employees will be less likely to experience burnout.

The findings also suggest that policymakers could invest in improving health systems' work environments by providing flexible work options and reducing workload through strategies such as increasing staffing. For example, given the shortage of healthcare workers, particularly nurses and physicians, in the United States, hiring international employees could help alleviate the staffing crisis. Policymakers could ease the hiring process by loosening visa requirements for international employees. In addition, health system leaders and policymakers should focus on internal factors contributing to burnout, such as mental health. Policies could be implemented to invest more in mental health resources, such as crisis hotlines. Leaders in health systems could also establish confidential peer support groups, enabling employees to discuss their mental health concerns without fear of their discussions being shared with colleagues or supervisors. Investing in OC and burnout mitigation strategies, such as peer groups, could significantly reduce burnout.

6.1. Contributions to the literature

This study makes several contributions to the existing literature. First, it is the first study to use a random forest model to predict burnout using perceptions of a positive OC as the DV, particularly in the context of the COVID-19 pandemic. A previous study only used burnout survey results to predict burnout symptoms in a machine-learning model.[23] Second, the random forest model could serve as a baseline for tuning and creating additional models to predict burnout using other aspects of OC, such as supervisor support and the availability of resources needed to perform one's job – factors not yet explored in the literature. Third, the model underscores the importance of cultivating a positively perceived OC to reduce burnout by demonstrating that OC can predict burnout scores. Fourth, these models introduce an innovative way to predict burnout and could be expanded to include employees outside of health systems. Finally, this study illustrates that advanced and complex ML techniques can effectively predict burnout.

6.2. Contributions to the healthcare industry

This study offers valuable insights with practical implications for the healthcare sector.

(i) Burnout symptom prediction and prevention
Based on the model and OC survey results, healthcare leaders, including hospital chief executive officers and human resource executives, can anticipate specific burnout symptoms, such as depersonalization among employees toward their coworkers, patients, and visitors. Depersonalization, which may negatively impact patient satisfaction, requires leaders to prioritize and improve their OC. Given that patient satisfaction is critical in healthcare, enhancing OC becomes a strategic imperative.

(ii) Burnout interconnection awareness
The findings highlight the strong predictive relationships among various burnout symptoms, such as callousness toward others and reluctance to retake one's current job. The strong association between burnout symptoms and turnover highlights the importance of addressing burnout to reduce costly staff attrition. Leaders should monitor early signs of burnout, as indicated by the model, and investigate its causes, including issues related to OC.

(iii) OC monitoring
Conducting regular employee satisfaction surveys helps leaders identify changes in OC and detect potential issues before they escalate.[56,57] Surveys should include questions specific to how employees perceive the level of support available from colleagues and supervisors.[58] When employees report feeling unsupported, leadership can take actionable steps, such as advocating for employee needs during executive discussions and ensuring that staff have the necessary resources, supplies, and equipment to perform their jobs effectively.

(iv) Actionable strategies for improvement

To enhance OC and reduce burnout, healthcare leaders can implement actionable strategies based on best practices. Some of these strategies may include:

- Flexible work schedules: Providing flexibility to employees helps them balance work and personal responsibilities, ensuring they come to work refreshed and with time for their loved ones.[59,60]
- Mental health resources: Offering access to confidential, 24/7 mental health support services can help employees manage stress, both at work and in their personal lives.[61,62]
- Promoting peer support systems: ENCOURAGING peer support groups or mentoring programs can help employees feel supported and less isolated at work.[63,64]
- Case studies for inspiration: Learning from successful case studies or applying concepts from recent literature can guide leaders in designing interventions aimed at reducing burnout and improving OC.

By actively using these strategies, healthcare organizations can create an environment that prioritizes employees' well-being, reduces burnout, and ultimately improves the quality of patient care. The model's finding that "feeling at wit's end" has low predictive power on perceptions of OC suggests that organizational leaders should not focus on an individual's feelings of frustration, as these may be temporary. Instead, leaders should focus on how employees treat visitors, coworkers, patients, and others in the health system. The high predictive power of callousness toward others indicates that leaders should focus on modeling empathy and appropriate behavior expectations for employees. Leaders can demonstrate empathy by showing consideration for different perspectives, particularly when addressing dilemmas. For example, when speaking with patients, leaders could use open-ended questions and offer choices rather than presenting authoritative statements with only one solution.[65] In addition, using clear, direct language can improve patients' understanding while demonstrating personal concern, such as asking how patients are feeling, can enhance engagement.

In addition, retaking one's current job showed strong predictive power on perceptions of OC, suggesting that leaders should focus on cultivating an OC in which employees are motivated to stay and are retained. Leaders cannot control or be responsible for employees' individual feelings, but they can make external changes to the OC that improve employee retention. Leaders should focus on creating a positive work environment by implementing changes such as flexible schedules and hybrid work arrangements, where employees work remotely for part of the week. Monitoring retention rates before and after implementing such changes can help assess the effectiveness of these efforts to cultivate an OC where employees want to remain.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: All authors
Formal analysis: Teray Johnson
Investigation: Teray Johnson
Methodology: All authors
Writing – original draft: Teray Johnson
Writing – review & editing: Sameh Shamroukh

Ethics approval and consent to participate

This research was approved by the Harrisburg University of Science and Technology Institutional Review Board (IRB# 20221026). Participants gave informed consent to participate in this study.

Consent for publication

Written consent was obtained at the beginning of the survey, and permission was granted by each participant to publish their data.

Availability of data

Data can be obtained by contacting the corresponding author.

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Appendix

Table A1. Departments

Department	Number of respondents
Administration	20
Board of Directors	4
Community Health	3
Diagnostic Imaging/Radiology	1
ED	4
Inpatient Psychiatry	1
Inpatient Surgery	2
Lab Services	1
Med/surg	2
OR/PACU	1
Pharmacy	1
Quality and Patient Safety	4
Step down/Transitional	1
Analytics	4
Case Management/Social Work	1
Finance	1
Graduate Medical Education	1
Information Technology	2
Marketing/Business Development	2
Operations	1
Strategy	5
Patient Experience	1
Radiation Oncology	2
Refused to Answer	3

Abbreviations: ED: Emergency department; OR: Operating theatre; PACU: Post-Anesthesia care unit.

Table A2. Positions

Position title	Number of respondents
Administrator/Assistant Administrator/Supervisor	18
Board Member	3
Consultant	4
Case Manager	1
Clerical	1
IT Support	2
Medical Assistant	12
Medical Doctor	10
Patient Coordinator/Access Representative	3
Chaplain	1
Physician Chief/Chair	1
Project Manager	1
Registered Nurse	7
Residency Coordinator	1
Others	2

Abbreviation: Information technology.

Table A3. Hospital size, location, and type

Parameter	Number of respondents
Number of beds	
6 – 24	3
25 – 49	0
50 – 99	3
100 – 199	7
200 – 299	3
300 – 399	5
400 – 499	8
500 or more	34
Location	
Rural	22
Urban	41
Type	
Federal	2
For-profit	16
Non-profit	45

Key

C30–Overall, the culture of the hospital is positive.
B1–When I go home after work, I feel emotionally drained.
B2–I understand my patients’ feelings.
B3–I understand visitors’ feelings.
B4–Knowing what I know now, I would take my current job all over again.
B5–My job interferes with my home-life.
B6–My job keeps me from spending the amount of time I would like with my family.
B7–I often get irritated by little annoyances.
B8–I suffer from anxiety.
B9–My mood often goes up and down.
B10–There are days when I’m “on edge” all the time.
B11–I feel fatigued when I get up in the morning.
B12–I feel like I’m at my wits’ end.
B13–I feel stimulated when I work with my colleagues.
B14–I deal very effectively with the problems of my patients and/or coworkers.
B15–I treat some of my patients and/or coworkers like they’re impersonal objects.
B16–In my work, I’m very relaxed when dealing with emotional problems.
B17–I’ve become more callous toward people since starting my current job.
B18–I feel exhilarated after working with or talking to patients.