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Evaluation of patient safety culture using a random forest algorithm

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ABSTRACT

Safety culture is a multidimensional concept that may be associated with medical errors and patient safety events in healthcare delivery systems. However, limited evidence is available regarding which safety culture dimensions drive overall patient safety. Moreover, the use of advanced statistical analysis has been limited in past studies of safety culture data. To address these issues, we use hospital-level aggregate survey data from U.S. hospitals to analyze the relationship between the defined safety culture dimensions and the patient safety grade. We use a tree-based machine learning algorithm, random forests, to estimate accurate and stable associations. The results of our analysis show that safety perception, management support, and supervisor/manager expectations are the leading drivers of patient safety grade. More specifically, safety problems in the work unit and work climate provided by hospital management are specific drivers of patient safety outcomes. The random forest model sheds new light on the most important cultural features relevant to patient safety.

1. Introduction

With awareness of the high cost and impact of medical errors [35], healthcare organizations have been encouraged to implement safety management initiatives [30,72]. Earlier studies have noted that the success of these initiatives is associated with the maturity of organizational safety culture [61,73]. It is therefore imperative to understand how the characteristics of safety culture align and motivate healthcare organizations towards safety enhancement and commitment [51].

In many safety-critical industries such as the petrochemical industry, capturing safety culture data is an important step to enhance safety performance [10]. These data often help leadership understand that reasons behind incidents are not necessarily only technical failures or human errors, but rather systems errors with cultural aspects that may include a commitment from all levels of management, communication within and across teams, and more generally the attitudes of providers and support staff [26,44,53]. Fundamentally, understanding safety culture identifies an organizations' characteristics by examining what happens or what is learned after a failure occurs [79].

Safety culture in healthcare is a multi-dimensional concept, referring to the consolidation of values, perspectives, perceptions, and standards that define an organization's commitment and effectiveness to administer patient safety [31,39]. Safety culture is described as the main challenge in patient safety and risk management studies and perhaps the most important single factor to determine the long-term impact in safety outcomes [76]. Other studies have shown that safety culture plays a key role in risk and safety awareness [7].

A recent systematic review of literature on safety culture showed that the assessment of safety culture in healthcare organizations is a topic of interest to researchers and practitioners worldwide [54]. Despite increasing attention, the multi-dimensional concept of safety culture remains challenging to assess and interpret. Safety culture involves many aspects of human and organizational behavior [34], with no comprehensive picture to explain its evident influence on patient safety. It is still debatable which set of safety culture attributes has the greatest influence on patient safety outcomes. Moreover, the measurement instruments often differ across studies [36,54], demonstrating the need for a reliable instrument to be adopted across different healthcare settings.

Earlier studies have shown that, with few exceptions, the methodological tools to measure patient safety culture (PSC) are limited to simple statistical models [54]. Such analyses may fail to capture or explain complex relationships and correlations between safety culture dimensions and attributes, leading to less rich information and thus

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sub-optimal decision-making by healthcare management in response to the data collected. Advanced analytic approaches such as machine learning tools can be used to address this challenge, but are not widely used in the context of PSC. The primary aim of this paper is to explore a methodology to analyze the relationship between PSC attributes and reported patient safety outcomes. We propose a machine learning algorithm, using a tree-based random forest model, to predict safety culture attributes with the greatest influence on patient safety outcomes. Our data analysis goes beyond the descriptive statistics of the typical survey to provide more explicit descriptions and deeper insights into the relationship between safety culture and patient outcomes.

The main contribution of this paper is to propose a machine learning algorithm in the specific context of PSC. Another contribution of this study is the application of the framework through the use of hospital-level aggregate safety culture survey data in that the results may serve hospitals to gain significant insights on multi-dimensional safety culture and its impact on patient safety.

The remainder of the paper is organized as follows. The relevant literature on safety culture, assessment tools, and supervised machine learning tools are presented in Section 2, followed by a description of the proposed random forest model in Section 3. Using hospital-level aggregate survey data, we present the results of the model in Section 4. Finally, discussion of the model and results, limitations, directions for future research, and our conclusions are presented in Section 5.

2. Review of relevant literature

2.1. Patient safety culture

Safety culture is described as "the way safety is done around here", highlighting the importance of how perceptions and beliefs influence attitudes and actions related to safety [50,71]. Patient safety is one component of healthcare quality, along with timeliness, equity, efficiency, and patient-centeredness [81]. The importance of safety culture is recognized for an organization to achieve continuous quality improvement goals [13]. The purpose of rigorous assessment of PSC is to build an evidence-based understanding of patient safety within an organization. This includes identifying strong and weak areas of safety culture, analyzing trends over time, determining organizational actions needed to improve patient safety, and making comparisons within and among healthcare departments and organizations [54]. Strong safety culture is linked to improved patient outcomes in various hospital settings [11,28,32,49,69].

Earlier studies in safety-critical industries aimed to show the relationship between safety culture and operational safety [38,58]. For instance, Sorensen [65] showed that this relationship can be demonstrated in two parts: (1) establish a relationship between safety culture (or related attributes) and operational safety; and (2) identify suitable performance indicators that can be used to infer changes in safety culture and therefore safety performance. In healthcare, many tools have been developed and implemented to consider and merge these two parts in the patient safety context since the early-2000s [74].

To assess safety culture, various tools and methods have been developed [4]. Safety Attitudes Questionnaire (SAQ) [59], Safety Organizing Scale (SOS) [77], Patient Safety Culture in Healthcare Organizations (PSCHO) [62], Manchester Patient Safety Assessment Framework (MAPSAF) [47] and Hospital Survey on Patient Safety Culture (HSOPSC) [54] are among the most commonly used and rigorously tested tools in healthcare worldwide. Most of the tools used in healthcare are predominantly questionnaire-based activities, as it is also a common practice in many other safety-critical industries [41,68]. Among these tools, the most common survey tool used in the safety culture context is the Hospital Survey on Patient Safety Culture (HSOPSC) [54]. Accessible to staff members from a wide range of roles, from hospital security to executive management, HSOPSC has been commonly used for psychometric analyses over the last couple of decades, and is accessible to all professionals interested in assessing the PSC in their hospital. Having been used by hundreds of hospitals in over 60 countries, the HSOPSC survey makes it possible to measure what dimensions of safety culture in hospitals are considered strong and weak; therefore, identifies opportunities for safer and better healthcare. The HSOPSC development was sponsored by the Agency for Healthcare Research and Quality (AHRQ) and Medical Errors Workgroup of Quality Interagency Coordination Taskforce. The HSOPSC has twelve composites, and each composite involves various attributes adding up to 42 questions (see Appendix Table A.1) to assess PSC [66].

Various analyses have been conducted with the use of the HSOPSC safety culture survey. For instance, the systematic review of Reis and colleagues [54] showed that the assessment of patient safety culture had received an increasing interest globally by researchers and practitioners. The review shortlisted 33 studies on HSOPSC from multiple countries between 2007 and 2016. Using the conventional HSOPSC assessment methodology in their healthcare institutions, studies classified the safety culture dimensions as either strong or weak. Most of the studies using HSOPSC revealed that the organization culture is weak with respect to patient safety. The studies emphasized the importance of several factors, such as increasing staff awareness about care and quality, increasing trust and cooperation between team members, and increasing awareness between staff to be able to confidently indicate what went wrong, amongst others. While various outcomes were observed in the literature, limited use of advanced statistical analysis was also noted in the analysis of the relationship between safety culture dimensions and patient safety. For example, it was found that only a couple of researchers used regression analysis [2,63] while most others ended up with descriptive statistics. Further, a very limited understanding was seen in earlier studies in terms of identifying the leading drivers of safety culture on patient safety.

Although many other frameworks, surveys, and assessment tools were developed to measure safety culture that an organization has, it may not always be possible to accurately measure the relationship between safety culture and patient safety outcomes [12,60]. Further, in this particular research context, the multi-dimensional safety culture, with possible interactions between attributes, and its association with patient safety might not be well understood using currently available tools. However, machine learning tools with their advanced statistical analysis capability may provide opportunities for better evaluation of PSC and its impact on patient safety. Further, such tools can provide significant insight to rank and interpret the feature importance used in the prediction [80]. Therefore, the analysis of safety culture assessments, including HSOPSC as the most common tool, may benefit from using machine learning tools, e.g. random forest algorithm, to yield more reliable predictions with high accuracy and versatility.

2.2. Random forest algorithms

The use of tree-based ensemble learning algorithms has gained interest since applications in various industries and domains such as agriculture [29], transportation [80], energy [46], and healthcare [18,70]. In healthcare settings, these methods have been used to predict clinical outcomes [6,55], costs [57], and healthcare utilization [15]. Tree-based algorithms are particularly recognized for providing realistic and easy-to-interpret results [23,37]. Further, these algorithms are reliable in prediction as they handle interactions automatically, even if large covariates are present [23].

Random Forests (RFs) is one of the tree-based ensemble methods used for regression and classification [78]. Recent studies presented encouraging results in both empirical studies [9,25,33,75] and theoretical results [8]. The RFs has also started gaining momentum in various healthcare applications [22,37].

RFs develops many decision trees [67]. These trees are constructed using a random subset of variables taken independently and with replacement from the original dataset [52]. RFs accommodate both categorical and numeric variables in prediction problems. One of the properties of the RFs is the built-in cross-validation that allows ranking the independent variables from the most effective to the least associated with the outcome variable. This adds value for feature extraction in multisource data analysis. A comprehensive introduction to RFs can be found in Breiman [9].

While RFs has merits to perform well with a range of functions on large and complex datasets, their potential has not been explored and evaluated in a particular safety culture context yet. We, therefore, aim to build upon this research to leverage the benefits of the RFs by adding a new application area of unique PSC context with a survey dataset. With the proposed research methodology detailed below, we aim to identify the most important features (e.g. composites and attributes from the HSOPSC survey) affecting patient safety grade.

3. Research methodology

3.1. Data sources

We compiled a dataset of hospital-level HSOPSC data from annual staff surveys conducted at 677 U.S. hospitals in 2016. The HSOPSC survey measures 12 safety culture composite scores, each consisting of three to four individual survey items, totaling 42 variables. Most survey items are measured using a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

To get the average score of each composite, the average positive response rate (total *agree* and *strongly agree* responses over total responses) was calculated to represent each composite with a percent scale. Similarly, *overall patient safety grade*, which we used as a primary outcome variable, asks participants to rate their work area/unit in their hospital with an overall grade on patient safety. We used its average positive response rate (total ‘excellent’ and ‘very good’ responses over total responses) as the outcome variable. Further, we included three hospital characteristics, categorical bed size, geographical region of the hospital, and teaching status (teaching or non-teaching hospital), as they may also play a role in patient safety. Table 1 describes all independent variables, including three hospital characteristics (categorical variables) and twelve safety culture composites (continuous variables).

The data were analyzed in two stages through the application of RFs. During Stage 1, we investigated the feature importance of the 12 composites along with the hospital characteristics to predict patient safety grade. During Stage 2, we investigated the importance of the 42 specific variables (see Table A.1) along with the hospital characteristics on patient safety grade.

Table 2
Parameter search space in grid search analysis.

Parameter	Range
max_depth	[2; 3; 4; 6; 7; 8; 9; 10; 15]
min_samples_leaf	[2; 3; 4; 5; 15]
min_samples_split	[2; 3; 5; 10; 15]
n_estimator	[200; 400; 600; 700; 800; 1000; 1500]

3.2. Random forest algorithm

In each model, data are randomly divided into two sets: training set (80% of the sample) and testing set (20% of the sample). At this stage, we identified hyper-parameters used commonly in RF algorithms [48]: (1) *n estimators* (number of trees in the forest); (2) max *depth* (maximum depth of the tree); (3) min*_samples_split* (minimum number of data points in a node before the node is split); and (4) min*_samples_leaf* (minimum number of data points allowed in a leaf node). We evaluated hyper-parameters to optimize the performance of the algorithm using an exhaustive grid search. In the context of machine learning, a grid search is applied for tuning purposes by selecting optimal parameter combinations. Table 2 summarizes the parameter search space used in the grid search analysis.

Following the grid search analysis, we employed three metrics to interpret the predictive performance in each model: mean absolute percentage error (MAPE), mean absolute error (MAE) and mean square error (MSE). In Eqs. (1)–(3) below, y_i is the actual value in the *ith* observation, while p_i is the prediction in the same observation within an size of the dataset.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} |y_i - p_i|/y_i \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - p_i| \tag{2}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} |y_i - p_i|^2 \tag{3}$$

In parallel with Stages 1 and 2 described earlier, we fit several models and selected models for composites (Models 1) and specific variables (Model 2). While Model 1 shows results for optimal combinations of hyper-parameters after tuning with the use of grid search [48] for composites, Model 2 represents the same for specific variables. As an important function of RFs, we also ranked the feature importance to visually represent the relative importance of each measure. To achieve this, the *Scikit-Learn* library in RFs is imported to measure a feature's importance by considering how much the tree nodes that use

Table 1
List of variables (continuous and categorical) for patient safety prediction.

No	Variables	Variable Code	Type	Survey Items	Unit/Remarks
1	Communication openness	POS_COMMUN	Continuous	C2, C4, C6	% positive
2	Feedback and communication about error	POS_FEED	Continuous	C3, C5	% positive
3	Frequency of events reported	POS_ERFREQ	Continuous	D1, D2, D3	% positive
4	Handoffs and transitions	POS_HANDOFF	Continuous	F3, F5, F7, F11	% positive
5	Management support for patient safety	POS_MGMT	Continuous	F1, F8, F9	% positive
6	Nonpunitive response to error	POS_NONPUN	Continuous	A8, A12, A16	% positive
7	Organizational learning - Continuous improvement	POS_ORGLRN	Continuous	A6, A9, A13	% positive
8	Overall perceptions of patient safety	POS_OVERALL	Continuous	A10, A15, A17, A18	% positive
9	Staffing	POS_STAFF	Continuous	A2, A5, A7	% positive
10	Supervisor/manager expectations and actions promoting patient safety	POS_SUPV	Continuous	B1, B2, B3, B4	% positive
11	Teamwork across units	POS_TEAMAC	Continuous	F2, F4, F6, F10	% positive
12	Teamwork within units	POS_TEAMIN	Continuous	A1, A3, A4, A11	% positive
13	Bed Size Category	BSC	Categorical	BSC	Class size: 8
14	Type of hospital	TEACH	Categorical	TEACH	Class size: 2
15	Geographical Region	REGION_REPORT	Categorical	REGION_REPORT	Class size: 9

Table 3
Descriptive summary for survey composites and outcome variable.

Variable	n	mean	sd	median	min	max	range
POS_OVERALL	672	0.66	0.09	0.66	0.36	0.90	0.54
POS_ERFREQ	672	0.67	0.07	0.67	0.43	0.94	0.51
POS_SUPV	672	0.78	0.07	0.79	0.17	0.96	0.79
POS_ORGLRN	672	0.73	0.07	0.73	0.15	0.93	0.79
POS_TEAMIN	672	0.82	0.06	0.82	0.26	0.96	0.70
POS_COMMUN	672	0.64	0.07	0.64	0.35	0.84	0.49
POS_FEED	672	0.68	0.08	0.69	0.17	0.89	0.72
POS_NONPUN	672	0.45	0.09	0.44	0.20	0.75	0.55
POS_STAFF	672	0.54	0.09	0.53	0.20	0.86	0.66
POS_MGMT	672	0.72	0.09	0.73	0.39	0.96	0.57
POS_TEAMAC	672	0.61	0.09	0.61	0.34	0.91	0.57
POS_HANDOFF	672	0.48	0.10	0.47	0.22	0.80	0.58
GRADE_AB	672	0.76	0.10	0.77	0.04	0.98	0.94

Table 4
Correlation strengths between continuous variables and patient safety grade.

Variable	Cronbach's alpha	Pearson Coefficient	P-value
POS_OVERALL	0.91	0.81	< 0.001
POS_ERFREQ	0.93	0.55	< 0.001
POS_SUPV	0.91	0.69	< 0.001
POS_ORGLRN	0.91	0.61	< 0.001
POS_TEAMIN	0.93	0.64	< 0.001
POS_COMMUN	0.88	0.66	< 0.001
POS_FEED	0.90	0.61	< 0.001
POS_NONPUN	0.95	0.62	< 0.001
POS_STAFF	0.81	0.71	< 0.001
POS_MGMT	0.77	0.76	< 0.001
POS_TEAMAC	0.95	0.68	< 0.001
POS_HANDOFF	0.80	0.58	< 0.001

that feature reduce impurity on average. Each node's weight is equal to the number of training samples and each feature's score is computed automatically following the training. Results are then scaled to the sum of all features equal to 1 [20].

4. Analysis and results

The goal of the analysis was to identify which safety culture composite scores and specific items are most closely associated with the overall patient safety grade.

Prior to analysis, we used descriptive statistics to identify missing data and potential distributional outliers. First, we merged survey data across hospitals for a dataset of 677 observations. Five hospitals had missing data for some survey items and composite-level calculations. Therefore, we excluded them and considered 672 records available for the final analysis. We summarized descriptive statistics for the measured composites in Table 3. The mean value in the table shows the average percent positive response for each of the 12 patient safety culture composites and the outcome variable.

All twelve safety culture composites were tested for their internal consistency through Cronbach's alpha. All composites surpasses the 0.70 reliability threshold [42] (see Table 4). Further, a linear correlation analysis of composites (continuous variables) with the patient safety grade was conducted to investigate the statistical properties. Further, the significance of each coefficient was tested using p-values and $\alpha = 0.05$. Results showed the associations between each composite and patient safety grade are statistically significant (see Table 4). To investigate the strength of the relationship between the composites, we also estimated the Pearson correlation between variables (see Appendix Table A.2 for more information).

The first application of random forest algorithms investigated the importance of composites on patient safety. We fit Model 1 with optimal hyper-parameter values as a result of the grid search analysis. Fig. 1 shows the feature importance summary from Model 1 training regression random forest model for composites and hospital characteristics.

Results in Model 1 show that three leading composites are *overall patient safety perception* (22.68%), *management support* (17.11%) and *supervisor/manager expectations* (12.88%), as follows:

— *Overall patient safety perception:* Procedures and systems are good at preventing errors and there is a lack of patient safety problems.
— *Management support:* Hospital management provides a work climate

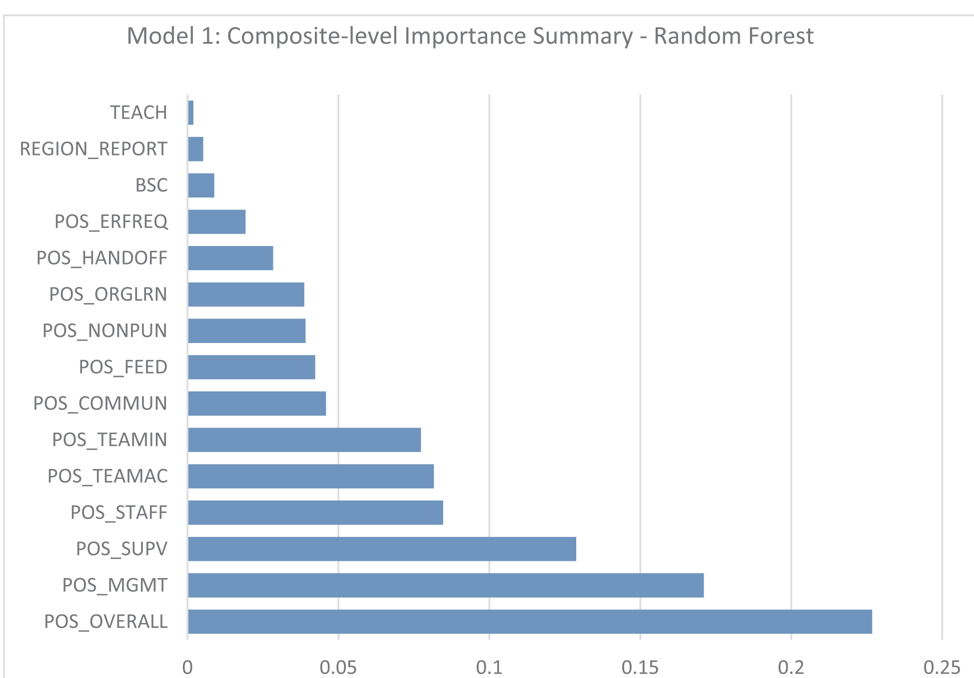

Fig. 1. Model 1: Composite-level importance summary from training regression random forest model (after tuning with exhaustive grid search).

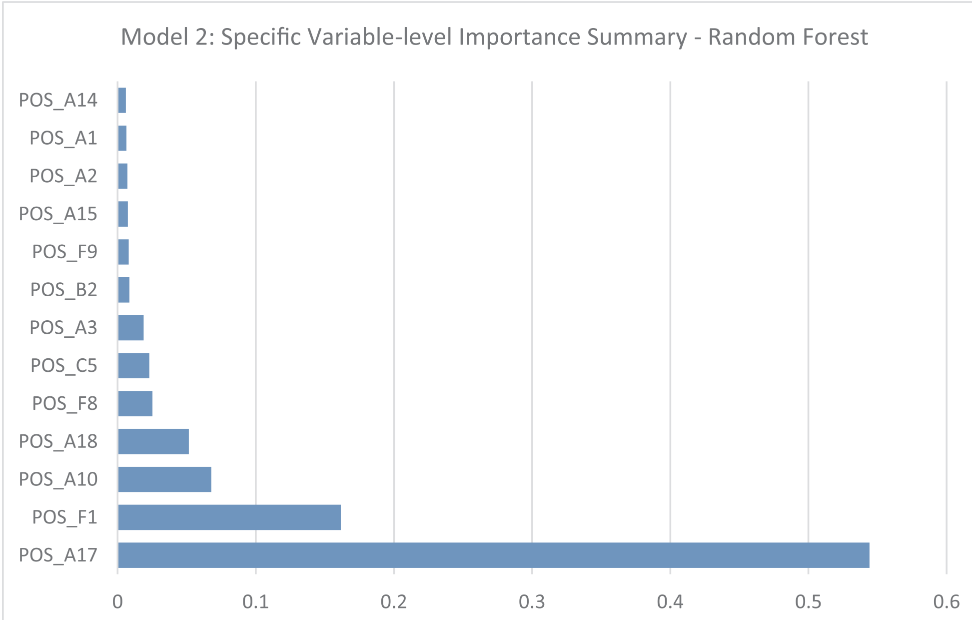

Fig. 2. Model 2: Specific variable-level importance summary from training regression random forest model (after tuning with exhaustive grid search).

Table 5
Model Results with relevant hyperparameters, error metrics and leading features.

Metrics/hyper-parameters/leading features		1st stage: analysis for composites Model 1	2nd stage: analysis for specific variables Model 2
Error Metrics	MAPE	23.26	22.52
	MAE	0.05	0.04
	MSE	0.01	0.01
Hyper-parameters	max_depth	10	5
	min_samples_leaf	3	5
	min_samples_split	5	2
	n_estimator	400	400
Leading Features	Most important feature as composite	Overall Safety Perception	–
	Second most important feature as composite	Management Support	–
	Third most important feature as composite	Supervisor/manager Expectations	–
	Most important feature as a specific variable	–	A17 (under overall safety perception composite)
	Second most important feature as a specific variable	–	F1 (under management support composite)

that promotes patient safety and shows that patient safety is a top priority.

— *Supervisor/manager expectations:* Supervisors/managers consider staff suggestions for improving patient safety, praise staff for following patient safety procedures, and do not overlook patient safety problems.

With our second application of random forests, we investigated the importance of specific survey items on the overall patient safety grade in Model 2. Fig. 2 shows the feature importance summary from Model 2 training regression random forest model for specific variables and hospital characteristics.

Results in Model 2 shows that *A17* (54.42%)*and F1* (16.16%) are the two leading variables associated with the overall patient safety grade, as follows:

A17. “We have patient safety problems in this unit” (*overall patient safety perception composite*)

F1. “Hospital management provides a work climate that promotes patient safety” (*management support composite*)

We further summarize the corresponding results with optimized hyperparameters in both stages for composite and specific variable models (see Table 5).

5. Discussion and conclusions

It is imperative for healthcare organizations to understand how to improve safety culture in a way that can create positive safety outcomes [28]. In this study, we developed a random forest algorithm to HSOPSC data to estimate the relative importance of the safety culture composite scores and individual survey variables to predict the overall patient safety grade. To our knowledge, this study is the first evaluation of random forest algorithms in the context of safety culture. We conclude that the random forest algorithm we developed exhibited useful predictive capability and provided insight about the relationship between specific aspects of safety culture and the overall patient safety grade.

Our model established that *overall safety perception, management support,* and *supervisor/manager expectations* are the most important three composites associated with overall patient safety grade. Within these composites, *safety problems in work units* and *work climate provided by the hospital management* are specific drivers of patient safety grade. Although our study is the first one showing the relative importance of the composites, the following studies also highlight the importance of these composites and specific variables.

The first study evaluating the HSOPSC survey with Portuguese data showed that the *management support* (37%) and *supervisor/manager expectations* (63%) are two of the important composites with low and high scores reported in three Portugal hospitals [16]. Similar results were

Table A.1
Survey composites and specific variables.

Survey ID	Composites and Specific Variables (positive percentage value is calculated for each)
POS_TEAMIN	**Composite 1. Teamwork Within Units -** *Teamwork within Units percent positive*
POS_A1	A1. People support one another in this unit.
POS_A3	A3. When a lot of work needs to be done quickly, we work together as a team to get the work done.
POS_A4	A4. In this unit, people treat each other with respect.
POS_A11	A11. When one area in this unit gets really busy, others help out.
POS_SUPV	**Composite 2. Supervisor/Manager Expectations & Actions Promoting Patient Safety -** *Supervisor/Manager Expectations and Actions Promoting Patient Safety percent positive*
POS_B1	B1. My supervisor/manager says a good word when he/she sees a job done according to established patient safety procedures.
POS_B2	B2. My supervisor/manager seriously considers staff suggestions for improving patient safety.
POS_B3	B3. Whenever pressure builds up, my supervisor/manager wants us to work faster, even if it means taking shortcuts. (Negatively worded)
POS_B4	B4. My supervisor/manager overlooks patient safety problems that happen over and over. (Negatively worded)
POS_ORGLRN	**Composite 3. Organizational Learning—Continuous Improvement** *Organizational Learning percent positive*
POS_A6	A6. We are actively doing things to improve patient safety.
POS_A9	A9. Mistakes have led to positive changes here.
POS_A13	A13. After we make changes to improve patient safety, we evaluate their effectiveness.
POS_MGMT	**Composite 4. Management Support for Patient Safety** *Management Support for Patient Safety percent positive*
POS_F1	F1. Hospital management provides a work climate that promotes patient safety.
POS_F8	F8. The actions of hospital management show that patient safety is a top priority.
POS_F9	F9. Hospital management seems interested in patient safety only after an adverse event happens. (Negatively worded) -
POS_OVERALL	**Composite 5. Overall Perceptions of Patient Safety** *Overall Perceptions of Patient Safety percent positive*
POS_A15	A15. Patient safety is never sacrificed to get more work done.
POS_A18	A18. Our procedures and systems are good at preventing errors from happening.
POS_A10	A10. It is just by chance that more serious mistakes don't happen around here. (Negatively worded)
POS_A17	A17. We have patient safety problems in this unit. (Negatively worded)
POS_FEED	**Composite 6. Feedback & Communication about Error** *Feedback and Communication about Error percent positive*
POS_C3	C3. We are informed about errors that happen in this unit.
POS_C5	C5. In this unit, we discuss ways to prevent errors from happening again.
POS_COMMUN	**Composite 7. Communication Openness** *Communication Openness percent positive*
POS_C2	C2. Staff will freely speak up if they see something that may negatively affect patient care.
POS_C4	C4. Staff feel free to question the decisions or actions of those with more authority.
POS_C6	C6. Staff are afraid to ask questions when something does not seem right. (Negatively worded)
POS_ERFREQ	**Composite 8. Frequency of Events Reported** *Frequency of Events Reported percent positive*
POS_D1	D1. When a mistake is made, but is caught and corrected before affecting the patient, how often is this reported?
POS_D2	D2. When a mistake is made, but has no potential to harm the patient, how often is this reported?
POS_D3	D3. When a mistake is made that could harm the patient, but does not, how often is this reported?
POS_TEAMAC	**Composite 9. Teamwork across Units** *Teamwork across Units percent positive*
POS_F4	F4. There is good cooperation among hospital units that need to work together.
POS_F10	F10. Hospital units work well together to provide the best care for patients.
POS_F2	F2. Hospital units do not coordinate well with each other. (Negatively worded)
POS_F6	F6. It is often unpleasant to work with staff from other hospital units. (Negatively worded)
POS_STAFF	**Composite 10. Staffing** *Staffing percent positive*
POS_A2	A2. We have enough staff to handle the workload.
POS_A5	A5. Staff in this unit work longer hours than is best for patient care. (Negatively worded)
POS_A7	A7. We use more agency/temporary staff than is best for patient care. (Negatively worded)
POS_HANDOFF	**Composite 11. Handoffs & Transitions** *Handoffs and Transitions percent positive*
POS_F3	F3. Things "fall between the cracks" when transferring patients from one unit to another. (Negatively worded)
POS_F5	F5. Important patient care information is often lost during shift changes. (Negatively worded)
POS_F7	F7. Problems often occur in the exchange of information across hospital units. (Negatively worded)
POS_F11	F11. Shift changes are problematic for patients in this hospital. (Negatively worded)
POS_NONPUN	**Composite 12. Non-punitive Response to Errors** *Nonpunitive Response to Error percent positive*
POS_A8	A8. Staff feel like their mistakes are held against them. (Negatively worded)
POS_A12	A12. When an event is reported, it feels like the person is being written up, not the problem. (Negatively worded)
POS_A16	A16. Staff worries that mistakes they make are kept in their personnel file. (Negatively worded)
	Patient Safety Grade
GRADE_AB	Please give your work area/unit in this hospital an overall grade on patient safety. *Percent of respondents giving their work area an A(excellent) or B(very good)*

reported in Palestinian public hospitals showing that *management support* (37%) and *supervisor/manager expectations* (56%) are two of the important composites with low and high positive scores [24]. Another study with a sample of six Scottish hospitals also reported *management support* (38%) was an important predictor for safety outcome measures [1]. Similarly, a study in France assessed the safety culture in seven hospitals and showed that *overall safety perception* and *supervisor/manager expectations* are among the most important dimensions impacting on the safety culture [43]. Some other studies are also supporting the importance of *overall safety perceptions* [5], *management support*

Table A.2
Inter-correlation for continuous variables (composites) using Pearson correlation.

VARIABLES	POS_OVERALL	POS_ERFREQ	POS_SUPV	POS_ORGLRN	POS_TEAMIN	POS_COMMUN	POS_FEED	POS_NONPUN	POS_STAFF	POS_MGMT	POS_TEAMAC	POS_HANDOFF
POS_OVERALL	1.00											
POS_ERFREQ	0.60	1.00										
POS_SUPV	0.77	0.56	1.00									
POS_ORGLRN	0.71	0.66	0.73	1.00								
POS_TEAMIN	0.66	0.48	0.73	0.70	1.00							
POS_COMMUN	0.73	0.58	0.75	0.67	0.71	1.00						
POS_FEED	0.68	0.75	0.72	0.83	0.65	0.76	1.00					
POS_NONPUN	0.74	0.46	0.70	0.55	0.56	0.77	0.55	1.00				
POS_STAFF	0.87	0.45	0.70	0.57	0.57	0.63	0.52	0.73	1.00			
POS_MGMT	0.88	0.63	0.75	0.81	0.64	0.69	0.73	0.66	0.75	1.00		
POS_TEAMAC	0.82	0.64	0.68	0.74	0.65	0.65	0.68	0.65	0.69	0.84	1.00	
POS_HANDOFF	0.73	0.60	0.59	0.65	0.49	0.56	0.57	0.61	0.67	0.74	0.88	1.00

[27,28,45,64] and *supervisor/manager expectations* [32,45] affecting safety culture in various healthcare settings and countries. While these studies are coherent with our findings, some other studies show the importance of other composites, such as staffing [3,56], teamwork [17,19,40] and communication [2,14]. The multi-dimensional concept of safety culture and individual and hospital-level characteristics may explain the differences in earlier studies.

The RF algorithm developed in this study is a potential approach to enhance safety culture by demonstrating the relative importance of specific variables on patient safety culture as measured by the overall grade assigned by employees. Within the same RF model, prediction accuracy improved with the implementation of grid search analysis to optimize hyperparameters. Future studies will benefit from thorough optimization for parameter tuning, and can evaluate other types of supervised and unsupervised machine learning algorithms to identify those with the best performance to predict safety culture outcomes. Future studies may also use other sources, such as sentinel event and incident reporting databases, to analyze and validate if there is a link between the highly ranked features and the contributory factors/root causes of past events/incidents.

This study has a number of limitations. Our findings are most relevant to the healthcare industry, and so the generalizability and transferability of the RF approach to other settings may be limited. We conducted our study on a sample of safety culture data from U.S. hospitals. Organizations will experience safety culture influenced by the context unique to each industry [21], translating organizational changes and culture different from healthcare. It remains unclear to what extent our study findings generalize to healthcare settings in other countries. Despite these limitations, our study provides a new approach to explain the relative importance of safety culture features on the overall PSC.

Healthcare organizations make huge investments and resource allocation to accelerate improvement in patient safety. To benefit from such investments, healthcare organizations should be aware of the important safety culture aspects identified in this study. Future studies may benefit from the use of the algorithm in a specific hospital with individual-level survey data to constitute a knowledge base for patient safety improvement. Cultural transformations should be accompanied by structural and procedural changes [36]. The results of this study may help prioritize change activities to achieve sustainable patient safety improvements.

Competing interests

Dr. Ozonoff receives research funding related to patient safety from the Agency for Healthcare Research and Quality (AHRQ) and the CRICO Risk Management Foundation (CRICO-RMF). The authors declare no other potential conflicts of interest with respect to the authorship and/or publication of this article.

CRediT authorship contribution statement

Mecit Can Emre Simsekler: Conceptualization, Methodology, Investigation, Writing - original draft. **Abroon Qazi:** Writing - review & editing, Validation. **Mohammad Amjad Alalami:** Software, Formal analysis. **Samer Ellahham:** Writing - review & editing, Validation. **Al Ozonoff:** Writing - review & editing, Resources, Data curation, Supervision.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix

Table A.1, Table A.2

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