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Research article

Comparison of Logistic Regression and Discriminant Analyses for Predicting Survival in Patients with Severe Trauma

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Abstract

The objective of this study was to evaluate the precision of survival predictions for severely injured patients by comparing logistic regression and discriminant analyses. Survival was defined as in-hospital survival, from the initiation of treatment to discharge from the hospital. The study utilized group classification accuracy as a measure to evaluate the efficacy of each method. Data analysis was conducted using severely traumatized patients recruited from the trauma center of Maharaj Nakorn Chiang Mai Hospital. The findings indicated that logistic regression analysis revealed a significant link between survival in severely injured patients and hospital arrival duration, respiratory rate, and blood lactate levels. This model achieved 95.0% accuracy in overall group classification. In contrast, discriminant analysis shows that blood pressure, respiratory rate, Glasgow Coma Scale, and blood lactate levels were significantly associated with trauma patient survival. The discriminant analysis demonstrated an overall classification accuracy of 93.0%.

Keywords: logistic regression; discriminant analysis; survival; emergency; injury prevention

1. Introduction

Emergency management of patients with severe trauma is critically important, requiring careful and appropriate medical intervention. Monitoring and assessment of patients are based on physiological and anatomical principles, including evaluation of vital signs, physical injury status, and consciousness level. Observable external responses typically serve as the basis for these assessments. However, cellular-level injury assessment is also essential, as it provides deeper insights into the patient's condition (Blow et al., 1999; Claridge et al., 2000; Meregalli et al., 2004). A rapid method for assessing cellular-level injury involves measuring blood lactate levels, which serve as a sensitive and specific biomarker. Blood lactate levels are used to predict the severity of illness and function as a prognostic indicator of mortality. Furthermore, they are also employed to evaluate cellular

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damage in critically ill patients with bloodstream infections and in severely injured patients (Mikkelsen et al., 2009; Moon et al., 2011; Lee et al., 2012)

Nevertheless, blood lactate levels alone may not serve as a comprehensive predictor of survival outcomes in severely injured patients. It is advisable to integrate this measure with additional clinical data to conduct a thorough assessment of the patient's condition. Relevant factors include age, gender, time to emergency room arrival, level of consciousness, cause of injury, injury severity, and the physiological response post-injury (Lai et al., 2018; Yucel et al., 2018; Yadollahi, 2019). Treatment outcomes can vary significantly, with increased survival probability contingent upon prompt and comprehensive care delivery.

This study utilized logistic regression and discriminant analyses to investigate factors associated with survival in severely injured patients and to predict the likelihood of mortality or survival. These two analytical techniques are frequently employed for classification and prediction in diverse disciplines. For instance, Tanupattarasorn et al. (2024) applied logistic regression to analyze the prevalence of dental caries and estimated the adjusted prevalence percentage. Viboonkit et al. (2024) employed discriminant analysis to examine the morphological variation of short mackerel in Thailand and evaluate the pattern of morphological variation between samples. In medicine, these methods have been used to predict disease outcomes. For example, logistic regression has been employed to examine the relationship between survival factors and traffic accident victims treated at a tertiary hospital in Phuket (Wongvatanakit et al., 2019). The study findings indicated that injury severity was the only factor associated with survival. Research on patient survival during hospital transport for motor vehicle accident victims in Thailand (Pooncharoen et al., 2019) revealed that factors influencing patient survival included gender, duration of initial treatment at the scene, duration of the transport from the scene to the hospital, and injury characteristics. Additionally, other studies (Yadollahi et al., 2017; Kunitake et al., 2018; Ostermann et al., 2018; Noland et al., 2019; Janthasri et al., 2020) have shown that post-injury bodily response, level of consciousness, cause of injury, injury severity, and age are factors related to survival in severely injured patients. Discriminant analysis has also been extensively used in research to predict the survival of patients with trauma (DeMaria et al., 1987; Ahmed et al., 2020; Boeira et al., 2023; Wu et al., 2023).

However, while several studies have compared logistic regression and discriminant analysis studies (Panagiotakos, 2006; Abdulqader, 2015; Kitbumrungrat, 2017; Sujarittham, 2018; Feng et al., 2019; Peerapan & Pasunon, 2019; Tonglore et al., 2023), none have specifically examined these two methods for predicting survival in severely injured patients. Thus, the objective of this study is to compare survival prediction accuracy for severely injured patients admitted to the emergency department using logistic regression and discriminant analysis. The aim is to achieve the highest predictive accuracy, facilitate precise treatment decisions, prevent adverse outcomes from delayed care, and provide a strategy to reduce the mortality risk for critically injured patients.

2. Materials and Methods

This study used secondary data collected from 100 severely injured patients admitted to the Emergency and Trauma Department at Maharaj Nakorn Chiang Mai Hospital (Tangchaisuriya et al., 2019). Patients with severe injuries were identified using a physiological response assessment tool following trauma, especially the Revised Trauma Score (RTS), which was employed to assess patients promptly upon their arrival in the emergency room. The RTS scoring system comprises three physiological parameters: the

degree of consciousness as measured by the Glasgow Coma Scale (GCS), systolic blood pressure, and respiration rate. Each metric was assigned a coded value ranging from 0 to 4, where 0 signifies critical severity and 4 denotes normal physiological function (Champion et al., 1989).

The exclusion criteria for this study were as follows: (1) patients with underlying chronic diseases such as liver disease, chronic renal failure, diabetes mellitus, cardiovascular disease, malignancy, chronic lung disease, and HIV infection; (2) patients taking medications that may affect blood lactate levels, including NRTIs (e.g., Stavudine, Zidovudine, Lamivudine), metformin, nitroprusside, isoniazid, and potassium cyanide; (3) patients referred from other hospitals without pre-treatment lactate data; (4) patients with burn injuries; and (5) pregnant patients. Therefore, detailed data on excluded patients were not available in the dataset. However, these variables may influence survival outcomes and should be considered in future studies.

To develop a predictive model for survival, various factors were considered, including gender, age (years), time to hospital admission (minutes), systolic blood pressure (mmHg), heart rate (beats per minute), respiratory rate (breaths per minute), Glasgow Coma Scale score, and blood lactate levels (mmol/L). In this context, survival refers to in-hospital survival, which included the time from the start of treatment until the patient was discharged from the hospital. In contrast, non-survival cases were identified as in-hospital mortality (Tangchaisuriya et al., 2019). We focused on predicting survival in severely injured patients using logistic regression and discriminant analyses, despite the potential to create multiple model structures with these factors. Data analysis was conducted using R: version 4.3.1 (R Core Team, 2023). The analytical details for each method are outlined below.

2.1 Logistic regression analysis

Logistic regression analysis is a technique that predicts the probability of an event or classifies data into groups. It is particularly useful for binary classifications, but it can also be applied to multiple group classifications. An effective logistic regression model should include appropriate independent variables that closely predict the probability of the event of interest. In this study, the dependent variable is binary, and there are p independent variables expected to influence it. The logistic regression model can express a linear relationship as follows:

$$\text{logit}(P(Y)) = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p \quad (1)$$

To predict the probability of the event of interest, the equation can be written as follows:

$$P(Y) = \frac{\exp(\beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p)}{1 + \exp(\beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p)} \quad (2)$$

where $P(Y)$ represents the probability of the outcome occurring.
β_0 represents the intercept.
β_j represents the coefficients for each independent variable where $j = 1,2,\ldots,p$.
X_j represents each independent variable where $j = 1,2,\ldots,p$.

This study identifies eight independent variables ($p = 8$): gender, age, time to hospital admission, systolic blood pressure, heart rate, respiratory rate, Glasgow Coma Scale score, and blood lactate levels.

We estimated the parameters using the Maximum Likelihood Estimate (MLE) method (McCullagh & Nelder, 1989). This process began by estimating the coefficients of the variables, using these estimates to construct an equation based on the data, and then iteratively recalculating to update the coefficients until they stabilize, achieving maximum likelihood for accurate prediction of the dependent variable. Subsequently, we evaluate the model's fit using the Hosmer and Lemeshow test. We evaluated the significance of the regression coefficients utilizing the Wald statistic at a significance level of 0.05. Finally, we assessed predictive accuracy through a classification table.

2.2 Discriminant analysis

Discriminant analysis is a statistical method similar to logistic regression regarding the dependent variable and equation configuration. The purpose was to find criteria for group classification and to formulate an optimal discriminant equation based on the data that can subsequently be utilized to predict the group of new samples with unknown group membership (Zelterman, 2022). Discriminant analysis requires that independent variables adhere to a normal distribution and that the covariance matrices of the independent variables are equal across groups (Hair et al., 2006). The relationship between the dependent and independent variables is linear. This study classifies patients into two groups: those who survived severe injuries and those who did not. The discriminant function is represented as follows:

$$D_i = \alpha_i + \beta_{i1}X_{i1} + \beta_{i2}X_{i2}\ldots. + \beta_{ip}X_{ip} \quad (3)$$

Where
- D_i represents the discriminant score of group i where $i = 1,2$
- α_i represents the constant of group i where $i = 1,2$
- β_{ij} represents the coefficients for each independent variable of group i and predictor j where $i = 1,2$ and $j = 1,2,\ldots,p$
- X_{ij} represents the independent variable of group i and predictor j where $i = 1,2$ and $j = 1,2,\ldots,p$

This study identified eight independent variables: gender, age, time to hospital admission, systolic blood pressure, heart rate, respiratory rate, Glasgow Coma Scale score, and blood lactate levels. Next, we performed variable selection using a stepwise method, adding each independent variable to the equation one by one. Each selected variable must significantly enhance the discriminative power of the function. Once we developed the equation, we used it to predict group membership of the dependent variable by substituting the values of the independent variables for a new observation, then calculating the discriminant score. The observation was assigned to the group with the higher discriminant score (Vanichbuncha, 2021).

3. Results and Discussion

We recognize that patients with severe trauma form a diverse group, and their survival is affected by many factors, such as the type and location of their injuries, underlying health conditions, and prior medication use. This study applied exclusion criteria to minimize clinical variability. The study excluded patients with chronic diseases (e.g., liver disease, chronic renal failure, diabetes mellitus, cardiovascular disease, cancer, chronic lung disease, and HIV infection), taking medications known to affect blood lactate levels (e.g., NRTIs, metformin, nitroprusside), burn injury patients, pregnant patients, and those without pre-treatment lactate data. Despite controlling for key clinical factors by excluding patients with chronic diseases or relevant medications, our study was limited by the absence of trauma details (e.g., injury type or location). Incorporating such data in future models could further improve predictive accuracy and clinical applicability. The results from the data analysis using logistic regression and discriminant analysis are shown in Table 1.

Table 1. Description of each variable and abbreviations

Variables	Description
sur	Patient survivor outcome (0 = non-survivor, 1 = survivor)
gender	gender (0 = female, 1 = male)
age	age (year)
time	time to hospital admission (minute)
BP	systolic blood pressure (mmHg)
PR	heart rate (beats per minute)
RR	respiratory rate (breaths per minute)
GCS	Glasgow Coma Scale score
BL	blood lactate levels (mmol/L)

Data from 100 severely injured patients were also analyzed in this study, of whom 71 survived and 29 did not. Descriptive statistics of the independent variables presented in Table 2 indicate that survivors exhibited significantly higher systolic blood pressure (BP) compared to non-survivors. The Glasgow Coma Scale (GCS) scores for survivors exceeded those of non-survivors, whereas non-survivors exhibited elevated blood lactate (BL) levels compared to survivors.

Table 2. Characteristics of the injured patients by outcome

	Outcome	
	Survivors	**Non-survivors**
n	71	29
gender (Male)	59	25
age, mean (SD)	39.501 (17.055)	47.069 (19.203)
time, mean (SD)	30.789 (13.862)	32.069 (17.552)
BP, mean (SD)	111.380 (34.883)	59.069 (20.017)
PR, mean (SD)	104.084 (22.602)	112.655 (28.088)
RR, mean (SD)	23.732 (4.229)	21.069 (4.566)
GCS, mean (SD)	8.746 (3.012)	4.103 (1.566)
BL, mean (SD)	5.584 (2.033)	14.047 (6.223)

Table 3 indicates that the independent variables that significantly correlated with survival in severely injured patients were time to hospital (time), respiratory rate (RR), and blood lactate (BL) at the 0.05 significance level. The model's fit was validated through the Hosmer-Leme show test (p-value > 0.05), and the Nagelkerke R Square value was 0.836, suggesting that the logistic regression model accounts for 83.6% of the variability in survival probabilities for severely injured patients. The equation for logistic regression is presented as follows:

$$\text{logit}\big(P(Y)\big) = 6.412 - 0.095Time + 0.301RR - 1.053BL$$

The Wilks' Lambda test results are shown in Table 4. They show that systolic blood pressure (BP), respiratory rate (RR), GCS score, and blood lactate (BL) were significantly different in the survival and non-survival groups at the 0.05 significance level (p-value < 0.05). These variables are thus important for classifying patient groups.

The assumptions underlying discriminant analysis were subsequently evaluated. Independent variables must be multivariate normally distributed and have equal covariance matrices across groups. Due to the initial failure of the four selected variables to satisfy the normality requirement, data underwent transformation via the Box-Cox Transformation (Box & Cox, 1964). The assessment of multivariate normality was conducted using a Chi-square Q-Q plot, revealing that the majority of data points were closely aligned with the reference line, exhibiting only minor deviations (Figure 1). Consequently, the variables BP, RR, GCS, and BL displayed characteristics of approximate multivariate normality.

Table 3. The results of coefficient of logistic regression model

	β	S.E.	Wald-test	p-value
Intercept	6.412	2.984	4.617	0.032
time	-0.095	0.043	4.822	0.028
RR	0.301	0.110	7.448	0.006
BL	-1.053	0.266	15.679	< 0.001
Hosmer-Lemeshow Test: χ^2 = 6.304, p-value = 0.613				
-2log likelihood = 32.350				
Nagelkere R Square = 0.836				

Table 4. Test of equality of group means for discriminant analysis

Variables	Wilks'Lambda	p-value
gender	0.999	0.704
age	0.963	0.055
time	0.998	0.700
BP	0.631	< 0.001*
PR	0.975	0.113
RR	0.962	0.006*
GCS	0.613	< 0.001*
BL	0.482	< 0.001*

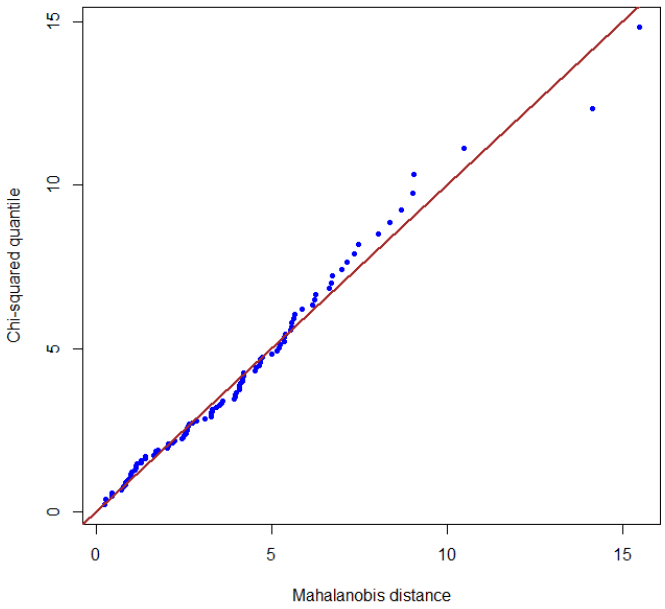


Figure 1. Chi-square Q-Q plot for data set

Furthermore, the Szekely and Rizzo test was also used to check for multivariate normality, and Box's M test was used to see if the covariance matrices were equal, as shown in Table 5.

Table 5 indicates that at the 0.05 significance level, the four variables, BP, RR, GCS, and BL, showed a multivariate normal distribution (p-value = 0.813). Additionally, the covariance matrices for the survival and non-survival groups of severely injured patients were equal (p-value = 0.115). A discriminant function was developed based on these results, as presented in Table 6.

Table 5. Multivariate normal distribution and homogeneity of covariance matrices test results

Multivariate Normal Distribution		**Covariance Matrices**	
Szekely and Rizzo	p-value	Box's M	p-value
0.906	0.813	10.703	0.115

Table 6. Classification function coefficients

	Coefficient	
	Non-survivors	**Survivors**
Constant	-2.557	-1.024
BP	-1.085	0.482
RR	-0.718	0.294
GCS	-1.065	0.492
BL	1.439	-0.554

Table 6 demonstrates that the variables employed to categorize severely injured patients were BP, RR, GCS, and BL, aligning with the group differences observed in Table 4. The discriminant equations for each group are presented below:

Non survivor

$$D_{nonsur} = -2.557 - 1.085BP - 0.718RR - 1.065GCS + 1.439BL$$

Survivor

$$D_{sur} = -1.024 + 0.482BP + 0.294RR + 0.492GCS - 0.554BL$$

For classification, a new patient is assigned to the group with the higher discriminant score.

Table 7 presents a comparison of model performance in terms of classification accuracy. Logistic regression achieved a classification accuracy of 95%, whereas discriminant analysis reached 93%. This indicates that logistic regression is slightly more accurate than discriminant analysis, with a minimal difference of 2%. These findings are consistent with previous studies (Panagiotakos, 2006; Abdulqader, 2015; Kitbumrungrat, 2017; Sujarittham, 2018; Peerapan & Pasunon, 2019; Tonglore et al., 2023) that concluded both methods offered similar classification effectiveness. Furthermore, Halperin et al. (1971) observed that logistic regression tended to yield superior performance when the majority of independent variables are qualitative.

Significant predictors for survival identified through logistic regression included time to hospital arrival, respiratory rate, and blood lactate levels, whereas discriminant analysis highlighted systolic blood pressure, respiratory rate, GCS score, and blood lactate levels. Both models identified respiratory rate and blood lactate levels as shared significant predictors for survival in severely injured patients, aligning with research by Odom et al. (2013), and Pintatham and Plongniras (2022), who observed that these factors were critical indicators for evaluating medical severity and informing treatment decisions to enhance survival probabilities.

Although variables including gender, heart rate, and age demonstrate no significant predictive value in either model, they are often regarded as important factors. Their impact on survival predictions may be minimal when more direct health indicators such as blood lactate levels and respiratory rates are included (Munter et al., 2017). This result suggests that depending solely on traditional demographic and physiological variables may not provide a comprehensive understanding of patient outcomes. Future research should focus on integrating these indicators to improve the accuracy of survival prediction in clinical settings.

This observation also raises significant concerns about the effectiveness of traditional trauma scoring systems. Trauma scoring systems, including TRISS (Trauma and Injury Severity Score) and RTS (Revised Trauma Score), have been widely used for trauma prognostication for many years (Boyd et al., 1987; Champion et al., 1989).

However, these systems often depend on variables that may not be accessible or that are challenging to calculate in real-time situations (Gabbe et al., 2003). In contrast, our logistic regression model presents a simpler and highly accurate approach by utilizing key clinical indicators, such as blood lactate levels and respiration rate, which can be quickly measured in emergency settings. Based on our dataset and context, our model achieves an accuracy rate of 95%, which exceeds the accuracy of traditional TRISS-based predictions reported in previous studies, typically ranging from 80% to 90% (Demetriades et al., 1998).

Table 7. Comparison of classification accuracy of logistic regression and discriminant analysis

Method	Variable	Percentage Correct		
		Non-survivors	Survivors	Overall
Logistic regression	time, RR, BL	93.1	95.8	95.0
Discriminant analysis	BP, RR, GCS, BL	96.6	91.5	93.0

4. Conclusions

This study examined factors associated with survival in severely injured patients by comparing prediction outcomes using two established statistical methods: logistic regression and discriminant analysis. Logistic regression identified time to hospital arrival, respiratory rate, and blood lactate levels as important predictors for survival, whereas discriminant analysis emphasized systolic blood pressure, respiratory rate, GCS score, and blood lactate levels. Both methods highlighted respiratory rate and blood lactate as shared significant predictors for survival in severely injured patients. The classification results indicated that logistic regression achieved slightly higher accuracy (95%) compared to discriminant analysis (93%), suggesting a better performance of logistic regression in this framework. However, both classification methods can be applied effectively to this dataset. The results support the applicability of either method in similar clinical datasets, depending on the specific context and analysis objectives. Therefore, it is important to evaluate the characteristics of the data and the objectives of the analysis when selecting the best method, since the choice can influence the identification of significant predictors and the overall accuracy of survival predictions. Future research may employ data simulation techniques to validate these findings against actual data and investigate the potential of machine learning algorithms for improving prediction accuracy.

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6. Authors' Contributions

Kemmawadee Preedalikit and Sulawan Yotthanoo contributed equally to this work. Both authors conceived and designed the study, performed data validation and formal analysis, prepared the figures and tables, drafted and critically revised the manuscript, and approved the final version.

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7. Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

Abdulqader, Q. M. (2015). Comparison of discriminant analysis and logistic regression: An application on caesarean births and natural births data. *Journal of the Institute of Natural and Applied Sciences*, *20*(1-2), 34-46.

Ahmed, F. S., Ali, L., Joseph, B. A., Ikram, A., Mustafa, R. U., & Bukhari, S. A. C. (2020). A statistically rigorous deep neural network approach to predict mortality in trauma patients admitted to the intensive care unit. *Journal of Trauma and Acute Care Surgery*, *89*(4), 736-742.

Blow, O., Magliore, L., Claridge, J. A., Butler, K., & Young, J. S. (1999). The golden hour and the silver day: detection and correction of occult hypoperfusion within 24 hours improves outcome from major trauma. *The Journal of Trauma*, *47*(5), 964-973.

Boeira, P., Tan, H., Yates, E., & Dhanda, A. (2023). Assessment of immune function and prediction of survival and infection in patients with severe alcoholic hepatitis: An exploratory study. *Journal of Gastroenterology and Hepatology*, *7*(4), 286-290. https://doi.org/10.1002/jgh3.12891

Box, G. E. P., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society*, *26*(2), 211-252. https://doi.org/10.1111/j.2517-6161.1964.tb00553.x

Boyd, C. R., Tolson, M. A., & Copes, W. S. (1987). Evaluating trauma care: The TRISS method. *The Journal of Trauma*, *27*(4), 370-378.

Champion, H. R., Sacco, W. J., Copes, W. S., Gann, D. S., Gennarelli, T. A., & Flanagan, M. E. (1989). A revision of the trauma score. *The Journal of Trauma*, *29*(5), 623-629. https://doi.org/10.1097/00005373-198905000-00017

Claridge, J. A., Crabtree, T. D., Pelletier, S. J., Butler, K., Sawyer, R. G., & Young, J. S. (2000). Persistent occult hypoperfusion is associated with a significant increase in infection rate and mortality in major trauma patients. *The Journal of Trauma*, *48*(1), 8-14. https://doi.org/10.1097/00005373-200001000-00003

DeMaria, E. J., Kenney, P. R., Merriam, M. A., Casanova, L. A., & Gann, D. S. (1987). Survival after trauma in geriatric patients. *Annals of Surgery*, *206*(6), 738-743. https://doi.org/10.1097/00000658-198712000-00009

Demetriades, D., Chan, L. S., Velmahos, G., Berne, T. V., Cornwell, E. E., Belzberg, H., Asensio, J. A., Murray, J., Berne, J. & Shoemaker, W. (1998). TRISS methodology in trauma: the need for alternatives. *British Journal of Surgery*, *85*(3), 379-384. https://doi.org/10.1046/j.1365-2168.1998.00610.x

Feng, J.-Z., Wang, Y., Peng, J., Sun, M.-W., Zeng, J., & Jiang, H. (2019). Comparison between logistic regression and machine learning algorithms on survival prediction of traumatic brain injuries. *Journal of Critical Care*, *54*, 110-116. https://doi.org/10.1016/j.jcrc.2019.08.010

Gabbe, B. J., Cameron, P. A., & Finch, C. F. (2003). Is the revised trauma score still useful? *ANZ Journal of Surgery*, *73*(11), 944-948. https://doi.org/10.1046/j.1445-1433.2003.02833.x

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis* (6th ed.). Pearson Prentice Hall.

Halperin, M., Blackwelder, W. E., & Verter, J. I. (1971). Estimation of the multivariate logistic risk function: A comparison of the discriminant function and maximum likelihood approaches. *Journal of Clinical Diseases*, *24*(2), 125-158. https://doi.org/10.1016/0021-9681(71)90106-8

Janthasri, A., Ngarmwong, N., Krisung, S., Chaosuan, Y., Phiraphanphanich, B., & Mamkhoonthod, W. (2020). Survival of trauma patients in Bangkok Hospital Pattaya. *Journal of Medicine and Public Health, Ubon Ratchathani University*, *3*(1), 1-12.

Kitbumrungrat, K. (2017). Classification groups for breast cancer with statistical method. *Veridian E-Journal, Science and Technology Silpakorn University*, *4*(5), 42-55.

Kunitake, R. C., Kornblith, L. Z., Cohen, M. J., & Callcut, R. A. (2018). Trauma early mortality prediction tool (TEMPT) for assessing 28-day mortality. *Trauma Surgery and Acute Care Open*, *3*(1), Article e000131. https://doi.org/10.1136/tsaco-2017-000131

Lai, C.-Y., Tsai, S.-H., Lin, F.-H., Chu, H., Ku, C.-H., Wu, C.-H., Chung, C.-H., Chien, W.-C., Tsai, C.-T., Hsu, H.-M., & Chu, C.-M. (2018). Survival rate variation among different types of hospitalized traumatic cardiac arrest: A retrospective and nationwide study. *Medicine*, *97*(8), Article e11480. https://doi.org/10.1097/MD.0000000000011480

Lee, Y., Lee, J. H., Seong, A. J., Hong, C. K., Lee, H. J., Shin, D. H., & Hwang, S. Y. (2012). Arterial lactate as a predictor of mortality in emergency department patients with paraquat intoxication. *Clinical Toxicology*, *50*(1), 52-56. https://doi.org/10.3109/15563650.2011.639716

McCullagh, P., & Nelder, J. A. (1989). *Generalized linear models* (2nd ed.) Chapman and Hall.

Meregalli, A., Oliveira, R. P., & Friedman, G. (2004). Occult hypoperfusion is associated with increased mortality in hemodynamically stable, high-risk, surgical patients. *Critical Care*, *8*(2), 60-65. https://doi.org/10.1186/cc2423

Mikkelsen, M. E., Miltiades, A. N., Gaieski, D. F., Goyal, M., Fuchs, B. D., Shah, C. V., Bellamy, S. L., & Christie, J. D. (2009). Serum lactate is associated with mortality in severe sepsis independent of organ failure and shock. *Critical Care Medicine*, *37*(5), 1670-1677. https://doi.org/10.1097/ccm.0b013e31819fcf68

Moon, J. M., Shin, M. H., & Chun, B. J. (2011). The value of initial lactate in patients with carbon monoxide intoxication: in the emergency department. *Human and Experimental Toxicology*, *30*(8), 836-843.

Munter, L. D., Polinder, S., Lansink, K. W. W., Cnossen, M. C., Steyerberg, E. W., & Jongh, M. A. C. D. (2017). Mortality prediction models in the general trauma population: A systematic review. *Injury*, *48*(2), 221-229. https://doi.org/10.1016/j.injury.2016.12.009

Noland, D. K., Apelt, N., Greenwell, C., Tweed, J., Notrica, D. M., Garcia, N. M., Maxson, R. T., Eubanks, J. W., & Alder, A. C. (2019). Massive transfusion in pediatric trauma: an ATOMAC perspective. *Journal of Pediatric Surgery*, *54*(2), 345-349. https://doi.org/10.1016/j.jpedsurg.2018.10.040

Odom, S. R., Howell, M. D., Silva, G. S., Nielsen, V. M., Gupta, A., Shapiro, N. I., & Talmor, D. (2013). Lactate clearance as a predictor of mortality in trauma patients. *The Journal of Trauma and Acute Care Surgery*, *74*(4), 999-1004. https://doi.org/10.1097/TA.0b013e3182858a3e

Ostermann, R. C., Joestl, J., Tiefenboeck, T. M., Lang, N., Platzer, P., & Hofbauer, M. (2018). Risk factors predicting prognosis and outcome of elderly patients with isolated traumatic brain injury. *Journal of Orthopaedic Surgery and Research*, *13*(1), Article 277. https://doi.org/10.1186/s13018-018-0975-y

Panagiotakos, D. B. (2006). A comparison between logistic regression and linear discriminant analysis for the prediction of categorical health outcomes. *International Journal of Statistical Sciences*, *5*, 73-84.

Peerapan, P., & Pasunon, P. (2019). Discriminant analysis and logistic regression analysis for predicting the decision making to choose the government organization to work for

of the fourth-year students in the Faculty of Management Science, Uttaradit Rajabhat University. *Romphruek Journal*, *37*(3), 44-54.

Pintatham, K., & Plongniras, W. (2022). Factors associated with 24 hours mortality of traumatic patients in Chiang Rai Province, Thailand. *Journal of Emergency Medical Services of Thailand*, *2*(1), 66-76.

Pooncharoen, T., Hoacharoensirichai, P., Chaisorn, R., Pongpan, P., Nithimathachoke, A., & Rojsaengroeng, R. (2019). Factors affecting the survival rate of prehospital traffic accident patients in Thailand. *Thai Journal of Emergency Medicine*, *1*(1), 27-39.

R Core Team. (2023). *A language and environment for statistical computing. Vienna.* https://www.r-project.org/

Sujarittham, S. (2018). Comparison of logistic regression analysis and discriminant analysis in sex Identification using 3D computed tomography image of Thai scapula. *Thai Science and Technology Journal*, *28*(1), 129-139.

Tangchaisuriya, U., Chenthanakij, B., Chotirosniranit, N., & Sutham, K. (2019). *Factors affecting lactate clearance and association of blood lactate with mortality in major trauma patients*. https://doi.org/10.13140/RG.2.2.20561.07528

Tanupattarasorn, J., Eso, M., & McNeil, R. (2024). The Influence of socio-demographic factors on the prevalence of dental caries among 12-year-old children, Narathiwat Province. *Current Applied Science and Technology*, *24*(6), Article e0260086. https://doi.org/10.55003/cast.2024.260086

Tonglore, O., Manatrinon, S., & Chaokaur, A. (2023). Discriminant analysis and binary logistic regression for prediction of milk production of dairy cattle farms. *KKU Science Journal*, *40*(4), 1195-1204.

Vanichbuncha, K. (2021). *Advanced statistical analysis with SPSS for windows*. (16th ed.) Chulalongkorn University, Bangkok.

Viboonkit, K., Boonmee, W., Thotsagotphairee, C., Tavitchasri, P., & Kanloung, T. (2024). Stock identification of short mackerel (*Rastrelliger brachysoma*) in the upper and middle gulf of Thailand by morphological characters. *Current Applied Science and Technology*, *24*(1), Article e0255758. https://doi.org/10.55003/cast.2023.255758

Wongvatanakit, P., Tadadej, C., Meyai, A., & Suriyawongpaisal, P. (2019). Relation of factor on survival outcomes among traumatic patients at the tertiary care hospital admitted for traffic accidents in Phuket province. *Srinagarind Medical Journal*, *34*(1), 52-59.

Wu, Y. T., Biswas, S., Matsushima, K., Schellenberg, M., Inaba, K., & Martin, M. J. (2023). Predicting the future in trauma: trauma and injury severity score loses accuracy and validity for late deaths after injury. *The American Surgeon*, *89*(10), 4077-4083. https://doi.org/10.1177/00031348231175501

Yadollahi, M. (2019). A study of mortality risk factors among trauma referrals to trauma center, Shiraz, Iran, 2017. *Chinese Journal of Traumatology*, *22*(4), 212-218. https://doi.org/10.1016/j.cjtee.2019.01.012

Yadollahi, M., Anvar, M., Ghaem, H., Bolandparvaz, S., Paydar, S., & Izianloo, F. (2017). Logistic regression modeling for evaluation of factors affecting trauma outcome in a level I trauma center in Shiraz. *Iranian Red Crescent Medical Journal*, *19*(1), 1-9.

Yucel, N., Demir, T. O., Derya, S., Oguzturk, H., Bicakcioglu, M., & Yetkin, F. (2018). Potential risk factors for in-hospital mortality in patients with moderate-to-severe blunt multiple trauma who survive initial resuscitation. *Emergency Medicine International*, *2018*, Article 6461072. https://doi.org/10.1155/2018/6461072

Zelterman, D. (2022). Discrimination and classification. In D. Zelterman (Ed.). *Applied multivariate statistics with R* (pp. 267-304). Springer. https://doi.org/10.1007/978-3-031-13005-2