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Workplace injuries, safety climate and behaviors: application of an artificial neural network

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This article proposes and tests a model for the interaction effect of the organizational safety climate and behaviors on workplace injuries. Using artificial neural network and survey data from 306 metal casting industry employees in central Anatolia, we found that an organizational safety climate mitigates workplace injuries, and safety behaviors enforce the strength of the negative impact of the safety climate on workplace injuries. The results suggest a complex relationship between the organizational safety climate, safety behavior and workplace injuries. Theoretical and practical implications are discussed in light of decreasing workplace injuries in the Anatolian metal casting industry.

Keywords: safety climate; safety behavior; workplace injuries; artificial neural network

1. Introduction

Lethal industrial incidents have occurred in previous years (e.g., 301 killed workers in a coal mine fire in Turkey, May 2014; 75 killed at a factory explosion in China, August 2014). This provides alarming evidence that people are dealing with precarious and unsafe working environments [1]. In 2016, Eurostat reported a staggering score of 2,640,588 serious work-related injuries from the manufacturing (including the metal) industry in the European Union [2]. The severity of the costs of accounting for these incidents inevitably prompted organizations to re-evaluate their safety policies. The safety climate is an aspect of the organizational climate [3,4].

The safety climate delineates workers' perceptions vis-à-vis the management policies, procedures, practices and behaviors which are conducive for their safety in the workplace [5,6]. Despite extensive study of this topic and the different dimensions used to measure the safety climate across industries, the most commonly encountered in the literature include management values (e.g., the extent of the management high-safety priority), safety systems (e.g., the level of perceived accident-preventive effectiveness of the safety procedures), safety communication (e.g., the widely shared level of safety-related information), safety training (e.g., the level of relevance, comprehensiveness and accessibility of training) [7–10], work pressure, risk and safety competence [11–13].

These dimensions depict the workers' perceived values and the priority that the organization assigns to safety [3,14,15]. Barbaranelli et al. [7] proposed that two approaches stand in the appraisal of safety climate. The first stresses measuring the safety climate from an industry-related or organization-related perspective, e.g., evaluating an organization safety climate based on its intrinsic characteristics or the characteristics of the industry to which it belongs. The second approach stresses the universality of the safety climate, which spans beyond the boundaries and specificities of each industry and comprises the most essential attributes of a safe working environment. In the present study, we consider the latter because while we admit that some industries or sectors present more exposure to danger and risk uncertainties than others, we believe that security is primary to every workplace as far as human life is concerned.

Previous research [6,8] in this stream assessed the safety climate from a cross-industry perspective. In addition, two levels of measurement of the safety climate stem from the literature: a group level and an individual level. The first reflects the initial conceptualization of the safety climate [4,9] as a social paradigm characterizing groups of employees rather than mere individual idiosyncratic perceptions; in this matter, it is operationalizable at the group level – which refers to the departments or units within a company, or the relevant supervisor's appraisal and considerations for safety – and at the organizational level – which refers to the aggregate individual perceptions of safety-related top/general management attitudes and company policies [16].

Later, Ostroff et al. [17] posited that the safety climate can also be conceptualized as the psychological safety climate, referring to the employee's perception of safety-related associations of policies and practices. Christian

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*Corresponding author. Email: me@mohammedabubakar.com et al.'s [18] meta-analysis provided support, evidencing a high occurrence of a safety climate individual level of analysis [14]. With respect to this article, the research will deal with the safety climate at an individual level. No study to the best of our knowledge has previously examined how the organizational safety climate and safety behavior simultaneously influence the extent to which workplace injuries happen. This study is thus the first to propose and test a model for the interaction effect of the safety climate and safety behavior on workplace injuries, which is the first aim and thus a theoretical contribution.

Prior studies relied heavily on correlation, regression, linear modeling and structural equation modeling. This study also aims to deepen our understanding of how the safety climate, safety behaviors and workplace injuries are associated using machine learning, more specifically, an artificial neural network (ANN). This method provides significant methodological contribution, as the non-compensatory ANN can complement the weaknesses of compensatory linear structural equation modeling [19]. In this sense, it helps to validate existing findings and also set the stage for future studies on artificial intelligence and machine learning application.

2. Materials

2.1. *Safety climate and workplace injuries*

As an aspect of the organizational climate, the safety climate is a social-cognitive construct [15] which entails supported and rewarded role behaviors by supervisors' actions and reactions, based on organizational events from which employees will assign cognitive interpretation and sense-making of their environment. According to social cognitive theory [20], psychosocial functioning emerges from a triadic reciprocal causation between cognitive and idiosyncratic factors, behavior and environmental events which affect each other bi-directionally [21].

Specifically, an employee faces three forces which shape and guide his course of action within the workplace, and he attempts to interpret the information coming from his external environment (organizational context) to adjust them to cognitive processes and behave subsequently to the resulting interpretations [4,22]. The events occurring within the organization operate as climate indicators about the primacy of salient facets, which address what is to be expected as a consensual behavior outcome [15,20].

Precisely, through continuing interpretative processes of event patterns and complex and equivocal circumstances in the workplace [4,23,24] into psychologically meaningful terms known as sense-making, employees will engage in a symbolic interactionism [15,25] which will position them in a cognitive exchange to meet a consensual explanation of the significance of the event, the practice and procedures in their workplace [24].

Thus, this social interaction will create a climate that is a convergent and collectively created meaning of the organizational settings, values and priorities which steps beyond the scope of individual perception, and will set a subjective–normative impact on individual and group behavior [4,14,15,21,24]. This explains how the safety climate represents the shared perception amid employees of the organizational safety priority.

Safety procedures and values have the likelihood to frame employees into careful and risk-free behavior leading to fewer workplace injuries; contrarily, a safety-undermining set of procedures and values will frame employees into careless and risky course of actions for the sake of efficiency or timing, and the effect will likely enhance the occurrence of injuries in the workplace [12,26]. Occupational injuries are the resultant of two antecedents according to the US National Institute for Occupational Safety and Health (NIOSH): physical hazards and psychological stressors. The former embraces excessive effort, ergonomics, workplace violence and pathogens exposure; the latter includes fatigue, role conflict and low control/high demand [27].

The safety climate has gained tremendous interest in the literature, for it has shown some association with safety outcomes [12,18]. Some recent studies have found that the safety climate affects the workplace injury occurrence level. Leitão and Greiner [14] reviewed 17 peer-reviewed quantitative studies and found supportive evidence for a supported or partially supported relationship between safety climate and injuries (for detailed information, see Tables 2–4 of this study). In large-scale, cross-sectional research with more than 15,000 employees from the general working population, Ajslev et al. [6] found that the amount of safety climate issues was positively associated with greater odds for an accident at work. Similarly, Anderson et al. [28] found that a 1-point increase in the safety climate score is associated with a 35% reduction in work injury among Washington State truck drivers.

Furthermore, Zadow et al. [29] reported that the psychosocial safety climate has a significant negative association with injury rates, and unreported work injuries in healthcare work settings. The metal casting industry is particularly characterized by an extreme and harsh working environment; employees' have greater likelihood of exposure to silica dusts which can provoke silicosis, or gases that are sometimes toxic when in large quantities. In addition, exorbitant noise can cause hearing dysfunction or loss when highly intense, and, lastly, heat (radiant and ambient) which is the principal factor in foundry jobs can also cause heat exhaustion, infrared burn or severe burns from metal in fusion or hot containers [30]. In this regard, we propose that if in such harsh working environments employees perceive that the safety-related policies and procedures are contingent to production efficiency or speed, e.g., safety appears to be below the scheme of priorities in the organization, then the likelihood for hazardous and non-hazardous incidents or injuries would be greater. Thus, the following hypothesis is proposed:

> H_1: employees' safety climate perception has a significant impact on workplace injuries.

2.2. *Moderating role of safety behavior*

Safety behavior depicts employees' actions for self-protection, with the ultimate goal of evading danger [31,32]. Different approaches have been used to characterize safety behaviors. For instance, Griffin and Neal [8] used the job performance taxonomy of Borman and Motowidlo [33] as task performance and contextual performance to split safety behavior into two components. The first, safety compliance, refers to the adherence and completion of core safety-related activities and wearing of personal protective equipment which are required by formal work procedures to keep the workplace in a minimum safety manner [8,34–36].

The second component, safety participation, refers to employees' behaviors that help develop a safety-supportive work environment, but which per se do not contribute to their personal safety; these include, among others, promoting and attending safety programs and meetings, provide safety suggestions and assistance to colleagues with safety-related issues, and a demonstrate safety initiative [4,32,34,36]. Aryee and Hsiung [34,p.28] also proposed two components of safety behaviors, namely safety initiative and unsafe behaviors, which the authors defined as employee willingness to 'contribute to the formulation of safety rules and regulations beyond compliance with these rules and regulations'.

A review by McSween [37] investigating the antecedents of US-based companies' industrial disasters proved that employees' behavior was the overwhelming cause of accidents/injuries at 76%. Our proposed model posits that safety behavior may act as a catalyst factor in how the perceived climate can affect occupational injuries, in either enhancing or mitigating that association. This relationship can be understood under the umbrella of the conservation of resource (COR) theory [38] and the social cognitive theory of self-regulation [39]. The COR theory bases its tenet on resource conservation and acquisition, e.g., people get motivation in protecting their current resources and accumulating new ones. In addition to this tenet, the two core principles posit that the loss of a resource is more salient than its gain (primacy of resource loss), and the investment of a resource is aimed at protecting the self from a resource loss or recovering from a resource loss (resource investment) [40].

As already mentioned, the casting industry work environment is tough and highly risky, and a perceived low safety climate is not helpful for workers in such a context. A resource loss and/or threat which result(s) in strain has the potential to motivate one in protecting the self against future loss [40]. In this vein, physical and psychological integrity will be a resource that a worker will engage himself in protecting, to avoid its loss (injuries or musculoskeletal disorder [MSD]). In the case of a low safety climate where the work environmental factors are not supportive of a worker's safety, such loss will be a threat to his/her well-being [40]. In addition, a tenet of Bandura's [39,p.249] social cognitive theory of self-regulation postulates that 'the causal agency resides in forethought and the self-regulatory mechanism by which it is translated into incentives and guides for purposive action'.

This suggests that an employee will consider the current safety climate context in his/her organization as an external factor and will map it with prospective actions (exhibit safe or unsafe behaviors) to forestall through a cognitive process the possible outcomes (injury avoidance or causation). The proactive anticipatory path that the employee will engage in is enhanced by his/her level of self-efficacy, which is the belief about one's capabilities having control over one's own functioning and events affecting one's life, and will determine the desired outcomes [39]. One's decision to invest in resources is based on personality aspects like conscientiousness [41], and Halbesleben et al. [40] suggested that the better management of resources with the purpose of mitigating negative influences at work seemed to be a characteristic of highly conscious people.

Safe behaviors will be the set of resources that a worker will invest in to avoid injuries in a case of low safety climate or to diminish the odds for potential injuries or MSDs. Research has proven that safe behaviors produce a negative impact on workplace injuries [17,34,42–45]. In this vein, we believe that positive safety behavior will lessen the odds of injuries in a high or low safety climate compared with negative safety behavior. In a low safety climate, there are high chances to have an incident or injury; in this regard, a worker's positive safety behaviors will likely mitigate the potential occurrence of injuries. In a high safety climate, the chances for incidents or injuries are rather controllable and limited; in that case, a worker's positive safety behaviors will nearly annihilate the narrow hazard probability of injuries. Thus, we formulate the following hypothesis:

> H_2: employees' safety behavior will moderate the relationship between the safety climate and workplace injuries, such that the impact of the safety climate on workplace injuries will be higher when safety behavior is high.

3. Methods

3.1. *Research context*

The Turkish metal casting industry continues to be challenged with injury rates that are higher than other industries. A report by Türkiye İş Güvenliği Uzmanları ve

İşyeri Hekimleri Topluluğu (TÜİSAG) [46], an organization responsible for workplace safety in Turkey, suggests that the industry has one of the highest injury rates. In a search for the cause of industrial injuries, we develop a framework that utilizes machine learning, more specifically, an ANN. Heinrich [47,p.4] wrote that 'In the occurrence of accidental injury, it is apparent that man failure is the heart of the problem, equally apparent is the conclusion that methods of control must be directed toward man failure'. To provide comprehensive answers for the Turkish metal casting industry**,** the current research model tested the interplay between the safety climate, safety behavior and workplace injuries.

3.2. Procedure

Figure 1 depicts the research model and the proposed hypotheses. Utilizing a judgmental sampling technique, data were obtained from the metal casting industry. The survey items were developed in English and then back-translated into Turkish by two linguistics experts. Ten employees were selected at random to participate in a pilot survey; the result show that the questions were fully understood as they did not have any difficulties. Then, a total of 500 questionnaires were distributed to the respondents. The questionnaires were accompanied with a cover letter explaining the voluntary nature of the study. Confidentiality was assured to decrease the potential social desirability bias and to reduce the threat of common method bias [48]. Some of the returned forms had missing data, and only 306 valid forms were utilized.

3.3. Measures

The safety climate was measured with 11 items borrowed from Kvalheim and Dahl [11]. The reliability of the scale items was measured with Cronbach's $\alpha = 0.947$, and the mean score was relatively high (*M* 3.755).

Safety behavior was measured with 11 items borrowed from Tucker and Turner [49]. Cronbach's α was above the cutoff point of 0.700, and the mean score was moderate ($\alpha = 0.949$, *M* 2.397).

Workplace injuries were measured with 10 items borrowed from Hemingway and Smith [50] ($\alpha = 0.922$, *M* 2.296). All variables were measured using a 5-point scale from 1 = *strongly disagree* to 5 = *strongly agree*.

Regarding demographic data, the sample consisted of 24.5% of workers between the ages of 36 and 40, 21.6% between 31 and 35 years, 19.6% between 26 and 30 years, 15.7% between 41 and 45 years, 9.8% below 26 years and the rest above 46 years. An overwhelming number of the respondents were male (94.8%) and the rest female. Furthermore, 80.1% of the respondents were married and the rest single. Moreover, 48.0% have a monthly income of TRY 1000–2000, 35.6% have TRY 2000–3000, 15.7% have more than TRY 3000 and the rest have less than TRY 1000.[1]

In terms of formal education, 54.2% of the respondents have high school diplomas, 20.3% have primary school certificates, 12.1% have college degrees, 9.2% have bachelor's degrees and the rest have higher degrees. In terms of organizational tenure, 34.6% of the respondents have between 4 and 7 years of work tenure, 28.1% have between 1 and 3 years, 21.6% have between 8 and 10 years, 10.8% have more than 10 years and the rest have less than 1 year of work tenure. In terms of work status, 28.1% are common laborers, 24.5% are machine operators, 17.3% are pourers, 11.1% are screeners, 9.8% are miners and the rest are unit chiefs.

We measured the ratio of accidents in the companies under investigation by asking employees the frequency of accidents: 39.2% of the respondents stated that accidents happen rarely, 33.0% said sometimes, 12.7% said often, 9.8% said very often and the rest stated never. We then moved ahead to ask the level of safety measures (e.g., safety education, training programs and seminars) taken by the organization in order to quantify the reliability of their responses. About 31.7% stated that such programs are held rarely, 29.1% stated frequently, 21.2% said sometimes, 10.5% said very frequently and the rest stated never.

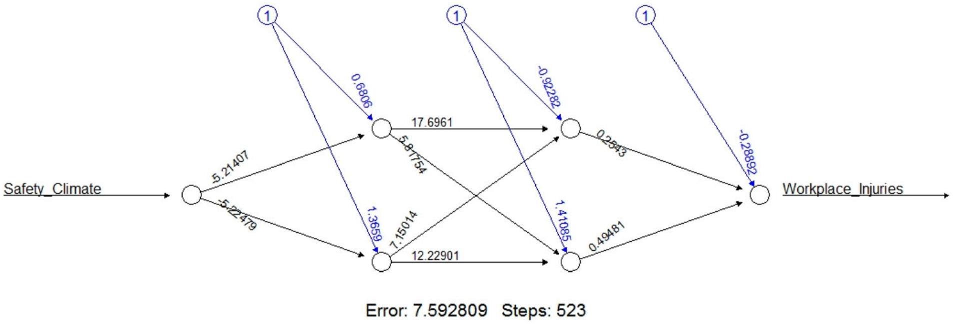

Figure 1. Neural network model for safety climate and workplace injuries.

4. Results

4.1. Artificial neural network analysis

Prior studies have utilized methods like structural equation modeling, linear modeling and regression analyses. What is lacking in the literature is machine learning that can predict human behaviors; employees are humans, and as such their behaviors cannot be rational with respect to accidents and injuries as noted by Simon [51]. This creates the need for methods that can anticipate and predict human behaviors. An ANN outsmarts other methods (e.g., regression and structural equation modeling) as it can detect both linear and non-linear relationships with high predictive accuracy [52]. Moreover, an ANN requires no multivariate assumptions such as normality, linearity or homoscedasticity to be fulfilled. This has received support from various scholars [52,53]. The extant theoretical and methodological reasoning makes an ANN suitable for study.

Table 1. GLM coefficients for workplace injuries.

Predictor variable	Estimate	*SE*	*t*	*ρ*
(Intercept)	3.592	0.297	12.064	0.001***
Safety climate	–0.331	0.075	–4.369	0.001***

***$p \leq 0.001$.
Note: Dispersion parameter for Gaussian family taken to be 1.084442; null deviance = 267.95, *df* = 229; residual deviance = 247.25, *df* = 228; Akaike information criterion = 675.35. Estimate = unstandardized regression coefficient; GLM = generalized linear model.

First, a composite score for each variable was computed, and then the direct relationship between the safety climate and workplace injuries using a generalized linear model (GLM) in R version 1.0.136 was tested. The outcome presented in Table 1 shows that the impact was negative and significant. Furthermore, the linear model produces a root mean square of error (RMSE) that is equal to 1.189. ANN multi-layer perceptron utilizing the Resilient Backpropagation with Weight Backtracking algorithm provided in R version 1.0.136 (neuralnet package) was employed for this study. Logistic function is used as the activation function for both hidden and output layers of the ANN model and the sum of squared errors (SSE) was used as the differentiable error function. The ANN predicted an RMSE of 0.071. Furthermore, the synaptic weights of the input nodes on the hidden and output nodes are shown in Figure 1. In Figure 2 the distribution of the generalized weights was below 0, suggesting a negative effect.

As a next step, we produce an interaction term by multiplying the aggregated scores of safety climate and safety behavior. Then, we tested the relationships via the GLM and ANN. Using the prediction function in the neuralnet GLM predicted a RMSE that is equal to 1.189, whereas the neural network predicted the model better with an RMSE of 0.065 and the number of hidden nodes generated was (3, 2). The synaptic weights of the input nodes on the hidden and output nodes are shown in Figure 3.

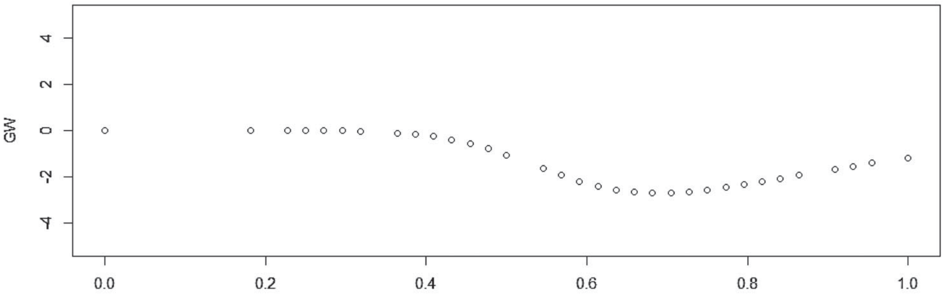

Figure 2. Plot for safety climate without a moderator.
Note: GW = generalized weights.

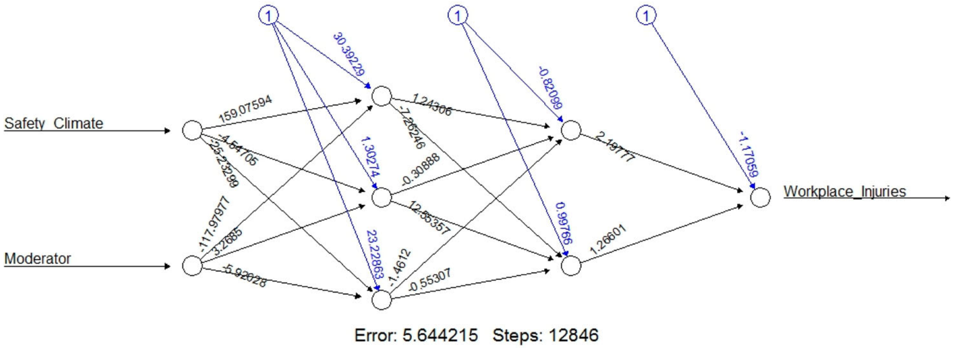

Figure 3. Neural network for the full model.

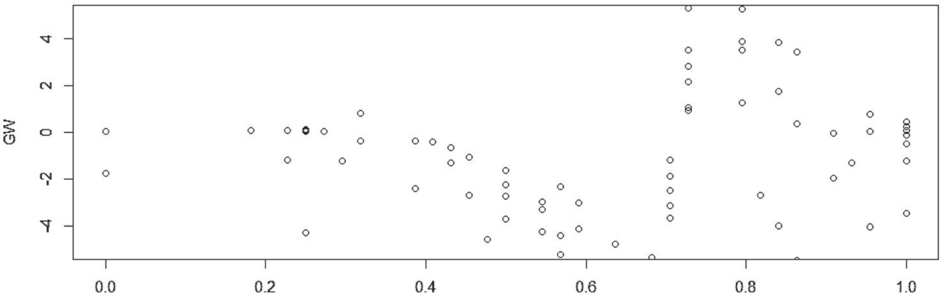

Figure 4. Plot for safety climate with a moderator (response variable: workplace injuries).
Note: GW = generalized weights.

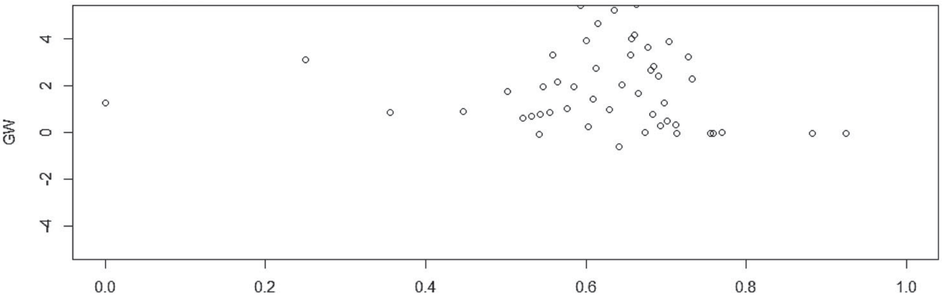

Figure 5. Plot for moderation (response variable: workplace injuries).
Note: GW = generalized weights.

The training process needed 12,846 steps until all absolute partial derivatives of the error function were smaller than 0.001. The estimated weights show that the safety climate exerts significant negative effects on workplace injuries in Figure 2. However, the addition of safety behavior into the model intensifies this effect. The distribution of the generalized weights in Figures 4 and 5 suggests that the safety climate when moderated by safety behavior has a non-linear effect as the variance of their generalized weights are mostly less than 1.

To bypass the problem of potential bias because of model over-fitting, a 10-fold cross-validation test was carried with a ratio of 75:25 data for training and testing. The RMSE from 10 networks was used to examine the accuracy of the model. The RMSEs presented in Table 2 show that the model prediction is reliable. Thus, H_1 and H_2 received empirical support. The codes for ANN analysis are provided in the Appendix.

Table 2. Artificial neural network RMSEs.

Neural network	Training	Testing
1	0.053	0.061
2	0.056	0.052
3	0.052	0.034
4	0.053	0.039
5	0.052	0.050
6	0.054	0.048
7	0.051	0.041
8	0.060	0.042
9	0.059	0.064
10	0.049	0.056
Mean RMSE	0.054	0.049

Note: RMSE = root mean square of error.

5. Discussion

5.1. Interpretation

The aim of the current analytic work was to perform a predictive analysis using an ANN to test the relationship between workplace injuries, safety climate and safety behaviors. Predictive analytics allows for repeated testing of a theoretical model that is held constant over a prolonged time span. Specifically, the study aimed at investigating the interactive effect of safety climate and safety behavior on workplace injuries. The safety climate negatively predicts workplace injuries, and safety behaviors when simultaneously added to the model amply and negatively predicted workplace injuries.

Our results evidence that the safety climate negatively predicted workplace injuries and, thus, confirmed H_1. This means that an organization which is mindful of the dangers hovering in its working environment and takes appropriate actions to preclude any misadventure will merely observe an inhibited workplace injury occurrence due to its preventive policies. This result is consistent with the findings reported by Christian et al.'s [18] meta-analysis and Leitão and Greiner's [14] systematic review of the effect of safety climate on occupational injuries. Moreover, for H_2 we found that safety behavior strengthens the relationship between safety climate and workplace injuries, i.e., the higher the safety behavior, the stronger the effect of safety climate on workplace injuries.

In other words, an organization's safety climate will inhibit the risk of injuries more when individual employees exhibit safe behaviors than when they do not. While other scholars advocated for safety behavior as a mediator, we proposed and demonstrated that safety behavior is a standalone factor which acts as an external variable to amplify the influence of an organization safe climate on its employees' physical integrity at work. Because this is the first study of its kind, no similar findings have been retrieved from the literature. Yet these results provide the ground for theoretical and practical implications.

5.2. *Theoretical and practical implications*

As already mentioned, safety behavior plays an interactive role with the safety climate to shrink the occurrence of injuries. Despite the suggestions of prior research that the safety climate predicts safety behavior (e.g., Barbaranelli et al. [7] and Liu et al. [35]), it is noteworthy that safety behavior becomes significant as one motivates the self in engaging in such behaviors, considering personal idiosyncratic factors. Precisely, Barbaranelli et al. [7] demonstrated that the safety climate affects safety knowledge and motivation which Christian et al. [18] noted as person-related proximal antecedents of safety outcomes. An explanation may be that these two can be contextually framed on the employee. However, person-related distal antecedents such as risk-taking propensity, locus of control, conscientiousness or extraversion [18], which are one's personality traits, may not be systematically framed from the organizational safety climate.

Thus, employees with safer behaviors may display signs of heightened conscientiousness, risk-aversive propensity and locus of control, no matter the nature of the existing safety climate. Conversely, the sensation-seeking facet of extraversion, carelessness and belief that one's faith is solely contingent on the surrounding environment would be some characteristics of individuals engaging in unsafe behaviors. Hence, one's safety behavior is also contingent on the personality and idiosyncratic characteristics that make this person. As such, an organization may put tremendous effort on its safety policies and its scrupulous implementation, yet it may not find absolute support from adventurous or careless employees as it would from mindful ones. A high safety climate mitigating effect on injuries will not be as efficient with unsafely behaving employees compared with safely behaving ones. Alternatively, a low safety climate would induce high injury occurrence more with unsafe behaviors than with safe behaviors. This therefore explains why safety behavior can also be considered theoretically as a moderator.

In addition, we can draw from the results that safety behavior is an employee's self-regulatory set of mechanisms that allows him/her to consistently interact with the prevailing working environment. Depending on the high or low-risk demand nature of the job henceforth, safety behavior will be used as a coping strategy in either conserving the available draining resources especially when the risk demands is relatively high, or investing in gaining new resources when the risk demands seem to be relatively low. A high-risk job poses a serious and permanent threat to one's physical and emotional integrity. It appears that engaging in such self-regulatory process with the scope of preventing any disaster can be contingent on the personality traits which shape one's appreciation level of danger, and preclude the self from risk-taking propensity. Thus, safety behavior cannot only be assumed as a mere singularity of the workplace safety macrocosm, but also as a salient catalyst that shapes and give a sense to workplace safety. Ultimately the individual, through his/her safe behaviors, will be the one to determine the existing safety climate instrumentality.

This study also draws implications for managers and professionals in the (central Anatolian) metal casting industry in particular, and in all other (high-risk) industries. Global awareness of occupational safety and health seems to have increased tremendously over the years at the macro-level [1]. Yet it is noteworthy that interest should be paid to the role each employee plays in achieving safety objectives at the organizational level. Accordingly, managers should consider implementing assessments and trainings to maintain higher safety standards among their employees as these have performance, reputational and cost consequences for their organizations.

5.3. *Contributions, limitations and suggestions for future research*

Although several researchers have advocated for a clear theoretical distinction between the safety climate, culture and behavior constructs, the three terms are often confused and used interchangeably [54–56]. Hence, this article contributed by empirically proving that the safety climate and behaviors are different, and that they are related constructs. This study is among the first to demonstrate that safety behavior plays an interactive role with the safety climate to prevent workplace injuries. Also, using a predictive analytic modeling approach to forecast the relationships is another contribution from the methodological front. To wrap up, this work has conveyed the message to practitioners that safety behaviors and the safety climate have a contextual relationship through predictive analysis. Therefore, organizations need to consider safety behaviors and climate evaluation in their safety surveys.

This study contributes to the current literature of workplace safety by linking the safety climate and workplace injuries through safety behavior in the metal casting industry. In doing so, several limitations were inherited. One, the research population is limited to metal casting firms in Central Anatolia, and not the whole of Turkey. Therefore, the scope and generalization of the current results should be considered with extreme caution. Future studies should be conducted in other sectors such as construction, mining and steel industries; a similar model could be tested in other countries to validate the current research model. Also, although ANN predictability is a methodological strength of this study, the present study's design was cross-sectional and, as such, its accountability for causal relationship cannot be absolute. Thus, future studies could utilize a longitudinal approach to support the current findings' cause-and-effect relationship over time. In addition, we made use of self-reported measures to collect data, and this can provide grounds for potential or persisting biases such as social desirability. We suggest future scholars should use multiple sources of data to diminish such disturbances as much as possible.

6. Conclusion

The current article has proposed and tested a moderation model featuring safety behavior as a moderator of the effect of the safety climate on workplace injuries. The results showed that safety behavior interacts with the perceived safety climate to significantly weaken the odds for occupational injuries. While safety behavior was evidenced as a mediator between the effects of the safety climate on injuries, our study proved that it can also moderate this relationship when it acts as a self-regulatory mechanism to refrain from any potential threat for physical integrity.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix. Neural network analysis (program codes)

```
# check for missing values
apply(guven_iklimi,2,function(x) sum(is.na(x)))

# 75% for training and the rest for testing
index <- sample(1:nrow(guven_iklimi),round(0.75*nrow(guven_iklimi)))

train1 <- guven_iklimi[index,]
test1 <- guven_iklimi[-index,]

# appling GLM on the model
lm.fit <- glm (Workplace_Injuries ∼ Safety_Climate, data = train1)

# generating results (e.g. estimates and t-values)
summary(lm.fit)

# testing the model with the test guven_iklimi part
pr.lm <- predict(lm.fit,test1)
MSE.lm <- sum((pr.lm - test1$Workplace_Injuries)ˆ2)/nrow(test1)
print(paste(MSE.lm))

########################################
# NEURAL NET FITTİNG
########################################

maxs <- apply(guven_iklimi, 2, max)
mins <- apply(guven_iklimi, 2, min)

scaled <- as.data.frame(scale(guven_iklimi, center = mins, scale = maxs - mins))

train_ <- scaled[index,]
test_ <- scaled[-index,]

library(neuralnet)
#nn <- neuralnet (Workplace_Injuries ∼ Safety_Climate, data = train_, hidden = c(2,2), err.fct = “sse”,
        linear.output = TRUE)
nn <- neuralnet (Workplace_Injuries ∼ Safety_Climate + Moderator, data = train_, hidden = c(3,2), err.fct = “sse”,
        linear.output = TRUE)
plot(nn)

par(mfrow = c(2,2))
gwplot(nn, selected.covariate = “Safety_Climate”, selected.response = “Workplace_Injuries”, min = -5, max = 5)
gwplot(nn,selected.covariate = “Safety_Behavior”, selected.response = “Workplace_Injuries”, min = -5, max = 5)
gwplot(nn,selected.covariate = “Moderator”, selected.response = “Workplace_Injuries”, min = -5, max = 5)

nn$result.matrix
columns <- c(“Safety_Climate”, “Moderator”)
#columns <- c(“Safety_Climate”)
covariate <- subset(test_, select = columns)
pr.nn <- compute(nn, covariate, rep = 1)

# Next step
pr.nn_ <- pr.nn$net.result*(max(test_$Workplace_Injuries)-
min(test_$Workplace_Injuries))+min(test_$Workplace_Injuries)
test.r <- (test_$Workplace_Injuries)*(max(test_$Workplace_Injuries)-
min(test_$Workplace_Injuries))+min(test_$Workplace_Injuries)

# Calculating MSE
MSE.nn <- sum((test.r - pr.nn_)ˆ2)/nrow(test_)

#Compare the two MSEs
print(paste(MSE.lm, MSE.nn))
#############################Cross validation for linear model###########################
library(boot)
set.seed(200)
lm.fit <- glm(Workplace_Injuries + Safety_Climate + Safety_Behavior + Moderator, data = guven_iklimi)
cv.glm(guven_iklimi,lm.fit,K = 10)$delta[1]

###########################FOR TRAİNİNG###########################
set.seed(450)
cv.error <- NULL
k <- 10
```

```
library(plyr)
pbar <- create_progress_bar(‘text’)
pbar$init(k)

for(i in 1:k)
{
       index <- sample(1:nrow(guven_iklimi),round(0.75*nrow(guven_iklimi)))
       train.cv <- scaled[index,]
       test.cv <- scaled[-index,]

 library(neuralnet)
nn <- neuralnet (Workplace_Injuries ~ Safety_Climate + Moderator, data = train.cv, hidden = c(3,3), err.fct = “sse”,
           linear.output = TRUE)

columns <- c(“Safety_Climate”, “Moderator”)
covariate <- subset(train.cv, select = columns)
pr.nn <- compute(nn, covariate, rep = 1)

pr.nn <- pr.nn$net.result*(max(train.cv$Workplace_Injuries)-
min(train.cv$Workplace_Injuries))+min(train.cv$Workplace_Injuries)

train.cv.r<-(train.cv$Workplace_Injuries)*(max(train.cv$Workplace_Injuries)-
min(train.cv$Workplace_Injuries))+min(train.cv$Workplace_Injuries)

cv.error[i] <- sum((train.cv.r - pr.nn)ˆ2)/nrow(train.cv)
print(paste(cv.error[i]))
 pbar$step()
}
mean(cv.error)
###########################FOR TESTİNG###########################
set.seed(450)
cv.error <- NULL
k <- 10
library(plyr)
pbar <- create_progress_bar(‘text’)
pbar$init(k)

for(i in 1:k)
{
       index <- sample(1:nrow(guven_iklimi),round(0.75*nrow(guven_iklimi)))
       train.cv <- scaled[index,]
       test.cv <- scaled[-index,]

       library(neuralnet)
nn <- neuralnet (Workplace_Injuries ~ Safety_Climate + Moderator, data = test.cv, hidden = c(3,3), err.fct = “sse”,
           linear.output = TRUE)

columns <- c(“Safety_Climate”, “Moderator”)
covariate <- subset(test.cv, select = columns)
pr.nn <- compute(nn, covariate, rep = 1)

pr.nn <- pr.nn$net.result*(max(test.cv$Workplace_Injuries)-
min(test.cv$Workplace_Injuries))+min(test.cv$Workplace_Injuries)

test.cv.r<-(test.cv$Workplace_Injuries)*(max(test.cv$Workplace_Injuries)-
min(test.cv$Workplace_Injuries))+min(test.cv$Workplace_
Injuries)

cv.error[i] <- sum((test.cv.r - pr.nn)ˆ2)/nrow(test.cv)
print(paste(cv.error[i]))
   pbar$step()
}

mean(cv.error)
```