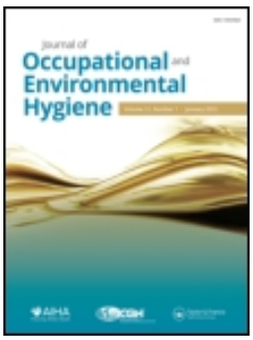

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Individualized Prediction of Heat Stress in Firefighters: A Data-Driven Approach Using Classification and Regression Trees

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The purpose of this study was to explore data-driven models, based on decision trees, to develop practical and easy to use predictive models for early identification of firefighters who are likely to cross the threshold of hyperthermia during live-fire training. Predictive models were created for three consecutive live-fire training scenarios. The final predicted outcome was a categorical variable: will a firefighter cross the upper threshold of hyperthermia – Yes/No. Two tiers of models were built, one with and one without taking into account the outcome (whether a firefighter crossed hyperthermia or not) from the previous training scenario. First tier of models included age, baseline heart rate and core body temperature, body mass index, and duration of training scenario as predictors. The second tier of models included the outcome of the previous scenario in the prediction space, in addition to all the predictors from the first tier of models. Classification and regression trees were used independently for prediction. The response variable for the regression tree was the quantitative variable: core body temperature at the end of each scenario. The predicted quantitative variable from regression trees was compared to the upper threshold of hyperthermia (38°C) to predict whether a firefighter would enter hyperthermia. The performance of classification and regression tree models was satisfactory for the second (success rate = 79%) and third (success rate = 89%) training scenarios but not for the first (success rate = 43%). Data-driven models based on decision trees can be a useful tool for predicting physiological response without modeling the underlying physiological systems. Early prediction of heat stress coupled with proactive interventions, such as pre-cooling, can help reduce heat stress in firefighters.

Keywords classification tree, data-driven models, decision tree, firefighters, heat stress, hyperthermia, prediction, regression tree

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INTRODUCTION

Firefighters face numerous dangers on their job on a daily basis. Exposure to hot environments is one of them. Performing physically intensive tasks in hot environments can lead to a slew of problems such as heat stress and fatigue which, in turn, increases cardiac load and may lead to cardiovascular events (myocardial infarction, brain infarction).[1,2] 48% of on-duty deaths among firefighters occur from cardiovascular events which are a major cause of morbidity.[3] Heat stress is associated with increases in heart rate (HR) and oxygen demand and theoretically increases the risk of ischemia and a sudden cardiac event. Heat strain, the physiological response to heat exposure, if left unchecked, may result in increased accidents and heat-related disorders.[4–7] Laboratory and field studies have shown that firefighters can experience buildup of heat stress and fatigue not only during their daily job, but also during training.[8–10] Technology exists that can be used to monitor vital signs of firefighters (including HR and core body temperature—CBT) in real time.[11,12] Such real-time monitoring tools coupled with established upper thresholds of hyperthermia and allowable maximum HR elevation,[13–14] can be used to detect if a firefighter reaches dangerous levels of HR and/or CBT. However, merely detecting when a firefighter crosses an established physiological limit is not sufficient. Prevention is indeed better than cure! There is a need for a tool that can be used to *predict* if a firefighter is going to cross established "safe" limits of physiological parameters. Such an early detection tool will provide fore-warning so that pro-active preventative measures can be implemented to keep firefighters' physiological parameters within "safe" limits.

It has been shown that the human body may be lacking in the mechanisms (sensory and/or cognitive) needed to predict the onset of heat stress.[15] Additionally, given the high pressure nature of their job, firefighters may ignore early signs of heat stress and fatigue. Hence, there is a need for an objective predictive tool that can be used to forecast if a firefighter is going to cross the upper limits of hyperthermia and physical fatigue during firefighting activities as well as during training drills. Several first-principles based physiological models have been developed that can be used to predict CBT and HR in both military personnel and in firefighters.[16–18] These approaches are based on modeling the

thermoregulatory system of the human body. Since it is difficult to accurately model each and every thermoregulatory unit in the body, such models may lead to inaccurate predictions. Generally, it is difficult to incorporate inter-individual variability in purely physiology based models.[19,20] Hence, while such models can be very useful for predicting aggregate response of a group, they may not be as useful for predicting an individual firefighter's response. Data-driven predictive models have been shown to outperform purely physiology based models for short-term prediction of core body temperature.[21,22] In this study we developed a new data-driven predictive approach, based on classification tree (CT) and regression tree (RT) techniques, that can be used to forecast whether or not an individual firefighter will cross the upper limit of hyperthermia.

Classification trees are essentially binary decision trees that use recursive partitioning to predict a categorical response for a given set of predictor values.[23,24] Classification trees have been used extensively as diagnostic tools and have been found, at times, to outperform traditional prediction methods.[25–27] Regression trees also use recursive partitioning to provide predictions of a quantitative response variable for any given set of predictor values.[23] Classification and regression trees are data mining tools that can prove to be useful in developing prediction models. These data mining tools are different from traditional logistic and multiple regression models, which help to identify significant predictors. Unlike traditional regression approach, decision tree-based methods take into account the interactions between variables and nested effects that occur only in subsets of individuals. Decision tree-based methodology has been used previously in the occupational exposure setting to predict an expert's likely exposure estimate based on patterns in a participant's questionnaire responses in an epidemiological study.[30,31]

The main objective of this article is to develop practical and easy to use predictive models that can be used by firechiefs and captains to identify firefighters who are likely to cross the upper threshold of hyperthermia during live-fire training. We compare the performances of CT and RT models for prediction. Early identification of at-risk firefighters would allow for proactive implementation of interventions to keep the firefighters' CBT within "safe" limits. Examples of such interventions can be cooling (using cooling vests), hydration, more physical training to withstand hot environment, and altering the length of training scenarios. It was hypothesized that sensitivity and specificity of predictive method developed in this study will be higher than 50%.

METHODS

The University of Cincinnati's Institutional Review Board approved the study and each participant provided informed consent before participating in the study.

Subjects

Twenty-eight full-time firefighters between the ages of 24 and 44 years with no known medical conditions were recruited from 2 different fire stations (referred to as Stn I and Stn II in Table Ia). The demographics of the firefighters are given in Table Ia. Participating firefighters were medically cleared for the study by the local fire department's occupational medical director.

Procedure

Live-fire training exercise: The training exercise was divided into three scenarios (referred to as Sc1, Sc2, and Sc3). The scenarios represented real life firefighting activities, (e.g., fighting first and second floor fires). Real-time measurements of CBT and HR were made during the live-fire training. Core body temperature was measured using FDA approved CorTemp (HQ, Inc., Palmetto, FL) radio pill. Heart rate was measured using a POLAR (HQ, Inc., Palmetto, FL) HR belt. A more detailed description of the data collection procedure can be found in Mani et al. 2013.[8]

Independent and Dependent Variables

The main objective of this study was to develop models to predict whether an individual firefighter would cross the upper threshold of hyperthermia (38°C) after a live-fire training conducted in three scenarios. In order to achieve the objective, we developed two types of models, one based on CT (for direct categorical classification) and another based on RT (for quantitative prediction). The response variable for the CT was the categorical variable (CAT): did a firefighter cross the upper threshold of industrial hyperthermia (CBT > 38°C)? – Yes/No. The response variable for the RT was the quantitative variable (QUANT): CBT (°C) at the end of each scenario (Sc1, Sc2, and Sc3). The predicted quantitative variable (QUANT) was compared to the upper threshold of hyperthermia (38°C) to predict if an individual firefighter would enter hyperthermia. For the development of a CT, the response variable was dichotomized before building the tree whereas for RT, CBT was dichotomized after building the tree. Comparisons were made to evaluate which method gave a higher successful prediction rate. The independent variables used as predictors were age,

TABLE Ia. Demographics

Fire Station	Number of Firefighters	Age (yrs.)		Gender	BMI (Kg/m2)	
		Mean (SEM)	Range	(M/F)	Mean (SEM)	Range
Stn I	8	33.5 (2.0)	24 – 41	7/1	25.9 (0.8)	21.4 – 29.5
Stn II	20	36.9 (1.1)	26 – 44	20/0	30.2 (1.0)	22.9 – 37.1

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TABLE Ib. Outcome measure for each scenario

Scenario	Outcome Measures
Sc1	CAT_{T1S1*}, $QUANT_{T1S1}$
Sc2	$CAT_{T1S2,}$ $QUANT_{T1S2}$
Sc3	$CAT_{T1S3,}$ $QUANT_{T1S3,}$ $CAT_{T2**,}$ $QUANT_{T2}$

* Subscript notations: T = Tier; S = Scenario. For example, T1S2 = Tier 1 Scenario 2.
** Subscript notations: T = Tier. For example, T2 = Tier 2.

body mass index (BMI), baseline HR, baseline CBT, and scenario duration. The outcome measures for each scenario are shown in Table Ib.

Heuristics of Classification and Regression Trees

To begin the analysis using CT, all the data is poured into the root node. The entropy of distribution of the dependent variable (CAT for this study) is calculated. Entropy provides an estimate of how chaotic the distribution of CAT is. A smaller value of entropy is indicative of less chaos. A predictor and a cut-off point for the predictor are chosen to split the root node optimally. A subject in the root node is moved to the left if that particular subject's predictor value is less than or equal to the cut-off point. Otherwise, the subject is moved to the right node. A predictor variable and a corresponding cut-off point is chosen for creating an optimal split at each node by minimizing the collective entropy of the distribution of CAT at each node until the classification process is completed. A similar process of recursive splitting (partitioning) is used for a RT, except that variance in the dependent variable, instead of entropy, is used as the decision criterion for splitting. The complexity parameter for splitting in the decision tree models was 0.01.The maximum number of allowed observations for a leaf node used in the CT and RT model development was 10 (unless all resulting observations in the leaf node belonged to the same category).

Model Development

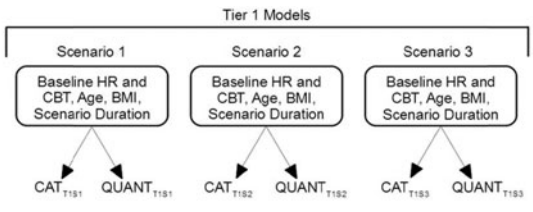
Overview of Models

Two tiers of models were developed. The first tier consisted of 6 models (3 CT models and 3 RT models) for predicting the dependent variables, one CT and one RT for each scenario: Sc1, Sc2, and Sc3 (see Figure 1). The second tier consisted of two models (1 CT and 1 RT) for predicting the response after Sc3, where dependent variables from Tier 1 models for Sc1 and Sc2 were included as predictor variables (see Figure 2). Tier 2 models were developed to investigate whether including the information from the end of the previous scenarios improves model performance for Sc3. The rationale for this investigation was the fact that the three scenarios were not independent. The scenarios were always in the order Sc1, Sc2, and Sc3, with the activities for all scenarios performed within a few hours. Additionally, it has been previously shown by the authors that there was a buildup of heat stress as the training scenarios progressed.[8] In order to predict the dependent variables for Sc2 and Sc3, heart rate (and CBT) at the end of rest periods after Sc1 and Sc2 were considered the baseline HR (and CBT) values for Sc2 and Sc3, respectively.

Construction and Validation of CT and RT Models

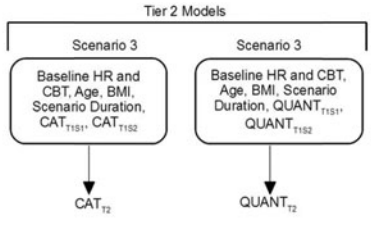
Classification trees were used to predict the categorical response (CAT): an individual firefighter crossed the limit of industrial hyperthermia at the end of a scenario—Yes/No. Regression trees were used to predict the end-of-scenario CBT for individual firefighters (QUANT). If the predicted end-of-scenario CBT for a firefighter was greater than 38°C, it was concluded that she/he would enter hyperthermia.

The most widely used method for validating decision trees is cross-validation. However, due to limited sample size, the "leave-one-out" method of validation was chosen.[28,29] Since there were 28 data points for each training scenario (Sc1, Sc2, and Sc3), we developed 28 CT (and RT) models leaving out one firefighter's data in each CT (and RT). The fitted models were based on data from 27 firefighters and they were used to predict the response for the *left-out* firefighter. If the predicted response was the same as the observed response, prediction



CAT: Predicted variable for CT – crossed upper threshold for hyperthermia (Yes/No)
QUANT: Predicted variable for RT – end-of-scenario CBT in ^{O}C
Subscript notations: T = Tier; S = Scenario. For example, T1S2 = Tier 1 Scenario 2.

FIGURE 1. Tier 1 Models – independent and dependent variables.



CAT: Predicted variable for CT – crossed upper threshold for hyperthermia (Yes/No)
QUANT: Predicted variable for RT – end-of-scenario CBT in ^{O}C
Subscript notations: T = Tier. For example, T2 = Tier 2.

FIGURE 2. Tier 2 Models—independent and predicted variables.

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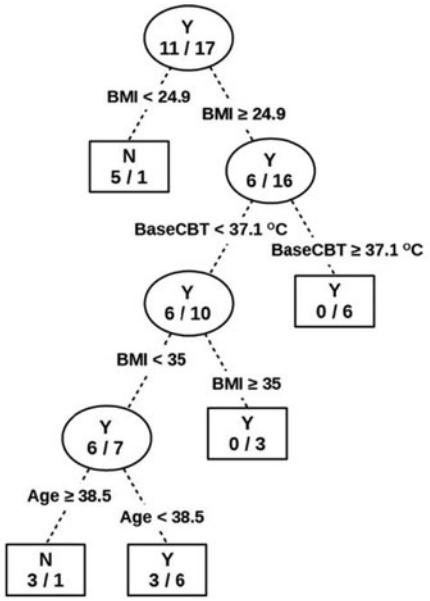

FIGURE 3a. Classification tree for predicting if a firefighter would cross the upper threshold of hyperthermia after the first scenario (Sc1) of the live-fire training.

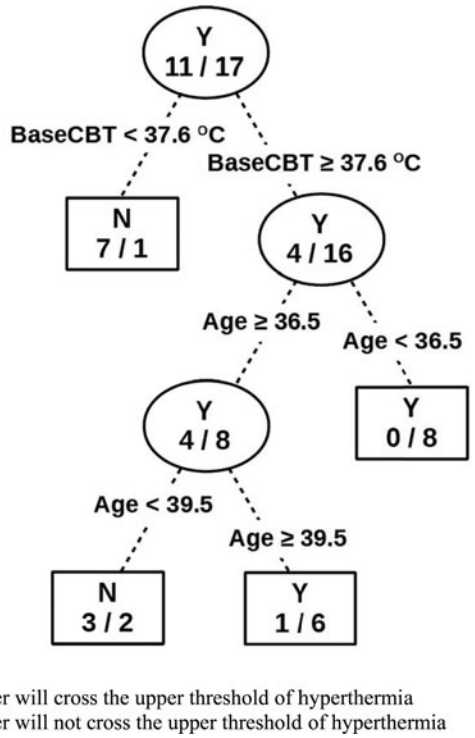

FIGURE 3b. Classification tree for predicting if a firefighter would cross the upper threshold of hyperthermia after the second scenario (Sc2) of the live-fire training.

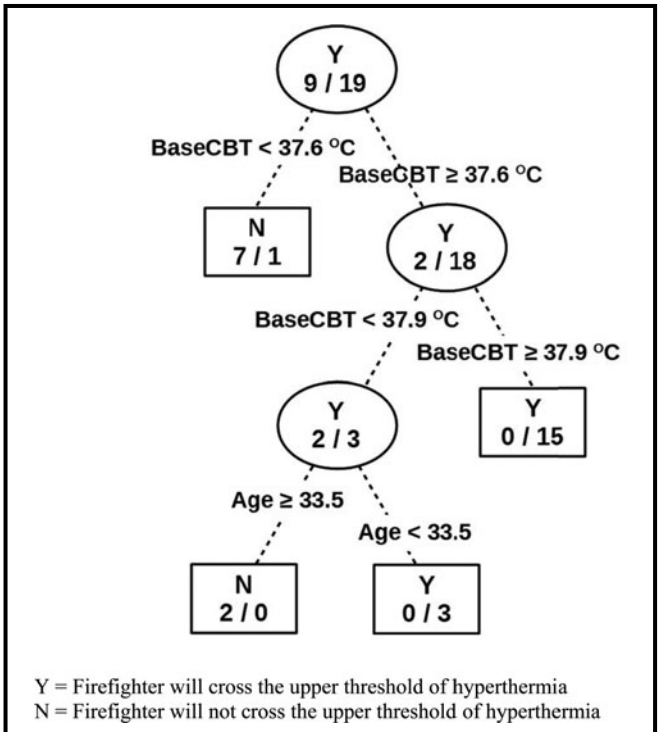

FIGURE 3c. Classification tree for predicting if a firefighter would cross the upper threshold of hyperthermia after the third scenario (Sc3) of the live-fire training.

was considered successful. The successful prediction rate was calculated as:

$$Successful_Prediction_Rate = 100^{*}(Number\ of \times correctclassifications)/(Total\ ,\ number\ of\ classifications)\,. \quad \textbf{(1)}$$

Successful prediction rates were compared for the CT and RT models. Further, the successful prediction rates were calculated separately for each level of the response variable (hyperthermia and no_hyperthermia) to assess the sensitivity and specificity of the models. Logistic and multiple regression were used to investigate the significance of the predictors used in this study. The predictors used in regression models were same as those used in the CT and RT models. Due to small sample size, only the main effects were used in the regression models. Findings from regression models with p-value less than 0.05 were considered statistically significant and those with p-value between 0.05 and 0.1 were considered marginally significant.

Using the Classification Trees Generated in this Study

Given a set of predictor variables for a firefighter (age, BMI, baseline HR, baseline CBT, and scenario duration), one can use the CT (such as that shown in Figures 3a, 3b, and 3c) to predict if the firefighter will cross the upper threshold of hyperthermia after a scenario. In order to use a CT, one starts from the root node (the top most node) and goes down the tree

TABLE II. Successful prediction rates of CT models for Sc1, Sc2 and Sc3 for predicting hyperthermia, no_hyperthermia and overall response for categorical dependent variable CAT

Scenario (Predicted Variable)	Success Rates (%) for CT Models		
	Success Rate (%) for hyperthermia response (Y) *	Success Rate (%) for no_hyperthermia response (N) *	Overall Success Rate (%) [Y and N combined]
Sc1 (CAT_{T1S1})	47% (8 out of 17)	36% (4 out of 11)	43% (12 out of 28)
Sc2 (CAT_{T1S2})	59% (10 out of 17)	64% (7 out of 11)	61% (17 out of 28)
Sc3 (CAT_{T1S3})	95% (18 out of 19)	78% (7 out of 9)	89% (25 out of 28)

*Firefighter will cross the upper threshold of hyperthermia: Yes (Y) / No (N)

making a decision to go left or right at each node, based on the values of the predictor variables, until a terminal node (leaf node) is reached. At any given node, if the decision condition is met, one proceeds left, otherwise decision is made to proceed to the right side. The value of the leaf node is accepted as the predicted response. Each node enclosed in a rectangle is a terminal node (leaf node). Each node is identified with one of the levels of the response variable (Y/N).

Using the Regression Trees Generated in this Study

Regression trees from this study can be used in a manner similar to the CTs. In order to use a RT, one starts from the root node (the top most node) and goes down the tree making a decision to go left or right at each node, based on the values of the predictor variables, till a terminal node (leaf node) is reached. At any given node, if the decision condition is met, one proceeds left, otherwise decision is made to proceed to the right side. The value of the leaf node is accepted as the predicted response. To make predictions using RTs, the predicted value of CBT was compared to the threshold of hyperthermia (38°C) to determine if an individual firefighter would enter hyperthermia.

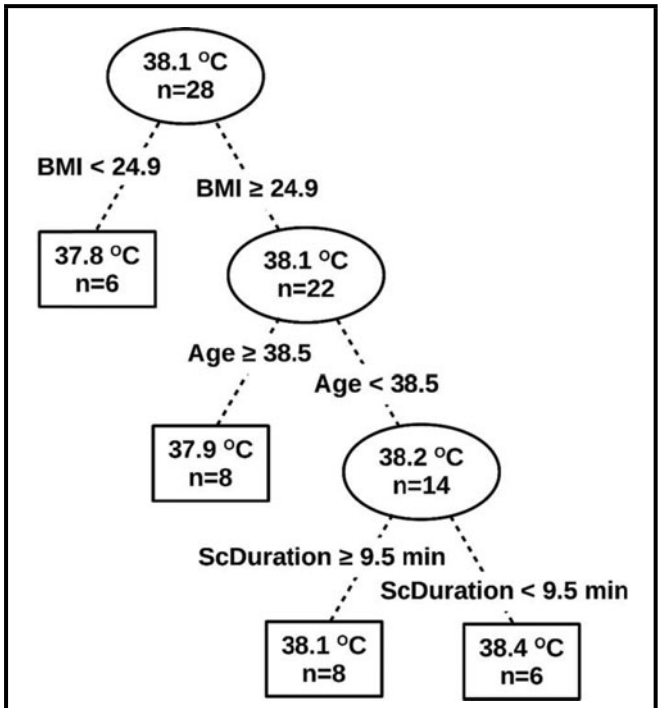

FIGURE 4a. Regression tree for predicting the end-of-scenario CBT of firefighters after the first scenario (Sc1) of the live-fire training. The predicted CBT values (°C) were compared to 38°C to determine if a firefighter would cross/not cross the upper threshold of hyperthermia.

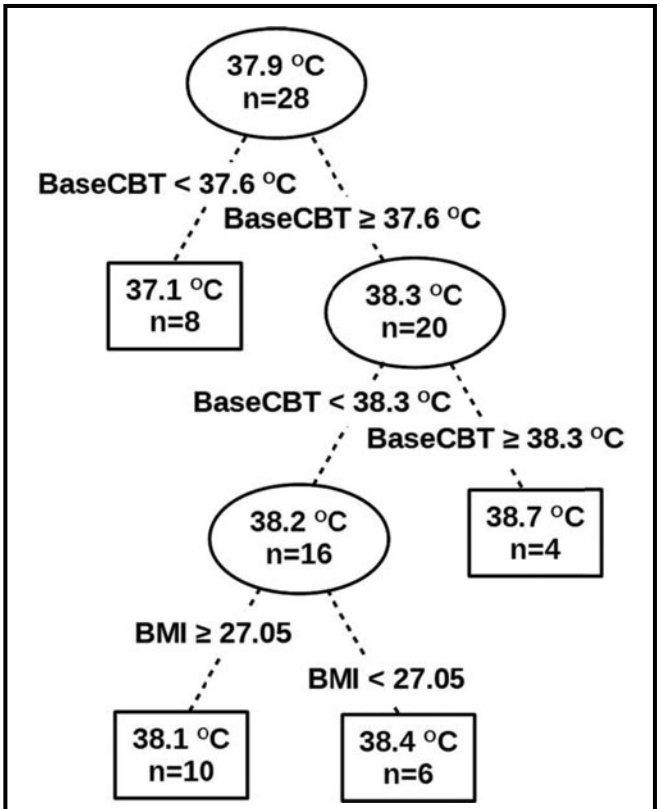

FIGURE 4b. Regression tree for predicting the end-of-scenario CBT of firefighters after the second scenario (Sc2) of the live-fire training. The predicted CBT values (°C) were compared to 38°C to determine if a firefighter would cross/not cross the upper threshold of hyperthermia.

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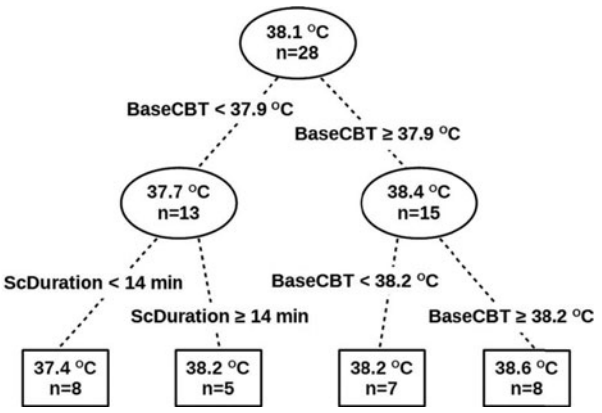

FIGURE 4c. Regression tree for predicting the end-of-scenario CBT of firefighters after the third scenario (Sc3) of the live-fire training. The predicted CBT values (°C) were compared to 38°C to determine if a firefighter would cross/not cross the upper threshold of hyperthermia.

Data Analysis

Using the time stamped HR and CBT measured in real-time, data corresponding to baseline, beginning and end of each scenario, and end of each rest period (in between scenarios) were obtained. The actual number of firefighters who crossed the upper threshold for hyperthermia after each scenario was calculated by comparing end-of-scenario CBT with the established threshold of industrial hyperthermia (38°C).[13] End-of-rest data (HR and CBT) was treated as baseline for the subsequent scenario.

Classification and regression trees were developed and evaluated (leave-one-out method) in R (Version 3.0.3). The R package *rpart* was used for generating and plotting the CTs and RTs.

RESULTS

Classification Tree Models

Classification trees for Sc1, Sc2, and Sc3: Figures 3a, 3b, and 3c show the Tier 1 CTs developed for predicting response after Sc1, Sc2, and Sc3, respectively. The Tier 1 and Tier 2 CTs developed for predicting the response after Sc3 were the same, showing no improvement in the model performance by including information from previous scenarios.

Leave-One-Out Validation of Classification Trees

The overall successful prediction rates for Sc1, Sc2, and Sc3 were: 43%, 61%, and 89%, respectively (Table II). The success rates for predicting hyperthermia outcome using CT were: 47%, 59%, and 95%, respectively. The success rates for predicting true positives (hyperthermia response) in the CT models were higher than the success rates for predicting negative response (no_hyperthermia) for Sc1 and Sc3. Since the Tiers 1 and 2 CTs developed to predict response after Sc3 were identical, their model performances (successful prediction rates) were identical as well. Hence, the model performance values for Tier 2 CT model are not presented here.

Regression Tree Models

Regression trees for Sc1, Sc2, and Sc3: Figures 4a, 4b, and 4c show the Tier 1 RTs developed for predicting end of scenario CBT response after Sc1, Sc2, and Sc3, respectively.

Leave-One-Out Validation of Regression Trees

The overall successful prediction rates for the RTs developed for Sc1, Sc2, and Sc3 were: 39%, 79%, and 82%, respectively (Table III). The success rates for predicting hyperthermia outcome using RT models were: 47%, 88%, and 95% for Sc1, Sc2, and Sc3, respectively. The success rates for predicting true positives (hyperthermia response) in the RT models were higher than the success rates for predicting negative response (no_hyperthermia) in all scenarios. The Tier 2 RT (tree not shown here) developed to predict response after Sc3 performed poorer than the corresponding Tier 1 RT (overall successful prediction rate of 71% vs. 82%). Thus, including information from previous scenarios did not increase the model performance for predicting response after Sc3.

Logistic and Multiple Regression

Alongside the CT and RT models, logistic and multiple regressions were used to investigate significance of predictors

TABLE III. Successful prediction rates of RT models for Sc1, Sc2 and Sc3 for predicting hyperthermia, no_hyperthermia and overall response using continuous dependent variable QUANT

	Success Rates (%) for RT Models		
Scenario (Predicted Variable)	**Success Rate (%) for hyperthermia response (Y) ***	**Success Rate (%) for no_hyperthermia response (N) ***	**Overall Success Rate (%) [Y and N combined]**
Sc1 ($QUANT_{T1S1}$)	47% (8 out of 17)	27% (3 out of 11)	39% (11 out of 28)
Sc2 ($QUANT_{T1S2}$)	88% (15 out of 17)	64% (7 out of 11)	79% (22 out of 28)
Sc3 ($QUANT_{T1S3}$)	95% (18 out of 19)	56% (5 out of 9)	82% (23 out of 28)
Sc3 ($QUANT_{T2S3}$)	79% (15 out of 19)	56% (5 out of 9)	71% (20 out of 28)

*Firefighter will cross the upper threshold of hyperthermia: Yes (Y) / No (N)

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TABLE IVa. Estimates of coefficients, and the corresponding p-values, from logistic regression with CAT as dependent variable

Independent Variable	Sc1 (CAT_{T1S1}) Estimate (p-value)	Sc2 (CAT_{T1S2}) Estimate (p-value)	Sc3 (CAT_{T1S3}) Estimate (p-value)
Age	−0.04 (0.67)	−0.09 (0.47)	−0.30 (0.14)
BMI	0.16 (0.20)	−0.15 (0.31)	0.39 (0.07)
Baseline HR	0.04 (0.39)	0.03 (0.35)	−0.04 (0.41)
Baseline CBT	0.26 (0.73)	0.97 (0.02)	1.48 (0.03)
Scenario Duration	−0.06 (0.48)	0.20 (0.25)	0.19 (0.07)

of dependent variables CAT and QUANT, respectively, from a traditional regression standpoint. The estimates of coefficients (and the corresponding p-values) from the logistic and multiple regressions are presented in Tables IVa and Table IVb, respectively. Baseline CBT was significant ($p = 0.03$) and BMI and scenario duration were marginally significant in the logistic regression ($p = 0.07$ for BMI and scenario duration). Baseline CBT was significant in the multiple regression as well ($p = 0.025$).

Final Proposed Prediction Tool

The CT and RT models predicted 79% and 89%, respectively, of the dichotomous hypothermia outcomes for Sc2 and Sc3. The successful prediction rate for Sc1 was less than 50% (43%). The most optimum models (highest overall successful prediction rate) for Sc2 and Sc3 were those based on RT (overall successful prediction rate = 79%) and CT (overall successful prediction rate = 89%), respectively (see Tables II and III). Here the finalized tools for predicting if a firefighter would cross the upper threshold of hyperthermia after second and third scenarios of live-fire training are presented. The tools are presented in the form of polygon plots (see Figures 5a and 5b) to summarize the information from the decision trees and facilitate the prediction process.

For Sc2 most optimum prediction was made solely based on the value of baseline CBT. If the baseline CBT was higher than 37.6°C, outcome was predicted as hyperthermia, otherwise outcome was predicted as no_hyperthermia (see Figure 5a). For Sc3, the most optimum prediction was achieved using baseline CBT and age as follows (see Figure 5b).

- If baseline CBT < 37.6°C, the predicted outcome response was no_hyperthermia.
- If 37.6°C $\leq$ baseline CBT < 37.9°C AND age < 33.5, the predicted outcome response was hyperthermia.
- If 37.6°C $\leq$ baseline CBT < 37.9 °C AND age ≥ 33.5, the predicted outcome response was no_hyperthermia.
- If baseline CBT ≥ 37.9°C, the predicted outcome response was hyperthermia.

DISCUSSION

Performance and Comparison of CT and RT Models

The CT and RT models proved to be useful prediction tools for Sc2 and Sc3 but not for Sc1 (see Tables II and Table III). Mani et al. previously showed that there is a buildup of heat stress (increase in core body temperature) with the progression of live-fire training.[8] Hence, higher accuracy from predictive models, like those presented in this paper, may be more important at the later stages of the training (e.g., Sc2 and Sc3) when firefighters have a higher chance of developing physiological heat strain.

Upon investigating the significance of predictor variables using more traditional parametric methods (logistic and multiple regression models), we found that none of the predictors were significant for Sc1 (see Table IVa and IVb). Regression analyses for Sc2 showed that baseline CBT was a significant predictor in logistic as well multiple regression. Similarly, for Sc3 baseline CBT and scenario duration were found to be, at least, marginally significant ($p < 0.1$) predictors of categorical

TABLE IVb. Estimates of coefficients, and the corresponding p-values, from multiple regression with QUANT as dependent variable.

Independent Variable	Sc1 ($QUANT_{T1S1}$) Estimate (p-value)	Sc2 ($QUANT_{T1S2}$) Estimate (p-value)	Sc3 ($QUANT_{T1S3}$) Estimate (p-value)
Age	−0.016 (0.623)	−0.023 (0.435)	−0.001 (0.976)
BMI	0.023 (0.575)	0.007 (0.870)	0.051 (0.187)
Baseline HR	0.005 (0.708)	−0.004 (0.635)	−0.003 (0.663)
Baseline CBT	0.001 (0.997)	0.633 (0.001)	0.341 (0.003)
Scenario Duration	−0.026 (0.353)	0.025 (0.220)	0.046 (0.025)

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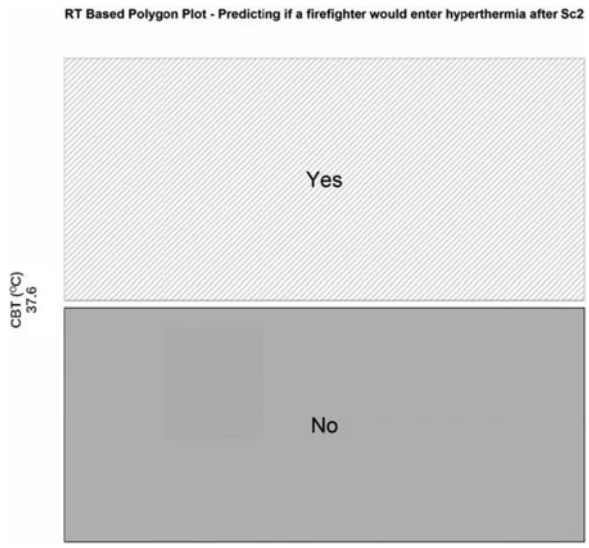

FIGURE 5a. Polygon plot based on RT developed for second scenario—proposed tool for predicting if a firefighter will enter hyperthermia after second scenario of live-fire training.

(CAT) and quantitative (QUANT) response (see Tables IVa and 5b). Body mass index was marginally significant ($p < 0.1$) in logistic regression but not in multiple regression. Interestingly, higher significance of predictor variables with progression of scenarios coincided with more accurate predictions from CT and RT models.

Both CT and RT models proved to be more successful in predicting hyperthermia response than no_hyperthermia response. Since the ultimate goal is to protect firefighters from heat stress, a lower number of false negatives (accurate prediction of hyperthermia response) is more desirable than fewer false positives (accurate prediction of no_hyperthermia response).

Classification tree models performed better than RT models, except for Sc2, with respect to overall successful prediction rates. However, the difference in this performance was from predicting no_hyperthermia response only. The successful prediction rates for positive response were the same for the CT and RT models for Sc1 and Sc3. The RT model provided higher prediction rate for hyperthermia response for Sc2 (88% vs. 59%). It is likely that the fire-chiefs and captains would

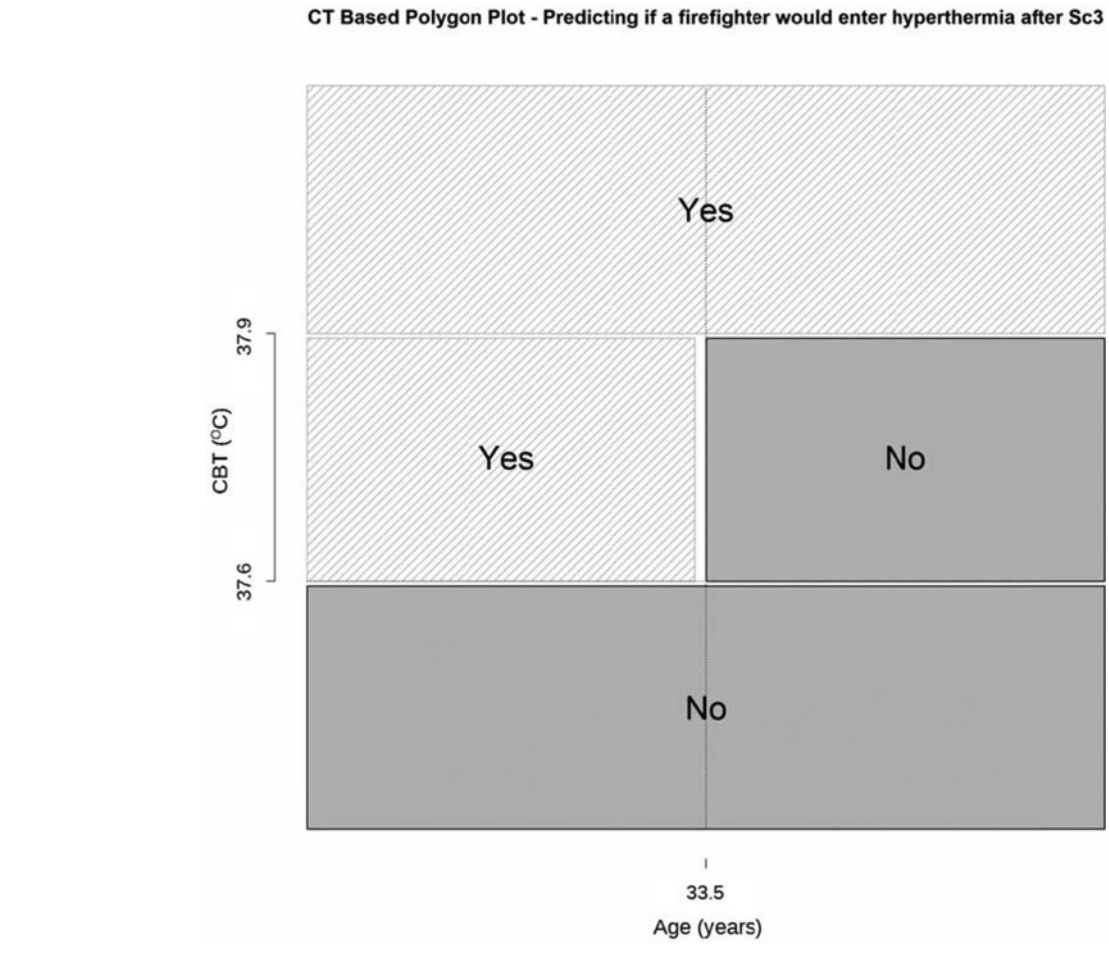

FIGURE 5b. Polygon plot based on CT developed for third scenario—proposed tool for predicting if a firefighter will enter hyperthermia after third scenario of live-fire training.

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be more interested in predicting if a firefighter would become hyperthermic, rather than a no_hyperthermia response. Hence, from a health and safety standpoint, CT and RT models may prove to be equally useful for Sc3. For Sc2, RT would provide better predictive power.

The RT and CT models for Sc2 and Sc3, respectively, performed better when compared to the prediction results from logistic regression models for the two scenarios. The overall successful prediction rates for Sc2 and Sc3 from the logistic regression model were 61% (vs. 79% from RT) and 71% (vs. 89% from CT), respectively. Hence, for the current dataset, the predictive models based on decision trees (CT and RT) outperformed a more traditional prediction based on parametric models. Since to the best of the authors' knowledge, this was the first study to use categorical prediction of heat stress in firefighters, comparisons to the findings published in the literature was not possible.

Comparison of Tier 1 and Tier 2 Models

The difference between Tier 1 and Tier 2 models used for predicting CBT response after Sc3 was inclusion of responses after Sc1 and Sc2 in the prediction space of Tier 2 models (see Figures 1 and 2). There was no difference between the performances of Tier 1 and Tier 2 CT models for predicting response from Sc3. Hence, including information from previous scenarios did not improve the predictive power of the CT model for Sc3. On the contrary, Tier 2 RT model's performance was poorer than that of the corresponding Tier 1 RT model (see Table III). The mean time lags between the ends of Sc1 and Sc3 was 75 min and that between the ends of Sc2 and Sc3 was 39 min. While the large time lag between ends of consecutive scenarios might partially explain no improvement in the prediction capability of CT models, understanding the drop in performance of RT models requires more investigation.

Utility and Implications of the Predictive Models

While it is important to know if a firefighter's core body temperature has crossed the upper threshold of hyperthermia, it is essential that no firefighter crosses hyperthermia in the first place. Predictive models such as those presented in this paper would help fire-chiefs and captains in identifying the firefighters who are at a higher risk of becoming hyperthermic. Early identification of these firefighters would be useful for implementing proactive preventative interventions to keep firefighters' CBT within "safe" limit. For example, if the model predicts that a firefighter would cross the upper threshold of hyperthermia during live-fire training, he/she can be given cooling vest to wear during the exercise or even pre-cooled. Precooling may not be feasible before actual fire run (due to sporadic and unpredictable nature of fire runs).

LIMITATIONS AND FUTURE STUDIES

The biggest limitation of this study was small sample size. Adequate sample size is needed for data-driven models to appropriately represent the distribution of responses (such as CBT) of physiological systems. Inadequate accuracy in predicting response from Sc1 might have been, partially, from the small sample size and the choice of predictor variables. Increasing the sample size may help in developing "better" trained models and exploring additional relevant predictor variables. Examples of such predictors can be percent body fat, expected cardiac load during the training scenario, metrics of performance on annual stress test and years of experience as firefighter. Furthermore, larger sample size would allow for additional data points for a more rigorous validation of the models. Despite the limitations, to the authors' knowledge, this study is one of the first to use decision trees (classification and regression trees) to develop a practical and easy to use tool for predicting the onset of heat stress in firefighters during live-fire training.

CONCLUSION

Data-driven models can prove to be very useful for predicting physiological responses when modeling all of the underlying physiological systems is not possible/feasible. Additionally, data-driven models can be used as a "develop from some and predict for all" tool. In this study, decision trees (classification and regression trees) were used to predict the increases in core body temperature of firefighters during live-fire training. Despite limited sample size the prediction models performed well for Sc2 and Sc3. Future studies should explore data-driven models for predicting physiological responses using larger sample size. Prediction models coupled with proactive interventions, such as cooling, can play a key role in reducing heat stress in firefighters.

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