Quantifying unmet ICU beds in tertiary hospitals in urban India using Propensity Score Matching

Maria Eriksson

# Abbreviations

ACS - American college of surgeons

ER - Emergency room

HIC - High-income countries

LMIC - Low- and middle-income countries

PSM - propensity score matching

RCT - Randomized case-control study

TITCO -Towards Improved Trauma Care Outcomes

TQIP - Trauma Care Improvement Program

# Abstract

## Background

## Methods

## Results

## Conclusion

# Introduction

## Trauma globally and in India

Trauma is a substantial global health problem that disproportionately affects low and middle-income countries (LMIC), resulting in significant mortality and morbidity (1). 4.8 million people die from trauma annually, 90% are in LMIC and 20% in India alone (2). Despite having only 1% of the global vehicle fleet, a disproportionate 10% of global traffic casualties occur in India (3). Half of trauma mortality in India occur in-hospital. There is no national trauma registry in India, but isolated studies have shown that in-hospital mortality within 30 days of hospitalization is higher than similarly injured patients in HIC hospitals (3). Globally, an estimated two million lives could be saved annually, if the appropriate and timely trauma care provided by hospitals in many high-income countries were available and provided in low to-middle-income countries (LMICs) (3).

Health care professionals in many LMIC testify that their medical assessment oftentimes is that a trauma patient should be admitted to the ICU, but are not because such resources are scarce, overloaded and unavailable. Their medical judgement is that the lives of these patients were salvageable, and that these patients died as a direct result of not being admitted to the ICU (4).

Trauma is a main cause of mortality and morbidity to otherwise healthy and young individuals, and dispropotionately affect this demographic. Most casualties affected the age group 30-45 years, followed by the age bracket 18-30 years (5). People in this demographic are also oftentimes the primary or sole breadwinners for their families. Therefore the detrimental impact of trauma go beyond mortality or substantial loss of disease-free years of life for the affected individuals, it also carries a considerable financial and social harm on their family members and communities (1) (5)

A diverse mix of public, for-profit and not-for-profit private actors provide health services in India, where private providers dominate. According to a WHO 2022 report, India has 76 709 non-ventilator supported and 39 476 ventilator-supported ICU beds (6). Because of the type and severity of injuries, ICU resources are often essential in care of trauma patients (7).

## Methods to examine trauma care and ensure equivalence

In order to improve and ensure equivalence of intra-hospital care, trauma quality improvement programs (TQIP) have been developed. The pilot and most notable example is the TQIP developed by the American College of Surgeons ACS. Since the implementation of the ACS pilot, TQIP has evolved to a broad term that include many kinds of processes to improve the quality of trauma care, such as mortality and morbidity conferences, using audit filters or comparing risk adjusted outcomes over time and between centres. The aim is to find discrepancies in treatment for patients presenting with similar conditions. This difference in in-hospital mortality is likely multi-factorial, and any factors have been proposed to explain it such as differences in triage and delay-of-care, as well as shortage of hospital resources including ICU beds (2) ,(1) . TQIPs aim to ensure patients get equivalent care within and across hospitals, to benchmark performance of health care providers versus their peers and to improve trauma care by developing best practice guidelines (8).

TQIP often originate in high-income countries (HIC), they are either not applicable nor easily transferred to the hospital conditions of LMIC (9) (10) (2). For trauma patients, there exist significant structural differences between HIC and LMIC. These differences are in factors such as injury mechanisms and severity, health care resources as well as patient make-up (9) (3) (1) (2). These differences make a direct transferral of HIC TQIP models onto LMIC irrelevant or misleading and there is a need to develop TQIP assessment applicable to local conditions.

## Knowlege gap

There are compelling reasons to believe there is a shortage of ICU beds in India, but the scope of this shortage as well as the potential for reduction of trauma mortality if this shortage would be remedied is unknown.

WHO and local health care workers believe there is a shortage of ICU beds in Indian hospitals, and that the lives of many patients would have been salvageable if the appropriate ICU resources had been available (6). The differences of in-hospital trauma mortality in Indian hospitals was double that of high-income countries, and part of this difference could be explained by a shortage of ICU beds in India (3) .

## Aim

Quantify the unmet need for ICU beds in tertiaty hospitals in urban India.

Apply statistical analysis to a large data set of Indian trauma patients and determine how many out of the patients that were not admitted to the ICU reasonably should have been admitted given their condition. Their numbers in proportion to the number of ICU-admitted patients is indicative of the relative shortage of ICU beds.

# Methods

## Study design

Observational retrospective cohort study using data from the Towards Improved Trauma Care Outcomes (TITCO) in India cohort.

## Setting

16 000 patients admitted to four public university hospitals in urban India are included in the TITCO dataset (7). Initially the data set included 16047 patients, but to improve anonymization 47 patients were deleted from the dataset as described in the chapter anonymization. The participating hospitals were King Edward Memorial hospital (KEM) and Lokmanya Tilak Municipal General Hospital (LTMGH), Mumbai, Jai Prakash Narayan Apex Trauma Center (JPNATC), All India Institute of Medical Sciences, New Delhi and The Institute of Post-Graduate Medical Education and Research and Seth Sukhlal Karnani Memorial Hospital (SSKM), Kolkata. When the data was collected all hospitals were tertiary hospitals. JPNATC had almost 180 beds in a dedicated trauma centre, KEM had no specific trauma ward, LTMGH was a public university hospital with a specific trauma ward with 14 beds and SSKM was a public university hospital with no specific trauma ward.

The participating hospitals are all public entities, so a majority of patients came from low socioeconomic circumstances in their respective communities.

The data was collected between July 2013 and December 2015 but the collection period for any individual hospitals did not cover necessarily this whole period.

A dedicated project officer involved in the data collection was on site five days per week, approximately eight hours a day. The project officers covered night, evening and morning shifts in a way so all shift variants were covered every month of collection. Project officers worked in the area where trauma patients arrived to the hospital and collected data for patients arriving during their shift through direct observation. If the officer observed an examination being performed but not documented in the patient records were allowed to ask health care staff for the result. If a trauma patient arrived when a project officer was not on site, they were identified from the log books of the nurses on staff in the emergency department and their data was collected from patient records.

## Participants

The eligibility criteria for TITCO were patients who presented with injuries from trauma at the emergency departments of the participating hospitals with a mechanism of road traffic, railway, fall, burn or assault. Patients who were dead on arrival were excluded, as were patients who only had isolated limb injuries.

## Ethical considerations

This study does not require ethical permission, it refers to data collected and shared openly.

Ethical approval for the collection of the data used was obtained from the boards of ethical approval in all four hospitals.

SSKM, LTMGH, KEM and JPNATC name of ethical review boards and approval reference numbers were IPGME&R Research Oversight Committee (IEC/279), Ethics Committee of the Staff and Research Society (IEC/11/13), Institutional Ethics Committee (IEC(I)/OUT/222/14), Institute Ethics Committee All India Institute of Medical Sciences (EC/NP-279/2013 RP-Ol/2013), respectively.

The ethical review boards of all hospitals granted a waiver of informed consent. The trauma patients of in this study included patients in poor physiological, psychological and physical state, oftentimes unconscious or with reduced level of consciousness. The data collected for this study were merely routine data that would have been collected under normal circumstances and did not involve any additional examinations. The collection did not in any way interfere, delay or alter the care provided. Therefore the research team and the ethical review boards concluded that obtaining informed consent would only unneccesarily burden patients and/or family members. Personal details such as names, insurance details or contact information were not recorded.

## Anonymization

Hospital identification number

Hospital name has been replaced with a identification number, and the conversion key has not been saved so there is not possible to reverse the conversion. Despite this, a high degree of anonymization can not be expected because the hospitals do have some distinguishable features and these are reflected in the data collected. For example, 70 % of the railroad accidents in the data set is in one of the hospitals, and one of the hosapitals is in close proximity to a big railroad hub.

Patient identification numbers

Patient names were never recorded, patients were identified by a identification number in the original unencrypted data set. In the anonymization process the identification number has been replaced with another random identification number, and the conversion key has not been saved so there is not possible to reverse the conversion.

Date observations

Dates recorded in the TITCO-I data set were shifted using a random offset of somewhere between 0 and 5 weeks for each patient, but without losing any relevant information. The offset was designed to not dissipate details that could be of potential use for researchers such as day of week and rough indication of season. The internal relations between dates have been preserved so that the timing of all recordings and discharge in chronological relation to admission are all intact.

It is important to note that all patients have sequence numbers that corresponded to the chronological order in which they arrived at any of the participating hospitals, and that sequence number has been kept intact. Keeping this sequence number variable intact allows for many useful operations such as examinations of trends in the data, while it is not possible to undo the date randomization by the sequence number variable, such an equation system is still underdetermined. Unfortunately this means it is also not possible to reconstruct the patient volumes at any given hospital on any given day and from that rate of resource engagement. Nor is it possible to distinguish if patients who were made to wait for their first assessment were so because their injuries were deemed as less severe or if it was because health care staff was overwhelmed which is an important distinction.

Age

Very old patients are few, they have been grouped together to prevent identification via the age parameter.

In addition, 47 patient data were randomly deleted to prevent identification via the sequence number variable.

Text based input 1% of the text-based inputs in ICD code fields and examination or operation findings were randomly deleted to obstruct identification by this variable.

## Variables and data sources/measurements

There are 193 possible observations recorded for each patient. A general presentation of these observations is in table\_nums(‘tab\_1’)

setwd("C:/Users/maria/Downloads/Packt Learning RStudio for R Statistical Computing 2012 RETAIL eBook-repackb00k/unmet-ICU-beds")  
load("table1\_1.rdata")  
  
knitr::kable(table1\_1, caption = "Data types collected in the TITCO-I dataset")

Data types collected in the TITCO-I dataset

|  | data type | count | completion rate |
| --- | --- | --- | --- |
| 2 | qualitative | 29 | 0.93 |
| 3 | quantitative | 27 | 0.71 |
| 4 | date | 7 |  |
| 5 | time | 7 |  |
| 6 | text | 123 | not possible to distinguish between No Findings and Not Documenteed |

The quantitative data include recorded parameters such as vital parameters, lab results, GCS total score and cumulative time in surgery or ICU, if applicable. Measurement or assessment techniques are standardized.

The qualitative data include categorical data such as coarse categorization or the accident mechanism and injury, details about arrival circumstances, and whether or not a patient had received a medical examination or intervention.

Text data are freehand examination results and operation categorizations, as well as assigned ICD codes. These data are vast and contain a lot of useful information, but also introduce a lot of challenges. There is a lack of standardization, user dependence, heterogenous grouping caused by using too general ICD codes, and datamining challenges for this type of data. If it may cause inaccuracies or practical challenges, it shall be omitted.

## Bias

The TITCO dataset are observational data collected from a clinical environment and not an experimental setting. Medical interventions, examinations and ICU admission are not randomized, they are a consequence of a patient’s medical condition. There exists a causal effect between the independent and the dependent variables: a patient is sent to the ICU precisely because of the severity of their condition. There is also a selection bias in which parameters are recorded, which examinations are typically performed and the detection rate of expected findings, introducing detection bias and potentially also observer bias. Observers performing user dependent examinations under stress which is oftentime the case for emergency room sonograms are bias is extra prone to observer bias. Around half of patients presenting with blunt trauma are subject to sonographic examination where the detection rate for expected findings are high, and unexpected findings made en passant are a byproduct that would not have been observed if the type of trauma did not motivate the sonogram. For this reason the frequency of examination findings could be put in relation to the proportion of tested patients, when comparing between subsets.

There exist a potential bias in the routines, resources and patient makeup of the participating hospitals. Because they are all tertiary hospitals, about two thirds of the patients have been referred from other health care providers, meaning that there is a selection bias in the patient populations. Further, hospitals with dedicated trauma wards have a propensity to receive transferred or police escorted patients with worse conditions and prognoses.

As stated in chapter Settings, most patients have low socioeconomic status. Low socioeconomic status is associated with higher levels of malnutrition and comorbidities and would have a negative effect on vital parameters and the capacity of patients to tolerate both injuries and interventions. This circumstance doesn’t affect the analysis and internal validity, but reduces the generalizability of the results.

Biases like these are expected in data collected in a clinical setting, the analysis model i chosen to adress this. Because the purpose of this thesis is to statistically assess how many patients that should have gone to the ICU but did not, these particular selection biases are not expected to skew the outcome, and therefore does not have to be addressed.

Hospitals with trauma wards could have lower admission criteria to the ICU than hospitals with no trauma ward. The same goes for all equipment any hospital has as well as the proficiency of their physicians. It is entirely imaginable that a hospital with radiologists proficient in ultrasound, ct or xray would increase the know-how of their colleagues in any particular technique, making the staff more more prone to perform certain examinations and more proficient in making relevant findings and thereby introducing detection bias and potentially also observer bias. Because examining admission criteria to the ICU is part of the analysis, any bias from differences in hospital admission criteria must be minimized. This is why the PSM model is trained using a training and validation subset as described in the chapter Statistical methods. If this proves insufficient and unsatisfactory it may be necessary to examine and address this bias by comparing ICU admitted patients between hospitals using the same PSM methodology, but this will go beyond the time frame and scope of this thesis.

## Study size

Data of 16000 trauma patients were collected at the participating hospitals over 2.5 years, as described in chapter Settings.

## Statistical methods

Propensity score matching (PSM) is useful method for identifying and assembling a control group from within a data set where there is causality between the independent and dependent variables, and a randomized case-control (RCT) study to offset or balance this bias is impractical, immoral or otherwise improper. Propensity score is a statistical variable, understood as the likelihood of a subject receiving treatment conditional on observations of relevant covariates of that subject before treatment. In RCTs it is known from study design, but it is generally unknown in observational data. The rationale for PSM is that while it is unknown, this variable can be fairly well estimated using logistic regression.

The theory being examined in this master’s thesis is that there exist a subset of the TITCO dataset that did not go to the ICU, but are very similar to the patients that did go to the ICU, in the covariates that caused ICU-treated patients to receive this intervention. The thesis is that these patients were not admitted to the ICU only for lack of such resources, not by a medical assessment. Translated into this context this means that in this data set exist a selection bias, there is causality between the independent variables medical conditions and interventions and the dependent variable ICU admittance. Patients were admitted to the ICU as a consequence of their medical condition. Performing a randomized case-control study and randomly assigning or withholding a live-saving treatment would obviously be immoral, but we believe that in the TITCO data set exist patients who were not admitted into the ICU not by volition but for scarcity of such resources. Such a group would be akin to an non-experimental control group and PSM can be used to identify and assemble it. If such a subset can be identified by PSM, that is indicative there exists shortage of ICU beds in tertiary hospitals in India.

The proportion of the subset of patients that should hade received ICU care based on our prediction model versus the subset that did receive ICU care is also the proportion of ICU bed shortage. If, for every patient that did receive ICU care, there was another patient with similar predictors that should hade received ICU care based on our prediction model but did not due to scarcity of ICU resources, that would mean the ICU resources are 50% of what they ought to be.

The propensity score model is developed using the Training Data and tested using the Validation Data. The workflow contains a series of steps. The output of each step is the input for later steps. The model is developed using Testing Data and is tested with Validation Data. By reverting back and adjusting assumptions in an iterative process, the model is continuously improved and the accuracy and validity is improved.

The first step of PSM is to randomly split the data set into two parts, 60% and 40%. The 60% part is Training Data used to develop the propensity score model, and the 40% part is the Validation Part. This is done because the inherent bias of the PSM method. The prediction model produced in step 3 is based on and fitted against the Training data and predictors are weighed so that the the model awards patients that did go to the ICU corresponding high propensity. This model can then be used to predict new patients propensity to go to the ICU based on their baseline predictor values, and by saving 40% in the Validation data set we have a set of patients that is new to the model on which we may test how well the model predict their fate. Training Data is used in steps 2-3 and the resulting model is then validated using Validation Data.

Second step is to identify predictor variables: covariates most predictive of the dependent variable, as described in chapter Predictor selection. In this context it means to first identify the conditions and medical interventions received that correlate best to being admitted to ICU care. This selection is based on clinical experience as well as analysis of the Training Data. In the data analysis all properties of the patients that were sent to the ICU will be compared to the patents who did not, in order to identify properties that distinguishes this cohort. Familiarity with the collection of source data is crucial to minimize the risk to choose irrelevant predictors and introduce error.

Third step is to build a multivariable logistic regression model with ICU care as the outcome and the predictors selected in the second step as independent variables using Testing Data.

Fourth step is to apply this model on patients from the Validation Data set, and see whether the model correctly prediced which patients in the Validation data received ICU treatment. Using the model, the standard variable propensity score is calculated for each patient in the Validation Data set. If the patients that were admitted to the ICU in the validation set receive appropriate propensity scores by the model constructed in step 2-3, the model is valid. The propensity score determines the likelihood that a patient will receive ICU care, given their condition.

Fifth step is PSM. In PSM members of the subset that did not get ICU care but had similar predictors - and therefore similar propensity scores - as the subgroup that did get ICU care, are matched to patients who did go to the ICU. There are a few different ways to perform this matching but they are all imperfect because propensity scores are unique and perfect matching is unattainable. There are control mechanisms and limitations but a risk of applying too fix or too loose matching criteria and inadvertently vastly under- or overestimate the need of ICU beds remain.

The two subgroups were patients admitted to the ICU, and the patients who were not. Admission to the iCU is a binary yes or no, length of stay has not been taken into Consideration.

## Missing Data

The data completion rate is presented in table\_nums(‘tab\_1’). As the base assumption, all quantitative variables collected for each patient are considered potential recordings. Data that are missing are assumed missing because care for a patient did not motivate the collection of the data. For example, if serum creatinine was not recorded, it is assumed that the collection of this variable was not relevant for care of the patient.

There are some variables that should reasonably have been collected and documented given the patient condition, but omission will not be cause of dismissal unless these variables are predictors.

All patients with incomplete observations for any predictors will be discarded. For relevant qualitative variables, missing data did not automatically warrant dismissal, if the missing data could be indirectly proven. For example if the quantitative yes/no for an examination like a CT scan was missing, it was deemed a ‘yes’ if there was a CT scan result recorded. If both were missing, the patient data was dismissed. All vital parameters are considered mandatory, irregardless of patient condition so patients without data of heart rate, systolic blood pressure or respiration rate at any time of their hospital stay, have been discarded.

All quantitative data from the original dataset that were entered as zero but where a zero value is physiologically impossible were replaced with NA values. Zero values for variables where it is possible to have zero values, such as respiration rate and heart rate were left as zeroes to not tamper with the data, although a zero value indicate that the variable probably was not measured. These amount to 250 and 155 entries respectively for the first observation within an hour and less than 100 for both for the second observation after 24 h, so the choice to include or exclude these observations won’t skew the data considerably.

Cohort study: If applicable, explain how loss to follow-up was addressed

Case-control study:If applicable, explain how matching of cases and controls was addressed

Cross-sectional study: If applicable, describe analytical methods taking account of sampling strategy

1. Describe any sensitivity analyses –>

## Predictor selection

Predictors are independent variables with strong causality with the dependent varaiable. Predictor variables will be selected using both clinical judgement and data analysis. Because causality is presumed, predictors must precede ICU admission. For example, though there is a strong correlation between ICU admission and mortality, mortality can not be a predictor because it did not cause ICU admission.

Clinical experience compels inclusion of vital parameters, regardless if there is any statistical motivation. Such variables are heart rate, systolic blood pressure and respiration rate.

The TITCO-I data set is analysed mathematically in pursuit of suitable predictor variables. The data set is divided into two subgroups, the cohort that were admitted to the ICU and the cohort that was not. In comparison between these subgroups, identify variables that distinguishes the former from the latter. The quantitative and qualitative properties were considered separately.

Mean and standard deviation for the quantitative data is analysed for the ICU and non-ICU cohort respectively. p- and t-values when comparing these cohorts to show if there are any statistically significant differences. It is plausible to construct new variables from quantitative data, such as trends.

Timer data can be used to construct quantitative variables delay-of-care. Second and third delays, corresponding to the delays between incident and hospital admission and between admission and first survey have been proposed to have high relevance for patient outcome (3) .

For the qualitative data, the propensity of each parameter for ICU admission is compared to the proportion of patients that were admitted to the ICU from the whole TITCO-I data set, about a third. If considerably more than a third of each qualitative parameter are admitted to the ICU, then that parameter is of interest. It has been relevant to combine qualitative parameters into aggregate qualitative varaibles. For example, the variable intubation at 1 hour has two options indicating the patient is intubated: “before arrival” meaning the patient was intubated at a their first health care facility and “yes” meaning the patient was intubated within the first hour. Because these two options both mean the patient was intubated after 1 hour, an aggregate parameter has been created for this. Because the data set also contain information of whether a patient was intubated within the first and 24th hour the parameter “intubated after 24 hours” were created that summarize the patients who were intubated on arrival, the patients who were intubated within the first hour and the patients who were intubated between 1 and 24 hours.

The free hand text based information available contain information about examination findings, surgery types and ICD codes. Many of these data fields contain crucial information about patient condition, but also present a few challenges as described in chapter: Variables and data sources/measurements. These text based data fields will be examined for entries that are more prevalent in the ICU cohort than the non-ICU cohort, and combined with clinical experience to select suitable predictors.

It is also plausible to include aggregate variables, by combining unrelated variables of the same type or across varaible types. Selection and construction of such aggregate parameters to be explored will be based on clinical experience not data analysis. An example of this is the heterogenous qualitative parameter “taken to the operation theatre”. Many operation types are strongly correlated to ICU admission - especially if they were performed within the first hour of admission - but most of the operations performed are lower priority orthopedic operations with no correlation to ICU admission. There is a need to combine operation timing and free text fields “operation type” and “intraoperative findings” to filter out operations with higher propensity for ICU admission.

# Results

## Missing data

Återkom: XX patients were discarded because of missing data

## Predictor selection

The quantitative data results see table\_nums(‘tab\_2’)

setwd("C:/Users/maria/Downloads/Packt Learning RStudio for R Statistical Computing 2012 RETAIL eBook-repackb00k/unmet-ICU-beds")  
load("table5.rdata")  
  
knitr::kable(table5, caption = "Means, standard devations of quantitative variables of ICU and non-ICU admitted patients, respectively and p- and t-values of comparison between the sets")

Means, standard devations of quantitative variables of ICU and non-ICU admitted patients, respectively and p- and t-values of comparison between the sets

| V1 | ICU\_mean | ICU\_sigma | noICU\_mean | noICU\_sigma | mean\_diff | p-värde | t-värde |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Age in years | 31.7943856 | 17.7263431 | 32.0560390 | 19.4158109 | 0.2616534 | 0.3946149 | -0.8513094 |
| Systolic blood pressure, first recording | 111.2095050 | 27.5511816 | 115.6758082 | 19.4232314 | 4.4663032 | 0.0000000 | -9.9796720 |
| Blood oxygen saturation, first recording | 93.8055600 | 12.5507739 | 98.8721691 | 5.2040041 | 5.0666091 | 0.0000000 | -22.0697873 |
| Respiratory rate, first recording | 18.8619281 | 5.0397223 | 19.5382814 | 5.0826257 | 0.6763533 | 0.0000000 | -6.2877406 |
| Heart rate, first recording | 94.8957931 | 21.5529571 | 89.5918483 | 14.4839394 | -5.3039449 | 0.0000000 | 15.7553849 |
| Glasgow coma scale, total, first recording | 10.7364099 | 4.5072617 | 12.6145083 | 3.6724655 | 1.8780984 | 0.0000000 | -25.2317741 |
| Systolic blood pressure, second recording | 112.6042205 | 20.1195252 | 117.9916003 | 15.7876409 | 5.3873798 | 0.0000000 | -14.3549634 |
| Blood oxygen saturation, second recording | 99.4058554 | 3.1767076 | 99.7865132 | 1.3367721 | 0.3806577 | 0.0000003 | -5.1533737 |
| Respiratory rate, second recording | 19.4038186 | 3.9692207 | 21.1491288 | 4.0794856 | 1.7453102 | 0.0000000 | -17.1446774 |
| Heart rate, second recording | 94.1849794 | 21.4668158 | 87.9647804 | 14.5570554 | -6.2201991 | 0.0000000 | 17.7522789 |
| Glasgow coma scale, total, second recording | 10.2711628 | 4.6272005 | 13.0862227 | 3.3026949 | 2.8150599 | 0.0000000 | -33.6936981 |
| Units of packed red blood cells transferred within one hour | 0.0695297 | 0.4426995 | 0.0174046 | 0.1805459 | -0.0521250 | 0.0000000 | 8.2882335 |
| Units of packed red blood cells transferred between one and twenty four hours | 0.4661584 | 1.1247582 | 0.2731969 | 0.6983430 | -0.1929616 | 0.0000000 | 11.4930783 |
| Length of surgery | 3.0839193 | 1.3620498 | 2.2466436 | 1.1078041 | -0.8372757 | 0.0000000 | 20.9268836 |
| Systolic blood pressure at start of surgery | 110.8596838 | 18.7199306 | 114.3514986 | 15.6244264 | 3.4918148 | 0.0000002 | -5.1904220 |
| Hemoglobin | 11.7639491 | 3.0428417 | 11.8612321 | 2.4687648 | 0.0972830 | 0.0626833 | -1.8616844 |
| Hematocrit | 35.5127530 | 7.8331565 | 36.1694136 | 7.9269359 | 0.6566605 | 0.0070890 | -2.6948437 |
| Blood glucose level | 160.5875544 | 79.5024934 | 130.6029826 | 55.2316432 | -29.9845719 | 0.0000000 | 18.8629105 |
| Serum creatinine | 0.9707055 | 1.4132554 | 0.6627406 | 0.7852057 | -0.3079648 | 0.0000000 | 14.2536146 |
| Blood urea nitrogen | 20.2045857 | 18.3590069 | 19.7025546 | 16.8667428 | -0.5020310 | 0.1071239 | 1.6114176 |
| Length of ventilation | 88.4353603 | 166.1147894 | 0.1011762 | 3.2118658 | -88.3341841 | 0.0000000 | 38.9134028 |
| Length of intensive care unit staty | 118.5233129 | 176.0793190 | 0.0000000 | 0.0000000 | -118.5233129 | 0.0000000 | 49.3680763 |
| Injury severity score | 12.9206166 | 7.8603549 | 11.3102178 | 9.4236425 | -1.6103987 | 0.0000000 | 11.0473465 |
| New injury severity score | 18.8019268 | 11.3479150 | 14.9232874 | 10.8130585 | -3.8786394 | 0.0000000 | 20.1325813 |
| time of care | 13.8893703 | 25.4262543 | 8.4757494 | 12.0715221 | -5.4136210 | 0.0000000 | 14.7396681 |
| time from accident to admission | 2.8610041 | 3.6793446 | 3.0565461 | 3.9675384 | 0.1955420 | 0.0028638 | -2.9826805 |
| time from admission to first survey | 0.1035184 | 0.6336374 | 0.7660912 | 1.2338886 | 0.6625728 | 0.0000000 | -43.9135862 |
| time from accident to first survey | 2.8373837 | 3.9854720 | 3.0456828 | 5.2664982 | 0.2082991 | 0.0076991 | -2.6654224 |

For many parameters the difference is small, perhaps because of a crowd out effect. For instance, the total Glascow coma scale score is high and quite similar for the non-ICU subset versus the ICU subset, the difference between the average of the groups is 2 points. However, low scores in either category is a high propensity to admit a patient to the ICU, as demonstrated in the comparison of quantitative parameters.

The proportions of the qualitative data are presented in

setwd("C:/Users/maria/Downloads/Packt Learning RStudio for R Statistical Computing 2012 RETAIL eBook-repackb00k/unmet-ICU-beds")  
load("qualitativetable.rdata")  
  
knitr::kable(qualitativetable, caption = "Proportion of patients admitted to the ICU for all variants of all quuantitative variables")

Proportion of patients admitted to the ICU for all variants of all quuantitative variables

| X | X.1 | all | ICU | no.ICU | NA. | Prop.ICU |
| --- | --- | --- | --- | --- | --- | --- |
| ‘Hospital identification number’ | 6273 | 2594 | 2552 | 1 | 41 | 100% |
|  | 7215 | 1842 | 355 | 1486 | 1 | 19% |
| ’ | 7842 | 6886 | 266 | 6620 | 0 | 4% |
|  | 8264 | 4677 | 2210 | 2465 | 2 | 47% |
| ‘Directly observed’ | ‘NA’ | 1 | 1 | 0 | 0 | 100% |
|  | ‘No’ | 12114 | 4016 | 8073 | 25 | 33% |
|  | ‘Yes’ | 3884 | 1366 | 2499 | 19 | 35% |
| ‘Inclusion criterion used’ | 0 | 40 | 14 | 26 | 1 |  |
|  | 1 | 10957 | 1605 | 9349 | 3 | 15% |
|  | 2 | 120 | 4 | 116 | 0 | 3% |
|  | 3 | 4882 | 3760 | 1081 | 41 | 78% |
| ‘Sex’ | ‘Female’ | 3628 | 782 | 2838 | 8 | 22% |
|  | ‘Male’ | 12371 | 4601 | 7734 | 36 | 37% |
| ‘Transferred from other health facility’ | ‘NA’ | 35 | 3 | 32 | 0 | 9% |
|  | ‘No’ | 4629 | 1922 | 2692 | 15 | 42% |
|  | ‘Yes’ | 11335 | 3458 | 7848 | 29 | 31% |
| ‘Mode of transport’ | ‘Ambulance’ | 10734 | 3223 | 7486 | 25 | 30% |
|  | ‘Carried by man’ | 24 | 11 | 13 | 0 | 46% |
|  | ‘NA’ | 234 | 6 | 227 | 1 | 3% |
|  | ‘Other’ | 14 | 4 | 10 | 0 | 29% |
|  | ‘Police’ | 1319 | 787 | 524 | 8 | 60% |
|  | ‘Private car’ | 1737 | 474 | 1261 | 2 | 27% |
|  | ‘Taxi, motor rickshaw’ | 1937 | 878 | 1051 | 8 | 46% |
| ‘Type of injury’ | ‘Blunt’ | 15196 | 5080 | 10079 | 37 | 34% |
|  | ‘NA’ | 7 | 2 | 5 | 0 | 29% |
|  | ‘Penetrating’ | 796 | 301 | 488 | 7 | 38% |
| ‘Arrived walking’ | ‘NA’ | 213 | 12 | 201 | 0 | 6% |
|  | ‘No’ | 15763 | 5367 | 10352 | 44 | 34% |
|  | ‘Yes’ | 23 | 4 | 19 | 0 | 17% |
| ‘Patient on supplemental oxygen when the first blood oxygen saturation was recorded’ | ‘NA’ | 3431 | 1900 | 1508 | 23 | 56% |
|  | ‘No’ | 8817 | 1904 | 6905 | 8 | 22% |
|  | ‘Yes’ | 3751 | 1579 | 2159 | 13 | 42% |
| ‘Glasgow coma scale, eye component, first recording’ | NA | 2198 | 302 | 1894 | 1 |  |
|  | 1 | 2892 | 1623 | 1262 | 7 | 56% |
|  | 1s | 34 | 3 | 31 | 1 | 9% |
|  | 2 | 1085 | 430 | 651 | 4 | 40% |
|  | 3 | 942 | 331 | 608 | 3 | 35% |
|  | 4 | 8848 | 2694 | 6126 | 28 | 31% |
| ‘Glasgow coma scale, verbal component, first recording’ | NA | 2200 | 304 | 1894 | 1 | 14% |
|  | 1 | 2355 | 1127 | 1224 | 4 | 48% |
|  | 1s | 707 | 559 | 144 | 1 | 79% |
|  | 2 | 1257 | 520 | 731 | 6 | 42% |
|  | 3 | 839 | 286 | 552 | 1 | 34% |
|  | 4 | 814 | 289 | 522 | 3 | 36% |
|  | 5 | 7827 | 2298 | 5505 | 24 | 29% |
| ‘Patient on supplemental oxygen when the second blood oxygen saturation was recorded’ | ‘NA’ | 6882 | 3090 | 3755 | 37 | 45% |
|  | ‘No’ | 2014 | 351 | 1660 | 3 | 17% |
|  | ‘Yes’ | 7103 | 1942 | 5157 | 4 | 27% |
| ‘Glasgow coma scale, eye component, second recording’ | NA | 6205 | 1099 | 5101 | 1 |  |
|  | 1 | 2250 | 1639 | 602 | 9 | 73% |
|  | 1s | 19 | 1 | 18 | 1 |  |
|  | 2 | 618 | 249 | 366 | 3 | 40% |
|  | 3 | 547 | 210 | 333 | 4 | 39% |
|  | 4 | 6360 | 2185 | 4152 | 23 | 34% |
| ‘Glasgow coma scale, verbal component, second recording’ | NA | 6208 | 1102 | 5101 | 1 |  |
|  | 1 | 664 | 191 | 473 | 0 | 29% |
|  | 1s | 2006 | 1790 | 205 | 1 |  |
|  | 2 | 565 | 181 | 381 | 3 | 32% |
|  | 3 | 488 | 145 | 342 | 1 | 30% |
|  | 4 | 490 | 180 | 307 | 3 | 37% |
|  | 5 | 5578 | 1794 | 3763 | 21 | 32% |
| ‘Intubation within one hour’ | ‘Before arrival’ | 486 | 407 | 78 | 1 | 84% |
|  | ‘No’ | 13676 | 3331 | 10310 | 35 | 24% |
|  | ‘Yes’ | 1837 | 1645 | 184 | 8 | 90% |
| ‘Surgical airway within one hour’ | ‘Before arrival’ | 81 | 48 | 31 | 2 | 61% |
|  | ‘No’ | 15879 | 5298 | 10539 | 42 | 33% |
|  | ‘Yes’ | 39 | 37 | 2 | 0 | 95% |
| ‘Intercostal drain within one hour’ | ‘Before arrival’ | 67 | 46 | 20 | 1 | 70% |
|  | ‘NA’ | 3 | 1 | 2 | 0 |  |
|  | ‘No’ | 14917 | 4724 | 10156 | 37 | 32% |
|  | ‘Yes’ | 1012 | 612 | 394 | 6 | 61% |
| ‘Taken to the operation theatre within one hour’ | ‘No’ | 15823 | 5262 | 10521 | 40 | 33% |
|  | ‘Yes’ | 176 | 121 | 51 | 4 | 70% |
| ‘Intubation between one and twenty four hours’ | ‘NA’ | 1 | 1 | 0 | 0 |  |
|  | ‘No’ | 15459 | 5024 | 10395 | 40 | 33% |
|  | ‘Yes’ | 539 | 358 | 177 | 4 | 67% |
| ‘Surgical airway between one and twenty four hours’ | ‘NA’ | 1 | 1 | 0 | 0 | 100% |
|  | ‘No’ | 15844 | 5306 | 10496 | 42 | 34% |
|  | ‘Yes’ | 154 | 76 | 76 | 2 | 50% |
| ‘Intercostal drain between one and twenty four hours’ | ‘NA’ | 1 | 1 | 0 | 0 |  |
|  | ‘No’ | 15839 | 5323 | 10472 | 44 | 34% |
|  | ‘Yes’ | 159 | 59 | 100 | 0 | 37% |
| ‘Taken to the operation theatre between one and twenty four hours’ | ‘NA’ | 2 | 2 | 0 | 0 |  |
|  | ‘No’ | 12038 | 3738 | 8266 | 34 | 31% |
|  | ‘Yes’ | 3959 | 1643 | 2306 | 10 | 42% |
| ‘Computed tomography’ | ‘NA’ | 44 | 0 | 43 | 1 | 0% |
|  | ‘No’ | 5092 | 1135 | 3943 | 14 | 22% |
|  | ‘Yes’ | 10863 | 4248 | 6586 | 29 | 39% |
| ‘Focused assessment with sonography in trauma’ | ‘NA’ | 2 | 0 | 1 | 1 | 0% |
|  | ‘No’ | 8158 | 840 | 7307 | 11 | 10% |
|  | ‘Yes’ | 7839 | 4543 | 3264 | 32 | 58% |
| ‘X-ray’ | ‘NA’ | 5 | 0 | 4 | 1 | 0% |
|  | ‘No’ | 7318 | 591 | 6724 | 3 | 8% |
|  | ‘Yes’ | 8676 | 4792 | 3844 | 40 | 55% |
| ‘Patient died’ | ‘NA’ | 1 | 0 | 0 | 1 |  |
|  | ‘No’ | 12360 | 3687 | 8643 | 30 | 30% |
|  | ‘Yes’ | 3638 | 1696 | 1929 | 13 | 47% |
| ‘Discharged against medical advice’ | ‘NA’ | 5 | 4 | 0 | 1 |  |
|  | ‘No’ | 14810 | 5037 | 9735 | 38 | 34% |
|  | ‘Yes’ | 1184 | 342 | 837 | 5 | 29% |
|  |  | NA | NA | NA | NA |  |
| Aggregated variables |  | NA | NA | NA | NA |  |
| Intercostal drain before or within an hour of arrival |  | 2323 | 2052 | 262 | 9 | 89% |
| Intercostal drain within 24 hours |  | 2482 | 2111 | 362 | 9 | 85% |
|  |  | NA | NA | NA | NA |  |
| Surgical airway before or within an hour of arrival |  | 120 | 85 | 33 | 2 | 72% |
| surgical airway within 24 hours |  | 274 | 161 | 109 | 4 | 60% |
|  |  | NA | NA | NA | NA |  |
| Operation within 24 hours |  | 4135 | 1764 | 2357 | 14 | 43% |

You can include code in this document like this:

## Warning: package 'tidyverse' was built under R version 4.2.1

## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.2 ──  
## ✔ ggplot2 3.3.6 ✔ purrr 0.3.4   
## ✔ tibble 3.1.8 ✔ dplyr 1.0.10  
## ✔ tidyr 1.2.0 ✔ stringr 1.4.1   
## ✔ readr 2.1.2 ✔ forcats 0.5.2

## Warning: package 'ggplot2' was built under R version 4.2.1

## Warning: package 'tibble' was built under R version 4.2.1

## Warning: package 'tidyr' was built under R version 4.2.1

## Warning: package 'readr' was built under R version 4.2.1

## Warning: package 'purrr' was built under R version 4.2.1

## Warning: package 'dplyr' was built under R version 4.2.1

## Warning: package 'stringr' was built under R version 4.2.1

## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()

## Warning: package 'tableone' was built under R version 4.2.1

You can also embed plots:



You can also mix text and code, so called inline code, like this: 7.

# Discussion

In order to limit the scope of this thesis work, a few quite relevant factors could not be considered. One of the most important factors was temporality. Emergency rooms everywhere face significant variations in patient loads over the week or special occasions such as the Diwali festival. A different approach completely but to the same effect would have been to consider the ICU wards at the participating hospitals and chronologically determine which patients did not receive ICU care because these wards were at capacity. Though intuitively it would seem possible to do given the TITCO-I dataset, it would have been very difficult to do practically.

Length of stay in hours is ICU care was recorded in the TITCO-I data set, but for the purpose of this thesis ICU admission has been reducedn to a binary ‘yes’ or ‘no’. Because it is not uncommon to discontinue ICU care prematurely in favor of patients with more dire needs, the next step would be to consider such circumstances.

# Conclusion

# References

1. Laytin AD, Debebe F. The burden of injury in low-income and middle-income countries: Knowing what we know, recognising what we don’t know. Emergency Medicine Journal [Internet]. 2019 Apr;emermed-2019-208514. Available from: <https://doi.org/10.1136/emermed-2019-208514>

2. Bhandarkar P, Patil P, Soni KD, O’Reilly GM, Dharap S, Mathew J, et al. An analysis of 30-day in-hospital trauma mortality in four urban university hospitals using the australia india trauma registry. World Journal of Surgery [Internet]. 2020 Oct;45(2):380–9. Available from: <https://doi.org/10.1007/s00268-020-05805-7>

3. Roy N, Gerdin M, Ghosh S, Gupta A, Kumar V, Khajanchi M, et al. 30-day in-hospital trauma mortality in four urban university hospitals using an indian trauma registry. World Journal of Surgery [Internet]. 2016 Feb;40(6):1299–307. Available from: <https://doi.org/10.1007/s00268-016-3452-y>

4. Malelelo-Ndou H, Ramathuba DU, Netshisaulu KG. Challenges experienced by health care professionals working in resource-poor intensive care settings in the limpopo province of south africa. Curationis [Internet]. 2019 Mar;42(1). Available from: <https://doi.org/10.4102/curationis.v42i1.1921>

5. Jayakumar DrR, Duvvuru DrRReddy, editors. Research trends in multidisciplinary research [Internet]. AkiNik Publications; 2022. Available from: <https://doi.org/10.22271/ed.book.1458>

6. Srivastava S, Karan AK, Bhan N, Mukhopadhya I, Organization WH, et al. India: Health system review. Health Systems in Transition. 2022;11(1).

7. collaborators T. Titco/titco-i: The original anonymized TITCO cohort of 16000 trauma patients. <https://github.com/titco/titco-I#citation>; 2017.

8. Newgard CD, Fildes JJ, Wu L, Hemmila MR, Burd RS, Neal M, et al. Methodology and analytic rationale for the american college of surgeons trauma quality improvement program. Journal of the American College of Surgeons [Internet]. 2013 Jan;216(1):147–57. Available from: <https://doi.org/10.1016/j.jamcollsurg.2012.08.017>

9. Tracy BM, Adams MA, Schenker ML, Gelbard RB. The 5 and 11 factor modified frailty indices are equally effective at outcome prediction using TQIP. Journal of Surgical Research [Internet]. 2020 Nov;255:456–62. Available from: <https://doi.org/10.1016/j.jss.2020.05.090>

10. Heaney JB, Guidry C, Simms E, Turney J, Meade P, Hunt JP, et al. To TQIP or not to TQIP? That is the question. The American Surgeon [Internet]. 2014 Apr;80(4):386–90. Available from: <https://doi.org/10.1177/000313481408000422>