ORIGINAL ARTICLE

# The Statistical Model for Prediction of Heat-Related Illnesses in Conscript Training Course

Kathawoot Deepreecha, MD, MSc[1], Surasak Buranatrevedth, MD, MPH, DrPH[2], Phongtapr Wiwatanadate, MD, PhD[3]

[1] Health Promotion and Preventive Medicine Division, Royal Thai Army Medical Department, Bangkok, Thailand; [2] Department of Community and Family Medicine, Thammasat University, Pathum Thani, Thailand; [3] Department of Community Medicine, Chiang Mai University, Chiang Mai, Thailand

**Background**: Heat-related illnesses (HRI) are a major health problem among conscripts. Risk assessment using statistical equations is one strategy to help prevent HRI at the individual level.

**Objective**: To create and evaluate an appropriate statistical model to predict HRI in basic conscript training courses.

**Materials and Methods**: The study employed a prognostic and prospective design, divided into two phases. The model was developed in the first phase while the second evaluated the model. In the model development phase, the sample comprised first and second turn conscripts. The model evaluation phase involved a sample of first and second turn conscripts not in the year of the model development phase. Data on personal and environmental factors were collected in the model development phase to adjust the score level to align with the risk level. In the evaluation phase, data were collected using variables obtained during model development by categorizing the risk groups into two levels, low and high, and sorting them according to their symbolic color. Data were analyzed in the development phase using binary logistic regression and clinical predictive rule. Scores in the model evaluation phase were analyzed using the Net Reclassification Index (NRI).

**Results**: In the model development phase, 2,217 subjects took part in the study, with a 100% response rate. The incidence of HRI was 1.6 per 1,000 persons/day. The predictive factors included alcohol consumption within seven days of military service, fever, systolic blood pressure, body mass index, and urine color. In the model evaluation phase, 2,217 subjects participated in the study, with a 100% response rate. When compared with symbolic color classification, a traditional risk assessment, the NRI was equal to 61.4% and considered to be appropriate.

**Conclusion**: The use of score scales based on factors in the statistical model proved to be a suitable additional method for predicting heat-related illnesses at the individual level.

**Keywords**: Statistical model; Heat-related illnesses; Conscripts

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Heat-related illnesses (HRI) represent a major health challenge in military training with a reported annual incident rate of up to 30 per 100,000 samples and an associated case fatality rate of 3.6 per 100 persons. In developed countries such as Japan, there were 53,843 cases of HRI in 2010[1]. In the U.K., the annual HRI rate was 20 per 100,000 sample[2], similar to that of Thailand. HRI can be divided into eight types, edema, rash, syncope, cramps, tetany, exhaustion, stroke, and rhabdomyolysis.

In conscript training course, factors associated with HRI typically included individual factors, environmental factors, and management risk factors. The major identified risk factors in soldiers were abnormal body mass index, inadequate hydration, either not acclimatized or having low acclimatization, and high ambient temperature[3,4].

The Royal Thai Army Medical Department is currently taking measures to prevent HRI among conscripts. Part of the screening or risk assessment process involves the use of symbolic colors, categorized by risk group[4]. However, risk assessment using current symbol colors has certain limitations, such as confusing or incorrectly grouping symbolic colors, or in the case of a group with multiple risk factors. This may result in inaccuracy in the risk assessment and in turn, the incidence of HRI. To separate risk groups, insufficient medical evidence exists to confirm the criteria used for screening to

**Correspondence to:**

Deepreecha K.

Health Promotion and Preventive Medicine Division, Royal Thai Army Medical Department, Bangkok 10400, Thailand.

**Phone**: +66-86-6262305

**Email**: koccmed@gmail.com

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prevent and surveille HRI. Assessing risk using statistical equations and clinical predictive rules is one approach that can help prevent HRI at the individual level although no such predictive criteria are currently available. This will lead to preventing HRI among conscripts undertaking other military training.

The present study aimed to create and evaluate an appropriate statistical model to predict HRI in basic conscript training courses to help prevent HRI at the individual level.

## Materials and Methods

The present study employed a prognostic and prospective design divided into two phases, model development and evaluation.

For the model development phase, the sample comprised conscripts that turns 2 and 1 in the year as turn 2 in November or in winter and turn 1 in May or in summer. Based on the information provided, the goal is to determine the number of events that will occur for each predictor in a risk assessment study. The present study involved active-duty soldiers and the incidence of heat illness during their first shift in the Royal Thai Army Medical Department[7]. According to the literature review and statistics from the Royal Thai Army Medical Department, there were 2,678 reported incidents of heat illness among active-duty soldiers in their first shift in 2018. It was assumed that each person may experience three events throughout the training period. Therefore, the total number of events is calculated as 2,678×3 = 8,034 events.

In the present study, there were 15 predictors, and the goal was to have at least 10 events for each predictor to meet the principle. Therefore, the total number of events required was 15×10 = 150 events.

To estimate the sample size needed to achieve 150 events, the authors use the formula: (sample size × total events) / total observed events = required events

Let's plug in the values: (sample size × 8,034) / 38,477 = 150

Solving this equation gave: sample size = (150×38,477) / 8,034 = 719.73

Rounding up to the nearest whole number, the estimated sample size needed was 720 cases. Therefore, based on this calculation, a sample size of around 720 cases would be required to achieve the desired 150 events for each predictor in the risk assessment study.

The authors used 800 conscripts in the present study that trained at the First, Second, Third, and Fourth Army Areas and Bangkok and its vicinity in Thailand. A multistage cluster sampling technique was applied to select training units (Army Area → province → conscripts training unit) while the study sample comprised all conscripts in the selected training. Study periods were between November and December in the second turn and between May and June in the first turn.

General data on individual factors were collected such as age, education, training unit and occupation before enlistment, underlying diseases, drug use, substance abuse, body temperature, blood pressure, urine color, weight, height, body mass index, and color classification of the risk group symbol[5-38] as independent variables. Data were collected using the normal measures set by Royal Thai Army Medical Department to conscript training unit. The HRI included heat rash, heat edema, heat cramps, heat tetany, heat syncope, heat exhaustion, heat stroke, and rhabdomyolysis[39], with only the most severe type in each affected conscript being counted. HRI was diagnosed by medical personnel who received training from medical units.

The model development phase[40-42] was divided into four steps. The predictive model was created in the first step by collecting data and then applying the autocorrelation test. When no correlation was found, binary logistic regression was used to analyze the data and generate a model by selecting variables to generate scores for predicting the incidence of HRI. The statistically significant variables were selected using the backward stepwise method by selecting variables with $p>0.1$ from the equation until the final model was obtained. Quantitative variables or continuous variables were transformed into categorical data using standard criteria such as fever and body mass index, and then selecting the predictive variables obtained from the model. An appropriate model was created using the –2 log-likelihood ratio. The scoring instrument was developed in the second step using the predictive variables obtained for the first step. Categorical variables were used to support the continuous variables or continuous data. The coefficient of the variable provided the lowest value equal to 1. The coefficient of the variables in the model was summed, and the quotient obtained to the decimal 0 or 5 was rounded to generate the next scoring scheme. The score level obtained was used to create a variable supporting the score, assigning it to the newly created variable. The discriminated risk scores were obtained in the third step by checking the prediction of HRI separated by disease using the calculation to determine the area under the ROC curve. An area less than 50% meant that the event could not be predicted. The validity or ability to predict for calibration, was assessed by the Hosmer-Lemeshow goodness-of-fit test. No statistical significance indicated a lack of consistency or possessing accuracy or ability to predict well. The intersection point was calculated from the positive likelihood ratio (LHR+) at two levels, low and high risk. The model performance was evaluated using the chi-square test for goodness of fit. In the fourth step, bootstrap validation was used to test the internal validity of the model by copying the data and analyzing the factors that constituted predictors. When the factors obtained from internal validation were close to the prediction value, the developed model was considered suitable.

During the model evaluation phase, variable data were collected on the conscript training unit obtained from model development by categorizing risk groups into two levels, namely low and high risk, according to the symbolic color. Then HRI data were collected daily for analysis by setting the form of a dependent variable as a binary outcome as the incidence/no incidence of HRI in that person, on a specific day. If one person had more than one disease in one day, the diagnosis with the highest severity would constitute the incidence. The data were calculated using the Net Reclassification Index (NRI)[43] using the following formula:

$$NRI = P(up|event) - P(down|event) + P(down|nonevent) - P(up|nonevent)$$

where P(up|event) is the number of people in the high-risk group with HRI, P(down|event) is the number of people in the low-risk group with HRI, P(down|nonevent) is the number of people in the low-risk group with no HRI, and P(up|nonevent) is the number of people in the high-risk group with no HRI.

A high NRI (more than 50%) indicates the classification of risk groups from the model obtained and would be appropriate in terms of impact analysis and model implementation. However, implementation did not take place in the present study.

For data analysis, IBM SPSS Statistics, version 20.0 (IBM Corp., Armonk, NY, USA) was employed.

## Ethical approval

The present research was approved by the Ethics Committee of Thammasat University on May 27, 2020, and the Royal Thai Army Medical Department on May 23, 2020, No. S077h/62. These principles emphasize the importance of respecting the autonomy and privacy of the participants, striving for overall benefit and knowledge generation, and ensuring fairness and equal opportunities in the selection and treatment of participants.

**Table 1.** General information on conscripts

| General information | n=2,217 |
|---|---|
| Age (years); mean±SD | 21.61±2.43 |
| Body mass index (kg/m²); mean±SD | 22.84±4.31 |
| Army area; n (%) | |
| Bangkok metropolitan area and its vicinity | 356 (16.1) |
| 1st army area | 533 (24.0) |
| 2nd army area | 404 (18.2) |
| 3rd army area | 332(15.0) |
| 4th army area | 592 (26.7) |
| Heat-related work history before enlistment; n (%) | |
| Yes | 391 (17.6) |
| No | 1,826 (82.4) |
| History of alcohol consumption for at least seven days before enlistment; n (%) | |
| No | 1,562 (70.5) |
| Yes | 655 (29.5) |
| History of drug use for at least seven days before enlistment; n (%) | |
| No | 1,723 (77.7) |
| Yes | 494 (22.3) |
| Underlying diseases; n (%) | |
| No | 2,007 (90.5) |
| Yes | 210 (9.5) |

SD=standard deviation

## Results

During the model development phase, 2,217 conscripts participated in the present study with a 100% response rate. The mean age was 21.61±2.43 years, and the mean body mass index (BMI) was 22.84±4.31 kg/m². Most participants (26.7%) of the participants received training in the Fourth Army Area, 82.4% had no heat-related work history before enlistment, 70.5% had no history of alcohol consumption at least seven days before enlistment, 77.7% had no history of drug use at least seven days before enlistment, 80.9% had no history of regular drug use, and 90.5% had no underlying diseases, as shown in Table 1.

There were 134 HRI incidences in the sample group over 70 training days, resulting in a morbidity rate of 0.86 per 1,000 persons/day, and the most frequent HRI was heat rash at 0.80 per 1,000 persons/day, as shown in Table 2.

**Table 2.** Incidence of HRI (over a training period of 70 days)

| Disease | Total (1,000 persons/day) |
|---|---|
| Rash | 124 (0.80) |
| Edema | 0 (0.00) |
| Cramps | 1 (0.006) |
| Syncope | 1 (0.006) |
| Tetany | 3 (0.02) |
| Exhaustion | 0 (0.00) |
| Stroke | 0 (0.00) |
| Rhabdomyolysis | 0 (0.00) |
| Total | 134 (0.86) |

No HRI autocorrelation could be observed at 14 days (r=0.260), so binary logistic regression was used to develop the model. Model development was performed by proceeding with step 1, selecting variables to be imported into the model including body temperature, body mass index, systolic blood pressure, diastolic blood pressure, urine color, alcohol consumption within seven days before enlistment, having a history of work exposure to heat, and history of regular drug use. The variables were selected using the backward stepwise method by selecting the variables with p<0.05 from the equation. The final model predictors included fever, body mass index, systolic blood pressure, urine color, and alcohol consumption within seven days before enlistment, with two models being developed. The first model predictors were categorical and the second was continuous. A suitable model was created by comparing the –2 log-likelihood ratio. The most appropriate model was the first model that included the following predictors, urine color, history of alcohol consumption at least seven days before enlistment, body temperature, systolic blood pressure, and body mass index. Employing all factors in both models, the validity or calibration, using Cox and

**Table 3.** Analysis of predictors

| Model | Factor | Incidence n (%) | β | Wald | OR (95% CI) | Score | –2 log-likelihood ratio | Cox and Snell $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 1 | Constant | | –6.088 | | | | 1849.821 | 0.002 |
| | Urine color 0 | 3 (2.2) | | 32.69 | | 0 | | |
| | Urine color 1 | 32 (23.9) | –1.795 | 8.72 | 0.16 (0.05 to 0.55) | 5.5 | | |
| | Urine color 2 | 76 (56.7) | –1.365 | 8.72 | 0.25 (0.08 to 0.82) | 4.5 | | |
| | Urine color 3 | 23 (17.2) | –0.32 | 5.32 | 0.73 (0.22 to 2.45) | 1 | | |
| | Having history of alcohol consumption at least seven days before enlistment | | | | | | | |
| | Yes | 51 (38.1) | 0.389 | 4.63 | 1.48 (1.04 to 2.10) | 1 | | |
| | Body temperature (°C) | | | | | | | |
| | <37.2 | 125 (93.3) | | | 1 | 0 | | |
| | ≥37.2 | 35 (26.1) | 1.883 | 28.81 | 6.57 (3.31 to 13.08) | 6 | | |
| | Systolic blood pressure (mmHg) | | | | | | | |
| | <139 | 99 (73.9) | | | 1 | 0 | | |
| | ≥140 | 35 (26.1) | 0.935 | 21.22 | 2.55 (1.71 to 3.79) | 3 | | |
| | Body mass index (kg/m$^2$) | | | | | | | |
| | ≤18.50 | 5 (3.8) | | 40.98 | | 0 | | |
| | 18.51 to 24.99 | 59 (44.7) | 0.335 | 0.51 | 1.39 (0.56 to 3.49) | 1 | | |
| | 25.00 to 29.99 | 35 (26.5) | 0.844 | 3.095 | 2.33 (0.91 to 5.98) | 2.5 | | |
| | ≥30.00 | 33 (25.0) | 1.745 | 12.90 | 5.73 (2.21 to 14.84) | 5.5 | | |
| 2 | Constant | | –10.755 | | | | 1856.119 | 0.002 |
| | Urine color | 134 (100) | 0.581 | 17.47 | 1.79 (1.36 to 2.35) | | | |
| | Having history of alcohol consumption at least seven days before enlistment | | | | | | | |
| | Yes | 51 (38.1) | 0.563 | 6.31 | 1.76 (1.13 to 2.72) | | | |
| | Body temperature (°C); mean±SD | 36.28±2.83 | –0.054 | 9.05 | 0.95 (0.10 to 0.98) | | | |
| | Diastolic blood pressure (mmHg); mean±SD | 63.76±26.58 | 0.026 | 35.02 | 1.03 (1.02 to 1.03) | | | |
| | Body mass index (kg/m$^2$); mean±SD | 22.84±4.31 | 0.133 | 45.61 | 1.14 (1.10 to 1.19) | | | |
| | Having heat-related work history before enlistment | | | | | | | |
| | Yes | 17 (12.7) | –0.508 | 3.77 | 0.60 (0.36 to 1.01) | | | |

SD=standard deviation

Snell $R^2$ values predicted HRI at 0.2%. In the selected model, predictors were used for scoring development. The most appropriate predictor with a high score was a body temperature of more than 37.2°C or fever, and the second urine color followed by a high body mass index as shown in Table 3.

The power to classify HRI was assessed using the area under the curve (under ROC, AuROC). According to the factors presented in Table 3, participants with. or without HRI were distinguished at 63.2% (95% CI 57.3 to 69.1) and considered to have a good level of discrimination ability and could be used to predict HRI, as presented in Figure 1.

An analysis of the overall score results revealed a full score of 21 points for body temperature, body mass index, systolic blood pressure, urine color, and alcohol consumption within seven days before enlistment. A mean score of 6.84±1.98 points with a median of 6.50 points, minimum of 0 points, and maximum of 22 points, was obtained by determining an appropriate cut-off point. Based on sensitivity and false positives (1-specificity) and the area under the curve at various intersections, the appropriate cut-off points were used to classify the risk into two levels, low and high. High risk was defined as a score of 7.75 with a sensitivity of 52.3%, a false positive of 22.5%, and an area under the curve of 64.9% (95% CI 59.8 to 70.0), as present in Figure 2.

The calibration test, using the Hosmer-Lemeshow goodness-of-fit, showed that there was no significant difference in the variables used in the prediction of diseases, as presented in Table 4.

Test of model performance, the model could predict HRI with statistical significance as shown in Table 5.

The bootstrapping method involving simple random sampling was used to evaluate the internal validity of 1,000 samples. The results revealed that the appropriate predictors were body mass index, fever, systolic blood pressure, and alcohol consumption within seven days before enlistment. Cox and Snell $R^2$ were able to predict the incidence of three HRI events per 1,000 persons/day, which was consistent with the developed model, as presented in Table 6.

During the model evaluation phase, the NRI was analyzed by comparing a (new) scoring method with symbol color classification, which is a traditional risk assessment. The NRI of the high-risk group from the symbol color classified as a high-risk group using the scoring method increased by 1.8% (95% CI 0.6 to 2.9). The NRI of the low-risk group from the symbol color classified as low risk using the scoring method

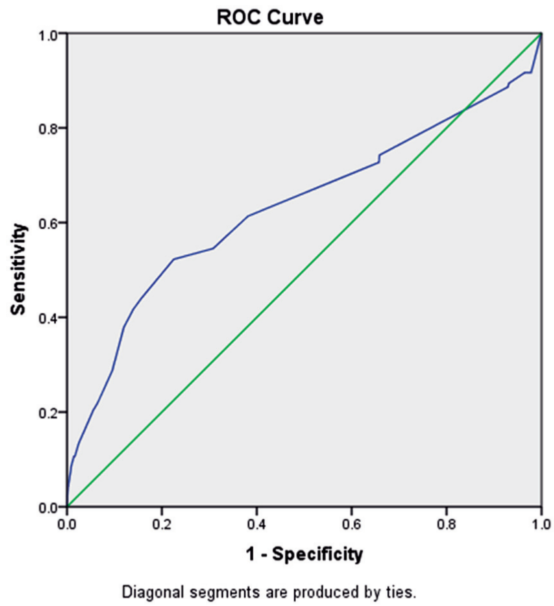


**Figure 1.** Distinguish area under the curve (under ROC, AuROC).

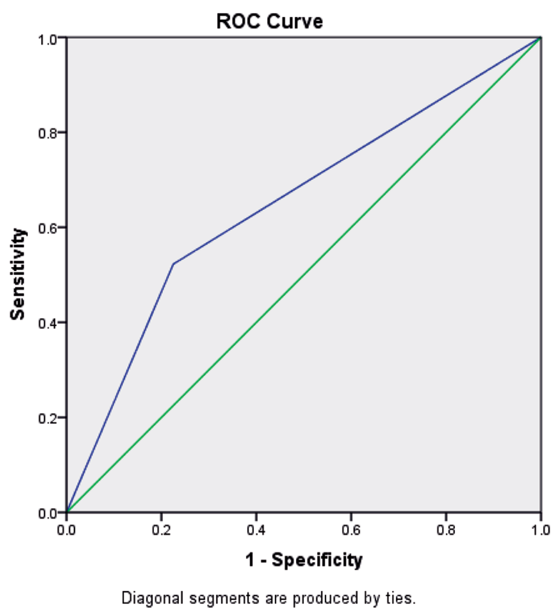


**Figure 2.** Area under the curve (under ROC, AuROC) at cut-off score (7.75 points).

**Table 4.** Calibration test

| Factor | Chi-square | df | p-value |
|---|---|---|---|
| Urine color | 9.993 | 6 | 0.125 |
| Alcohol consumption within seven days before enlistment | | | |
| Body temperature | | | |
| Systolic blood pressure | | | |
| Body mass index | | | |

**Table 5.** Model performance

| | | Incidence of HRI; n (%) | | Chi-square | p-value |
|---|---|---|---|---|---|
| | | Yes (n=132) | No (n=87,533) | | |
| Incidence of HRI | Low risk (<7.75 points) | 63 (47.7) | 67,819 (77.5) | 66.762 | <0.001 |
| | High risk (≥7.75 points) | 69 (52.3) | 19,714 (22.5) | | |

HRI=heat-related illnesses

**Table 6.** Appropriate predictor factors

| Factor | ORs (95%CI) | –2 log-likelihood ratio | Cox and Snell $R^2$ |
|---|---|---|---|
| Body mass index (kg/m²) | | –1095.884 | 0.003 |
| ≤18.50 | 1 | | |
| 18.5 to 24.99 | 0.872 (0.310 to 2.447) | | |
| 25.00 to 29.99 | 1.043 (0.345 to 3.150) | | |
| ≥30.00 | 4.246 (1.452 to 12.421) | | |
| Body temperature (°C) | | | |
| <37.2 | 1 | | |
| ≥37.2 | 3.871 (1.185 to 12.647) | | |
| Systolic blood pressure (mmHg) | | | |
| <139 | 1 | | |
| ≥140 | 3.445 (2.121 to 5.595) | | |
| Alcohol consumption within seven days before enlistment | | | |
| No | 1 | | |
| Yes | 1.795 (1.160 to 2.776) | | |

ORs=odds ratios; CI=confidence interval

**Table 7.** Absolute Net Reclassification Index of the new model

| | | | Risk classification by color symbol; n (%) | | | Total; n (%) | NRI (95% CI) |
|---|---|---|---|---|---|---|---|
| | | | Low risk | High risk | Total | | |
| Risk classification by score | Low risk | Event | 2 (0.1) | 0 (0.0) | 2 (0.1) | 1,825 (100) | 61.4 (59.7 to 63.1) |
| | | Non-event | 1,456 (79.8) | 367 (20.1) | 1823 (99.9) | | |
| | High risk | Event | 0 (0.0) | 1 (0.3) | 1 (0.3) | 387 (100) | |
| | | Non-event | 196 (50.6) | 190 (49.1) | 386 (99.7) | | |
| | Total | Event | 2 (0.09) | 1 (0.04) | 3 (0.13) | 2,212 (100) | |
| | | Non-event | 1,652 (74.68) | 552 (25.18) | 2,209 (99.87) | | |
| Total | | | 1,654 (74.8) | 558 (25.2) | 2,212 (100) | | |

NRI=Net Reclassification Index; CI=confidence interval

increased by 59.6% (95% CI 57.6 to 61.5), while the sum of the NRI was 61.4% (95% CI 59.7 to 63.1), as shown in Table 7.

## Discussion

The purpose of the present study was to create and evaluate a suitable statistical model to predict the incidence of HRI during conscript training. The proposed model was expected to help prevent HRI among conscripts and others participating in military training.

General information on the history of heat exposure before enlistment revealed that most conscripts had no history of heat exposure before enlistment. This was due to their modern lifestyle. Most conscripts were office workers or students without a history of exposure to heat. Additionally, being unfamiliar with heat may constitute a risk factor for HRI. This finding was consistent with the studies of Nutong et al.[11] and Casa et al.[37].

As for other factors, most participants had no history of alcohol consumption or drug use within at least seven days before enlistment. No history of regular drug use and no underlying diseases were demonstrated during the recruitment/screening process for the Army Corps. During screening of military service candidates on active duty, individuals should be selected appropriately in terms of preparation and public relations. When entering military service, selected individuals should be able to prepare well and reduce the risk factors for HRI.

An analysis of heat-related morbidity rates in the present study revealed a figure of 1.6 per 1,000 persons/day, which was consistent with the rate of the Royal Thai Army Medical Department of 2/63 to 1/65, on average, equal to 2.4 per 1,000 persons/day.

The sample in conscript training unit experienced mild illnesses. There are effective protection measures in place to reduce the occurrence of sickness. HRI such as heat rash, heat cramps, and heat syncope can indeed be common in environments with high temperatures or heat exposure.

The analysis results for predictive factors revealed that the appropriate model included alcohol consumption within seven days before enlistment. Fever with a body temperature greater than 37.2°C in the axil, systolic blood pressure, body mass index, and urine color, were consistent with the study and announcement by the Royal Thai Army Medical Department(3,10-14,16,18-30,32-35). Exposure to hot weather during training will increase body temperature and the risk of HRI, aligning with the Royal Thai Army Medical Department announcement and the studies conducted by Nutong et al.(11) and Kenny et al.(39).

A high body mass index increases the risk of HRI. This may be because the patient's body has a large amount of fat, causing heat to accumulate in the body. This is consistent with the announcement by the Army Medical Department and the studies of Nutong et al.(10), Bouchama et al.(14), and Wallace et al.(23).

A darker urine color and an increase in urination were found to raise the risk of HRI. This is because darker urine is an indicator of dehydration in active-duty troops. As the urine color becomes darker, it indicates greater dehydration. However, an inverse effect could be observed in the present study due to good prevention measures. Increased access to water caused the urine color of most active-duty soldiers to appear at the normal color level, which is urine color 1 to 2, thus making it a protective factor in HRI.

High systolic blood pressure was found to indicate a significant risk of developing HRI. This was likely to be caused by the heart contracting. High blood pressure produces body heat constituting a risk factor for HRI.

Alcohol consumption within seven days before enlistment was an important risk factor for HRI because consuming alcohol causes the blood vessels to dilate, elevating the body temperature. This corresponds to the announcement of the Royal Thai Army Medical Department and the study by Nutong et al.(11).

When taking into account the factors to create a prediction score, patients with or without heat illness could be distinguished as 63.2% (95% CI 57.3 to 69.1) and considered as good predictors of HRI.

When categorized by risk level, the appropriate cut-off point for low and high risk was 7.75 points with a sensitivity of 52.3% and a false positive of 22.4%. Notably, 22.5% and 64.9% of the area under the curve (95% CI 59.8 to 70.0) were deemed suitable for predicting HRI.

According to the model evaluation, the color symbol risk group discrimination analysis announced by the Royal Thai Army Medical Department was found to be comparatively easy to use for the scoring of prediction factors. Moreover, the use of symbolic colors proved to be the best practice. However, when combining rotations, the segregation of risk groups using symbolic colors proved to be better than using a score scale. Nevertheless, the prediction revealed no difference in the rate of events since the use of scoring involves a combination of personal factors without considering the environment as a predictive factor. This was because, in training, all active-duty soldiers interact in the same environment. The different climatic factors may have influenced the sorting process. In addition, sorting by symbolic color involved both quantitative and qualitative measures due to the need for individuals to be separated. Individual differences may have affected the sorting results or sorting methods, especially when more than one factor was involved. Using the symbolic color with the highest intensity to define the risk group could ensure the training was safe, reducing the risk of HRI and incorporating good preventive measures, thereby reducing the incidence of HRI. Furthermore, scoring may be used as an adjunct measure in conjunction with conventional symbolic color classification since it has proven to be suitable in cases where it is not possible to distinguish the risk using conventional symbolic colors alone.

The present study provides a suitable model (scoring) for predicting HRI. The use of personal factors to separate risk groups in active-duty training by the Army could be extended to other armies as appropriate. Risk discrimination by scoring involves preliminary screening only. It helps to resolve problems when applying the symbolic color criteria of the Royal Thai Army Medical Department. However, the model could not clearly identify the unit for consideration. Moreover, when appropriate measures are taken in relation to risk groups, they could be combined with daily risk screening to help reduce the rate of HRI in training new soldiers.

Due to the current incidence of HRI, the Royal Thai Army should focus on preventive measures and vigilance to avoid such events. Specifically, data on the incidence of severe HRI such as heat exhaustion and heat stroke should be combined among training units to offer good protection and reduce risk. Since the incidence of HRI does not reach the target, the developed model is considered to be appropriate as an additional measure for screening or discriminating within risk groups. In cases where discrimination by color symbols is impossible, such as in the presence of more than one risk factor, grading would be appropriate. The present study has certain limitations in identifying HRI as far as the Royal Thai Army is concerned. In particular, emphasizing preventive measures and vigilance could provide protection against severe HRI, such as exhaustion and stroke. As a result, the incidence of HRI would decrease. Another limitation of the model is that the use of NRI is for comparison only and a new tool would be able to classify risk groups into new and old. It could also be employed to stratify two or more groups. The effectiveness of prediction using the symbolic colors (traditional) and the rating scale (new) should be compared using discriminant power differences and the area under ROC for greater applicability.

The present study suggests that the model be used to assess the risk of HRI among conscripts. In surveillance, only the most influential factors arising from the present study should be used to prevent HRI in conscript training. In the future, the model could be developed into a program or application for trainees. Stationed soldiers could screen themselves. It should be used in conjunction with risk assessment with the symbolic colors of the Royal Thai Army Medical Department as the main measure. The score scale could provide an additional screening measure. However, risk groups should use measures according to the announcement of the Royal Thai Army Medical Department. High-volume groups determined from the score scale or symbolic color should be properly protected. In the future, studies could combine both methods for appropriate risk screening. The efficacy of interventions according to risk group should be studied when classifying by rating scale to ensure they are properly protected.

## What is already known on this topic?

The important factors of this topic have previously been acknowledged and a suitable model using a scoring scale used to predict HRI in conscript training, used in conjunction with the symbolic color classification of the Royal Thai Army Medical Department is available. The model has been used in cases where the symbolic color cannot be distinguished and is suitable for military training (in the field).

## What this study adds?

This study shows the important risk factors for predicting HRI such as urine color, alcohol consumption, body temperature, and body mass index. These risk factors can be controlled by placing greater focus on access to water in outdoor work, implementing an anti-drinking campaign, improving personal health surveillance such as regular temperature taking, and implementing a weight loss campaign to reduce body mass index, all of which will help to reduce the incidence of HRI.

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## Conflicts of interest

The author declares no conflict of interest.

## References

1. Division of Health Impact Assessment, Department of Health, Ministry of Public Health. Introduction, health impacts from heat for public health officials. Nonthaburi: Division of Health Impact Assessment; 2016. p. 10.
2. Rangsin R. Exertional heat illness: Epidemiology

and prevention. In: Phumhiran P, Prayoonwiwat W, editors. Heat stroke. Bangkok: Textbook project Phramongkutklao College of Medicine; 2013. p. 17-29.
3. Deepreecha K, Buranatrevedh S. Factors associated with heat related illnesses among soldiers: a systematic review. J Med Assoc Thai 2020;103(Suppl 4):5-9.
4. Division of Health Promotion and Preventive Medicine Royal Thai Army Medical Department. Announcement Royal Thai Army Medical Department advice and prevention, surveillance, treatment of heat related illnesses. Bangkok: Royal Thai Army Medical Department; 2017.
5. Carter R 3rd, Cheuvront SN, Williams JO, Kolka MA, Stephenson LA, Sawka MN, et al. Epidemiology of hospitalizations and deaths from heat illness in soldiers. Med Sci Sports Exerc 2005;37:1338-44.
6. Shunsuke N, Tohru A. Epidemiology of heat illness. JMAJ 2013:56:162-6.
7. Division of Health Promotion and Preventive Medicine Royal Thai Army Medical Department. Lecture notes on preventing heat illness [Internet]. 2018 [cited 2018 Sep 15]. Available from: https://amed.rta.mi.th/rtamed/prevent/index.php.
8. Naval Medical Department. Training to get used to the heat, operating a manual protection process. Watch out for the dangers of heat from the training of Royal Thai Navy personnel (for medical officers) [Internet]. 2017 [cited 2018 Sep 15]. Available from: http://www2.nmd.go.th/preventmed_joomla/images/stories/pdf/hs/standard%20HS/สำหรับหน่วยฝึก.pdf.
9. Phuengfoo P, Phaengpho S, Tanak W., Deepreecha K. Efficacy of the use of the HPPM Exercise Program to reduce body heat accumulation. In the training of active-duty troops with a body mass index of more than 28 kg per square meter. Army Med J 2018;71:79-85.
10. Phumhiran P, Prayoonwiwat W. Exertional heat illness. In: Phumhiran P, Prayoonwiwat W, editors. Heat stroke. Bangkok: Textbook project Phramongkutklao College of Medicine; 2013. p. 20-2.
11. Nutong R, Mungthin M, Hatthachote P, Ukritchon S, Imjaijit W, Tengtrakulcharoen P, et al. Personal risk factors associated with heat-related illness among new conscripts undergoing basic training in Thailand. PLoS One 2018;13:e0203428.
12. Pumchandh N, Tedsana V, Ngow S, Rangsin R, Aimpun P, Mungthin M, et al. Monitoring of the bed time body temperature and body weight to prevent the occurrence of heat stroke in the Royal Thai Army recruits, Lopburi Province, Thailand. J Med Assoc Thai 2012;95 Suppl 5:S1-5.
13. Wijerathne BTB, Pilapitiya SD, Vijitharan V, Farah MMF, Wimalasooriya YVM, Siribaddana SH. Exertional heat stroke in a young military trainee: is it preventable? Military Med Res 2016;3:8.
14. Bouchama A, Dehbi M, Mohamed G, Matthies F, Shoukri M, Menne B. Prognostic factors in heat wave related deaths: a meta-analysis. Arch Intern Med 2007;167:2170-6.
15. Jacklitsch B, Williams J, Musolin K, Coca A, Kim JH, Turner N. NOISH Criteria for a recommended standard: occupational exposure to heat and hot environments. Cincinnati, OH: DHHS (NIOSH) Publication; 2016.
16. Miyaki Y. Pathophysiology of heat illness: Thermoregulation, risk factors and indicators of aggravation. JMAJ 2013;56:167-73.
17. Hakre S, Gardner JW, Kark JA, Wenger CB. Predictors of hospitalization in male Marine Corps recruits with exertional heat illness. Mil Med 2004;169:169-75.
18. Kark JA, Burr PQ, Wenger CB, Gastaldo E, Gardner JW. Exertional heat illness in Marine Corps recruit training. Aviat Space Environ Med 1996;67:354-60.
19. Kovats RS, Hajat S. Heat stress and public health: a critical review. Annu Rev Public Health 2008;29:41-55.
20. Gronlund CJ. Racial and socioeconomic disparities in heat-related health effects and their mechanisms: a review. Curr Epidemiol Rep 2014;1:165-73.
21. Tustin AW, Lamson GE, Jacklitsch BL, Thomas RJ, Arbury SB, Cannon DL, et al. Evaluation of occupational exposure limits for heat stress in outdoor workers - United States, 2011-2016. MMWR Morb Mortal Wkly Rep 2018;67:733-7.
22. Stacey MJ, Parsons IT, Woods DR, Taylor PN, Ross D, S JB. Susceptibility to exertional heat illness and hospitalisation risk in UK military personnel. BMJ Open Sport Exerc Med 2015;1:e000055.
23. Wallace RF, Kriebel D, Punnett L, Wegman DH, Wenger CB, Gardner JW, et al. Risk factors for recruit exertional heat illness by gender and training period. Aviat Space Environ Med 2006;77:415-21
24. Pryor RR, Bennett BL, O'Connor FG, Young JM, Asplund CA. Medical evaluation for exposure extremes: Heat. Wilderness Environ Med 2015;26(4 Suppl):S69-75.
25. University of Connecticut, Korey Stringer Institute. Heat stroke risk factors: What puts an individual at risk for heat stroke? [Internet]. 2014 [cited 2018 Sept 15]. Available from: https://ksi.uconn.edu/emergency-conditions/heat-illnesses/exertional-heat-stroke/heat-stroke-risk-factors/.
26. Chuang WC, Gober P. Predicting hospitalization for heat-related illness at the census-tract level: accuracy of a generic heat vulnerability index in Phoenix, Arizona (USA). Environ Health Perspect 2015;123:606-12.
27. Gubernot DM, Anderson GB, Hunting KL. Characterizing occupational heat-related mortality in the United States, 2000-2010: an analysis using the Census of Fatal Occupational Injuries database. Am J Ind Med 2015;58:203-11.
28. Racinais S, Alonso JM, Coutts AJ, Flouris AD, Girard O, González-Alonso J, et al. Consensus recommendations on training and competing in the

heat. Br J Sports Med 2015;49:1164-73.
29. Semenza JC, Rubin CH, Falter KH, Selanikio JD, Flanders WD, Howe HL, et al. Heat-related deaths during the July 1995 heat wave in Chicago. N Engl J Med 1996;335:84-90.
30. Naiyapat W, Limjitkorn M, Supeesutsiriwan P. Screening for risk factors. Exploration of knowledge and awareness of prevention heat illness from active-duty military training. R Thai Army Med J 2014;67:47-58.
31. Krueger-Kalinski MA, Schriger DL, Friedman L, Votey SR. Identification of risk factors for exertional heat-related illnesses in long-distance cyclists: experience from the California AIDS Ride. Wilderness Environ Med 2001;12:81-5.
32. Cleary M. Predisposing risk factors on susceptibility to exertional heat illness: clinical decision-making considerations. J Sport Rehabil 2007;16:204-14.
33. Smalley B, Janke RM, Cole D. Exertional heat illness in Air Force basic military trainees. Mil Med 2003;168:298-303.
34. Moore AC, Stacey MJ, Bailey KG, Bunn RJ, Woods DR, Haworth KJ, et al. Risk factors for heat illness among British soldiers in the hot Collective Training Environment. J R Army Med Corps 2016;162:434-9.
35. Gardner JW, Kark JA, Karnei K, Sanborn JS, Gastaldo E, Burr P, et al. Risk factors predicting exertional heat illness in male Marine Corps recruits. Med Sci Sports Exerc 1996;28:939-44.
36. Erwin SD. Identification of internet risk factors and Intervention to prevent exertional heat illnesses in hikers: A systematic review. Submitted in partial fulfillment of the requirements for the Northern Arizona University, School of Nursing. Flagstaff, AZ: Northern Arizona University; 2015.
37. Casa DJ, Armstrong LE, Ganio MS, Yeargin SW. Exertional heat stroke in competitive athletes. Curr Sports Med Rep 2005;4:309-17.
38. Kenny GP, McGinn R. Restoration of thermoregulation after exercise. J Appl Physiol (1985) 2017;122:933-44.
39. Centers for Disease Control and Prevention. Warning signs and symptoms of heat related illness [Internet]. 2017 [cited 2019 Mar 15]. Available from: https://www.cdc.gov/disasters/extremeheat/warning.html.
40. Electricity Generating Authority of Thailand. Meaning of model [Internet]. 2017 [cited 2018 Sep 15]. Available from: http://tairgle.egat.co.th/index.php?option=com_content&view=article&id=7&Itemid=419&lang=th.
41. Chianchana C. Model creation and development. J Silpakorn Educ Res 2017;9:1-11.
42. Wiwattanadate P. Generalized estimating equations. In: Wiwattanadate P, editor. Health risk assessment and modeling. Chiang Mai: Chiang Mai University; 2561. p. 197-204.
43. Kerr KF, Wang Z, Janes H, McClelland RL, Psaty BM, Pepe MS. Net reclassification indices for evaluating risk prediction instruments: a critical review. Epidemiology 2014;25:114-21.