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Key drivers of trucking safety climate from the perspective of leader-member exchange: Bayesian network predictive modeling approach

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ABSTRACT

Purpose: Safety climate, which is defined as workers' shared perceptions of organizational policies, procedures, and practices as they relate to the true or relative value and importance of safety within an organization, is one of the best indicators of organizational safety outcomes. This study identifies key drivers of safety climate from the perspective of leader-member exchange (LMX). LMX is a theory describing the nature and processes of social interactions between a supervisor and a subordinate. This study examines the impact of individual drivers and combinations of drivers on safety climate through Bayesian Network simulations to predict practices which most effectively improve safety climate in the trucking industry.
Method: Survey data were collected from 5083 truck drivers in a large U.S. trucking company. Bayesian Network analysis was used to identify key drivers (factors) of safety climate and the best joint strategies for improvement. The impact of the drivers on safety climate was assessed and the simulation identified their potential impact independently and in concert with other drivers.
Results: The results from Bayesian Network analyses showed that the effects of LMX on organization- and group-level safety climate were conditionally dependent on four other drivers including psychological ownership, supervisory integrity, situation awareness, and safety communication. Among the five contributing factors, supervisory integrity and LMX had the strongest independent effects on organization- and group-level safety climate. Moreover, the results indicated that the best two joint strategies for promoting organizational (company/top management level) safety climate were LMX and psychological ownership as well as LMX and situation awareness, whereas the best two joint strategies for improving group (workgroup/supervisor level) safety climate were joint optimization of LMX and safety communication as well as LMX and psychological ownership.
Implications: Based on the study results, the strategies that may have the most potential to improve trucking safety climate are: enhancing leaders' ability to engage in high-quality exchanges (e.g., caring about employees), developing training to encourage employees/leaders to deliver on promises, and providing employees with more autonomy to enhance their ownership.

1. Introduction

The trucking industry has the second highest occupational fatality frequency among all industries in U.S. In 2017, 841 truck occupants died but truck-involved crashes killed 3920 others, including pedestrians and cyclists (NHTSA., 2019). In the transportation and warehouse industry sector, which includes the trucking and freight transportation industry, 874 workers were killed in 2018. The fatal work injury rate per 100,000 full-time equivalent workers was 14.0, which was also the second highest in the U.S. (Bureau of Labor Statistics, 2018). In order to curtail the loss of human lives and promote workers' well-being in the trucking industry, a systemic approach to safety management is critical.

The present study focuses on safety climate, the shared perceptions by members on an organizations' enacted efforts to improve workplace safety and health (Zohar, 1980, 2010). Organization-level and group-level safety climate denote shared safety climate perceptions at

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the company or top management level and the workgroup or supervisor level (Zohar, 2003). Safety climate has been shown to be a leading indicator of safety behavior and safety outcomes, not only in the trucking industry (Huang et al., 2013a; Lee et al., 2019c) but also in other hazardous industries like the utility/electricity industry (e.g., Huang et al., 2013b) and the fire service sector (Taylor et al., 2019). Available meta-analytic studies suggest safety climate had a strong association with safety performance (Christian et al., 2009; Nahrgang et al., 2011).

More specifically, Huang, et al. (2013a) used data from five U.S. trucking companies ($n = 5534$) and showed that an increase in organization-level safety climate score by 1 point (on a 5-point scale) was associated with a decrease in lost work days due to injury by 0.56 day ($SE = 0.03$), while a group-level safety climate (i.e., workgroups within the organization) score increase of 1 point (on a 5-point scale) was associated with a decrease in lost work days due to injury by 0.46 ($SE = 0.02$). Lee, Huang, Sinclair, et al. (2019c) showed similar findings based on a longitudinal design, noting a mediating effect of safety behavior on the safety climate to injury severity relationship. Furthermore, it was demonstrated that positive safety climate in the trucking industry was associated with higher truck drivers' job satisfaction and lower turnover rates (Huang et al., 2016). These findings emphasize the importance of bolstering safety climate in the trucking industry.

For the effective management of safety climate, identification of the most feasible safety climate antecedents (drivers) is important (Lee et al., 2019b; He et al., 2019). Research has demonstrated that the leader-member exchange quality plays a crucial role in the emergent processes of safety climate (Zohar et al., 2014). To this end, the present study aims to develop and empirically validate a theoretically-driven conceptual model of key factors contributing to trucking safety climate based on the leader-member exchange theory (LMX) (Graen and Uhl-Bien, 1995), an overarching theory describing the nature and processes of social interactions between a supervisor and a subordinate.

1.1. Theoretical background

LMX theory is rooted in social exchange theory (Blau, 1964), which suggests that the social interaction between the two parties (e.g., employee-employee; employee-supervisor, employee-organization) follows the rule of reciprocity. The safety literature echoes this proposition of social exchange and identifies the reciprocal relationship between managerial support for workplace safety and employees' compliance to safety rules/regulations and participation in workplace safety efforts (DeJoy et al., 2010; Huang et al., 2016). The social exchange theory stresses that high quality exchange relationships between management and employees are reciprocal and characterized by trust, respect, identification, and mutual obligation. It facilitates mutual learning and accommodation, benefitting organizational performance (Kurtessis et al., 2015). Although safety scholars have used the social exchange theory perspective to identify organization-level factors contributing to safety climate, how the exchange quality between the supervisor and the subordinate (LMX quality) impacts safety climate has received relatively little research attention. At the supervisor-subordinate level, the exchange quality is also critical to safety climate and behavior through different venues (Hofmann and Morgeson, 1999; Zohar et al., 2014). Many important elements contributing to better job performance such as psychological ownership have been ignored in the safety literature. Workplace safety behavior requires employees to actively engage in safety-related issues. They must make decisions regarding safety in hazardous conditions, and voice concerns for safety and high exchange relationships necessary for the promotion of safety climate. Since high exchange quality contributes to employee empowerment (Kim and George, 2005), employee participation (Davies et al., 2011) and voice behavior (Chan and Yeung, 2016), LMX is a meaningful antecedent to safety climate. In fact, Zohar et al. (2014) showed that LMX was positively associated with employee ownership, while these two elements jointly led to greater safety climate and safety compliance behavior using truck driver samples. Building upon the study by Zohar et al. (2014), the current study uses the LMX theory to propose a safety climate emergence model to highlight the critical role of the exchange quality between the supervisor and the employee in safety climate from the following processes: *safety communication*, *psychological ownership*, *supervisory integrity, and situational awareness.*

First, *safety communication* is the building block of trust, which is at the core of high quality exchange relationships (Scandura and Pellegrini, 2008). In the context of workplace safety, management that genuinely cares about workers' safety and well-being tends to openly communicate with workers in regards to their safety needs, address their safety concerns, motivate workers' safety behaviors, and elicit better safety performance. Through safety communication, employees can have a deeper understanding of the reasons for these safety practices, especially of how their safety behavior is related to organizational effectiveness.

Second, high LMX promotes employee *psychological ownership* because supervisors are representative of the company. High LMX helps to build a sense of connectedness to organizations, which promotes behaviors complying with organizations' norms and expectations (Hirschi, 1969). Indeed, employees' sense of affiliation with their organization is associated with their engagement in safer work practices (Neal et al., 2000; Clarke and Ward, 2006).

Third, *supervisory integrity* will cause supervisors to be perceived as more trustworthy, which promotes trust in exchange relationships with subordinates being more willing to comply with the supervisors. Moreover, when leaders and subordinates have a strong LMX relationship, both parties are more likely to take organizational norms and rules seriously. This leads to an increased chance of their behaving in accordance with established organizational standards and practices and a decreased chance of their violating or cutting corners of organizational norms and policies. Both behaviors are indicative of supervisory integrity (Van Iddekinge et al., 2012; Hinkin and Schriesheim, 2015).

Finally, LMX can increase employee *situation awareness* by facilitating constructive social learning (Tucker et al., 2016) among organizational members. According to Clarke (2013) and Rafferty and Griffin (2004), a positive and supportive leadership might enhance employees' interest in and awareness of problems and key issues inherent in their work environment. Applying this to the safety leadership domain, LMX can improve workers' situation awareness (Endsley and Robertson, 2000a;b), which is critical for accident/injury prevention and safety performance at work. Also, Borjali et al. (2013) showed the significant and positive association between situation awareness and safety climate. Meanwhile, LMX might be associated with minimal power distance between leaders and followers, while LMX can facilitate congruent organizational values, both fostering open discourse (Fairhurst et al., 1987). Hofmann and Morgeson (1999) found a significant and positive association between LMX and safety communication. Mearns and Flin (1999) noted safety communication as one of the key attributes of safety climate.

In sum, with high LMX quality, supervisors and employees often practice *safety communication*. Employees can develop a greater sense of belonging to their organizations (*ownership*) and perceive a greater level of *supervisory integrity* in terms of having greater intention to adhere to espoused organizational norms and practices. Employees can gain a better understanding of workplace hazards via improved *situation awareness* and proactive knowledge/information exchange. The role making, role taking and sense making processes of LMX provide a platform for the emergence and advancement of safety climate (Weick, 1995; González-Romá et al., 2002; Zohar, 2010). Positive LMX and social exchange help workers form congruent and unified mental models regarding the safety aspects of the workers' organization based on empathic listening and mutual interaction. They also motivate workers to align their behaviors to their leaders' espoused and enacted safety efforts because it fulfills their sense of organizational value, priority, and perceived responsibility. Jointly considered, a conceptual model was identified for the present study in which LMX is associated with four organizational variables (ownership, supervisory integrity, situation awareness, and safety communication) that are also associated with two different dimensions of trucking safety climate: organization- and group-level safety climate.

1.2. Predictive modeling with Bayesian network

Safety climate emerges through the interplay among various organizational and work-related factors (Murphy et al., 2014). The interrelations among the five target organizational factors (LMX, ownership, supervisory integrity, situation awareness, and safety communication), as well as target safety climate variables considered in the present study, can be complicated. Specifically, unlike the assumptions of traditional regression analysis, which has been widely utilized in psychological research, non-linear relationships among study variables are possible. For instance, one variable can be associated with another variable only at a certain range of the variables, or their relationship can be curvilinear. Also, strong correlations among the interested variables can increase the chance of multicollinearity problems. Additionally, complex interactions (i.e., up to five-way interactions) among the study variables in traditional regression analysis are not examined because of the difficulty in interpretation and analytic limitations. A Bayesian Network modeling approach is robust in regards to these issues.

Bayesian Network modeling (Pearl, 1988) offers a directed acyclic graph (network diagram), which consists of nodes and arrows. The nodes are treated as random variables (continuous or categorical quantities, or even latent variables) and the arrows (a.k.a., arcs, edges) represent probabilistic relationships. The aim of Bayesian Network modeling is to examine the probabilistic conditional dependency between the nodes, which can be theoretically specified or identified with a data-driven exploration. Bayesian Network modeling utilizes machine learning algorithms for efficiently coping with the uncertainty and complexity of component interactions within a system as a whole (Murphy, 2001; Lee et al., 2019a), enabling flexible modeling of higher-order interactions among the study variables. Also, Bayesian Network modeling, unlike the standard regression modeling approach, does not rely on correlations among the variables and, instead, views a complex system in a modular way. Conditional probabilities between specific system components are examined first and the other components later to maximize the predictive accuracy of the entire model. This helps to avoid the multicollinearity problem (Sebastiani and Perls, 2008; Curtis and Ghosh, 2011). Furthermore, probabilistic dependencies among study variables are represented with a conditional density function which doesn't impose any linearity constraint (Murphy, 2001; Imoto et al., 2003; Kamimura et al., 2003).

Moreover, Bayesian Network modeling allows a predictive modeling approach which is useful for the diagnosis of workplace safety. Mohammadfam et al. (2017) stated that "BN is very useful for prediction and diagnosis; this feature is very important in safety interventions because they are commonly expensive and their effects can only be observed in the long term." In a similar vein Lee et al. (2019a) noted that "(Bayesian Network model) permits the simulation of many different 'what if' scenarios, allowing the researcher to explore any revealed relationship in greater detail." Another important advantage of the predictive modeling approach with Bayesian Network lies in the validation process. After a Bayesian Network model is constructed, either in an exploratory (data driven) or confirmatory (theory driven) manner, parameters can be "learned" using part of the existing data. Then, using the rest of the data, the Bayesian Network model with identified parameters can be used to predict the particular states (for categorical variables) or distribution (for continuous variables) of the study variables, represented as nodes. In this process, the validation test's focal unit can be either individual probabilistic dependency, represented by an arc connecting two nodes (e.g., based on Euclidean distance), or the entire model (e.g., leave-one-out cross-validation, sensitivity analysis). These methods offer an insight on how the study variables are jointly associated, which is critical for the joint optimization of the organizational and managerial systems for occupational safety and health promotion (Murphy et al., 2014). In sum, this paper contributes to safety climate literature by taking the LMX perspective to identify key drivers of safety climate using a novel, systemic Bayesian Network approach as well as the best joint strategies combining LMX and other key drivers (e.g., psychological ownership) to optimize safety climate improvements. Furthermore, the Bayesian Network approach could be used to simulate the key drivers to predict probable changes in safety climate before the actual implementation of safety climate interventions.

Research Question 1: To what extent do five factors (i.e., LMX, psychological ownership, supervisory integrity, situation awareness, and safety communication) influence safety climate?

Research Question 2: What are the best joint strategies of the above workplace factors for improving safety climate?

2. Methods

2.1. Sample

We sent out 9513 surveys to truck drivers from a large U.S. trucking company headquartered in a Midwestern state and received 5803 back (response rate = 61 %). Freight transportation services of the company included regional, long-haul, and intermodal logistics, plus supply chain management. After omitting cases with more than three missing values for the seven study variables, 4497 valid responses were used for the present study. Average age of the final sample was 47.7 (SD = 10.7) and average tenure was 12.4 years (SD = 33.5). Among the drivers in the final sample, 73.8 % were employees while 16.9 % were contractors who were freelance owners and operators of their own commercial trucks. Also, 82.6 % were solo drivers while 8.1 % were team drivers (no response from 9.3 %).

2.2. Measures

2.2.1. Leader-member exchange (LMX)

LMX was measured with six items taken from the LMX-7 scale (Graen and Uhl-Bien, 1995). Items were based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Among the seven items, six items were chosen and some words were adapted to improve the suitability with the context of the trucking industry. A meta-analytic study of Gerstner and Day (1997) demonstrated solid psychometric properties of the LMX-7 scale. Example items included: "My dispatcher understands my problems and needs well enough" and "My working relationship with my dispatcher is effective." Satisfactory internal consistency was detected (Cronbach's $\alpha = 0.86$).

2.2.2. Ownership

Work ownership was measured with five items taken from the psychological work ownership scale (Van Dyne and Pierce, 2004), modifying the wording of some items to better fit the context of the trucking industry. Items were based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Example items included: "Drivers feel as if they own their cargo" and "I feel a very high degree of personal ownership for this truck, like it's mine." Satisfactory internal consistency was detected (Cronbach's $\alpha = 0.77$).

2.2.3. Supervisory integrity

To measure employees' perceptions of the integrity of their supervisors, six items were used, based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Among the original eight items of Simons and Mclean-Parks (2000), six items that were most pertinent to the trucking industry were chosen and wording was adapted for suitability to the trucking industry. Example items included: "My supervisor does what he/she says he will do" and "My supervisor practices what he/she preaches." Satisfactory internal consistency was detected (Cronbach's α = 0.88).

2.2.4. Situation awareness

To measure employees' situation awareness in regards to their work environment, four items were used, based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The items were selected from the questions used by Endsley and Robertson, 2000a,b) and modified to improve contextual pertinence to the trucking industry. Example items included: "During truck inspections, I am extra careful to check for loose parts and/or leaking fluids" and "When I disagree with someone (e.g., dispatchers, mechanics, trainers), I always try to understand why they are making a different recommendation or decision." Satisfactory internal consistency was detected (Cronbach's α = 0.77).

2.2.5. Safety communication

To measure employees' perceptions on safety communication, eight items were used, based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The scale, developed and validated by Huang, et al. (2018), was based on two dimensions representing both top-down and bottom-up communication. An example item of the top-down communication dimension was, "Safety information is always brought to my attention by my immediate supervisor;" an example item of the bottom-up communication dimensions was, "I feel comfortable discussing safety issues with my immediate supervisor." Huang et al. (2018) provided empirical evidence supporting the construct validity of the safety communication scale. Satisfactory internal consistency was detected (Cronbach's α = 0.74).

2.2.6. Trucking safety climate

To measure the trucking safety climate in terms of organization- and group-level safety climate, the Huang et al. (2013a) trucking industry-specific safety climate scale was utilized, comprising 40 items (20 items for organization-level safety climate, OSC; 20 items for group-level safety climate, GSC). Items were based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Construct and criterion-related validities of the scale were well documented in Huang et al. (2013a). Organization-level safety climate pertained to the policies and practices of the company and example items included: "My company cares more about my safety than on-time delivery" and "My company turns a blind eye when a supervisor bends some safety rules." Group-level safety climate pertained to procedures and practices of dispatchers and example items included: "Dispatchers are strict about driving safely even when we are tired or stressed" and "My dispatcher pushes me to keep driving even when I call in to say I feel too sick or tired." Satisfactory internal consistency was detected for both organization-level (Cronbach's α = 0.92) and group- level (Cronbach's α = 0.94) safety climate. Items used in the present study are displayed in Table 1.

2.3. Data analysis

To prepare the data for the Bayesian Network modeling, 269 cases with two or fewer missing values out of seven study variables in each case were imputed based on the predictive mean matching approach (Little, 1988; Morris et al., 2014). It was conducted with "mice" R package (Buuren and Groothuis-Oudshoorn, 2010). This process was necessary because most of the structure learning algorithms for Bayesian Network modeling (except for Naïve Bayes algorithm, which has a strong independence assumption) do not allow missing values in the data (Bayesfusion, 2019). Orak et al. (2019) had noted that increasing the sample size can improve the model prediction accuracy in general.

As described in the introduction section, a theory-based conceptual model was specified in which LMX was connected with four organizational variables: ownership, supervisory integrity, situation awareness, and communication, as well as organization- and group-level safety climate. Then, parameters (probabilistic dependencies) were learned

Table 1
Using Dempster–Shafer theory's rules of combination in integrating opinions from different experts.

Expert	LMX → Safety Communication	LMX ⟵ Safety Communication	LMX ↑ Safety Communication
Expert 1	0.60	0.40	0.00-member exchange
Expert 2	0.65	0.30	0.05
Expert 3	0.80	0.20	0.00
Mass	0.93	0.07	0.00
Expert	Safety Communication → GSC	Safety Communication ⟵ GSC	Safety Communication ↑ GSC
Expert 1	0.60	0.30	0.10
Expert 2	0.50	0.50	0.00
Expert 3	0.70	0.30	0.00
Mass	0.82	0.18	0.00

Note: OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange.

using the randomly selected 70 % of the data.

Bayesian Network modeling was constructed and tested using GeNIe 2.4 (Bayesfusion, 2019). Broadly, there were two steps: learning and validation. Learning (a.k.a., training) means the estimation of model parameters. In machine learning, including Bayesian Network analysis, it is very important for the model to learn with a data set that is independent from the data set which is used for model validation (Penny and Roberts, 1999), because failure to do this could overestimate the model validity, which is known as overfitting. Our analysis adhered to this principle and only 70 % of the data (n = 3147) was used for learning (Gevaert et al., 2006; Vanthienen and De Witte, 2017). Expectation maximization (EM) algorithm (Cooper and Herskovits, 1992; Heckerman et al., 1995) with a random restart was used for the model parameter learning. EM, which is one of the most widely used Bayesian Network parameter learning techniques, attempts to maximize the probabilistic model's expected log likelihood (i.e., an index of model fit) (Murphy, 2001).

Validation is to test for the predictive accuracy of the learned Bayesian Network model and it was done with the remaining 30 % of the data (n = 1350) which was not used for the modeling learning. Specifically, leave-one-out (LOO) cross validation and receiver operating characteristic (ROC) curve analysis were utilized for the present study. In LOO, the Bayesian Network is learned again on n-1 records and tested for its predictive accuracy on the remaining one record, while the process is repeated n times. LOO is the most efficient evaluation method, although it may be computationally expensive when the dataset is large (Bayesfusion, 2019).

Originating from signal detection theory, ROC curve analysis is an excellent way of demonstrating the quality of a model independent of the classification decision. It shows the possible accuracy ranges of the Bayesian Network model-based prediction for target variables. The ROC curve provides helpful diagrams for predictive accuracy. In the diagrams, a diagonal line shows a baseline ROC curve of a hypothetical classifier that is by chance. If a Bayesian Network model is helpful in precise prediction of a particular state of a target variable, the ROC curve is located well above this diagonal line. The area under this ROC curve is called the area under the ROC curve (AUC). An AUC greater than 0.9 is considered excellent, between 0.8 to 0.9 indicates very good predictive accuracy, 0.7 to 0.8 is representative of good predictive accuracy, 0.6 to 0.7 reflect average prediction accuracy, and if it is below 0.6, its predictive accuracy is poor (Choi, 1998).

Expert knowledge was used to update and complement the Bayesian Network model specified with theory. To refine the BN structure, a graphical model was constructed in the form of a directed acyclic graph (DAG) representing interrelationships among all studied variables (i.e., safety climate and its antecedents) on the basis of both expert knowledge and data-driven machine learning approaches (see Fig. 1). The BN can be constructed in two ways: using data-driven structure learning algorithms (i.e., constraint-based and score-based methods) and utilizing experts' knowledge. The former approach generally requires a large volume of data, especially when the targeted BN structure is complicated and involves a great number of variables, whereas the latter approach largely relies on expert knowledge that may be inconsistent with our data. We reasoned that combining both experts' knowledge with data-driven machine learning approaches could facilitate the process of identifying the most probable, as well as theoretically-sound, BN model. Specifically, we established the first model based on previous theories and experts' knowledge and then used structural learning algorithms to find the most probable model. To construct an initial BN structure, we applied the Dempster-Shafer theory to synchronize opinions from three experts (see examples in Table 1). The approach is helpful in reducing the inconsistencies of information collected from multiple sources and has been adopted by other researchers previously (Zhao et al., 2012; Mohammadfam et al., 2017). The process involves five steps:

1) Select three experts who have experience in conducting research in safety climate. In order to select ideal candidates, conduct interviews to assess candidates' knowledge about safety climate models and research.
2) Define three possible relationships between each pair of variables (e.g., A and B) in the following ways: A predicts B (A → B), B predicts A (B → A); and there is no relationship between A and B (A ↑ B).
3) Ask the three experts to assign a value representing the probability for each of three possible relationships. Note that the sum of the three possible probabilities from each expert must be equal to one.
4) Deploy the Dempster-Shafer theory to combine the probabilities obtained from ten experts.
5) Select the relationship with the maximum mass value to represent the relationship between two variables (e.g., A and B).

3. Results

Overall model fit measure for the BN model (see Fig. 2, the best and worst scenarios are presented in Figs. 3–4) was *Log(p)* = -17416.33. Before examining the overall predictive accuracy of the model, strength of influence per each predictor was examined based on Euclidean distance (Oniśko and Druzdzel, 2014). Euclidean distance focuses on the absolute differences between probabilities of the two variables (nodes) and suggests the strength of influence between the two nodes connected by that arc. Average strength of influence operates as the plain average

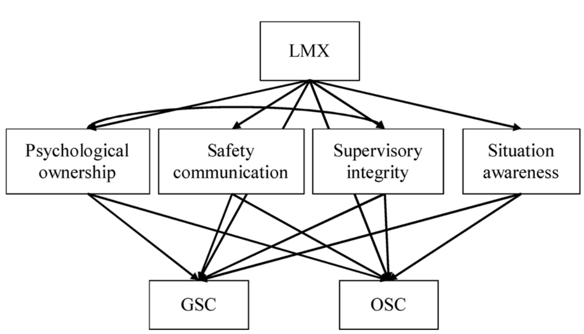

Fig. 1. The Bayesian Network model for the current study; arrows represent the proposed relationships based on the LMX theory, machine learning analyses, and experts' input.
LMX = leader-member exchange, OSC = organization safety climate, GSC = group safety climate

over distances, and weighted strength of influence weighs the distances by the marginal probability of the parent variable (node). Table 2 presents the strength of influence of five predictors related to safety climate. As indicated in this table, supervisory integrity and LMX have the strongest direct influences on OSC and GSC.

Predictive accuracy and confusion tables are the most popular tools used by researchers to evaluate the predictive performance of their BN models. Table 3, known as the confusion table, summarizes the results obtained from the test sample (30 % of the data sample). As evident from this table, the BN model constructed in the current study is able to predict organization- and group-level safety climate with an overall accuracy of 70 %. Specifically, the predictive accuracy for OSC and GSC was 65 % and 75 %, respectively. The accuracy of the BN in predicting low, medium, and high OSC was 72 %, 52 %, and 74 %, respectively, whereas the accuracy of the BN in predicting low, medium, and high GSC was 76 %, 61 %, and 85 %, respectively. The ROC curves are presented to show predictive accuracy in diagrams. As indicated in the ROC curves (see Fig. 5), OSC has very good predictive accuracy (AUC = 0.86 and 0.85 for low and high OSC, respectively) and GSC has excellent predictive accuracy (AUC = 0.91 for both low and high GSC).

The sensitivity of GSC and OSC to changes in joint effects was assessed and the results are shown in Table 4 (only top two joint effects on GSC and OSC are presented). As expected, increasing the level of the joint variables could lead to increased GSC and OSC. For example, when LMX and psychological ownership increased, the proportion of high OSC increased with 0.14. In other words, the higher the LMX and psychological ownership, the higher the probability of better OSC.

The results (see Table 5) indicate that the most effective joint strategy for OSC improvement is the combination of LMX and psychological ownership (e.g., giving employees more autonomy). When both LMX and psychological ownership were rated high, 81 % of those participants perceived high OSC. The results also indicated that the most effective joint strategy for GSC improvement is the combination of LMX and psychological ownership. When both LMX and psychological ownership were rated high, 93 % of those participants perceived high GSC.

4. Discussion

The current study contributes to the safety climate literature in several ways. First, taking the perspective of LMX theory, we constructed a reliable predictive model of safety climate by identifying supervisor-related factors contributing to the safety climate perceptions. Furthermore, by applying the Bayesian Network machine learning approach, we were able to simulate and identify the impacts of five key drivers in relation to possible changes in safety climate and compare the relative impacts of the five drivers. Second, among the five organizational contributing factors, supervisory integrity and LMX had the strongest independent effects on OSC and GSC. Third, the model results showed that the effects of LMX on OSC and GSC were conditionally dependent on the other four factors which were psychological ownership, supervisory integrity, situation awareness, and safety communication. Finally, the best joint strategies for improving OSC are the joint optimization of psychological ownership and LMX as well as situation awareness and LMX, whereas the best joint strategies for improving GSC are the joint optimization of safety communication and LMX as well as psychological ownership and LMX.

4.1. Theoretical implications

Using the LMX theory as the foundation, we were able to construct a theory-driven trucking safety climate model and examine its predictive validity using the Bayesian Network approach. Although supervisors have long been identified as key players in promoting safety climate (Kapp, 2012), our theoretically-driven model provides the rationale behind why and how the supervisor matters. Consistent with the LMX literature (e.g., Dulebohn et al., 2012), we found that exchange quality

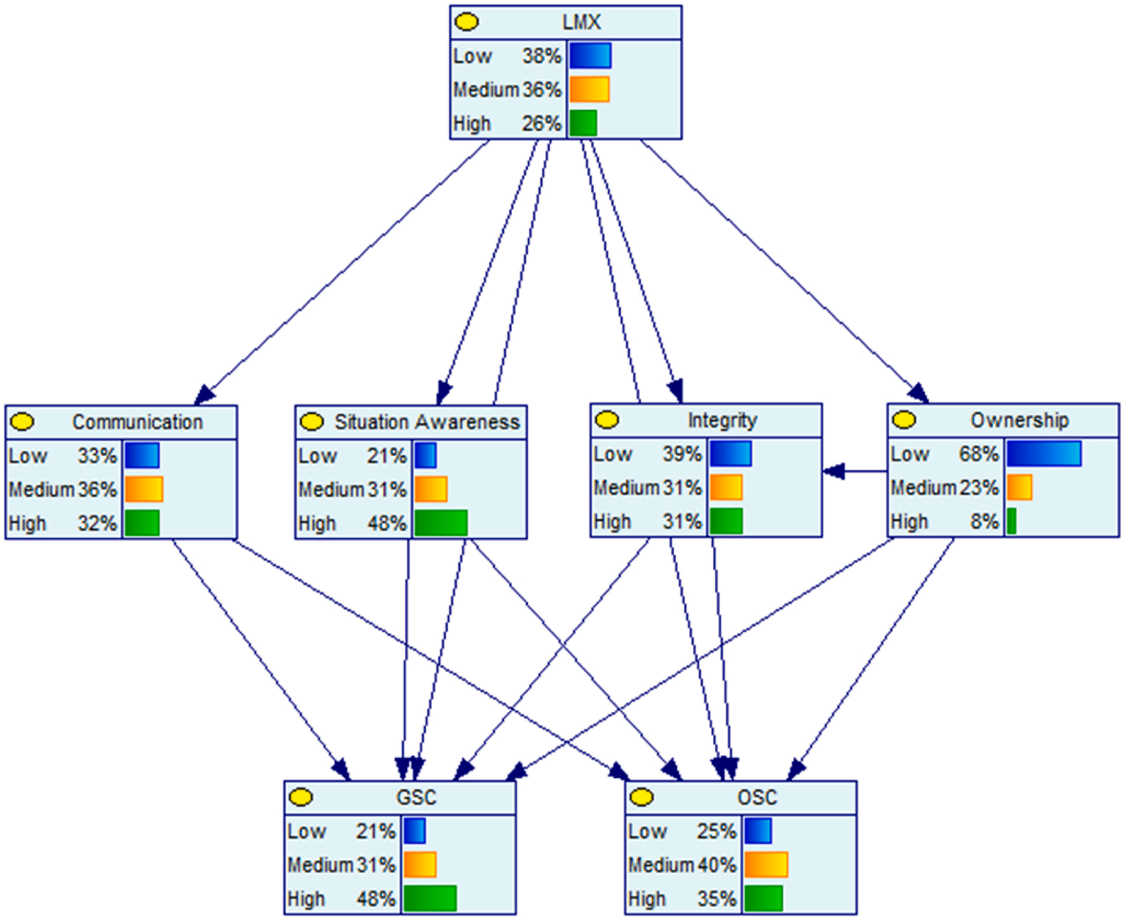

Fig. 2. Final Bayesian Network Model.
OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange

plays a critical role in employee safety-related job attitudes and performance. Based on our results, LMX and supervisory integrity are the most influential predictors of safety climate quality. This finding emphasizes the role of trust when supervisors instill safety attitudes and behaviors in their employees. Only when employees perceive the supervisors genuinely practice safety behavior and truly care about them, will the employees perceive positive GSC and OSC.

Second, the study found, that the best joint strategies for improving both OSC and GSC include psychological ownership. This highlights the important role, played by employees' feelings of having a stake in the company, in promoting a workplace of positive safety climate. That is, employees need to feel they psychologically own the company and the equipment (e.g., truck) in order to perceive a positive safety climate (Zohar et al., 2014). Safety behaviors are dynamic as the environment hazards and accidents can be unpredictable. For employees to proactively perform safety behaviors and accept organizational safety-related policies, employees need to feel their behavior is related to the organization and they have autonomy over the equipment.

Third, the core of manifestation of OSC and GSC may be different as one of the best joint strategies for improving OSC is situation awareness and LMX, whereas the best joint strategies for improving GSC is safety communication and LMX. That is, GSC tends to associate with actual safety behaviors performed by employees whereas OSC is more relevant to organizational policies and knowledge concerning safety. Therefore, open communication would be more critical to improving GSC, as supervisors need to explain, coach, and provide feedback on employees' safety attitudes and behaviors. In contrast, situation awareness reflects the extent to which an employee proactively seeks and is aware of the situational information. Such behavior tends to involve interaction among employees from different departments or companies. Therefore, situation awareness would be more important for OSC.

Finally, the use of a Bayesian Network approach also offers more flexibility in the prediction of OSC and GSC. Unlike the linear modeling approach, the multiple combinations of a Bayesian Network approach can be used to examine the posited organizational contributing factors to trucking safety climate in prediction of a specific state (i.e., low, high) of either OSC or GSC. That is, with the Bayesian Network approach, it is possible to identify one set of predictors for high OSC and a different set of predictors for low OSC.

4.2. Practical implications

Our findings suggest that LMX and psychological ownership are the key drivers for both OSC and GSC. Therefore, organizations should encourage positive supervisor behaviors that may promote high LMX. One way of doing so is to increase organizational support for the supervisor, as such support will not only increase LMX, but also increase subordinates' perceived organizational support from increased LMX (Eisenberger et al., 2014). Examples of organizational support relevant to safety include employee well-being programs and benefits. Only when employees perceive good intentions from the organization and the supervisor, will employees perceive positive safety climate. Organizations could promote employees' psychological ownership by engaging in frequent and high-quality communication with employees and providing employee benefit packages (e.g., reduced insurance premiums).

The finding that the OSC and GSC can have different key drivers suggests that different strategies are needed for improving each of them.

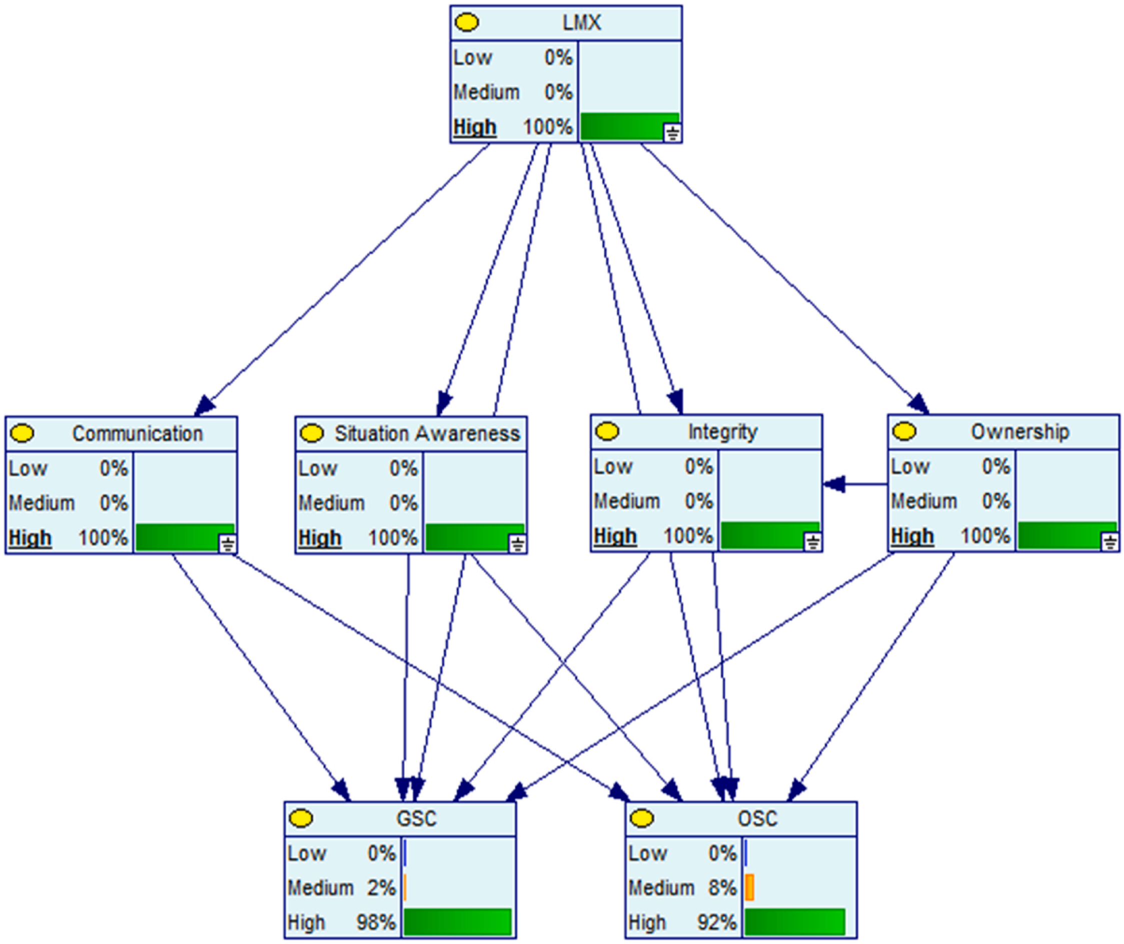

Fig. 3. The Best Scenario of Final Bayesian Network Model.
OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange

For example, situation awareness is a key antecedent of OSC and company training may be a means to increase employee situation awareness. Communication is key to GSC and an open communication policy and supervisor training in communication skills may be helpful for enhancing communication.

Finally, the model can be used to align managerial practices, safety leadership, and safety climate improvement efforts. For example, the model can be useful for the design of trucking safety climate intervention programs by identifying weaknesses and strengths. For example, knowing that the key predictors for both OSC and GSC are LMX and psychological ownership suggests the intervention should incorporate the elements that promote LMX and psychological ownership as a first priority. In the design of intervention programs, the emphasis on situation awareness and open communication needs to be different for OSC and GSC. With the guidance of this predictive model, practitioners will be able to better pinpoint the key factors leading to better safety climate and design the implementation program accordingly.

4.3. Limitations and future research directions

Some limitations of the current study deserve attention. First, the current research used a cross-sectional design with a self-report method. These approaches limit the causal inferences of the findings. Further studies may consider multi-sources or a longitudinal design to provide stronger evidence for the validity of the model. However, as the goal of our study was to provide a predictive model of safety climate, this limitation should not pose a severe threat to the potential contribution of our study. Second, the findings of this study may be applicable only to the participating trucking company. Other trucking companies should consider the extent to which the company profile resembles the survey company before applying our findings in practice. However, as the proposed safety climate diagnostic approach was theory driven and the LMX literature has received much support from data collected in a variety of companies and industries, we are confident that the model could be applied broadly to other companies and industries. Future studies that examine the model in other companies and industries can provide further examination on the generalizability of the proposed safety climate diagnostic model. Third, although it is a strength that BNA was used in the current study to simulate the potential impacts of key drivers to predict probable changes in safety climate, no actual safety climate interventions are conducted following the simulation. It would be more powerful if, in future studies, interventions are conducted based on the simulation results to validate and demonstrate the actual impact. Finally, although the joint impacts on safety climate of five key variables in the LMX literature were examined in the current study, more key drivers can be included and examined at once utilizing the power of BNA. Future studies can extend the list of potential key drivers to include more variables in the study (e.g., physical, psychological, personnel, technical, policy).

The long-term goal of this line of research is to develop and test efficient safety climate interventions that will enhance safety and reduce injuries in the workplace. Specifically, we propose an approach that first develops a theory-driven (LMX) model of safety climate and then examines the ecological validity of the model with a data-driven (BN) approach. This project provides an analytical approach to 1) identifying the individual and joint impact of key drivers of safety climate, 2)

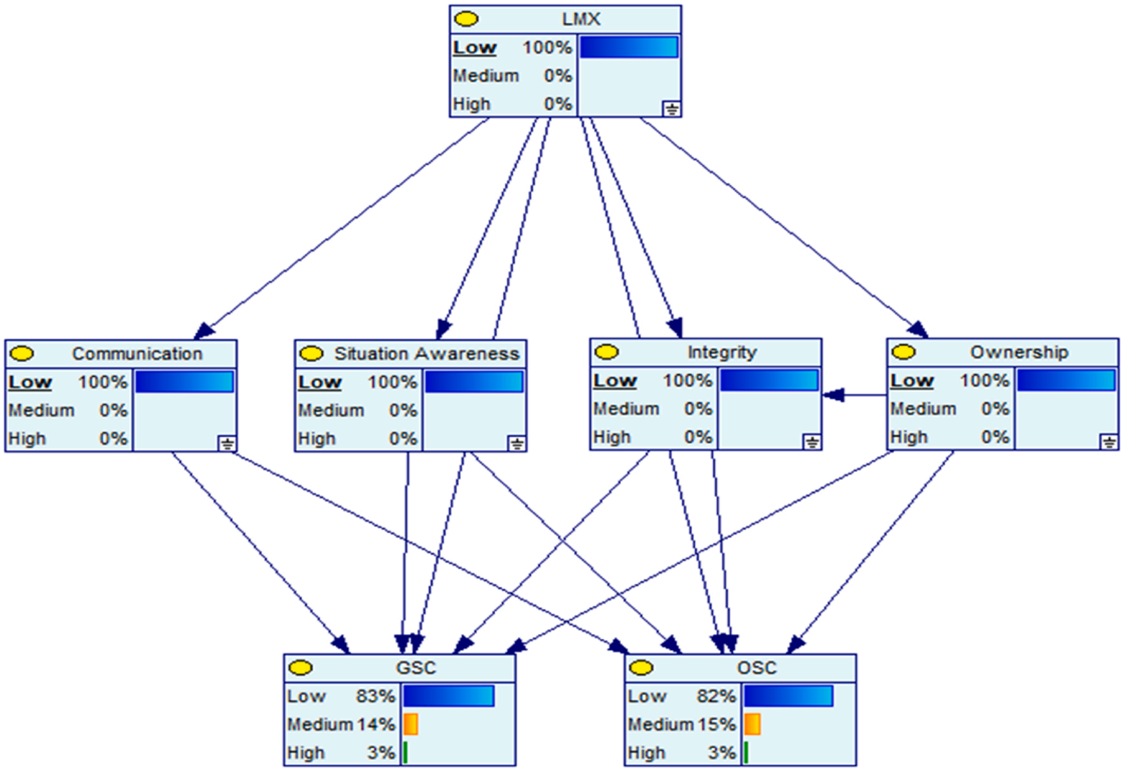

Fig. 4. The Worst Scenario of Final Bayesian Network Model.
OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange

Table 2
The strength of influence of five drivers in predicting safety climate.

Predictor	Outcome	Averaged strength of influence	Weighted strength of influence	Rank
Supervisory integrity	GSC	0.33	0.33	1
LMX	GSC	0.31	0.31	2
Psychological ownership	GSC	0.30	0.30	3
Safety communication	GSC	0.28	0.28	4
Situation Awareness	GSC	0.27	0.27	5
Supervisory integrity	OSC	0.33	0.33	1
LMX	OSC	0.29	0.29	2
Psychological ownership	OSC	0.34	0.34	3
Safety communication	OSC	0.30	0.30	4
Situation Awareness	OSC	0.32	0.32	5

Note: OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange.

evaluating organizational needs for further development of interventions that could optimize safety climate improvements, and 3) simulating the key drivers to predict probable changes in safety climate before the actual implementation of safety climate interventions. By using this deductive and theory-driven approach, our conceptual model can be easily generalized to other companies and industries as the model was not developed inductively from observing companies and workers in a specific context. With the advanced statistical approach that takes into account the base rate probability in the field, the findings will offer greater relevance in terms of practical implementation. This general

Table 3
Confusion table of the BN constructed in the present study.

Predicted OSC by the model			Actual OSC	Accuracy	Overall accuracy
Low	Medium	High			
252	81	17	Low	72 %	65 %
92	262	150	Medium	52 %	
14	113	369	High	74 %	
Predicted GSC by the model			Actual GSC	Accuracy	Overall accuracy
Low	Medium	High			
224	64	6	Low	76 %	75 %
88	249	84	Medium	59 %	
11	82	542	High	85 %	

Note: BN = Bayesian Network, OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange.

approach can be applied to any industry. This can, in turn, lead to safer work environments and work practices, and fewer accidents and injuries as well as improved job satisfaction and quality of life.

Author statement

We, the named authors, declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author is the sole contact for the Editorial process. She is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

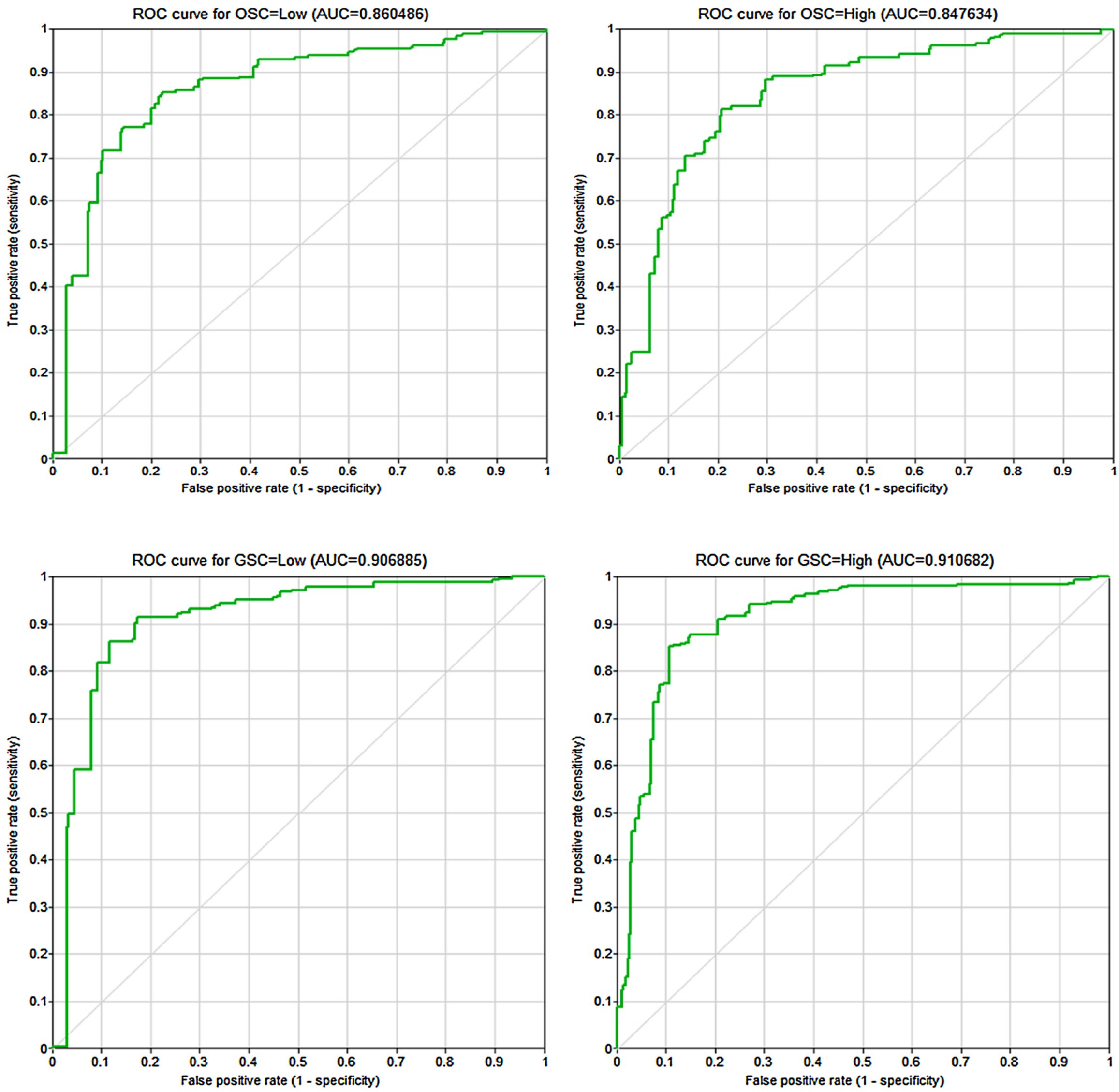

Fig. 5. ROC curves indicating the predictive accuracy of low and high OSC and GSC.
Note. ROC = receiver operating characteristic, AUC = area under curve, OSC = organization safety climate, GSC = group safety climate.

Table 4
Top two joint factors for OSC and GSC.

OSC		GSC	
Contributing factors to high OSC	Derivative (basic sensitivity measure)	Contributing factors to high GSC	Derivative (basic sensitivity measure)
LMX & Psychological ownership	0.14	LMX & Safety communication	0.10
LMX & Situation Awareness	0.09	LMX & Psychological ownership	0.07

Note: OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange.

Table 5
The joint strategies with the greatest effect on safety climate in this company.

Strategy	Proportion of High OSC	Proportion of High GSC
(“LMX” = high) + (“Psychological Ownership” = high)	81 %	93 %
(“LMX” = high) + (“Situation Awareness” = high)	70 %	
(“LMX” = high) + (“Safety communication” = high)		93 %

Note: OSC = organization safety climate, GSC = group safety climate, LMX = leader-member exchange.

Declaration of Competing Interest

The authors whose names are listedafter after the title certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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