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Are the same parameters measured at admission and in the ICU comparable in their predictive values for complication and mortality in severely injured patients?

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Abstract

Introduction Numerous studies have investigated variables that predict mortality and complications following severe trauma. These studies, however, mainly focus on admission values or a single variable. The aim of this study was to investigate the predictive quality of multiple routine clinical measurements (at admission and in the ICU).

Methods Retrospective cohort study of severely injured patients treated at one Level 1 academic trauma centre. Inclusion criteria: severe injury (ISS ≥ 16 points), primary admission and complete data set. Exclusion criteria end-of-life treatment based on advanced directive, secondary transferred patients. Primary outcome: mortality, pneumonia, sepsis. Routine clinical parameters were stratified based on measurement timepoint into Group TB (Trauma Bay, admission) and into Group intensive care unit (ICU, 72 h after admission). Prediction of complications and mortality were calculated using two prediction methods: adaptive boosting (AdaBoost, artificial intelligence, AI) and LASSO regression analysis.

Results Inclusion of 3668 cases. Overall mean age 45.5 ± 20 years, mean ISS 28.2 ± 15.1 points, incidence pneumonia 19.0%, sepsis 14.9%, death from haemorrhagic shock 4.1%, death from multiple organ failure 1.9%, overall mortality rate 26.8%. Highest predictive value for complications for Group TB include abbreviated injury scale (AIS), new injury severity score (NISS) and systemic Inflammatory Response Syndrome (SIRS) score. Highest predictive quality for complications for Group ICU include late lactate values, haematocrit, leukocytes, and CRP. Sensitivity and specificity of late prediction models using a 25% cutoff were 73.61% and 76.24%, respectively.

Conclusions The predictive quality of routine clinical measurements strongly depends on the timepoint of the measurement. Upon admission, the injury severity and affected anatomical regions are more predictive, while during the ICU stay, laboratory parameters are better predictor of adverse outcomes. Therefore, the dynamics of pathophysiologic responses should be taken into consideration, especially during decision making of secondary definitive surgical interventions.

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Level of evidence: III (retrospective cohort study).

Keywords Polytrauma, Prediction, Complications, Artificial intelligence

Introduction

Severe traumatic injuries remain a significant public health concern globally, contributing to substantial morbidity and mortality rates [1]. In the acute phase following trauma, patients are at a heightened risk of developing complications that can significantly influence their clinical outcomes [2, 3]. Identifying early predictors of adverse events, such as mortality, sepsis, pneumonia, haemorrhage or thrombosis, is paramount in trauma research, as it enables clinicians to initiate timely interventions and optimise patient management strategies [4, 5]. We will be focusing on mortality, sepsis and pneumonia. These adverse events are common for multiple reasons. Pneumonia is often ventilator associated, due to a lack of movement of the patient or hospital associated [6]. Sepsis is common in trauma patients due to dysregulated immune reaction to the initial trauma and surgical interventions [7]. Reducing these adverse effects can in turn reduce mortality.

While numerous studies have investigated the predictive value of admission variables (haemoglobin, haematocrit, prothrombin, lactate, ISS, NISS, APACHE) for adverse outcomes in trauma patients, there is a scarcity of research focusing on the dynamic changes in pathophysiological parameters over time [8, 9]. The initial assessment of trauma patients in the emergency department (ED) or trauma bay is crucial for initiating resuscitative measures and identifying life-threatening injuries [5]. However, the predictive nature of variables measured at admission may differ from those assessed during the subsequent clinical course. In the literature, lactate clearance and CRP dynamics have been analysed for their predictive nature after the admission [10, 11]. However, those studies have mostly just focussed on a single parameter and the direct comparison of multiple parameters at two different timepoints such as admission vs. 72 h is scarce in the literature.

Therefore, the goal of this study was to investigate the predictive ability of routine clinical parameters, such as clinical, hemodynamic and laboratory values that were taken at admission and to compare their prediction for mortality and complications with the same parameters measured during the ICU stay at 72 h after admission. With that, we hope to improve the predictive nature of these values in the hours after admission, allowing us to better predict mortality and sepsis as an outcome, in return allowing us to improve our treatment.

In other words, should a surgeon pay special attention to the same or different parameters during ICU rounds compared to the initial assessment in the trauma bay? Shifting the focus from early damage control, being the focus in the trauma bay to treatment and timing according to the physiological and dynamic changes.

We hypothesise that the parameters at admission and in the ICU are comparable in predicting mortality and complications severely injured patients.

Methods

The institutional ethics committee (BASEC 2020-00703) approved the study protocol of this retrospective cohort study. Reporting of data strictly follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement. The study was approved upon establishment of the database.

Data registry and variables

The polytrauma data registry includes severely injured patients that were treated at one academic trauma centre between 2008 and 2018. The data registry served as the local registry for severely injured patients with an ISS of 16 or above and includes collected medical data. The cutoff of an ISS of 16 or above was selected, as this is a widely recognised definition of a polytraumatised patient [12]. Data in the registry includes measurements of injury severity, injury distribution, and repetitive measurements of pathophysiologic measurements over time. Injury severity and injury distribution were quantified utilising the abbreviated injury scale (AIS) which differentiates different anatomical areas and classifies the respective injury severity from 1 (minor) to 6 (deadly) [13]. Further measurements of interest included demographic variables.

Pathophysiologic measurements included variables of haemorrhage, coagulation, temperature, and soft tissue damage. Soft tissue damage includes the presence of intracranial haemorrhage, the presence of lung contusion, abdominal injuries or the type of fracture.

The data war automatically extracted from the patient records documented in our in-hospital clinical information system.

Participants

This study was conducted on severely injured trauma patients who were treated at one Level 1 academic trauma centre. Inclusion criteria were severely injured

patients, which are commonly defined as having an ISS of 16 points or higher [14]. Further inclusion criteria were a complete or near complete data set that allows analysis and statistical testing for our outcome data points. Secondary transferred patients, patients with end-of-life management based on their advanced directive, as well as patients who died before arrival in the trauma bay were excluded from this study. Variables were excluded a priori if they had ≥ 60% missing values to ensure reliability. For the early timepoint (TB) all available values were included in the model without automated imputation; all missing values were excluded. However, for the statistical analysis of the ICU parameters, automated imputation was used, since more datapoints were available over time to allow for a more accurate estimation of the missing values.

Outcomes and definition

The primary outcomes of this study were mortality and complications. Complications of interest include the development of pneumonia or the development of sepsis, of which the definition has changed over time and, therefore, refers to the current definition at the time of documentation (Sepsis-2 and Sepsis-3 definition) [15, 16]. The presence of these adverse events was based on the documentation in the data registry, which was extracted from the patient's diagnosis list in our clinical information system.

The outcome variables were analysed based on the data measurements at admission in the trauma bay (Group TB) and in the ICU 72 h after admission (Group ICU), which led to six categories (death, sepsis, and pneumonia for both admission and 72-h cases). Even though the term "Group" might suggest two different populations, this stratification only relies on the timepoint of measurement of the exact same cohort. The outcomes/complications were not bound to the 72 h, but whether or not they occurred during the hospital stay of the respective patient. Early death was defined as death within the first 72 h after trauma.

Statistics

Continuous variables are displayed as mean with standard deviation (SD) or median and interquartile range (IQR) as appropriate, categorical variables witch count (n) and percentage. Group comparison was performed with paired sample *t* test. For complete prediction analysis, two different prediction models were utilised: an AI model (AdaBoost) and Least Absolute Shrinkage and Selection Operator (LASSO) [17, 18]:

A baseline model prioritising maximum accuracy was built using adaptive boosting via the AdaBoost package in R [19]. This artificial intelligence is a machine learning ensemble method that combines multiple weak learners (decision trees) to create a strong learner. After establishing baseline accuracy, less complex yet interpretable models were pursued. Least Absolute Shrinkage and Selection Operator (LASSO) logistic regression was chosen for its variable selection capabilities, with Group LASSO used in certain cases to ensure all levels of categorical variables were included or excluded together. However, the artificial intelligence itself does not provide information regarding the variables that were utilised. Hence why LASSO regression was used to determine the best possible variables. To ensure the reproducibility of the findings, the AdaBoost algorithm was optimised through the use of grid search with cross-validation. This process involved the tuning of several key parameters, including the number of trees, the learning rate, the tree depth, and the minimum samples per leaf. The selection of these values was conducted with the objective of achieving a balanced accuracy and generalization. For LASSO regression, cross-validation was utilised to ascertain the optimal regularization strength (lambda), thereby ensuring an optimal trade-off between model complexity and performance. The performance of both models was evaluated using ROC curves, sensitivity, and specificity, with fixed random seeds and clearly defined validation methods to ensure consistency.

Considerations during model construction included assessing accuracy against the no-information rate, prioritising sensitivity and specificity, and adjusting probability cutoff points to mitigate false negatives. Probability cutoff point: logistic regression outputs probabilities categorized using a cutoff of 0.25 to enhance sensitivity in identifying critical outcomes. Yet, depending on the data a different cutoff point was determined by the model automatically, as it adapts to the data. This allows for the model to be refined and adapt to the data allowing the model not to be simplified to much for the data analysed, furthermore, preventing overfitting of the model. However, if too many variables are included the model may result in underfitting. Therefore, a selection of the most sensitive and specific data is essential. To optimise sensitivity and ensure that high-risk patients were not overlooked, probability cutoffs (e.g., 0.1 and 0.25) were adjusted based on ROC curve analysis, with a focus on prioritising sensitivity over specificity in medical predictions. Lower cutoffs enabled the capture of more critical cases; while accepting a higher false positive rate, a strategy deemed preferable in clinical settings, where the failure to identify a high-risk patient could have severe consequences. To prevent overfitting, cross-validation (fivefold for AdaBoost, tenfold for LASSO) was employed, along with regularization and tree depth limits, ensuring the generalisation capability

of the models and preventing overfitting to the training data. The employment of these methodologies ensured a harmonious equilibrium between the predictive accuracy and the clinical relevance of the models, thereby mitigating the risk of overly optimistic performance on the training data set.

A validation of analysis was performed utilizing 20% of the data set. This is the standard approach to perform internal validation testing (80% used for training and 20% used for validation). The separation of the data occurs randomly, to prevent data sets which are too representative. Training a model with more data allows the model to avoid overfitting; however, the model still needs to be able to be checked for accuracy with data that has not been used for training. One of the benefits is that an overfitting of the model can be controlled to a certain extent. The complete analysis was performed utilizing R (R Core Team (2023). R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/).

Results

From initially 1063 individual variables in the data frame, 243 variables were removed due to (near) emptiness or limited trustworthiness. This resulted into 820 individual variables for the respective timepoints being analysed for included 3668 patients.

Demography

This study included 3668 patients, the mean age was 45.8 years (SD ± 20.2 years), while the mean Glasgow Coma Scale (GCS) score was 8.8 (SD ± 5.5). Majority of the patients were male ($n = 2694$, 73.4%). The population tended to be slightly overweight with a BMI of 25 (SD ± 4.38). The median Injury Severity Score (ISS) was 25 (IQR 17–34), and the median (NISS) was 34 (IQR 25–50). The anatomic-specific injury severity is displayed in Table 1. AIS Head was the highest with a mean of 2.8 (SD ± 2.0), followed by AIS Thorax with a mean of 1.6 (SD ± 1.7) and AIS Extremity with a mean of 1.4 (SD ± 1.4).

Physiologic parameters

Almost all physiologic parameters at Group TB were significantly different from Group ICU also respective to the large sample size. The C-reactive protein (CRP) in Group TB was significantly lower at 13.72(± 41.14) compared to 131.31 (± 73.22) ($p < 0.001$). The pH-value did not show significant differences due to the high standard deviations (Group TB = 7.31 ± 0.13 vs. Group ICU = 13.10 ± 203.91, $p = 0.301$). Base excess was significantly lower in Group TB (−3.77 ± 5.26) compared to Group ICU (1.42 ± 2.75) ($p < 0.001$). Lactate values in the trauma bay were significantly higher (TB = 2.94 ± 2.53) compared to measurements at the ICU (1.18 ± 1.02) ($p < 0.001$). Further parameters that were significantly higher at admission ($p < 0.001$) were Haematocrit, Haemoglobin, heart rate and mean arterial pressure (MAP). The Quick was significantly higher in the group ICU (TB = 78.80 (28.52) vs. ICU = 91.74 (27.78) (< 0.001). Thrombocyte count did not yield significant differences (TB = 299.50 ± 4953 vs. ICU = 152.13 ± 69.99) ($p = 0.101$) as well as the systolic blood pressure (TBO = 130.75 ± 27.55 vs. ICU = 127.85 ± 54.21) ($p = 0.260$, Table 2).

Table 1 Demographic variables of study population;

Parameter (N = 3668)	Mean	Standard deviation (SD)
Age (years)	45.8	20.2
Male (n, %)	2694 (73.4%)	
BMI	25.00	4.38
Glasgow coma scale (GCS)	8.8	5.5
Injury severity/pattern		
AIS Head	2.8	2.0
AIS Face	0.6	1.0
AIS Thorax	1.6	1.7
AIS Spine	0.8	1.4
AIS Extremity	1.4	1.4
AIS Pelvis	0.6	1.2
AIS Skin	0.5	0.8
ISS (median, IQR)	25	17–34
NISS (median, IQR)	34	25–50

AIS Abbreviated Injury Scale, *BMI* Body Mass Index, *ISS* Injury Severity Score, *NISS* New Injury Severity Score, *Std.* standard deviation, *IQR* interquartile range

Table 2 Physiologic parameter at time of admission to the trauma bay vs. at 72 h at the ICU;

Parameter (mean ± SD)	Group TB	Group ICU	*p* value
CRP	13.72 (41.14)	131.31 (73.22)	< 0.001
pH	7.31 (0.13)	13.10 (203.91)	0.301
Base excess	− 3.77 (5.26)	1.42 (2.75)	< 0.001
Lactate	2.94 (2.53)	1.18 (1.02)	< 0.001
Haematocrit	33.68 (8.28)	28.55 (5.34)	< 0.001
Haemoglobin	11.44 (4.03)	9.94 (5.39)	< 0.001
Thrombocyte count	299.50 (4953.40)	152.13 (69.99)	0.101
Quick	78.80 (28.52)	91.74 (27.78)	< 0.001
Heart rate	90.17 (22.09)	84.24 (24.13)	< 0.001
Systolic blood pressure	130.75 (27.55)	127.85 (54.21)	0.260
Mean arterial pressure	93.12 (25.70)	86.43 (13.70)	< 0.001

CRP C-reactive protein, *pH* pondus hydrogenii

Outcome parameters

Patients stayed in the hospital for an average of 17.0 (SD ± 18.7 days), and in the intensive care unit (ICU) for 8.2 days on average (SD ± 10.5 days). The mean duration of ventilator support was 5.1 days (SD ± 8.1 days). Complications were observed in 24.7% of patients, with pneumonia affecting 19.0% and sepsis occurring in 14.9% of cases. In addition, incidences of septic shock, and mortality were noted at rates of 3.2% and 26.8%, respectively (Table 3).

Prediction of mortality

Group TB

Adaptive Boosting (AdaBoost) achieved an overall accuracy score of 88.28%, surpassing the no-information rate of 72.01%. A probability cutoff of 0.1 was utilised to obtain these results. In addition, a Receiver Operating Characteristic (ROC) curve and a table comparing actual vs. predicted values were generated, based on validation using 20% of the data set. Notably, the model exhibited a sensitivity of 84.88% and a specificity of 89.60%. The prediction of early mortality based on the adaptive boosting provided an odds ratio (OR) of 48.37 (95% CI 30.13–77.64, $p < 0.001$).

Using Group LASSO for predicting death based on the admission variables provided an OR of 25.75 (95% CI 14.07–47.13, $p < 0.001$). These models yielded to the inclusion of following primary parameters: AIS head, AIS face and AIS of extremity injuries as the most relevant parameters (Table 4).

Group ICU

The 72-h data set to predict death, AdaBoost exhibited an accuracy of 89.40%, which closely aligns with the no-information rate of 89.75%. This model provided an OR of 6.19 (95% CI 1.69–22.64, $p = 0.013$). The confusion matrix was generated using a 25% cutoff, resulting in a sensitivity of 6.90% and a specificity of 98.82%.

The LASSO logistic regression model outperformed AdaBoost, achieving an accuracy of 89.97% compared to the no-information rate of 89.69%. Moreover, the sensitivity of this model using a 25% cutoff clearly surpassed that of AdaBoost (43.24% vs. 6.90%). The LASSO logistic regression yielded an OR of 15.59 (95% OR 6.79 to 35.82, $p < 0.001$) (Fig. 1). Most predictive parameters for mortality in Group ICU were Haematocrit, Leucocyte count and lactate (Table 5).

Table 3 Outcome parameter,

Parameter	Mean	Standard deviation (SD)
Length of hospital stay (days)	17.0	18.7
Length of intensive care stay (ICU, days)	8.2	10.5
Duration of ventilator support (days)	5.1	8.1
	%	
All complications (%)	24.7	
Pneumonia	19.0	
Sepsis	14.9	
Bacteraemia	7.9	
Septic Shock	3.2	
Mortality	26.8	

ICU Intensive Care Unit

Table 4 Trauma bay parameters (TB) that improve prediction of mortality, pneumonia, or sepsis

Parameter	Mortality	Pneumonia	Sepsis
AIS Head	X	X	
AIS Face	X		X
AIS Extremities	X		
AIS Thorax		X	X
AIS Abdomen		X	
AIS Pelvis		X	X
AIS Soft tissue		X	X
NISS			X
RTS			X
SIRS-Score			X

Prediction of pneumonia

Group TB

The overall accuracy achieved with ADA Boost was 81.1% using a cutoff at 0.25. However, the accuracy of the no-information rate slightly surpassed this at 81.7%. Due to missing values within our data set, a random forest approach was not feasible. The yielded variables form the AdaBoost analysis resulted in an OR of 30.08 (95% CI 3.65–247.81, p = 0.0001) in the LASSO regression analysis. The AdaBoost analysis yielded the following important primary variables for the prediction of pneumonia based on admission values: AIS thorax, AIS abdomen, AIS integument and RTS (Table 4).

Group ICU

The accuracy of AdaBoost model for predicting pneumonia after 72 h is 77.20% vs. a no-information rate of 75.80%. The sensitivity and specificity for this model were calculated using a cutoff of 25% and are 48.76% and 86.28%, respectively. The AdaBoost prediction model yielded an OR of 5.98 (95% CI 3.77–9.49, $p < 0.001$).

The Group LASSO model for predicting pneumonia after 72-h outperforms the AdaBoost model, although there is a slight decrease in accuracy, the sensitivity is

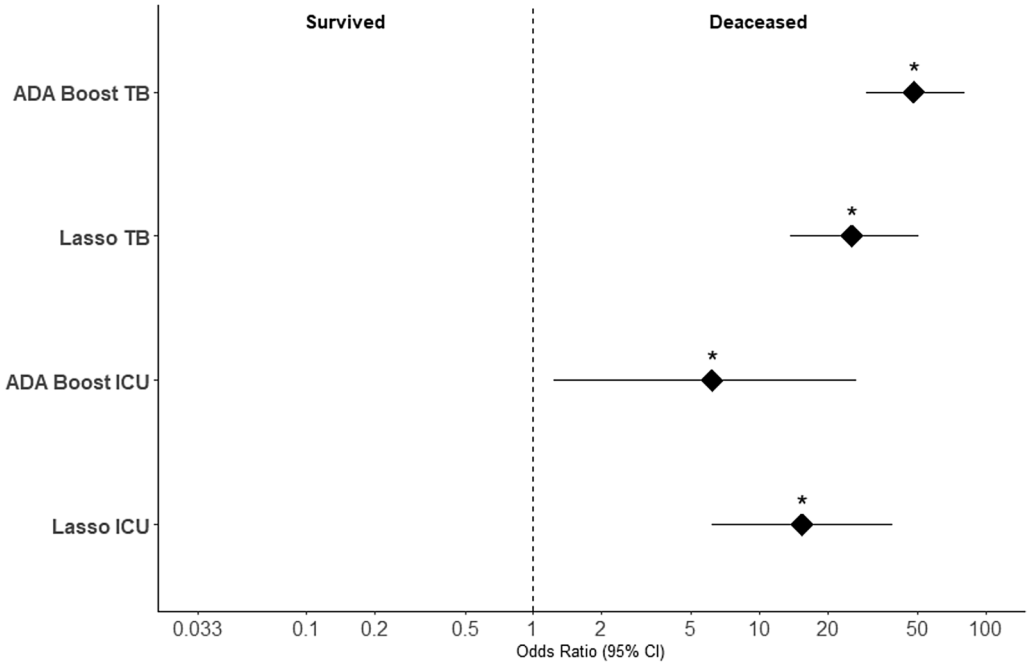

Fig. 1 Prediction of mortality is higher when variables at the trauma bay are utilised when compared with the same variables at the ICU

Table 5 ICU parameters (72 h) that improve prediction of mortality, pneumonia, or sepsis

Parameter	Mortality	Pneumonia	Sepsis
Haematocrit	X		X
Leucocyte count	X		X
Lactate	X	X	X
Base-excess		X	X
CRP		X	X

almost twice as high using the 25% cutoff. The accuracy for Group LASSO is 70.42% (vs. 73.63% no-information rate), and the sensitivity and specificity are 86.59% and 64.63%, respectively. Group LASSO prediction model yielded an OR of 11.79 (95% CI 5.91–23.52, $p<0.001$). Relevant primary variables included lactate, base excess and CRP (Fig. 2) (Table 5).

The prediction of pneumonia showed to be more precise when the ICU variables were utilised rather than the trauma bay admission variables. (OR of 11.79 (95% CI 5.91–23.52, $p<0.001$) vs. OR of 30.08 (95% CI 3.65–247.81, $p=0.0001$) in the TB), Fig. 2.

Prediction of sepsis

Group TB

The ADA Boost method has an accuracy of 84.9% at a cutoff of 0.5. The no-information rate is slightly better in the sepsis prediction with an accuracy of 85.5%. This means that it is very hard to predict sepsis better than just predict that all patients have no sepsis in hospital. This is since sepsis is a rare event in the data set. The Group LASSO with only columns with less than 60% missing values achieves an accuracy of only 81.1% with a cutoff at 0.3. The no-information rate for this test set was only 79.6%. The Group LASSO for the 2-h sepsis model with the important variables from the ADA Boosting performs better with an accuracy of 81.9% at a cutoff of 0.25. It yielded an OR of 7.6 (95% CI 2.79–20.67, $p=0.0001$). The utilised primary variables at admission which predicted sepsis included AIS thorax, AIS pelvis, AIS integument, age, body mass index (BMI) and leukocytes, haematocrit, CRP and pH (Table 4).

Group ICU

The AdaBoost accuracy predicting sepsis after 72 h at the 50% cutoff is 81.77% vs. a no-information rate of 80.00%. The sensitivity is rather low at 25.66%, while the specificity is 95.80%. It yielded an OR of 7.87 (95% CI 4.22–14.68, $p<0.001$). Group LASSO model for predicting sepsis after 72-h outperforms the AdaBoost model in terms of sensitivity, while the accuracy is lower at 75.71% (vs. non-information rate of 79.66%). The sensitivity and specificity of this model using a 25% cutoff are 73.61% and 76.24%, respectively. Group LASSO yielded an OR of 8.95 (95% CI 4.95–16.17, $p<0.001$) (Fig. 3). The

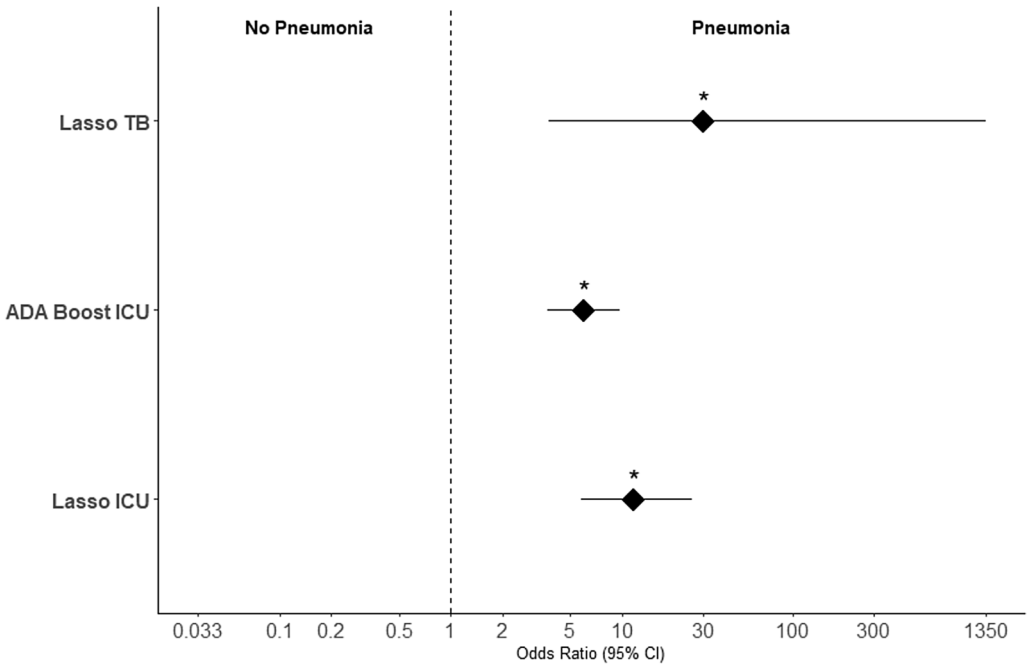

Fig. 2 Prediction of pneumonia is more precise when variables on the ICU are utilised when compared to the admission variables in the trauma bay

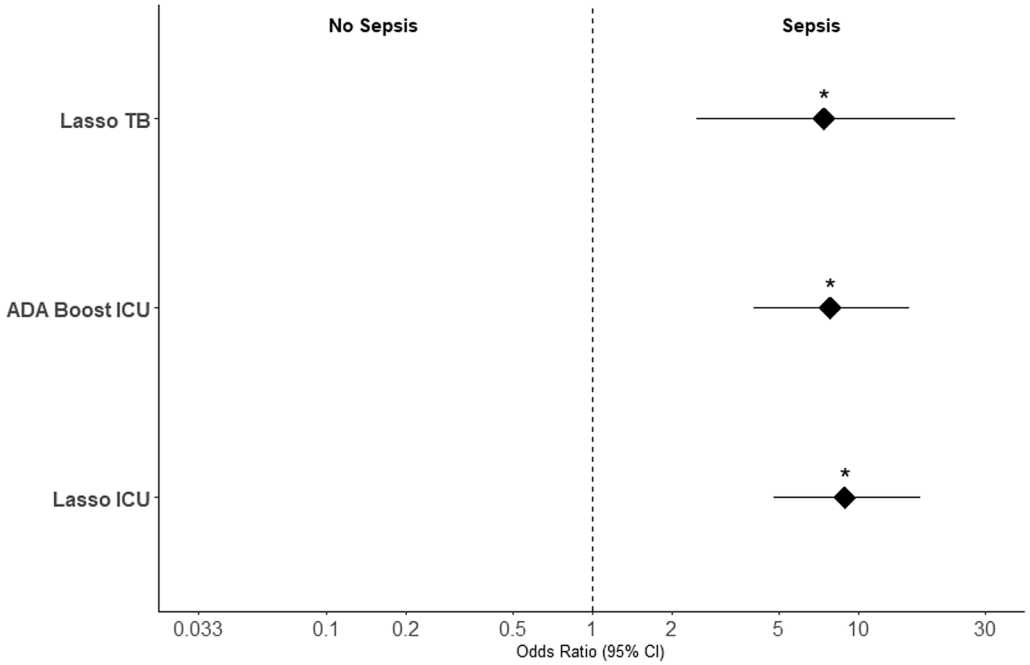

Fig. 3 Prediction of sepsis is improved when the prediction model includes variables available on the ICU when compared to trauma bay admission values

most predictive parameters were haematocrit, leucocyte count, lactate, base-excess and CRP (Table 5).

The prediction of sepsis showed to be more precise when the ICU variables were utilised rather than the trauma bay admission variables. (ICU OR of 8.95 (95%

CI 4.95–16.17, $p < 0.001$) vs. TB OR of 7.6 (95% CI 2.79–20.67, $p = 0.0001$)) (Fig. 3).

Discussion

With this study, we were able to show that testing of certain variables such as pH, lactate, haemoglobin, base excess and GCS at different timepoints leads to a varying predictive capability. This means that certain values, such as the injury distribution and severity, have a better predictability at admission, while laboratory parameters have an improved predictive power during the ICU stay. Current literature on predictive parameters in trauma patients predominantly focuses on admission or single variables, overlooking the potential changes in patient status that occur during the clinical course [9]. This study addresses this gap by comparing the predictive quality of variables obtained at admission to the trauma bay with those measured 72 h after admission in the ICU. To include all possible variables, AdaBoost, an artificial intelligence machine was utilised to detect the best possible benchmark. To detect the best variables that were included in this machine-learning algorithm, LASSO regression analyses were utilised. We were able to show amongst other results that:

1) The predictive ability of clinical variables for mortality, pneumonia, or sepsis are strongly dependant on the time of observation and differ from admission compared to the ICU.
2) In the early assessment, measurements of injury severity and injury distribution showed the highest predictive ability for mortality.
3) At 72 h, inflammatory and hemodynamic parameters were more reliable predictors for mortality, pneumonia, and sepsis and outperformed overall injury severity.

It appears that the dynamic measurement of pathophysiological parameters changes the predictive quality for mortality, pneumonia, or sepsis. The dynamic measurements of variables reflects disease progression [20]. Trauma patients often experience rapid changes in their physiological status during the acute phase of injury [21]. Dynamic measurements allow clinicians to track the progression of pathophysiological processes over time, providing valuable insights into the evolving nature of the patient's condition [22]. These measurements also reflect the treatment success during and after resuscitation [20, 23].

Certain complications, such as sepsis or organ dysfunction, may develop or worsen over time following a traumatic injury [24, 25]. By continuously monitoring pathophysiological parameters, clinicians can detect early signs of complications and intervene promptly, potentially preventing adverse outcomes [10]. Allowing the treatment to be guided accordingly, for example, delaying or prioritising certain surgical procedures and adjusting intensive care unit treatment to the current physiological condition of the patient.

This study demonstrates that early mortality is associated with a high injury severity and injury distribution (i.e., traumatic brain injury), whereas for patients that survive the initial 72 h, the successful resuscitation reflected by the physiologic parameters is crucial.

Overall, the dynamic measurements of pathophysiological parameters play a crucial role in trauma care by providing clinicians with timely, actionable information to guide clinical decision-making, enhancing and improving patient monitoring, and improving patient outcomes [5]. The choice of admission values aimed to detect risk factors for early mortality or complications. It appears that the same variables lose their predictive capability over time.

Our findings reveal further, distinct predictive patterns between the measurements upon admission and the measurements 72 h after admission during the ICU stay. Adaptive Boosting (AdaBoost) provided a strong initial benchmark, while LASSO regression analysis facilitated variable selection.

In the initial assessment, especially variables of traumatic brain injuries are most predictive for mortality. Traumatic brain injuries remain the most relevant predictor for early death [26]. The mortality rate from haemorrhage reduces constantly [3]. This might be due to improved diagnostics and treatment protocols. The findings from this study are consistent with previous research that emphasises the significance of injury severity measurements in predicting mortality and complications during the early stages of trauma management [27–29]. However, our results also highlight the importance of incorporating dynamic variables, such as inflammatory and hemodynamic markers, in predicting adverse outcomes at later timepoints [30]. This suggests that the predictive power of certain parameters may change over time, necessitating ongoing monitoring and reassessment to optimise patient care.

Furthermore, this study highlights the limitations of relying solely on admission variables for predicting adverse outcomes in trauma patients. While these variables provide valuable initial insights, they may not capture the full complexity of patient conditions as they evolve over time. By incorporating measurements taken at multiple timepoints, this study offers a more nuanced understanding of the factors influencing patient outcomes and provides a foundation for the development of tailored monitoring and intervention strategies.

Strengths and limitations

Artificial intelligence and machine learning algorithms improve big data analyses beyond the standard testing. One major limitation of standard regression analysis is the choice of included variables. These are based on the subjective choice of the clinician that observed the predictive relevance of certain variables or on exploratory testing. The analysis in this study included all possible variables that were included in our data registry to develop the benchmark for predicting complications. One limitation is the artificial intelligence itself does not provide information regarding the variables that were utilised. Therefore, LASSO regression analysis is required to detect the best possible variables. While the predictive capability of these methods is not identical, they provide comparable results.

Second, the artificial intelligence can only utilise variables that were included in the data registry. The registry encompasses the timespan from 2008 to 2018 and is subject of the respective physician's discretion or, i.e., scoring systems (interobserver reliability), changing definitions (i.e., sepsis) and evolving treatment strategies. As a results, a patient admitted in 2008 may not have been diagnosed and or treated the way they would have been if they had been treated in 2018 for multiple reasons. For one, the definition of, for example, sepsis has changed over the course of our study period. This leads to the fact, that the prediction model for sepsis in this study might be inferior compared to mortality and pneumonia, as these remained consistent over the entire timespan. However, due to the retrospective nature of this study, we were not able to determine, whether the patients diagnosed under the Sepsis-2 definition would also have been diagnosed under the Sepsis-3 definition. Therefore, the analysis performed was the closest and most feasible approximation possible under the given circumstances. There might be other, lesser-known variables that were not documented or were excluded from the data set but might provide better prediction for certain adverse events.

Prediction models that have been trained on one retrospective data set alone may be over-fitted to this specific cohort, which most likely also is the case in this study. The predictive power may change in the future if new strategies and further parameters are incorporated in clinical practice. In addition, this kind of big data analysis often results in significant observations concerning small differences that might not be clinically relevant. In addition, we only focused on polytraumatised patients ($ISS \geq 16$) admitted to one Level 1 academic trauma centre, which might make our results not transferable to less severely injured patients or trauma patients in general. Other institutions which are not a Level 1 academic trauma centre may have less severely injured patients, which—in return—can mean that our data may not be representable to their data set. Patients who required specific treatments or specialities are usually directly transferred to Level 1 trauma centres or are transferred after initial diagnosis in a regional/municipal hospital. As this study utilises a patient registry that encompasses a long collection period, certain definitions (i.e., sepsis) may have changed within the observed study period. Therefore, the diagnosis always refers to the regarding definition of the current timeframe and unfortunately could not be standardised overall in a retrospective manner. To limit the restrictions of our (retrospective) single-centre experience, we performed an additional internal validation. An external validation and prospectively collected data would provide further insights concerning our results. If the study were performed in a multi-centre setting there may also be differences regarding injury mechanism, treatment options and patient demographics. In other countries, the demography of the patient collective may considerably vary from that observed in Switzerland. It can be assumed that this could have an influence on the observed results. Furthermore, not every hospital in every region has the same access to treatment options as our hospital has, this can further influence the outcomes of patients and the complications and mortality observed. This extensive time of observation also explains the overall higher mortality/complication rates compared to data nowadays, as they have relevantly decreased over time.

Furthermore, this study relied on routinely collected measurements. Clinical scores and parameters were routinely assessed; however, differences in timing, frequency, and measurement techniques could influence data accuracy. There was also a potential for misclassification bias, such as diagnostic labels (e.g., sepsis and pneumonia), as these were based on physician-documented diagnosis rather than strict retrospective application of standardised criteria, which could lead to a variability in case identification. A physician may have an outdated und unclear definition of sepsis and pneumonia in mind when diagnosing a patient with said complication than another physician leading to a potential misclassification bias. Furthermore, a physician may document a complication, while a different physician may not.

Conclusion

The prediction of complications is both time sensitive and dependent on the specific complications in severely injured patients. Early mortality (Mortality within the first 72 h) is best predicted with variables of severity of brain injury. Late complications are best predicted with variables of inflammation, haemorrhage or soft tissue damage. Continued and dynamic reassessments can

help us improve the prediction of adverse events in the severely injured patient.

Abbreviations

AdaBoost	Adaptive boosting
AIS	Abbreviated Injury Score
ATLS	Advanced trauma life support
CRP	C-reactive protein
ED	Emergency Department
GCS	Glasgow Coma Scale
ICU	Intensive care unit
ISS	Injury Severity Score
LASSO	Least absolute shrinkage and selection operator
MAP	Mean arterial pressure
NISS	New Injury Severity Score
OR	Odds ratio
ph	Pondus hydrogenii
RTS	Revised Trauma Score
SIRS	Systemic inflammatory response syndrome
STROBE	Reporting of Observational Studies in Epidemiology
TB	Trauma Bay

Author contributions

L.G.: Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. Y.K.: Conceptualization, Methodology, Writing – review & editing. F.K.: Conceptualization, Methodology, Writing – review & editing. J.H.: Conceptualization, Methodology, Writing – review & editing. M.T.: Conceptualization, Methodology, Writing – review & editing. K.S.: Methodology, Writing – review & editing. R.P.: Methodology, Writing – review & editing. M.M.: Formal analysis, Methodology, Writing – review & editing. H-C.P. Conceptualization, Methodology, Writing – review & editing, Supervision. S.H.: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Project administration, F.K.L.K.: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Project administration.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethical approval and consent to participate

Approved by the institutional ethics committee (BASEC 2020-00703).

Competing interests

The authors declare no competing interests.

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