Sheffield Hallam University
Materials and Engineering research Institute
Department of Engineering and Mathematics

Artificial Intelligence and Statistical Techniques to Predict Probability of Injury Survival

Mohammed Saleh

Supervisors:

Professor Reza Saatchi (Sheffield Hallam University)
Professor Derek Burke (Sheffield children's Hospital)
Professor Fiona Lecky (Sheffield University)

December 2018

Declaration

This is to certify that I am responsible for the work submitted in this report.

Signed…….Saleh……..…

Date……27/05/2019…….....

ABSTRACT

The aim of this study is to design, develop and evaluate artificial intelligence and statistical techniques to predict the probability of survival in traumas using knowledge acquired from a database of confirmed traumas outcomes (survivors and not survivors). Trauma in this study refers to body injuries from accidents or other means. Quantifying the effects of traumas on individuals is challenging as they have many forms, affect different organs, differ in severity and their consequence could be related to the individual's physiological attributes (e.g. age, fragility, premedical condition etc). It is known that appropriate intervention improves survival and may reduce disabilities in traumas. Determining the probability of survival in traumas is important as it can inform triage, clinical research and audit. A number of methods have been reported for this purpose. These are based on a combination of physiological and anatomical examination scores. However, these methods have shortcomings as for example, combining the scores from injuries for different organs is complicated.

A method for predicting probability of survival in traumas needs to be accurate, practical and accommodate broad cases. In this study Sheffield Hallam University, Sheffield Children's Hospital, Sheffield University and the Trauma Audit and Research Network (TARN) collaborated to develop improved means of predicting probability of survival in traumas. The data used in this study were trauma cases and their outcomes provided by the TARN. The data included 47568 adults (age: mean = 59.9 years, standard deviation = 24.7 years) with various injuries. In total, 93.3% of cases had survived and 6.7% of cases had not survived. The data were partitioned into calibration (2/3 of the data) and evaluation (1/3 of the data). The trauma parameters used in the study were: age, respiration rate (RR), systolic blood pressure (SBP), pulse (heart) rate (PR) and the values obtained from two trauma scoring systems called Abbreviated Injury Score (AIS) and Glasgow Coma Score (GCS). Intubation and Pre-exiting Medical Condition (PMC) data were also considered.

Initially a detailed statistical exploration of the manner trauma these trauma parameters related to the probability of survival outcomes was carried out and the results were interpreted. The resulting information assisted the development of three methods to predict probability of survival. These were based on Bayesian statistical approach called predictive statistical diagnosis (PSD), a new method called Iterative Random Comparison classification (IRCC) and the third method combined the IRCC with the fuzzy inference system (FIS). The performance of these methods was compared with each other as well as the method of predicating survival used by the TARN called Ps14 (the name refers to probability of survival method reported in 2014).

The study primarily focused on Trauma Brain Injury (TBI) as they represented the majority of the cases. For TBI, the developed IRCC performed best amongst all methods including Ps14. It predicted survivors and not survivors with 97.2% and 75.9% accuracies respectively. In comparison, the predication accuracy for Ps14 for survivors and not survivors were 97.4% and 40.2%.

The study provided resulted in new findings that indicated the manner trauma parameters affect probability of survival and resulted in new artificial intelligence and statistical methods of determining probability survival in trauma.

ACKNOWLEDGMENTS

This study would not have been possible without the kind and continuous support of my supervisors and collaboration from the Trauma Audit & Research Network (TARN). I would like to extend my sincere thanks to them all.

I would like to express my great thanks to my director of studies Professor Reza Saatchi, for his guidance, support, encouragement, valuable suggestions and comments on various aspects of my PhD study. Special thanks to my PhD supervisors Professor Derek Burke and Professor Fiona Lecky for their time and very valuable guidance and assistance throughout the study. The medical inputs were very important to the developments in this study.

I am grateful to invaluable support provided to this study by the TARN staff: Ms Maralyn Woodford (executive Director), Ms Antoinette Edwards (Operations Director & Deputy to the Executive Director), Ms Gemma Reed (Administrator and Personal Assistant) and Mr Phil Hammond (Data Validation). I am very grateful to the TARN for agreeing to make their trauma data available to this research study.

Thank you very much.

Publications

1. Saleh, M., Saatchi, R., & Burke, D. (2017). Analysis of the influence of trauma injury factors on the probability of survival. International Journal of Biology and Biomedical Engineering, vol.11, pp.88-96.

2. Saleh, M., Saatchi, R., Lecky, F., & Burke, D. (2018). Predictive statistical diagnosis to determine the probability of survival in adult subjects with traumatic brain injury. Technologies, vol.6, no.,41, pp.1-16.

3. Saleh, M., Saatchi, R., Lecky, F., & Burke, D. (2017). Fuzzy logic to determine the likelihood of survival for trauma injury patients. ın: Harnessing the power of technology to improve lives. Studies in Health Technology and Informatics, IOS Press, vol. 242, pp.385-388.

4. SALEH, Mohammed, SAATCHI, Reza, LECKY, Fiona and BURKE, D. (2017). Computational analysis of factors affecting the probability of survival in trauma injuries. In: 2017 4th International Conference on Mathematics and Computers in Sciences and in Industry, Corfu, Greece, 24 August 2017 - 27 August 2017. IEEE, 114-118.

5. SALEH, Mohammed, SAATCHI, Reza and BURKE, D. (2017). Fuzzy logic to determine the likelihood of survival for trauma injury patients. In: 14th AAATE 2017 Congress.

6. Saleh, M., Saatchi, R., Burke, D., & Lecky, F. (2017, May). Development of artificial intelligence techniques to determine the likelihood of survival in trauma injuries. Seminar Presentation, MERI Research Symposium, Sheffield Hallam University, Sheffield.

Table of contents

List of figures

List of tables

List of acronyms

AAAM	Association for the Advancement of Automotive Medicine
AI	Artificial Intelligence
AIS	Abbreviated Injury Scale
AP	Anatomic Profile
APACHE	Acute Physiology and Chronic Health Evaluation
ASCOT	A Severity Characterisation of Trauma
CCI	Charlson Comorbidity Index
COPD	Chronic Obstructive Pulmonary Disease
CRAMS	Circulation, Respiratory, Abdominal/Thoracic, Motor and Speech Scale
CVA/TIA	Cerebrovascular Accident/ Transient Ischemic Attack
DRISS	Drug-Rock Injury Severity Score
DS	Developed system
ED	Emergency Department
ESI	Emergency Severity Index
EX	Expert System
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FREC	Faculty Research Ethics Committee
GA	Genetic Algorithm
GAP	Glasgow Coma Scale, Age, and Systolic Blood Pressure
GCS	Glasgow Coma Scale
GUI	Graphic User Interface
HARM	Harborview Assessment for Risk of Mortality
HR	Heart Rate
ICISS	ICD- 9-CM Injury Severity Score
IRCC	Iterative Random Comparison Classification
ISS	Injury Severity Score
LOC	Standardise assessment of level of consciousness
LOD	Logistic Organ Dysfunction Score
MFs	Membership Functions
MLP	Multilayer Perceptron
MODS	Multiple Organ Dysfunction syndrome
MOF	Multiple organ failure
NFS	No Specific Structure
NN	Neural Networks
OIS	Organ Injury Scales
PATI	Penetrating Abdominal Trauma Index
PEFR	Peak Expiratory Flow Rate
PGCS	Paediatric Glasgow Coma Scale
PI	Prognostic Index
PMC	Pre-Existing Medical Conditions

PR	Pulse Rate
PS	Probability of Survival
PSD	Predictive Statistical Diagnosis
PTS	Paediatric Trauma Score
RAPS	Rapid Acute Physiology Score
REMS	Rapid Emergency Medicine Score
RR	Respiratory Rate
RTS	Trauma Revised Trauma Score
SAPS	Simplified Acute Physiology Score
SBP	Systolic Blood Pressure
SCH	Sheffield Children Hospital
SHU	Sheffield Hallam University
SIRSS	Systemic Inflammatory Response Syndrome Score
SOFA	Sequential Organ Failure Assessment Score
TARN	Trauma Audit and Research Network
TI	Trauma Index
TIB	Trauma Brine Injury
TMPM	Trauma Mortality Prediction Model
TRISS	Trauma Score - Injury Severity Score
TS	Trauma Score
WBC	White Blood Cell

List of Symbols

b_0	Regression coefficients
μ_A	Degree of membership in fuzzy logic
e	Constant= 2.718282
M	Mean value
Γ	Beta function
$\boldsymbol{\Theta}$	Vector of classification

Chapter 1 Introduction

Injury is a primary cause of death and disability (Mullins 1999), accounting for 10% of global burden of non-surviving cases (Laytin et al., 2017). A number of scoring systems have been reported to quantify the severity of injury by considering measurable or observable status of the patient's medical condition (Dillon et al, 2006). Trauma scoring systems can be beneficial for a number of situations (Wisner 1992; Kim 2012). These include (i) triage, a procedure to assess severity of medical condition for the purpose of setting treatment priority; (ii) prognostic evaluation, a procedure to support predication and management of injury outcomes and (iii) research studies to compare patient groups on the basis of injury outcomes and assessing medical care and treatments. Trauma scoring systems can be classified into anatomical, physiological and a combination of both. Anatomical scoring systems quantify the extent of individual anatomical injuries, taking into account the body injury sites by appropriate weightings (coefficients) however these weightings are often not known when the patient visits hospital after a civilian trauma where most injury mechanisms are blunt (e.g. falls and road traffic collisions) (Fani-Salek et al, 1999). Physiological scoring systems are based on cardiovascular, neurological and respiratory abnormalities. They provide mechanisms to determine the likelihood of mortality and inform triage; but can lack precision (Fani-Salek et al, 1999). Combined anatomical and physiological scoring systems integrate the strengths of the anatomical and physiological scoring systems to improve their estimation of the probability of survival (Meredith et al, 1995).

Trauma scores together with host factors such as Gender, age and pre-existing medical condition (PMC) are used in models to determine probability of survival (Reith et al, 2017; Moon et al, 2013; Chawda et al., 2004; Pike et al, 2017; Kuwabara et al, 2010).

1.1 Background and Purpose of the Study

Assessing the level of severity of injury in a hospital's emergency department (ED) is highly demanding due to diversity of injury types, individual vulnerabilities (e.g. varied age groups), large number of possible physiological measures (e.g. heart rate, temperature, blood pressure, respiration rate etc.) as

well as complexities in anatomical assessments (e.g. evaluating a head injury). Early intervention in many medical and traumatic conditions can improve survival outcome and reduce disabilities.

Injury is the main cause of death and disability (Mullins, 1999) and survival of a severely injured person depends on the specialized care delivered in a timely manner. Therefore, a careful assessment of the severity of injuries is essential to reduce disabilities and mortalities. Trauma scoring systems improve triage decisions, identify patient unexpected trauma outcomes, generate audit information and provide objective information for external and internal outcome comparisons (Lefering, 2002). Figure 1.1 shows a triangle of work related injuries in the UK in 2010/ 2011 and their severities reported by (Health and Safety Executive 2012). However, many injuries occur outside work environment.

Figure 1-1Injury severity triangle 2010-11 (Health and Safety Executive 2012)

The extent of injury severity could be classified as nominal, ordinal or interval (Health and Safety Executive 2012). Majority of characterizations of injury severity are in nominal scales where verbal classifications are used to describe injury. They are valuable in simplifying communication between parties. Ordinal approaches use a positive entire numbers to provide a score to an injury

severity. Several groupings such as fractures and many neurosurgical, orthopedic and common injury classifications fall into this type. Interval scales likewise give numbers however there is an implicit probability of some reliability in the intervals between the numbers (Champion 2002).

A number of injury severity scoring systems were reported in the last decades. These are intended to accurately and consistently quantify injuries by considering measurable or observable status of the patient's medical conditions. The main benefits of trauma scoring systems are (Wisner, 1992): triage which sets priorities to treat patients; prognostic evaluation which enables the prediction and management of injury outcomes; and research and evaluation which compares patient groups on injury outcomes and examines the effects of treatments.

In order to obtain the anatomical and neurological injury related information, a number of standard scoring systems are available. A commonly used system for assessing anatomical injuries is the Abbreviated Injury Scale (AIS) (Gennarelli et al, 2006). It was introduced in 1971 by the Association of the Advancement of Automotive Medicine to aid vehicle crash investigators. It has since been revised to be more relevant to medical audit and research. AIS classify injuries in all body regions according to their relative importance. In order to determine an overall trauma injury score for patients with multiple trauma injuries, the Injury Severity Score (ISS) could be used. This is an anatomical scoring system with the maximum total score of 75 that selects the highest AIS values in each body region (Barker et al, 1974). The three most severely injured regions (corresponding to 3 largest scores) have their scores squared and then summed to produce the ISS value. However, ISS has a number of limitations in identifying the implication of the injury sites (Fani-Salek et al,. 1999). For example, brain traumas have different implications compared with skin bruising. ISS is nevertheless used for as an anatomical scoring system in methods such as the TARN Ps14 in order to determine probability of survival. The TARN is a UK center involved in researching trauma and its team receives injury information from the UK hospitals code them according to the AIS system. The TARN has proposed Ps14 (probability of survival prediction proposed in 2014) to predict probability of survival. In this study methods to determine probability of survival in traumas are developed and evaluated.

1.2 Aim and Objectives

The primary aim of this research is to develop and evaluate improved methods of determining probability of survival in traumas. Its objectives are:

i. Analyze the trauma cases from the available TARN data base to ascertain the interrelationships between trauma parameters such as age, Gender, respiration rate, systolic blood pressure, pulse rate, abbreviated injury scale Glasgow coma score, pre-existing medical conditions and intubation with the probability of survival.

ii. Use analysis information from (i) to develop improved methods of predicting probability of survival.

iii. A critically evaluate the methods developed in (ii) against each other and against Ps14 for different traumas but with the main focus of traumatic brain injury (TBI) were carried out.

iv. Publish findings in peer reviewed journals and conferences.

1.3 Study's Contribution

The study's contributions in relation to its objectives were:

i. A detailed analysis trauma parameters including age, gender, respiration rate, systolic blood pressure, pulse rate, abbreviated injury scale, Glasgow coma score, pre-existing medical conditions, intubation and these are used to the probability of survival in TBI was carried out. It was found all these parameters are significant in determining probability of survival. The investigations indicated the manner AIS and GCS values for different body regions relate to the probability of survival. Matlab© and SPSS© were used in these analysis to provide visual representation of the findings in the form of graphs, plots, distributions and clustering. These packages were also used to complement the visual information with tables summarizing the findings. The associated results are mostly

included in Chapter 5 but related information also appears in the following chapters.

ii. Three methods to predict probability of survival for TBI were proposed. One is based on a statistical Bayesian method called predictive statistical diagnosis (PSD). The second was a novel method referred to as Iterative random comparison classification (IRCC). IRCC uses a randomly selected group of cases with predefined group size as part of its operation and by interactively repeating the process determine the probability of survival. The third method combined IRCC with fuzzy inference system (FIS) to accommodate pre-existing medical conditions (PMC) and intubation information. The use of FIS required careful knowledge representation and knowledge coding. Fuzzy logic is a valuable technique to accurately representing complex imprecise information. More details related to the development of the methods are included in chapter 3 and 4.

iii. A critically evaluation of the methods developed in (ii) against each other and against Ps14 for different traumas was carried out. A number of body regions such as head and face etc. were also included in the evaluation but as the main fatalities in the available database were due to TBI, the focus of the study was on TBI. The main challenge for all methods was to improve prediction for not survivors as compared with the existing Ps14 method as Ps14 already had a high accuracy for the survivors. The three methods proposed in this study managed to significantly improve the probability of prediction for not survivors. For example for TBI, there were 1224 survivors and 224 not survivors. The predication accuracy for not survivors for Ps14, PSD and IRCC were 40.1%, 50.0% and 75.9%. The predicating accuracies for Ps14, PSD and IRCC for survivors were 97.3% 90.8% and 97.2%. The details of the results that also include head and face injury, head and chest injury, head, face and chest injury are provided in chapters 6 and 7.

iv. The study has so far resulted in two journal papers, one book chapters and two conferee proceedings. There is scope for at least two further journal papers, one in preparation.

1.4 Thesis Outline

Chapter 2 Literature Review

The previous studies associated with determining probability of survival and technological background for types of trauma scoring systems are explained and compared.

Chapter 3 Technologies Used in the Study

The theoretical and technological background for medical methods and other techniques that are used in this study towards achieving the set aims are described.

Chapter 4 Methodologies

The methodologies to obtain the results included in the thesis are explained.

Chapter 5 Investigation of interrelation between trauma parameters and survival outcomes

A statistical analysis of the subject details and their injuries as well as the interrelationship between probability of survival and the injuries are carried out and the results are presented.

Chapter 6 Trauma Knowledge Representation and Coding

The development of the knowledge representation and coding to assist with determining the probability of survival is explained.

Chapter 7 Probability of Survival Estimation Method

The operations and the results for the three methods of determining probability of survival are explained and their merits and limitations are analysed against the exiting Ps14 method.

Chapter 8 Conclusions and Future Work

The study's conclusions, main findings and suggestions for future work are outlined.

1.5 Chapter Summary

The study's background, aim and objectives were discussed. The trauma scoring systems and processing methods and systems developed to predict the probability of survival were described. An aim of the study was development of robust probability of survival calculation methods. These will be described in the following chapters.

Chapter 2 Literature Review

2.1 Introduction

Trauma is one of the most important concerns in health care that can lead to mortality and morbidity. Documentation of trauma data facilitates comparison between patient care and outcomes from different medical centres. Triage of trauma is used to assess level for prioritising of injured people for treatment or transport that depend on their severity of injury. Primary triage is performed at the scene of an accident and follow up triage at the hospital (Patient 2015).

Trauma scores provides audit and research tools to study the outcomes of trauma and its care. Many different trauma scoring systems have been developed; some are based on physiological scores e.g., Glasgow Coma Scale (GCS), others rely on anatomical descriptors e.g., Abbreviated Injury Scale (AIS).There are also combinations of both systems. However, there is no single universally accepted system as each system has its own merits. This chapter is divided into three main parts are: review of trauma scoring systems, artificial intelligence techniques based on trauma scoring systems and methods to extract keywords from Text.

2.2 Review of Trauma Scoring Systems

The trauma scoring systems can be divided into anatomical, physiological and combined. However, some other artificial intelligence techniques have been also used to predict probability of survival (Ps). These are summarised in Table 2-1.

Table 2-1Types of trauma scoring systems.

Anatomical Indices	Physiological Indices	Combined Anatomical/ Physiological Score	Artificial Intelligence Techniques base on Trauma Scoring Systems
• Abbreviated Injury Scale (AIS) and (MAIS) • Injury severity score (ISS) and (NISS) • Anatomic Profile (AP) • Trauma mortality prediction model (TMPM) • International Classification of Diseases-based ISS (ICISS) • Organ Injury Scales(OIS) • Penetrating Abdominal Trauma Index (PATI)	• Glasgow coma scale(GCS) • Paediatric Glasgow Coma Scale (PGCS) • Revised Trauma Score(RTS) • Trauma Score(TS) • Emergency Severity Index(ESI) • Acute Physiology and Chronic Health Evaluation(APACHE) • Rapid Acute Physiology score(RAMS) • Rapid Emergency Medicine Score (REMS) • Prognostic Index(PI) • Sequential Organ Failure Assessment Score (SOFA) • Multiple Organ Dysfunction syndrome (MODS) • Systemic Inflammatory Response Syndrome Score (SIRSS) • MULTIPLE ORGAN FAILURE (MOF) • Circulation, Respiratory, Abdominal/Thoracic, Motor and Speech Scale(CRAMS) • Glasgow Coma Scale, Age, and Systolic Blood Pressure (GAP) • Logistic Organ Dysfunction Score(LOD) • Simplified Acute Physiology Score(SAPS)	• Trauma Score-Injury Severity Score Methodology (TRISS) • The trauma audit and research network (TARN Ps14) • Harborview assessment for risk of mortality (HARM) • A Severity Characterization of Trauma (ASCOT) • Drug-Rock Injury Severity Score(DRISS) • Trauma Index (TI) • Pediatric Trauma Score (PTS)	• Neural Network(NN) • Fuzzy Logic(FL) • Genetic Algorithm(GA) • Expert System(ES) • Artificial Intelligent Virtual Reality (AIVR) • Machine Learning (ML) • Deep learning (DL)

2.2.1 Anatomical Systems

Abbreviated Injury Scale (AIS) is an anatomical trauma scoring system. It was introduced in 1971 by the Association for the Advancement of Automotive Medicine (AAAM). This association was founded in 1957 and is a professional multidisciplinary organisation for reducing vehicle crash injuries.

AIS describes injuries in nine body parts, head, neck, face, thorax, spine, abdomen, upper limbs, lower limbs, and external (Kim 2012). Maximum AIS (MAIS) is used to express total severity. MAIS does not linearly increase and decrease by varying likelihood of mortal. To provide solution for these limitations, the injury severity score (ISS) was presented (Stevenson et al. 2001). ISS was introduced in 1974 to determine the overall injury assessed by AIS. ISS is an ordinal scale and anatomically constructed that is between 1 and 75 by sum of square three highest scores of AIS (Champion 2002). ISS has an

ability to engage anatomic parts of injury in formulating an expectation of outcomes (Chawda et al., 2004). However, it has some limitations that it could expect less accurate in the case of multi-injuries in the same body region. Another drawback of the ISS is that all injuries are given an equal AIS score irrespective of body region where is injured. The last revision of the ISS is known as the New Injury Severity Score (NISS). The NISS is computed as the sum of squares of the three most significant (severe) AIS (1990 revision) injuries and it has improved the forecast of survival and enhanced routine, statistically, than the ISS (Stevenson et al. 2001). (Osler et al., 1997) NISS was tested as modification of the ISS; it is the sum of the squares of the AIS scores of a patient's three most severe injuries, irrespective of body parts.

Anatomic Profile (AP) trauma scoring system has some similarities to ISS, however it has limitations (Champion 2002). These limitations are based on the use of a one-dimensional score to represent the spectrum of injured body regions and severities and from the ISS definition that excludes all but the most serious injury in any body parts. Therefore, AP routines use four factors to calculate injured patient: A, B, and C for severe injuries (AIS >= 3) which are head and neck, thorax, and other defined body parts separately, and D defines any region of body which is not serious injury. It combines the parts using the taking the square root of the sum of the squares (Champion 2002)

$$AP = \sqrt{A^2 + B^2 + C^2 + D^2} \qquad 2\text{-}1$$

Likewise, Trauma Mortality Prediction Model (TMPM-ICD9) is the an injury-severity assessment system that uses empirical valuation from ICD-9-CM codes (Glance et al., 2009). TMPM-ICD9 is useful method for risk-adjustment model once injuries are verified using ICD-9-CM coding. It probably to be used to risk-adjust result assessment for trauma report cards at hospital (Glance el at., 2009). It is also provided result that it expresses a probability of non-surviving depends on the most five severe ICD-9-CM-coded injuries. Empiric scales of injury severity for each of the trauma ICD-9-CM codes were assessed using a regression-based method, and then used as the source for a new Trauma Mortality Prediction Model (TMPM-ICD9). TMPM-ICD9 was compared with International Classification of Diseases-based ISS (ICISS) model and the

findings showed TMPM-ICD9 demonstrates a greater model performance (Glance el at. 2009).

ICISS is also an anatomical injury system that uses ICD-9 codes. It was introduced in 1996 to address the limitations of the ISS (Chawda et al., 2004). This method is termed the ICD-9 Injury Severity Score (ICISS) and uses survival risk ratios (SRRs) calculated for each ICD-9 discharge diagnosis. SRRs are derived by dividing the number of survivors in each ICD-9 code by the total number of patients with the same ICD-9 code. The ICISS is calculated as the simple product of the SRRs for each of the patient's injuries. The ICISS has some advantages over the ISS because it permits all the injuries to contribute to the prediction, and multi injuries are more accurately demonstrated. Moreover, it uses information about all the injuries, composed with the patient's three severe injuries. Nevertheless, it is hard to compare the performance of clinics (Chawda et al.,2004). The routine of the ICISS seemed to be unstable because its performance could be altered by the type of formula and SRRs used (Tohira et al., 2012).

In 1987 Organ Injury Scaling (OIS) was introduced by the Committee of American Association for the Surgery of Trauma (A.A.S.T.) (Moore el at., 1989). This is used to devise injury severity scores for separate organs to enable clinical research. OIS uses the body organs: spleen, liver and kidney. The subsequent classification system is basically an anatomic description, measured from 1 to 5, expressing the minimum to the greatest severe injury.

Penetrating Abdominal Trauma Index (PATI) was developed in 1981.This method is used to predict trauma patients at risk of postoperative difficulties (Chappuis et al., 1991). It also provides an effective way to examine and help as a tool in the decision-making procedure once dealing penetrating abdominal trauma. For instance, in this study there are 56 patients and 28 of them were randomised into individually group. Data were concurrently composed and difficulties and outcome recorded. The majority of cases in each group were young men. The typical age for the primary repair group was 26 years (range, 17 to 58 years). There were 27 males and 1 female in the primary repair group and 25 males and 3 Female in the diversion group and for the diversion group, 23 years (range, 14 to 61 years). Diversion is distinct as (1- exteriorization of

the injury, 2- resection of the injury with exteriorization of either exteriorization and proximal segment or 3- debridement, if specified, and simple closure of holes with formation of a loop or end stoma proximal to the injury). Primary repair is demarcated as (1- debridement, if designated, with simple closure of the holes or 2- resection of a segment of large bowel containing perforations monitored by anastomosis). The small bowel was the additional organ injured most routinely (Table 2-2). Injury number, involving colon injury, was similar in both groups (Table 2-3).

Table 2-2 Associated Intra-abdominal injuries.

Organs	Primary Repair	Diversion
Small bowel	15	21
Duodenum	7	4
Stomach	6	4
Liver	6	4
Major vascular	5	4
Kidney	4	3
Pancreas	2	2
Ureter	1	3
Diaphragm	2	-
Gallbladder	1	-
Spleen	1	-

Table 2-3 Total number of organs injured.

Number	Primary Repair	Diversion
1	2	3
2-3	19	19
>4	6	7

2.2.2 Physiological Indices

There are a number of physiological trauma scoring systems, e.g. Glasgow Coma Scale (GCS). GCS was introduced in 1974 to standardise assessment of level of consciousness (LOC). It is also relatively simple to apply and is used in a variety of medical assessment cases. For instance it is used to determine the urgency of care and for neurological examinations (Fani-Salek et al., 1999). Children who are two years and younger, they are assessed by its revised version called Paediatric Glasgow Coma Scale (PGCS). The main reason for using PGCS instead of GCS is that many of the assessments for adult patients

are not be suitable for children. The PGCS comprises three assessments: verbal, eye and motor responses. Three values are considered individually as well as their sum (Holmes et al., 2005).

Another physiological trauma assessment system is called Revised Trauma Score (RTS). It incorporates the GCS, systolic blood pressure and respiratory rate as shown in Table 2-4. This index is determined by adding up the results from the values of the three components and multiplying them by their corresponding weights (Champion et al. 1989).

Table 2-4 Revised trauma score.

Code	Glasgow Coma Scale	Systolic Blood Pressure (mmHg)	Respiratory Rate (Breaths per Minute)
4	13–15	>89	10–29
3	9–12	76–89	>29
2	6–8	50–75	6–9
1	4–5	1–49	1–5
0	3	-	-

Another physiological method is Trauma Score (TS). It was introduced to alter the Triage Index in order to use systolic blood pressure and respiratory rate and the GCS to calculate the degree of coma. TS Score is between 1 (worst prognosis) and 16 (best prognosis) and can be calculated by sum of scores which are given to the component variables (Champion 2002).

Another technique is Emergency Severity Index (ESI) has applications to provide a reliable evaluation of injury severity and likely prediction of patient disposition (Tanabe et al., 2004). It uses a five-level algorithm this algorithm uses respiratory rate (RR), heart rate (HR), pulse oximetry (SpO2), temperature (T), and peak expiratory flow rate (PEFR) (Wuerz et al., 2001). This mothed can provide clinically related stratification of patients into five groups according to a range of urgency. This means that it depends on patient case severity and supply that needs (Gilboy el al 2011).

Acute Physiology and Chronic Health Evaluation (APACHE) was implemented to predict hospital mortality between critical adult patients (Zimmerman et al., 2006).

Rapid Acute Physiology Score (RAPS) was developed and verified for practice as a severity scale in serious care transports. RAPS is also an abbreviated version of the Acute Physiology and Chronic Health Evaluation (APACHE-II)

use only variables regularly available on all patients which are transported. Therefore, it uses four parameters which are (respiratory rate, blood pressure, pulse, and Glasgow Coma Scale). In terms of range, it is from 0 (normal) to 16 (worst) (Rhee et al., 1987). There is similar short form name called Rapid Emergency Medicine Score (REMS). REMS is an abbreviated version of APACHE II. It has earlier been specially calculated as a predictor of in-hospital mortality for nonsurgical patients presenting to the ED. REMS is determined that REMS has predictive accuracy comparable to the well-known but more complicated APACHE II (Rhee et al., 1987).

The prognostic index (PI) was established in 1980 and it was derived to enable complete separation of fatal and nonfatal cases and when consequently used in a nine index cases and properly forecasted the outcome (Walter et al., 2001). This method could reflect the ability of the prognostic index to distinguish among patients at low and high risk of death.

The Emergency Severity Index (ESI) uses a reliable severity evaluation and likely forecast patient disposition (Tanabe et al., 2004). It has five-level ESI algorithm which was presented to triage nurses at two university hospital EDs, and executed into training with reinforcement and adaptation management plans. This method has it owns components that can enable it to predict the resource consumption. ESI uses RR = respiratory rate; HR = heart rate; SpO2 = pulse oximetry; T = temperature; PEFR = peak expiratory flow rate (Wuerz et al., 2001) . This method can provide clinically related stratification of patients into five groups according to a range of urgency. This means that it depends on patient case severity and supply that needs.(Gilboy el al 2011).

Sequential Organ Failure Assessment (SOFA) was introduced by European Society of Intensive Care and Emergency Medicine during a consensus conference (Cabré et al .,2005). According to this conference, initially called the “sepsis-related” organ failure assessment, SOFA can be useful equally to all ICU patients. Moreover, SOFA score is composed scores from six organ systems, classified from 0 to 4 according to the degree of dysfunction/failure. Organ systems also measured in the SOFA score are: respiratory (PO22/FIO2), cardiovascular (vasoactive drugs, blood pressure), haematological (platelet

count), renal (diuresis and creatinine), liver (bilirubin) and neurological (Glasgow Coma Score).But some of medical practitioners are not familiar with SOFA score while decisions on limiting life support were made (Cabré et al., 2005).

Multiple Organ Dysfunction syndromes (MODS) is used to develop clinical syndrome triggered by several motivations that it is the main reason of mortality and morbidity in patients who admitted to intensive care units. It routines for cardiovascular assessment which is based on the so-called “pressure-adjusted heart rate” (PAR), defined as the product of the heart rate (HR) multiplied by the ratio of the right atrial pressure (RAP) to the mean arterial pressure (MAP) (Cabré et al .,2005).

Systemic Inflammatory Response Syndrome Score (SIRSS) is one of the clinical expressions which deals with the action of difficult intrinsic mediators of the severe stage reaction (Nyström 1998). This method can be triggered by measurement of pancreatitis, trauma, infection, and surgery. Moreover, it can also compromise the function of several organ systems causing in Multiple Organ Dysfunction Syndrome (MODS). Therefore, the MODS and SIRSS are classified expressions of the inflammation related to serious patient (Nyström et al., 1998). In this study the SIRSS was expressed by two or more of the following conditions: "temperature 38°C or 36°C; heart rate 90 beats/min; respiratory rate 20 breaths/min or PaCO2 32 torr (4.3 kPa); WBC 12,000 cells/mm3, 4000 cells/mm3 or 10% immature (band) forms". But in finding, the SIRSS for other signs as an example, the appearance of C-reactive protein are better designated as the severe stage reaction. In addition, several patients with SIRSS showed different degrees of organ dysfunction whereas some developments to progress multiple organ failure.

Multiple organ failure (MOF) is influenced epidemic parts in several intensive care units (ICU). It uses to predict non-surviving case in the surgical ICU (Deitch et at. 1992). MOF score deals with four organs (lungs, kidneys, liver and heart) are regularly measured for dysfunction and scored from 0 (no dysfunction) to 3 (severe dysfunction)(Zallen et al .,1999). This method was examined in sepsis and the severity of bacterial sepsis and was assessed reflectively in 37 intra-abdominal-sepsis and 55 trauma patients with MOF. Finally, the severity of MOF was graded, and an analysis was made of day of onset, incidence,

sequence, severity, and mortality of organ failures. There is no difference was initiated between groups in severity, sequence, or mortality of organ failures (Goris et at. 1985).

Circulation, Respiratory, Abdominal-Thoracic, Motor and Speech Scale (CRAMS). This method is commonly appropriate physiological trauma scoring. CRAMS works based on five parameters (respiration, circulation, trauma to the trunk, speech and motor) on a 0–2 scale. A score of 0 shows severe injury or absence of the factor; a score of it > 2 signify no deficit (Fani-Salek el at., 1999). Therefore, the overall likely score ranges from 0 which for a corpse to 10 for an uninjured patient. Including zero as the score for death which makes this method is more effective than the GCS. Where even a corpse could take more than 3 scales and when CRAMS score is <=8 that means critical trauma, while a score of 9 or 10 designates mild trauma. It discriminates between mild and critical trauma levels and it can be useful to avoid over-triage to trauma middles and even though dependable for triage part. Nevertheless, it may not be constantly validated on repeating scrutiny. Even though, reliable for triage part, CRAMS is incomplete in its capability to predict the need for operation (Fani-Salek el at., 1999).

Glasgow Coma Scale, Age, and Systolic Blood Pressure (GAP). GAP is one of the trauma scoring systems that could be used to perfectly forecast in-hospital mortality and it's also more practical than many other trauma scoring systems those are used in the emergency department (Kondo et al., 2011). For example, in this study, GAP was assessed based on the records of 13,463 trauma cases in a derivation data set defined by using via logistic regression. Some scoring systems that are Revised Trauma Score, Trauma and Injury Severity Score were compared with GAP. The calculation of GAP scores included GCS score that was from 3 to 50 points, patients age were less than 60 years (three points) and SBP (> 120 mmHg, six points; 60 to 120 mmHg, four points). The c-statistics is a measure of goodness of fit for binary outcomes in a logistic regression model. In this study c-statistics uses for the GAP scores (0.965 for short-term mortality and 0.933 for long-term mortality) were superior than or similar to the trauma scores computed by means of other scales. Related to

existing instruments, its results show that the GAP scoring system reclassified all cases but one in the correct direction (Kondo et al., 2011).

Logistic Organ Dysfunction Score (LOD) was developed to support an impartial tool for measuring severity classifications for organ dysfunction in the ICU and likelihood of mortality (Le Gall et al., 1996). In this study, LOD scores classified from 1 to 3 points of organ dysfunction for 6 organ measures: hepatic, hematologic, renal, cardiovascular, neurologic and pulmonary. This is from 1 to 5 LOD points allocated to the stages of severity (Timsit et al., 2002) .Its scores were also affected in measuring severity during the first day in ICU.

Simplified Acute Physiology Score (SAPS) is one of trauma scoring systems it is widely known in many hospitals (Le Gall et al., 1993). This technique uses for universal severity of disease and outcome prediction .It assesses acute age, pathophysiology, pre- and comorbidity, state at admission, and underlying disease. The underlying disease classification has a self-determining role for outcome of hospital dealing with severe patients (Schuster et al,. 1997). This technique is initially point for future assessment of the productivity of intensive care units (Le Gall et al., 1993).

2.2.3 Combined Anatomical and Physiological Score or Methods to Determine Probability of Survival

There were a number of proposed methods to determine probability of survival (Ps). A number of trauma injury severity scoring systems were reported that are intend to accurately and consistently quantify injuries by considering measurable or observable status of the patient's medical conditions. The main benefits of determining or scoring of Ps are (Fani-Salek et al., 1999):

Triage: This sets priorities to treat patients.

Prognostic evaluation: This enables predication and management of injury outcomes.

Research and audit management: These compare patient groups on injury outcomes and examine the effects of treatments.

Trauma and Injury Severity Score (TRISS) is a method that uses anatomical and physiological scoring systems to determine the Ps for adults sustaining

injuries from blunt and penetrating mechanisms (Schluter 2011). It is estimated by

$$p_s = \frac{1}{1+e^{-b}} \qquad 2\text{-}2$$

$$b = \alpha_i + \beta_{AGE,i} \times \beta_{RTS,i} \times RTS + \beta_{ISS,i} \times ISS$$

where *i* = 1 is for blunt mechanism and *i*=2 is for penetrating mechanism, α_i is a constant for mechanism i, $\beta_{AGE,i}$ is the coefficient associated with AGE and mechanism i, $\beta_{RTS,i}$ is the coefficient associated with RTS and mechanism *i*, $\beta_{ISS,i}$ and is the coefficient associated with ISS and mechanism *i*. RTS is obtained by

$$RTS = \beta_{RR} \times RR + \beta_{SBP} \times SBP + \beta_{GCS} \times GCS \qquad 2\text{-}3$$

where β_{RR} is the coefficient associated with respiration rate (RR), β_{SBP} is the coefficient associated with systolic blood pressure (SBP), and β_{GCS} is the coefficient associated with GCS. TRISS however has a number of shortcomings as explained in (Siritongtaworn et al., 2009). The parameter Age Score =0 if age <55 years and 1 if age > 55 years. The coefficients b_0 to b_3 depend on the type of trauma as indicated in Table 2-5.

Table 2-5 The TRISS coefficients.

Coefficient	Blunt Trauma or Age < 15 years	Penetrating Trauma
b_0	-1.247	-0.6029
b_1	0.9544	1.1430
b_2	-0.0768	-0.1516
b_3	-1.9052	-2.6676

TRISS has been criticised because of

- It incorporates the problems associated with ISS.
- It cannot include tubed patients as respiration rate and verbal responses are not obtainable.

- It does not account for mix of patients and thus making comparisons between trauma centers difficult (Siritongtaworn et al., 2009).

In 2004 Trauma Audit and Research Network (TARN) (Trauma Audit and Research Network 2017) proposed a Probability of Survival model called Ps04. This model uses age, gender, Injury Severity Score (ISS) and Glasgow Coma Score (GCS) and intubation. In 2014, Ps14 model was introduced by incorporating Charlson Comorbidity Index (CCI) to the assess Pre-Existing Medical Conditions (PMC). To predict probability of survival in Ps14, age, gender, GCS and intubation and PMC parameters are required. It determines the percentage of probability of survival by performing retrospective measure of a new patient with same profile on TARN database. For example, if Ps = 53%, then 53 out of every 100 people have profiles that survived and 47 people died based on formula.

$$p_s = \frac{e^b}{1+e^{-b}} \qquad 2\text{-}4$$

Where e=2.718282 and b is defined as the linear combination of the regression coefficients and the values of the corresponding patient's characteristics (ISS, GCS, modified CCI, age and gender).

Harborview Assessment for Risk of Mortality (HARM) is an effective tool for a predictive likelihood of in-hospital mortality for trauma patients. This technique has consistently outperformed both ICD- 9-CM Injury Severity Score (ICISS) and the Trauma and Injury Severity Score (TRISS) methods (Al west et al., 2000). It is also valuable for both calibration and discrimination using information that is readily accessible from hospital discharge coding, and without requiring ED physiologic records (Al west et al., 2000).

Severity Characterisation of Trauma (ASCOT) was introduced in 1990 (Champion et al., 2002). It is used to improve Trauma Score-Injury Severity Score (TRISS). It relates emergency department admission parameters of GCS, systolic blood pressure, respiratory rate, age of patient, and AIS-85 anatomic injury scores by means of dealing with ISS limitations.

The Drug-Rock Injury Severity Score (DRISS) was introduced by emergency physicians and illustrates exactly how trauma severity scores can be advanced or adapted for new, specific situations (Fani-Salek et al., 1999). The DRISS is also one of a new combined trauma scoring system which has developed particularly to be more accurately and powerfully triage injured patients at rock concerts. The method efficiently compares medical resource which use unlike measures. It uses values for intoxicants as a result of the high rate of drug/alcohol practise at rock concerts. While not yet validated, DRISS can be beneficial for categorising who are injured into the groups of those needing more care, those who are carefully cured and released (Fani-Salek et al., 1999).

The Trauma Index (IT) is usually used to rapidly assess patients with severe trauma. It has assignment for injury severity which are (minimal injury= 1, moderate injury= 3 or 4 and severe injury= 6) and parameters are based on (regions, type of injury, cardiovascular status, central nervous system status and respiratory status). Trauma index = (points for region + points for type of injury + points for cardiovascular status+ points for CNS (centre nervous system) status + points for respiratory status). Interpretation minimum score with trauma: 2, maximum score: 30 and scores >7 need admission to the hospital. The method has limitation as the trauma index is not intended for burn patients (Medal Military Medicine 2010).

A Paediatric Trauma Score (PTS) is introduced as a combined method of a triage means and PTS was developed as a way of helping rapid precise assessment of the children who is injured in a routine that it can protect inclusive initial assessment. It is also a scoring system that it assesses based on six common determinants of clinical condition in the injured child. Each of the six factors is assigned a scoring containment that -1 (major or immediate life-threatening injury), + 1 (minor or potentially major injury) or finally +2 (minimal or no injury). The arrangement of this method uses manner well-matched with typical advanced trauma life support procedure. Suitable diagnoses of multiply injured child not only requires precise initial assessment, but also a relies on the variances in paediatric physiology affecting potential morbidity (Tepas et al., 1987).

2.2.4 Artificial Intelligence Techniques based on Trauma Scoring Systems

Artificial Intelligence techniques such as fuzzy logic (FL), neural networks (NN), expert systems and genetic algorithm (GA) were successfully used to solve several medical problems.

Fuzzy logic (FL) is a computational model that for processing information in way that it is similar to human communication and intellectual processes (Allen and Smith 2001; Güler and Barisci 2002 ; Elkfafi et al., 1997). It has been used in defining and forecasting some cardiac diseases and depth of anaesthesia.

FL was used in a new diagnostic system for classifying the severity of 26 traumatic brain injuries. Trauma, Glasgow coma scores and electroencephalography were used for assessing the system (Güler et al., 2008). They found a reasonable agreement between the results of neurologists and systems outputs for normal, serious and maximum electroencephalogram data. Therefore, FL can be a potential tool for determining the severity of trauma (Güler et al., 2008).

Artificial neural networks (neural computing) are highly simplified models of human brain. They are generally complex, nonlinear and parallel structures that can learn to perform tasks that are difficult to solve through conventional sequential programming (like C) or by mathematical formulae (Haykin 2009). Artificial Neural Network (ANN) was also used to compare with standard outcome predictors to determine physiological indices and probability of survival (Pearl et al., 2008). As result of this ANN was shown to be able to predict mortality better than standard outcome predictors.

Genetic Algorithm (GA) is an optimisation method (Kentala et al., 1999) that is modelled on the concept of evolution to identify the best solution amongst possible options. In medical field, GA has been used in applications such as identifying people at risk of a coronary artery disease and to determine reasonable outcomes (Kentala et al., 1999).

Likewise, expert system was used to advise advanced trauma life support (ATLS) trained surgeons (Clarke et al. 1988). This advice was compared to physicians-in-training. In this study 13 medical students and surgical residents and 5 cases were actual care situations those presented to the developed system. The classifications of the expert system were better than those of any individual trainee. The variances were statistically substantial for two of the three principal residents, 5 of 9 residents overall, and all 4 students. This primary validation of a prototype developed system is positive for the view of a computerized decision support system that can assist surgeons to make opening definitive managing strategies for patients who have major trauma.

Traumatic brain injury was examined by an artificial intelligent virtual reality (VR)-based. This is in order to understand the vocational problem-solving skill training programme designed to improve career opportunities (Man et al. 2013). Findings showed that there is enhancement in selective memory processes and observation of memory function. Across-group assessment exhibited that the VR group achieved more positively than the therapist-led one with regard to objective and subjective result measures and improved vocational results.

In another study they used different types of artificial intelligence and machining learning (ML) techniques to examine and evaluate injury severity. This system was developed of a multipara meter machine learning algorithm and hybrid system to predict the essential for life-saving interventions (LSIs) in injury patients (Liu et al. 2014). In this study, the model used statistical tools those are based on and maxima, slopes and means of several vital sign dimensions corresponding to 79 trauma records of cases generated over 110,000 feature groups, which were used to implement, train, and develop the model. Comparisons among several machine learning models showed that a multilayer perceptron would accurately implement the algorithm in a hybrid system consisting of a machine learning component and basic detection rules. Deep Learning (DL) was also used in the United States for predicting diabetic retinopathy. Diabetic retinopathy is a foremost reason of vision loss mainly among working-aged people (Wong et al. 2016). Therefore, DL was assessed diabetic retinopathy screening by using a big data base of images and data was divided into three sets. The total number of images is 128175 for training set and two for validation 9963 and 1748 images. Results showed this model

was significantly performed by 87% to 90% sensitivity, 98% specificity for identifying referable diabetic retinopathy. It was distinct as worse and moderate referable diabetic macular enema (DME) or diabetic retinopathy.

Correspondingly, related eye and diabetic retinopathy diseases were predicted by deep learning technique (Tinge et al. 2017). This study used retinal images from multi-ethnic people with diabetes and 494 661 retinal images. The model was trained for predicting diabetic retinopathy using possible glaucoma 125 189 images and 76 370 images and age-related macular degeneration (AMD) 72 610 images, and presentation of the model was evaluated for predicting diabetic retinopathy by 112 648 images, possible glaucoma using 71 896 images and AMD by 35 948 images. As a result of this assessment of retinal images from multi-ethnic cohorts of patients with diabetes, the model obligated high sensitivity and specificity for detecting diabetic retinopathy and associated eye diseases.

2.3 Methods to Extract Keywords from Text

A number of methods to search for information in a text, given some keywords were reported. Shah *et al (*2003) used a data mining technique to detect keywords content of different sections of a typical scientific article. 104 articles published in *Nature Genetics* were used for this purpose.

Aho *et al (*1975) used an efficient algorithm to detect all incidences of a determinate number of keywords in a string of text. The algorithm created a limited state pattern matching machine from the keywords and then used the pattern matching machine to procedure the text string in a single pass. The algorithm was used to improve the rapidity of a library bibliographic search program.

Extracting word-Level paraphrasing is a complex and critical indicator to context (Xian-Jiang et al, 2012). Multi-feature word-level Chinese paraphrase extracting techniques were reported by (Xian-Jiang et al., 2012). One technique used data mining for the target word and its nominee paraphrases were taken from the Internet. Another technique used a stratified probability statistical model. Their

study showed that retrieving candidate paraphrases from large-size quantities by using data mining technique can be effective.

A method to extracting signature word from abstract Web page was reported by (Pang et al., 2012). They used meta data and special tags of the HTML to design a weighting function that allowed for the frequency, length and word location.

There are approaches for automatic keyword extraction from documents. Keywords extractions from the linguistic and non-linguistic methods were used to obtain the linguistic features of the words, sentences and document (Madane et al, 2012). They used part-of-speech, syntactic structure and semantic qualities.

An Intelligent method was used to extract engineering characteristic indexes in paragraph contents of a word document of a transmission and transformation study (Pedia Content Solutions Pvt. Ltd 2015). It created an engineering characteristic index library to serve as a substance database and from them the required information was extracted.

Chapter 3 Techniques Used in the Study

3.1 Overview

This chapter explains the operations of the trauma scoring systems, artificial intelligence (AI) techniques and statistical analysis techniques used in this study. Particular attention is given to AIS and GCS as they are most relevant to the study. For AI, specific consideration is given to fuzzy logic and Iterative Random Comparison Classification (IRCC). The Predictive Statistical Diagnosis (PSD) is also described.

3.2 Trauma Scoring Systems Operations

3.2.1 Abbreviated Injury Scale (AIS)

AIS provides anatomical indices and editions 2008 and 2016 edition available. It gives comprehensive injury descriptions for diverse conditions in body regions with levels of severity. An example of this code is shown in Table 3-1 (AAAM 2005, 2008).

Table 3-1 AIS code and injury description (AAAM 2005 updating 2008).

Specific Anatomical Structure or Patient Condition	AIS Code
Injuries to the Head NFS	100099.9
Crush Injury Must involve massive destruction of skull, brain and intracranial contents.	113000.6
Penetrating superficial; ≤ 2cm beneath entrance	116002.3
Penetrating major; >2cm penetration	116004.5
Avulsion superficial; minor; tissue loss ≤100cm^2	110802.1

Table 3.1 shows the description of injured condition in first column and associated AIS code field. The first six digits describe the injury description and last digit explains the severity level as shown in Table 3-2.

Table 3-2 AIS numeric to specific injury description.

AIS Code Digits	Numeric Conventions of Specific Injury Description
1	Body Region (head, neck, face, thorax, spine, abdomen, extremity and external)
2	Type of Anatomic Structure (Whole area, Vessels, Nerves, Organs and Skeletal)
3 and 4	Specific Anatomic Structure (e.g. Amputation, Burn, Crush and Penetration)
5 and 6	Level of specific injuries are assigned consecutive (e.g. 02 for first condition and 04 for second condition)
7	AIS Severity Code as explained below

AIS has six levels of severity, from 1 to 6 and number nine indicates an unknown severity as described in Table 3-3.

Table 3-3 AIS severity level code.

AIS Code Severity	Description
1	Minor
2	Moderate
3	Serious
4	Severe
5	Critical
6	Maximum
9*	Unknown

3.2.2 The Glasgow Coma Scale (GCS)

GCS uses physiological measurements. They use three clinical/observational indices to derive a numerical score for conscious level where 15 is normal response and 3 is no response, even to deep pain. The value of GCS is the sum of three best motor response components for the patient. GCS scores of 3 to 8 denote severe, 9 to 12 is moderate and 13 to 15 is for a mild head injury as shown in Tables 3-4 (Kim 2012).

Table 3-4 The Glasgow Coma Scale (GCS).

Eye Opening (E)	Best Verbal Response (V)	Best Motor Response (M)
4= spontaneous	5 = normal conversation	6 = normal
3 = to voice	4 = disoriented	5 = localises to pain
2 = to pain	3 = incoherent words	4 = withdraws to pain
1 = none	2 = incomprehensible	3 = decorticate (flexion)
	1 = none	2= decerebrate (extension)
		1 = none
		Total=E+V+M

3.3 Artificial Intelligence Techniques Operations

3.3.1 Fuzzy Logic

Fuzzy logic is an AI method to be used in this study therefore much more detailed explanation of its operation as compared to other AI methods are provided.

The strength of fuzzy logic is due to the mapping of input-output relationships through a number of rules, its flexibility to deal with inexact and uncertain information and then drawing conclusions (Jantzen, 1998) (Khoukhi and Cherkaoui, 2008) (Muyeen and Al-Durra, 2013). Unlike crisp (binary) logic that has a sharp boundary between True and False, fuzzy logic facilitates continuous transition as shown in Figure 3-1 (Cirstea et al, 2002)

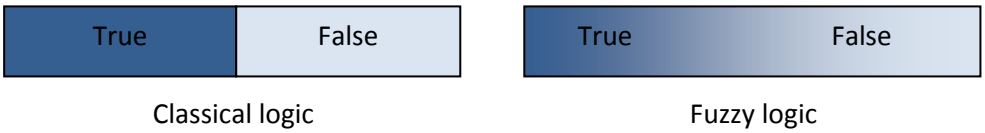


Figure 3-1Binary logic versus fuzzy logic.

3.3.2 Fuzzy Inference System (FIS)

Fuzzy Inference System (FIS) is built on fuzzy logic and allows decision making. It has four main components: fuzzification, rules base, inference engine, and defuzzification as shown in Figure 3-2 (Jantzen, 1998).

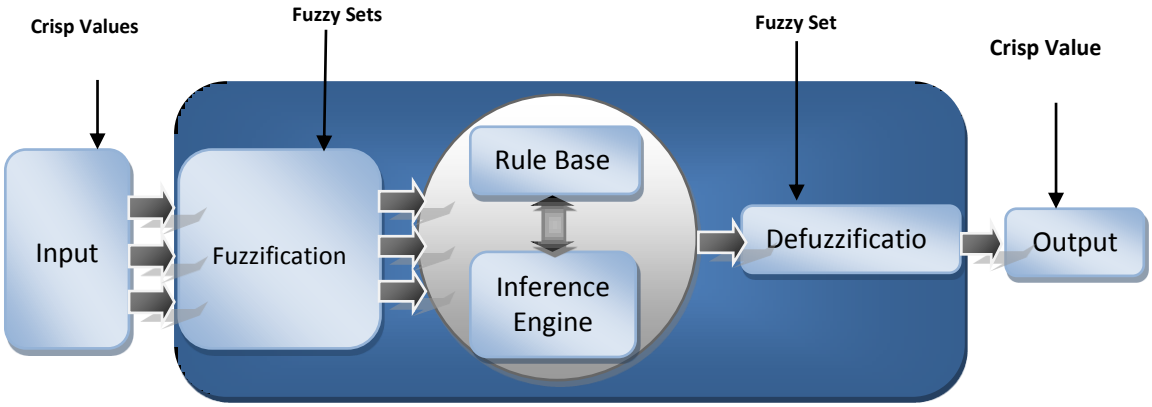


Figure 3-2 Block diagram of fuzzy inference system (Jantzen, 1998).

FIS is used to interpret (i.e. fuzzify) the crisp inputs into linguistic variables, and depending on a set of predefined rules, it computes linguistic output values where in turn are converted (i.e. defuzzified) into real crisp output value (Naoum-Sawaya and Ghaddar, 2005) and (Saraireh et al, 2008). The following subsections outline each component of FIS.

3.3.3 Fuzzification

This is a process of converting numerical input into linguistic terms and defining their degrees of belonging to the suitable fuzzy sets via membership functions. In fuzzy sets, an element x_i in the universe of discourse X is assigned a degree of membership $\mu(x_i)$ as shown in Figure 3-3 (Cirstea et al, 2002). A membership function indicates regular transition from a full belonging to a fuzzy set to not-belonging at all with intermediate values presenting degrees of belonging (Al-Sbou et al, 2006). In fuzzification process, different membership functions can be applied. For example, triangular, trapezoidal and gaussian as explained below (Alonso, 2014).

Triangular membership function: Expressed by a lower limit a, an upper limit b, and a value m, where a < m < b as shown in Figure 3-3.

$$\mu_{A^2}(X) = \begin{cases} 0 & X \le a \\ \frac{x-a}{m-a} & a < X \le m \\ \frac{b-x}{b-m} & a < X \le m \\ 0 & X \ge b \end{cases}$$

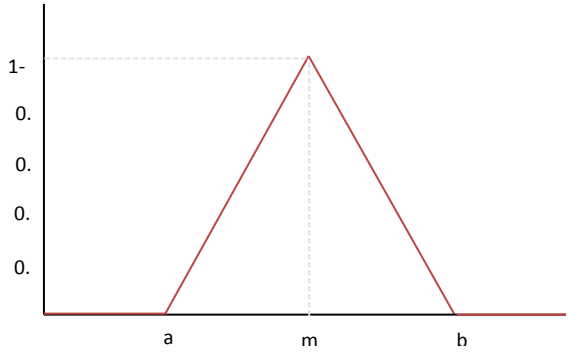


Figure 3-3Triangular membership (Alonso, 2014).

Trapezoidal membership function: expressed by a lower limit a, an upper limits d, a lower support limit b, and an upper support limit c, where a < b < c < d. This is shown in Figure 3-4.

$$\mu_{A^2}(X) = \begin{cases} 0 & (X < a) \text{ or } (x > d) \\ \frac{x-a}{b-a} & a \le X \le b \\ 1, & b \le X \le c \\ \frac{d-x}{d-c}, & c \le x \le d \end{cases}$$

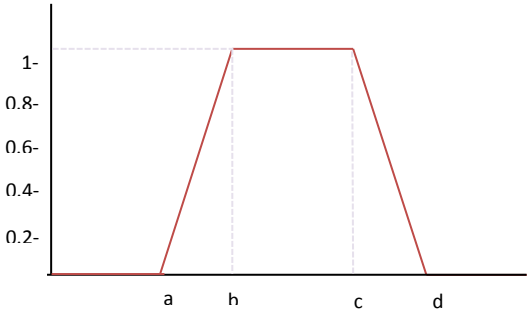


Figure 3-4 Trapezoidal membership (Alonso, 2014).

Gaussian membership function: expressed by a central value *m* and a typical standard deviation *k* > 0. The parameter *k* determines the function's width (Alonso, 2014).

$$\mu_{A^2}(X) = e^{-\frac{(x-m)_1^2 1}{2k^2}}$$

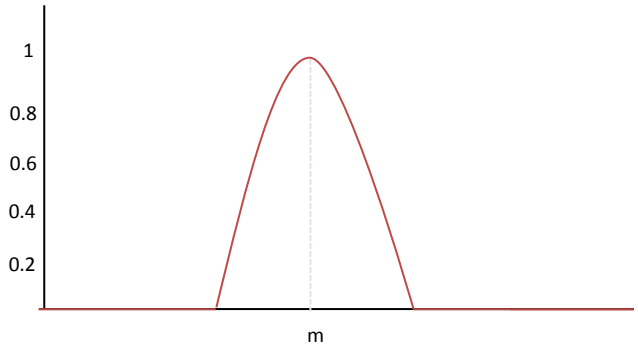


Figure 3-5 Gaussian memberships (Alonso, 2014).

3.3.3 Rule Base

A set of IF-THEN rules are represented in linguistic terms. They are the foundations of decision making process in FIS. The number of rules is dependent on the number of inputs and outputs variables as well as the number of membership functions interrelated with them (Jantzen, 1998). The general form of IF-THEN rules is:

IF (Antecedent) AND (Antecedent) ……THEN (Consequent).

Where the antecedent relates the linguistic variable to a fuzzy set, and the consequent represents the conclusion from IF term. Each rule may have one or more connectives (i.e. fuzzy operators). The most common fuzzy operations for IF-THEN rules are intersection, union, and complement which are respectively implemented by fuzzy operators AND, OR, and NOT (Klir and Yuan, 1995) (Ross, 1995) respectively. For instance, given that μ_X and μ_Y are the degrees of membership functions for fuzzy sets *X* and *Y* respectively, the application of fuzzy operators AND, OR, and NOT can be defined as (Ross, 1995):

$$\begin{aligned} &AND: \mu_X \cap_Y = min\,(\mu_X, \mu_Y) \\ &OR: \mu_X U_Y = max\,(\mu_X, \mu_Y) \\ &NOT: \mu_{\neg X} = 1 - \mu_X \end{aligned} \qquad 3\text{-}1$$

3.3.4 Inference Engine

Fuzzy inference engine uses fuzzified inputs along with the rules to perform inference (i.e. the process of implication and then aggregation) (Jantzen, 1998). The fuzzified inputs can be related to more than one rule to specify how well each rule describes the existing situation by computing the degree of certainty for the IF condition. More than one rule might be triggered at the same time describing the specific condition. Individually these rules produces Consequent or Conclusion to be taken in the THEN condition. This process is performed by implication method which is defined as the shaping of output membership functions. The input for the implication is a single number given by the antecedent of the rule, and the output is a fuzzy set. The truncated output fuzzy sets from the implication process which describes the firing strength of the rules is then processed by an aggregation method. In the aggregation process, the truncated output fuzzy sets from the implication process are unified to produce one output fuzzy set (Ross, 1995).

3.3.5 Defuzzification

This is the process that converts the output linguistic value (i.e. the aggregate output fuzzy set) into a real numeric value. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number. Nevertheless, the aggregate of a fuzzy set covers a range of output values which in turn must be defuzzified to produce a single output value from the set. There are numerous techniques that can be used for defuzzification process such as centroid, bisector, middle of maximum, largest of maximum, and smallest of maximum. Also defuzzification has two fuzzy inference methods: Mamdani and Sugeno. The procedure of fuzzifying the inputs and applying the fuzzy operator during the fuzzy inference process are similar in both methods. However, the main difference between Mamdani and Sugeno is the manner the outputs are determined. Mamdani-type FIS is based on defuzzification process to generate crisp output from output fuzzy set, while Sugeno-type FIS uses weighted average to compute the crisp output (Arshdeep and Amrit, 2012). Mamdani FIS has output membership functions whereas Sugeno FIS has no output membership functions. Due to the interpretable and intuitive nature of the rule base, Mamdani-type FIS is widely used particularly for decision support

application (Haman and Geogranas, 2008). Therefore, Mamdani-type FIS is used in this study. The information flows through the process of fuzzy inference system: commencing from fuzzifying inputs, through the process of applying fuzzy operator, implication method, aggregation method, and terminating by defuzzification process (Abdul Aziz and Parthiban, 2006) (Yamamoto and Morooka 2005). The centroid method of defuzzifier equation 3-2 for the distinct case is

$$Z_{out} = \frac{\sum_{i=1}^{N} Z_i \cdot \mu_{out}(Z_i)}{\sum_{i=1}^{n} \mu_{out}(Z_i)} \qquad 3\text{-}2$$

This method computes the centre of the area formed by the sum of all the output terms of the fuzzy controller. Figure 3-6 shows its membership functions used in a study for the linguistic variable and referred to as Thrust. It has two non-zero linguistic terms: Without-Thrust, with membership degree 0.6, and Positive-Medium, with membership degree 0.4. The defuzzified controller output is the position of the centre of gravity of the union of the term areas and the result is $Z_{out=22}$ (Yamamoto and Morooka, 2005).

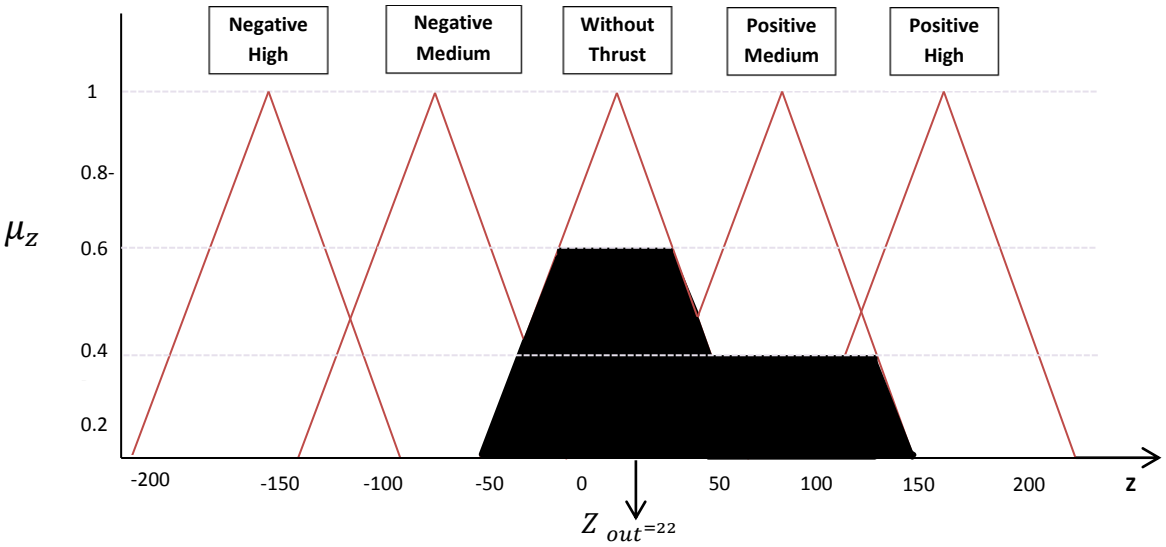


Figure 3-6 An example of defuzzification (Yamamoto and Morooka, 2005).

3- 4 Predictive Statistical Diagnosis (PSD)

PSD uses Bayesian statistics to determine to which of a given set of predefined types *t,* a measurement expressed by a feature vector (***x***) belongs (Aitchison et

al, 1980 and Aitchison et al, 1977). It uses example cases of known types, represented in a training data set to obtain the values of its calibration parameters. Once these parameters are calibrated, it can classify an unknown case into the types represented by *t*.

The probability that an observation vector $\boldsymbol{x}$ and parameter vector $\boldsymbol{\theta}$ belongs to the type t_1 is given by Bayesian statistics as

$$p(t_1 \mid \boldsymbol{x}, \boldsymbol{\theta}) = \frac{p(t_1)\, p(\boldsymbol{x} \mid t_1, \boldsymbol{\theta})}{p(\boldsymbol{x})} \qquad 3\text{-}3$$

where $p(t_1)$ is the prior probability of type t_1, $p(\boldsymbol{x}|t_1,\boldsymbol{\theta})$ is the probability density function of $\boldsymbol{x}$ for a given type t_1. Equation 3-3 can be rewritten as predictive density function for an observation $\boldsymbol{x}$ on a case of type *t* assessed on the training data $\boldsymbol{Z}$ as (Aitchison et al, 1980 and Aitchison et al, 1977).

$$p(t_1 \mid \boldsymbol{x}, \boldsymbol{\theta}) = \frac{p(t_1) q(\boldsymbol{x} \mid t_1, \boldsymbol{Z})}{\sum_{t=t_1}^{t_n} p(t) q(\boldsymbol{x} \mid t, \boldsymbol{Z})} \qquad 3\text{-}4$$

To determine above, $q(\boldsymbol{x}|t_1, \boldsymbol{Z})$ can be replaced with (Aitchison et al, 1977)

$$q(\boldsymbol{x} \mid t_1, \boldsymbol{Z}) = St_d\left(\nu_t, \boldsymbol{m}_t, \left(1 + \frac{1}{n_t}\right)\boldsymbol{S}_t\right) \qquad 3\text{-}5$$

where there are n_t cases of type *t* with feature vectors $\boldsymbol{x_1}$, $\boldsymbol{x_2}$, … $\boldsymbol{x_n}$; v_t is the degrees of freedom given by $n_t - 1$, $\boldsymbol{m}_t$ and $\boldsymbol{S}_t$ are the mean and the covariance matrices respectively. $\boldsymbol{S}t_d$ represents a *d*-dimensional student *t* density determined as

$$\boldsymbol{S}t_d(\nu, \boldsymbol{b}, \boldsymbol{c}) = \frac{\Gamma[0.5(\nu+1)]}{\pi^{0.5d}\Gamma\{[0.5(\nu-d+1)]\}|\nu\boldsymbol{c}|^{0.5}} \times \frac{1}{\left[1 + (\boldsymbol{x}-\boldsymbol{b})^T(\nu\boldsymbol{c})^{-1}(\boldsymbol{x}-\boldsymbol{b})^{0.5(\nu+1)}\right]} \qquad 3\text{-}6$$

where the variables *v*, *b* and *c* relate to equation 3-5 as $v = v_t$, $b = \boldsymbol{m}_t$ and $\boldsymbol{c} = \left(1+\frac{1}{n_t}\right)\boldsymbol{S}_t$. Γ is the gamma function, *T* and −1 represent matrix transpose and inversion operations, respectively. Using Equation 3-4, $p(t_1|x, \theta)$ is

determined for the cases of known types. Then to compute the probabilities for the unknown cases (i.e., those on the validation data set), Equation 3-6 uses the observation vector $\boldsymbol{x}$ for cases of known types but retains the mean ($\boldsymbol{m}_t$) and covariance ($\boldsymbol{S}_t$) matrices to identify an unknown type. The parameters $\boldsymbol{m}_t$ and $\boldsymbol{S}_t$ are calibration information for the PSD.

3-5 Operation of the Iterative Random Comparison Classification (IRCC)

IRCC is a new method of probability of survival prediction developed in this study. In this section the justification for using IRCC method and the principle behind its operation are described. It operates by comparing the injury profile of the trauma case being examined against the injury profiles of the trauma cases with known outcomes (survivors and not survivors) from a TARN data set. The parameters processed by IRCC were age, GCS, AIS, PR, SBP and RR. These parameters had significant within group (i.e. survivors or not survivors) variations and thus the comparison of the test case against the complete set would have reduced the sensitivity of the approach. Instead, IRCC compares the test case against randomly selected groups of cases (full description of IRCC is provided in the next section). To illustrate this point, Table 3.5 provides the average of trauma parameters for complete head injury cases consisting of 4124 cases of 3553 (86.2%) were survivors and 571 (13.8%) were not survivors. The Euclidean distance (ED_{SN}) between the trauma parameters of survivors and not survivors from this table is

$$ED_{SN}=\sqrt{\begin{matrix}(65.75-81.13)^2+(4.25-4.75)^2+(14.34-11.16)^2+\\(144.33-155.90)^2+(17.72-18.57)^2+(81.30-84.15)^2\end{matrix}}=19.74$$

The corresponding Euclidean distances for the averages of the trauma parameters for survivors and not survivors for the three subgroups in Table 3.5 are (each random sample contained 6 survivors and 6 not survivors, the justification of selecting 6 cases is provided through an analysis later in this thesis):

$$Group\ A\text{:}\ ED_{SN}=\sqrt{\begin{matrix}(79.6-69.98)^2+(4.17-4.5)^2+(14.67-9.17)^2+\\(157.83-141.33)^2+(21.2-16.83)^2+(85.17-87.33)^2\end{matrix}}=20.47$$

$$Group\ B\colon\ ED_{SN} = \sqrt{\begin{matrix}(46.92-80.43)^2+(3.67-4.83)^2+(14.17-12.33)^2+\\(131.17-185.17)^2+(18.17-18.67)^2+(76.83-84.17)^2\end{matrix}} = 64.01$$

$$Group\ C\colon\ ED_{SN} = \sqrt{\begin{matrix}(43.53-88.48)^2+(4.17-5)^2+(13.5-8.83)^2+\\(134.17-168.33)^2+(17.83-18.83)^2+(81.83-88.83)^2\end{matrix}} = 57.10$$

The average of Euclidean distances for the three randomly selected groups was 47.19. This shows (47.19-19.74)/19.74 ×100= 139.06% increase in the differentiation of survivors and not survivors.

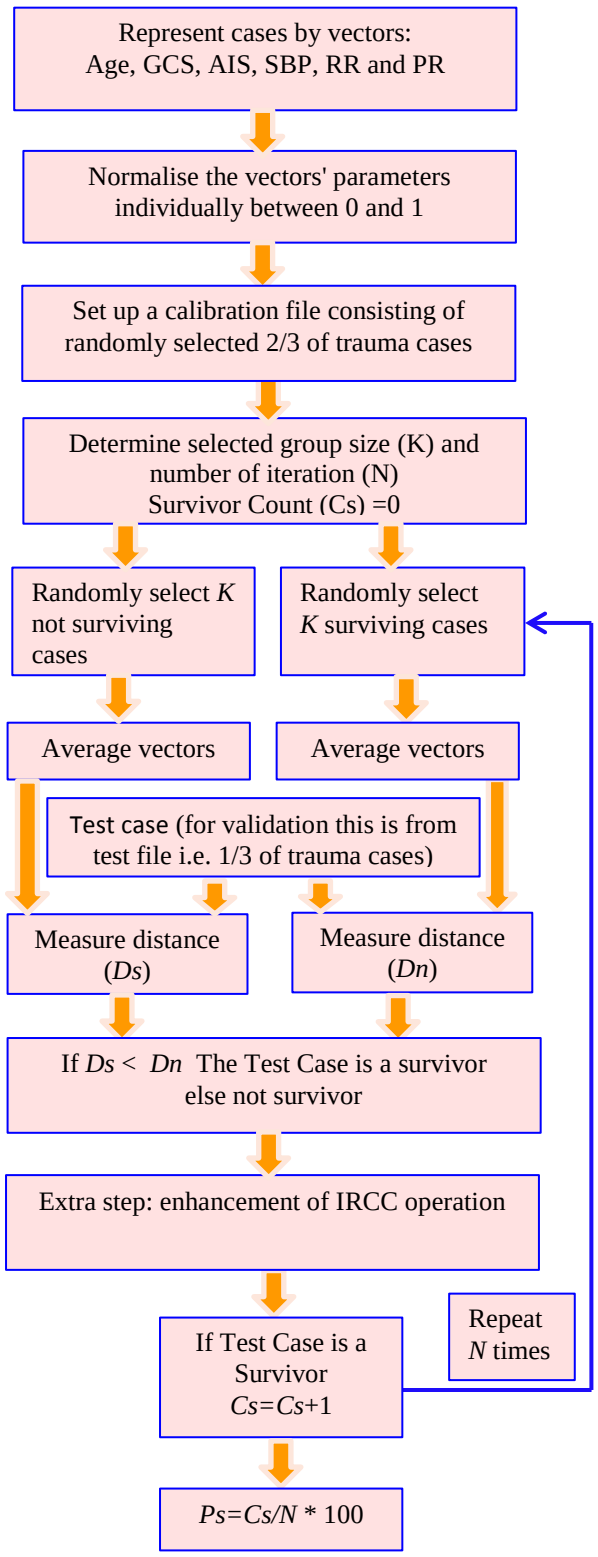
Table 3-5 Average and standard deviation of trauma parameters for head injury, all cases.

Parameters	Outcomes	Mean	STD
Age (years)	**Survivors**	65.75	21.96
	Non-survivors	81.13	12.91
AIS	**Survivors**	4.25	0.72
	Non-survivors	4.74	0.53
GCS	**Survivors**	14.34	7.07
	Non-survivors	11.16	8.49
SBP (mmHg)	**Survivors**	144.33	26.84
	Non-survivors	155.90	34.01
RR (bpm)	**Survivors**	17.72	3.72
	Non-survivors	18.57	5.49
PR (bpm)	**Survivors**	81.30	18.18
	Non-survivors	84.15	21.30

Table 3-6 Average and standard deviation of trauma parameters for head injury for three randomly selected samples. The samples are represented by groups A, B and C and consists of 6 survivors and 6 not survivors.

Parameters	Outcomes	Selected Sub-Group (A)		Selected Sub-Group (B)		Selected Sub-Group (C)	
		Mean	STD	Mean	STD	Mean	STD
Age (years)	Survivors	79.60	8.05	46.92	21.69	43.53	26.73
	Non-survivors	69.98	23.70	80.43	19.90	88.48	10.04
AIS	Survivors	4.17	0.98	3.67	0.82	4.17	0.41
	Non-survivors	4.50	0.84	4.83	0.41	5.00	0.00
GCS	Survivors	14.67	0.52	14.17	1.60	13.50	1.64
	Non-survivors	9.17	5.04	12.33	2.25	8.83	5.53
SBP (mmHg)	Survivors	157.83	22.35	131.17	22.87	134.17	22.99
	Non-survivors	141.33	21.20	185.17	32.60	168.33	32.18
RR (bpm)	Survivors	21.20	2.56	18.17	3.92	17.83	2.71
	Non-survivors	16.83	3.97	18.67	4.50	18.83	1.83
PR (bpm)	Survivors	85.17	23.34	76.83	19.53	81.83	24.29
	Non-survivors	87.33	20.18	84.17	13.50	88.83	16.13

The operation of the IRCC relies on comparing the trauma parameters for the case being examined against multiple randomly selected subgroups and then the overall percentage match is determined. The details of the IRCC operation are outlined in Figure 3-7. A further flowchart explaining IRCC is provided in Figure A.1, Appendix A.



3-7 Flow chart of the IRCC operation.

Each trauma parameter is individually normalised between 0 and 1 by taking into account the maximum and minimum values for the parameter, the formula used for this purpose is

$$Normalised\ parameter = \frac{parameter\ value - minimum}{maximum - minimum} \qquad 3\text{-}7$$

The normalisation ensured that the parameters with a larger range to do not dominate those with smaller range with the IRCC operations are performed. A calibration file consisting of randomly selected 2/3 of the trauma cases and a test file consisting of the remaining 1/3 trauma cases are created. The IRCC is initialised by selecting comparison group size (K) and the number of iterations. The survivor count number (Cs) is set to 0.

At the next stage K surviving cases and K not surviving cases are randomly selected from the validation file. The parameters of their trauma vectors are individually averaged. This lead to averaged test vectors, i.e.

For survivors: $V_s = [age_{sa}, GCS_{sa}, AIS_{sa}, SBP_{sa}, RR_{sa}, PR_{sa}]$ 3-8

For not survivors: $V_n = [age_{na}\ GCS_{na}, AIS_{na}, SBP_{na}, RR_{na}, PR_{na}]$ 3-9

where the subscript '*sa*' and '*na*' represent average value for the parameters of the survivors and not survivors respectively.

The vector for the test case is obtained. This is represented by

Test case:

$V_t = [age_{ta}, GCS_{ta}, AIS_a, SBP_{ta}, RR_{ta}, PR_{ta}]$ 3-10

where the subscript '*ta*' represents average value for the parameters of the test case. The test case in development phase is from the validation file to allow the performance of the method to be established but there after could be a case with known outcome (survivor or not survivor). The Euclidian distances between the vectors of the test case and those for survivors (D_s) and not survivors (D_n) are obtained,

$$Ds = \sqrt{\begin{matrix}(age_{sa} - age_{ta})^2 + (GCS_{sa} - GCS_{ta})^2 + (AIS_{sa} - AIS_{ta})^2 \\ +(SBP_{sa} - SBP_{ta})^2 + (RR_{sa} - RR_{ta})^2 + (PR_{sa} - PR_{ta})^2\end{matrix}} \quad 3\text{-}11$$

$$Dn = \sqrt{\begin{matrix}(age_{na} - age_{ta})^2 + (GCS_{na} - GCS_{ta})^2 + (AIS_{na} - AIS_{ta})^2 \\ +(SBP_{na} - SBP_{ta})^2 + (RR_{na} - RR_{ta})^2 + (PR_{na} - PR_{ta})^2\end{matrix}} \quad 3\text{-}12$$

The values D_s of D_n are compared and if $D_s < D_n$ then the Survivor Count (C_s) is incremented by 1. This is repeated for the specified number of iterations (N). The probability of survival (as percentage) is the calculated by

$$Ps = \frac{Cs}{N} * 100 \qquad 3\text{-}13$$

Chapter 4 Methodologies

In this chapter, the methodological framework which forms the basis of the current work is presented. This work was carried out in collaboration with the Trauma Audit and Research Network (TARN). The TARN database contains tens of thousands trauma cases with their associated outcomes. . The details of trauma are also included as further explained later in this chapter. To use this database, it was important to conduct its statistical analysis with the view to determine relevant information pertaining to different injuries under consideration. This assisted the processes of trauma knowledge representation and visualisation that in turn led to knowledge coding. The primary purpose of this study is to develop methods to determine probability of survival in traumas. Figures 4-1 and 4-2 depict the overview of the methodology of the procedures followed in his study.

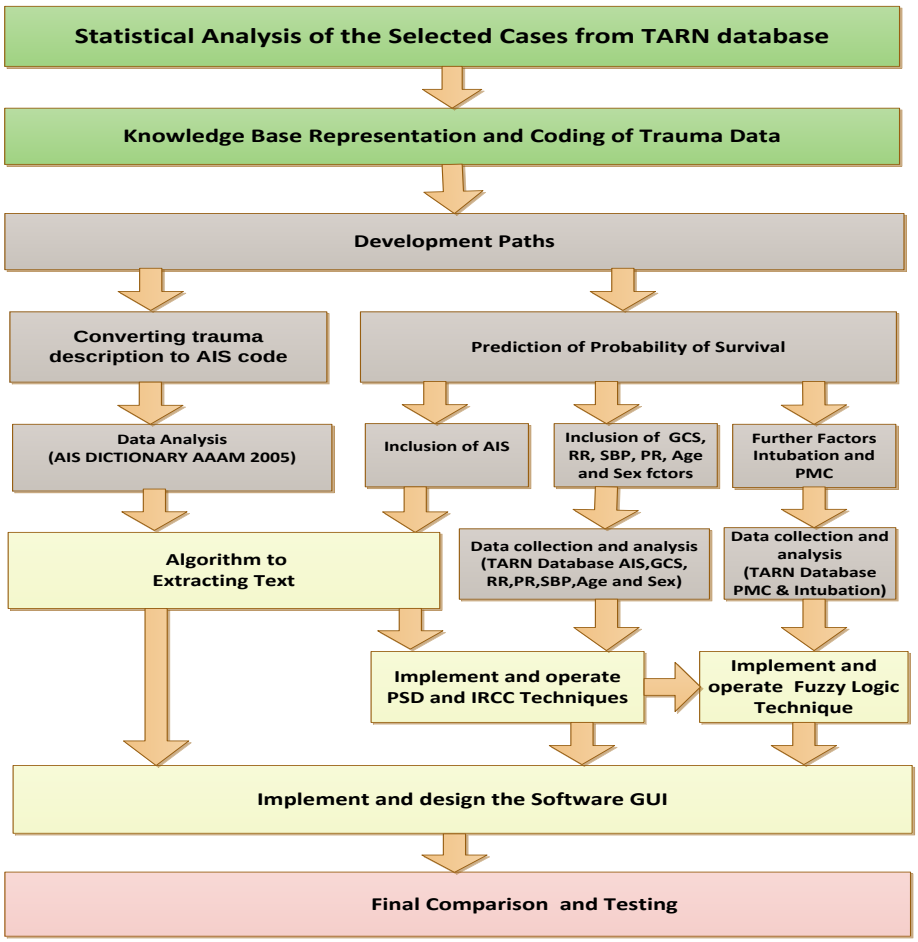


Figure 4-1 The overall methodological framework of the research.

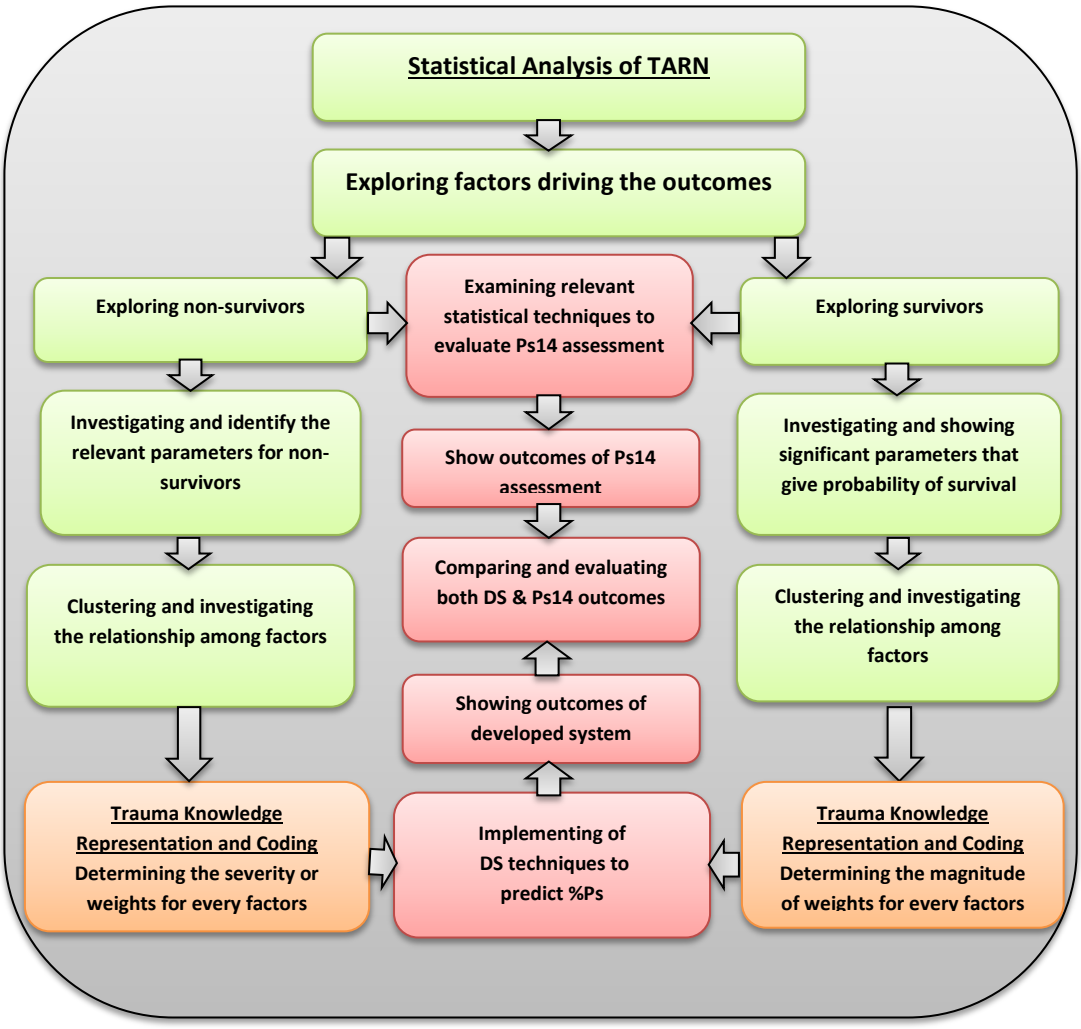


Figure 4-2 The framework for statistical analysis to establish trauma knowledge representation, coding and evaluation.

As shown in Figure 4-2, three processing stages were involved namely statistical analysis (represented by green blocks), trauma knowledge representation and coding (represented by orange blocks) and system implementation and evaluation (indicated by the pink blocks).

4.1 Ethics

Based on the Research Ethic Policy of Sheffield Hallam University (SHU) (Sheffield Hallam University 2015) which states that:

"Any research undertaken by staff or students (undergraduate or post graduate) of the University which involves direct contact with human participants, whether clinical, biomedical or social research, or the secondary use of human and animal materials or specimens, or where there may be any other ethical issues, should be subject to ethical review." (Sheffield Hallam University 2015)"

Ethic clearances were obtained at Sheffield Hallam University (appendix B). The TARN data were anonymised and it was not possible to relate them to

individual patients. The data were stored on the University's networked Research Store called Q drive for all copies in accordance with the TARN agreement's with the University (appendix C).

4.2 Development of a User Interface to Developed System

An interface that enabled the user to be guided through the AIS stated injuries types for various body regions and the automatically generated the associated AIS code was developed in Matlab. This was tested for accuracy and the test results are provided in Chapter 7. The limitation of the approach was that doctors could not enter the patient's injuries in their own way and they were required to select predefined injuries. This could result in inconsistency of coding between doctors. Therefore a new approach for determining the AIS code and probability of survival was developed. The method allows the doctor to enter the AIS code for injuries in their own way. The process of converting this description to AIS code is explained in the next sections. Once AIS code is determined, its value together with GCS, RR, SBP, PR, Gender, Age, Intubation and PMC are processed by developed system (DS) to determine probability of survival.

4.3 Artificial Intelligence Methods of Determining Probability of Survival

The operations involved in determining AIS code and probability of survival relied on analysis of TARN data that had several thousand trauma cases. The tasks to develop the system are shown in Figure 4-3.

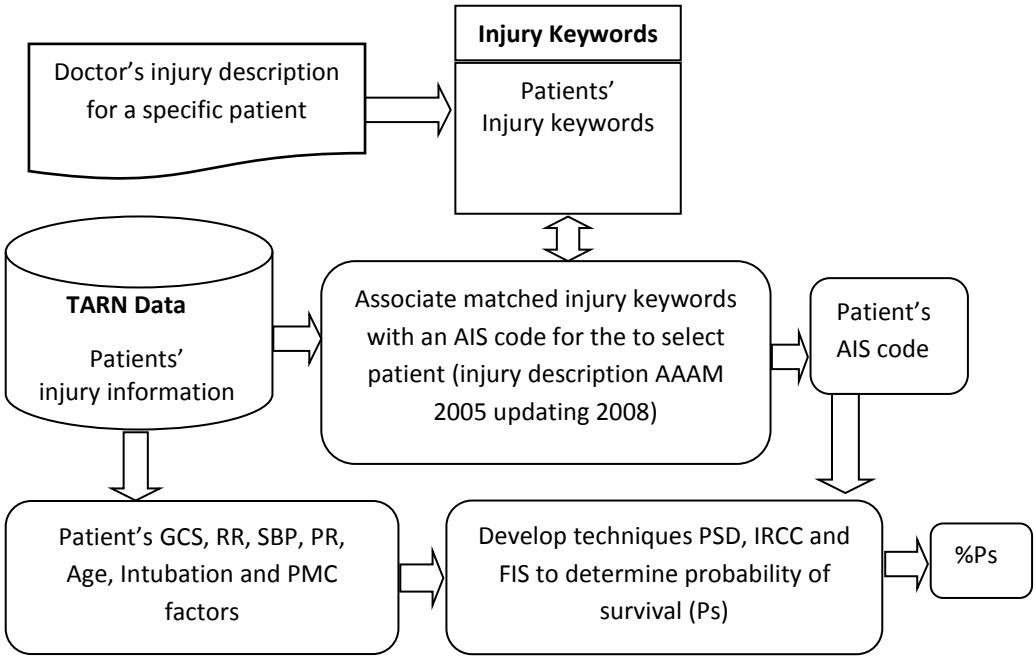


Figure 4-3 Operations to determine AIS code and probability of survival.

With the aid of staff from TARN, the TARN data were analysed and specific patients' injuries keywords associated with each case were already determined (in the database). To determine the AIS code for a specific patient, a keyword matching scheme was developed to search for the closest match in the TARN database and from it the AIS code was produced based on (injury description AAAM 2005).

The information from AIS code, GCS, RR, SBP, PR, Age, Intubation and PMC of the cases were then processed by PSD, artificial intelligence methods, IRCC and FIS to determine the probability of survival. To develop this using PSD, IRCC and FIS appropriates, TARN data were used as part of the trauma knowledge representation and coding.

4.3.1 Implementation of IRCC and PSD system developed

IRCC and PSD technique were set up and evaluated using two separate data. One is 2/3 of the overall data and was used as calibration of the method and the remaining 1/3 of the cases were used for evaluation of the methods. The subjects in each set were randomly chosen. The output of processing was

probability of survival (Ps). Figure 4-4 shows the stages to setup PSD and IRCC.

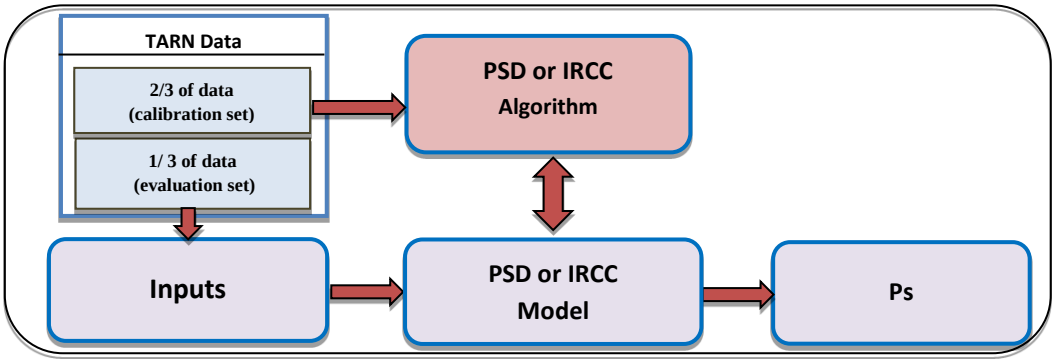


Figure 4-4 Block diagram of IRCC and PSD techniques.

The main inputs to the probability of survival calculation methods were. AIS code, GCS, RR, SBP, PR and Age. However, there were two other factors (Intubation and Pre-existing Medical Conditions (PMC)) which were considered at later stages of the developments to improve the accuracy of the method but these were only available for some individuals. The FL technique was implemented to combine IRCC outcomes with PMC and intubation. Further analysis and explanation of the approaches are provided in chapter 6, where knowledge representation and coding are outlined.

4.3.2 Implementation of FIS

4.3.2.1 Input member functions

The fuzzy inference system (FIS) had two inputs, each represented by a number of membership functions as shown in Figure 4-5. The inputs were the IRCC output and other factors, i.e. intubation and PMC. The reason for combining IRCC output with Intubation and PMC score was to further improve the results. Figure 4-6 shows IRCC output's membership functions represented by 5 membership functions, labelled as categories 1 to 5. Further details about how the membership functions were organised are provided in chapter 6. For the second input to the FIS that expressed PMC and intubation, four membership functions were used labelled as Both, Intubation, Unspecified and PMC. As shown in Figure 4-7 these membership functions were part of knowledge coding explained in chapter 6.

Figure 4.8 Shows typical rules relating the inputs and output of the FIS (further details are provided in Chapter 6)

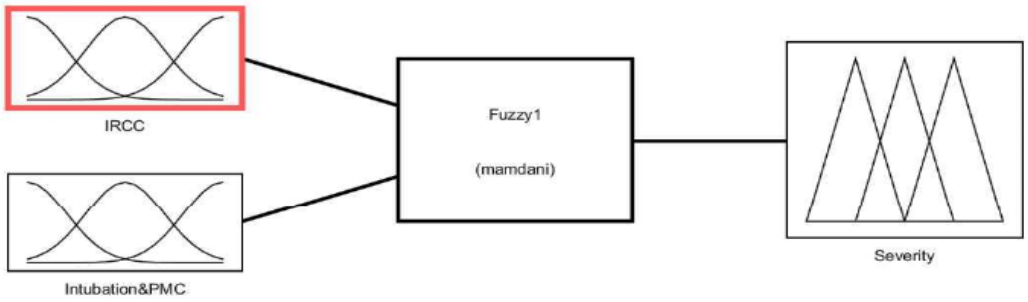


Figure 4-5 Structure of a fuzzy inference system.

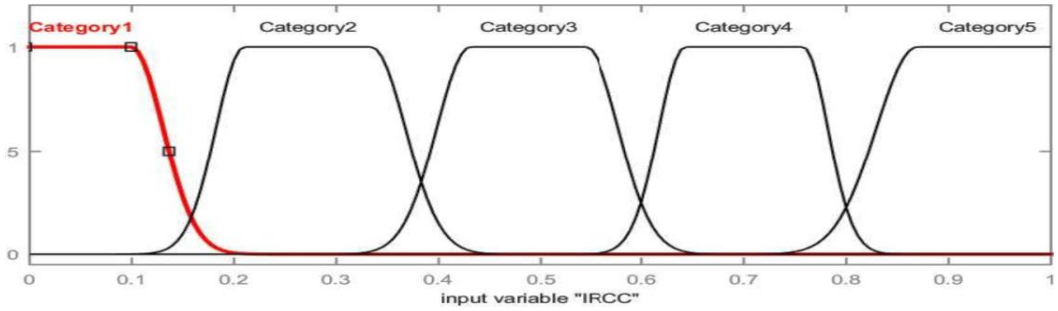


Figure 4-6 Membership functions for IRCC output.

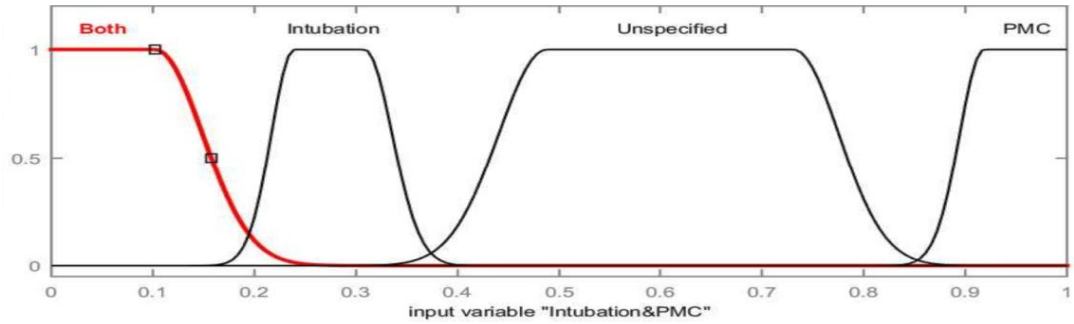


Figure 4-7 Membership functions of PMC and intubation.

1. If (IRCC is Category1) and (Further-Factors is Both) then (Severity is Level1) (1)
2. If (IRCC is Category1) and (Further-Factors is Intubation) then (Severity is Level1) (1)
3. If (IRCC is Category1) and (Further-Factors is PMC) then (Severity is Level1) (1)
4. If (IRCC is Category2) and (Further-Factors is Both) then (Severity is Level1) (1)
5. If (IRCC is Category2) and (Further-Factors is Intubation) then (Severity is Level1) (1)
6. If (IRCC is Category2) and (Further-Factors is PMC) then (Severity is Level1) (1)
7. If (IRCC is Category3) and (Further-Factors is Both) then (Severity is Level1) (1)
8. If (IRCC is Category3) and (Further-Factors is Intubation) then (Severity is Level2) (1)
9. If (IRCC is Category3) and (Further-Factors is PMC) then (Severity is Level2) (1)
10. If (IRCC is Category4) and (Further-Factors is Both) then (Severity is Level1) (1)
11. If (IRCC is Category4) and (Further-Factors is Intubation) then (Severity is Level2) (1)
12. If (IRCC is Category4) and (Further-Factors is PMC) then (Severity is Level3) (1)
13. If (IRCC is Category5) and (Further-Factors is Both) then (Severity is Level2) (1)
14. If (IRCC is Category5) and (Further-Factors is Intubation) then (Severity is Level3) (1)
15. If (IRCC is Category5) and (Further-Factors is PMC) then (Severity is Level4) (1)

Figure 4-8 Typical rules relating the inputs and output of the FIS.

The last stage of the FIS is defuzzification where the output of the FIS is determined. Figure 4-9 shows output membership functions used for this purpose. Figure 4-10 shows as example of the DS operation with inclusion of PMC and intubation.

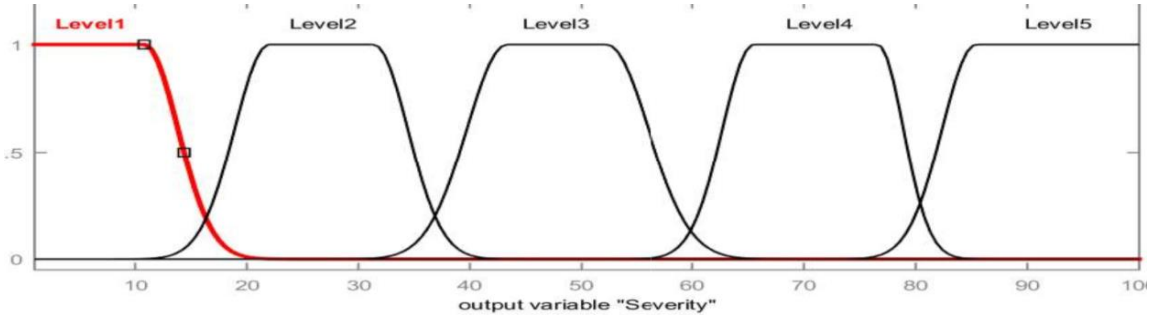


Figure 4-9 Output membership of probability of survival.

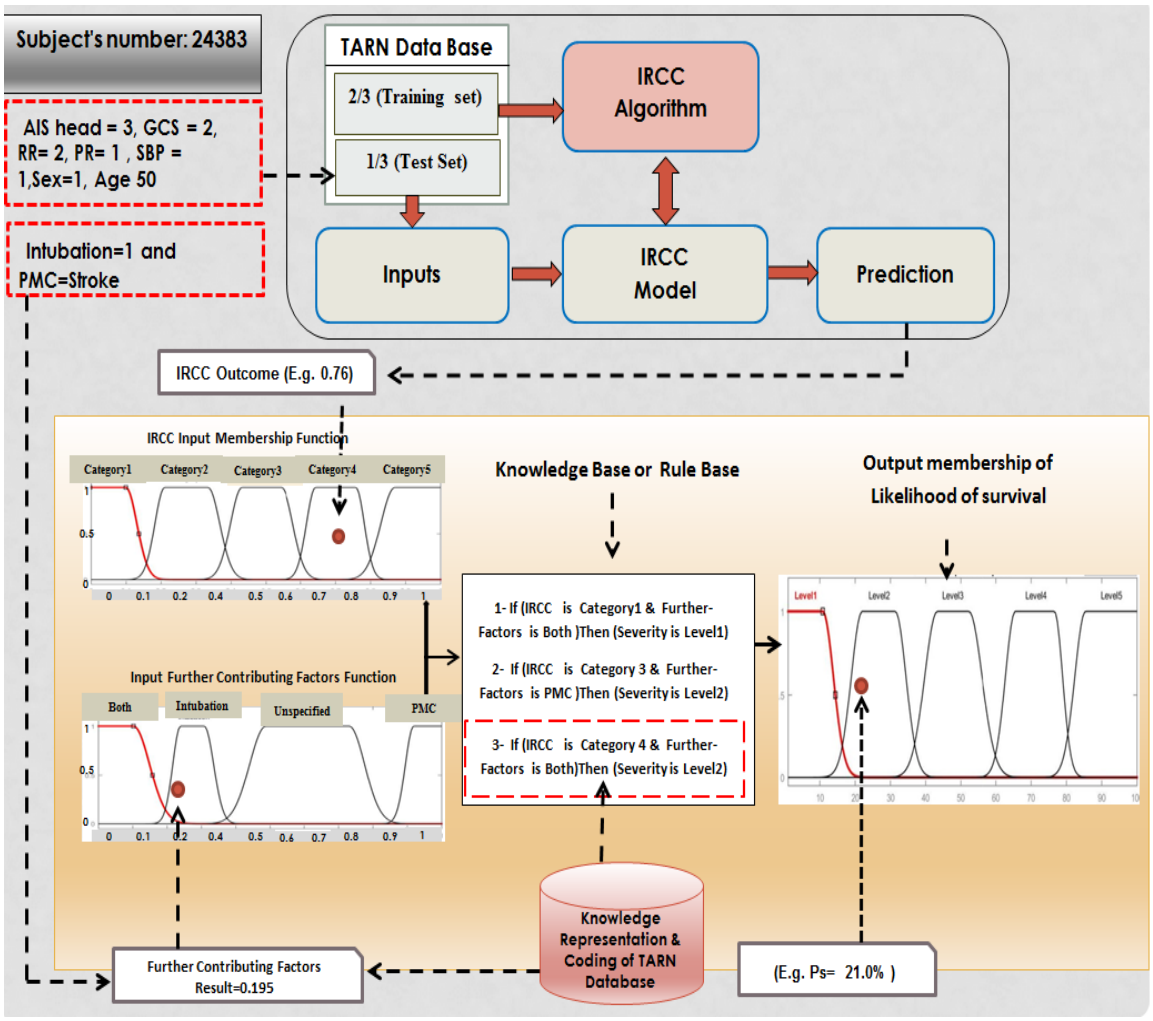


Figure 4-10 Prototype of DS mechanism when patient has further factors.

4.4 Chapter summary

In this chapter, the approaches followed developed for determining the probability of survival are outlined. An overview of the procedural framework of the research for using the trauma parameters including the AIS code to predict of probability of survival is presented. A description of the manner the FIS and IRCC outputs were combined with further PMC and intubation is also provided. In the chapter that follows, statistical analysis of the TARN database is presented.

Chapter 5 Investigation of interrelation between trauma parameters and survival outcomes

5.1 Overview

An analysis of the data used in the study was performed using a number of packages, each package a specific purpose. Microsoft Excel© was used to a spread sheet. SPSS© and Matlab© were used to carried out statistical analysis and data processing respectively. The data processing and statistical analysis data are explained in the following sections.

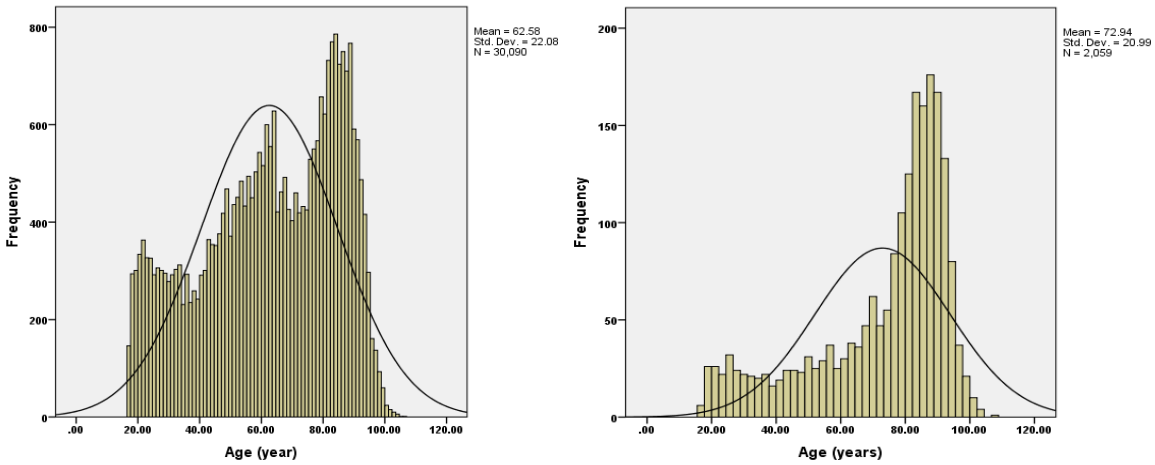
5.2 Introduction of TARN Database Trauma Characteristics

The data analysis investigated the number, Age, Gender, injury types of trauma cases, used in the study. There were about 10% more males than females and 97% of the injuries were in the blunt category and the rest, penetrating type. A blunt traumatic injury is caused by the application of mechanical force to the body or when the body strikes a surface in which the skin is not penetrated. A penetrating traumatic injury is caused when a sharp object such as knife penetrates the body. The proportion of cases that survived (lived after the trauma) was 93.3% and the remaining cases not survivor (died) as shown Table 5-1.

Table 5-1Overview of all injury trauma cases.

Gender (%)		Mean Age (years) (standard deviation)	% Injury Type		Injury outcome		Total
Male	Female		Blunt	Penetrating	Survivors	Not Survivors	
26098 (54.7%)	21604 (45.3%)	60.7 (24.8)	97.6%	2.4%	44499 (93.3%)	3203 (6.7%)	47702

Figures 5-1a and b show the distributions (histograms) indicating the effect of age on the individuals surviving and not surviving in trauma. The age distribution for survived cases shows peaks at 20, 60 and 80 years but for those that did not survive, there is a single dominant peak at about 90 years. The peaks in the distribution of cases that survived do not infer that more injuries occur at those ages but there are more subjects with those ages in the analysed data. Figure 5-2 shows the number of cases for different injury mechanisms. The dominant injuries in order of magnitude are: fall less than 2 meters, vehicle incident collisions, fall more than 2 meters and blow(s).



5-1 (a) Age distribution of individuals surviving (left) and (b) those not surviving (right).

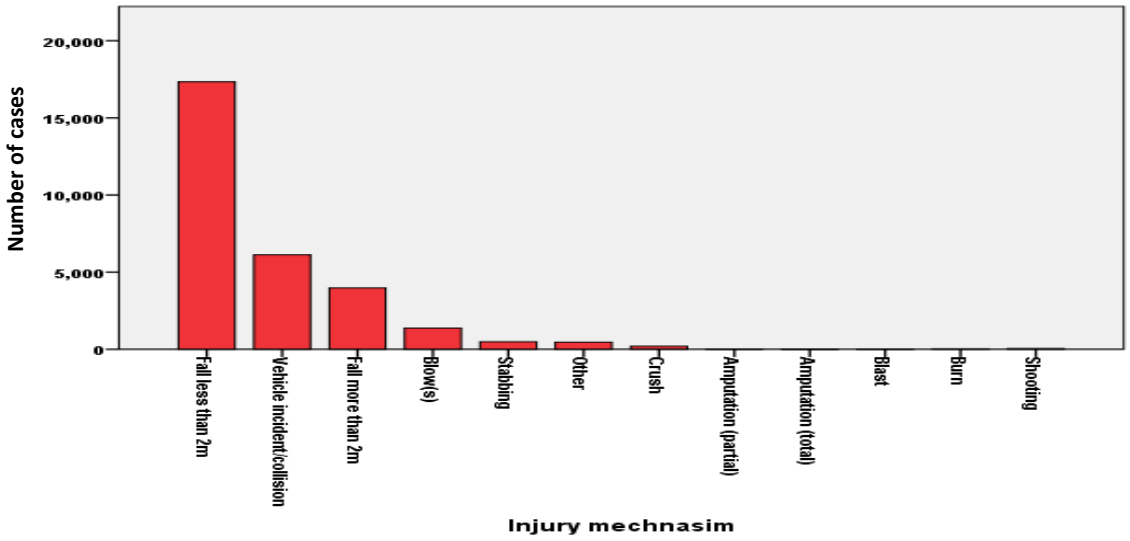


Figure 5-3 The injury numbers in relation to AIS defined body regions. Lower limbs injuries followed by head, thorax, spine and upper limbs are the main affected regions.

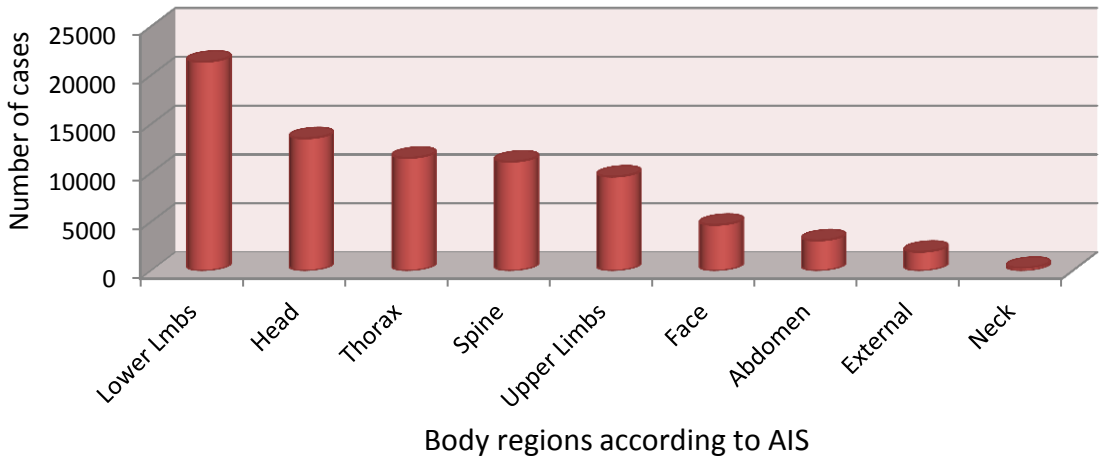


Figure 5-3 Injury numbers in relation to the AIS defined body regions.

Figure 5-4 provides the percentages of cases with AIS injury scores 3-6 that did not survive. The majority of these cases had head injury (43.93%) and next highest percentages were for thorax (22.04%) and lower limbs injuries (15.55%).

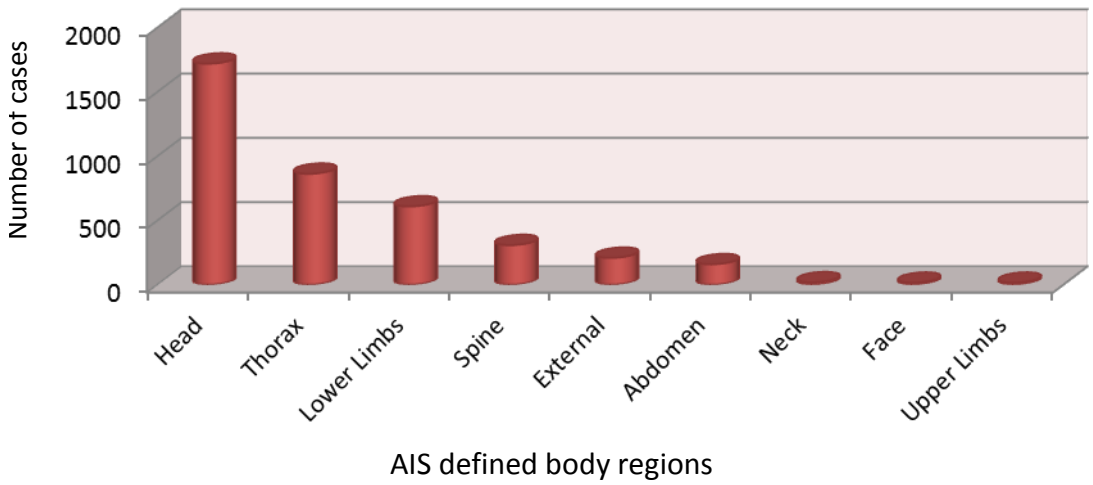


Figure 5-4 Body region injuries with AIS scores 3-6 and associated number of cases that did not survive.

Figures 5-5a and b show the distributions the ISS scores for (a) those that survive and (b) those that did not. For those that survived the ISS values peak around 15 and for those that did not, the ISS distribution has multiple peaks; with the largest at round 30.This shows that increasing number of ISS is not the reason that leads to not-surviving. Due to this fact Figure 5-5b shows that Ps14 is not very effective in determining the probability of survival for cases where survival is not reported.

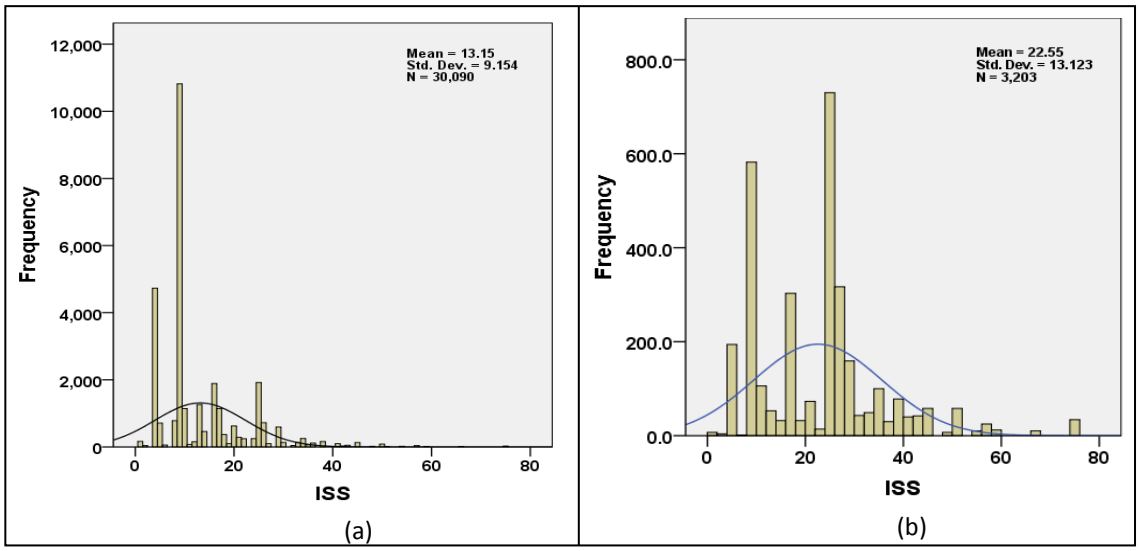


Figure 5-5 (a) Distribution of ISS values for (a) those that survived and (b) those that did not survive.

Figures 5-6a and b show the probability of survival distribution as measured by Ps14. The Ps14 values for cases who did not survive peaks between 80 to 100 but for those who survived, has a more uniform distribution. Therefore the method has not been very sensitive in determining probability of survival for cases who did not survive.

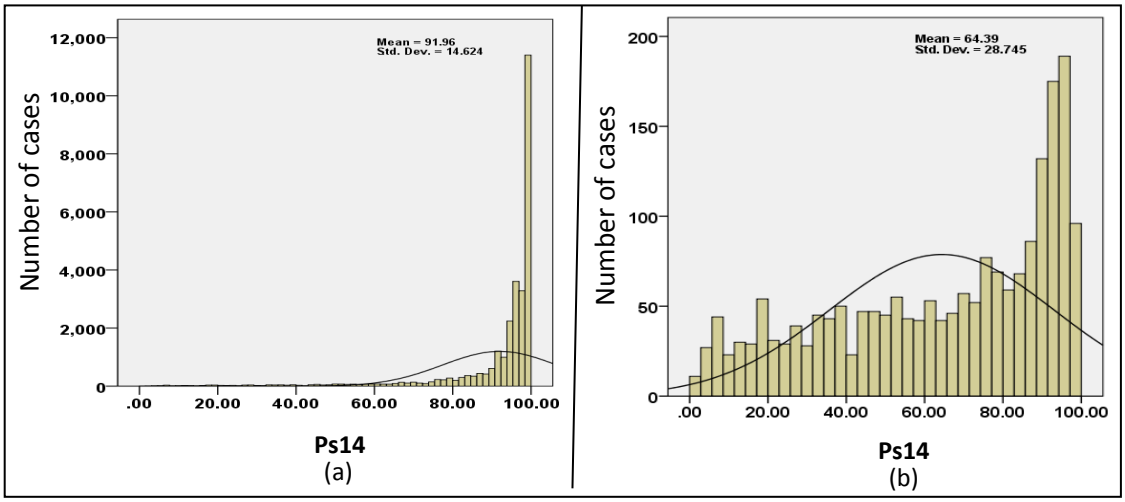


Figure 5-6 (a) Ps14 values for subject who survived (left) and (b) those did not (right).

Figure 5-7a shows the number of cases with GCS less than 13 and more than 12 that survived. Figure 5.6b shows similar information for those that did not survive. Comparing the proportion of cases with GCS less than 13 in both figures. Figure 5.6b shows GCS < 13 in not survivors is close to GCS >12 by 93% but Figure 5.6a displays only 0.5% from total cases classified GCS >12. This means GCS has impact of not survivors when it's scores less than 13. In other words, GCS <13 maybe affected when it is associated with other factors in certain conditions and this is seen in Figures 5-15, 16, 17, 18.

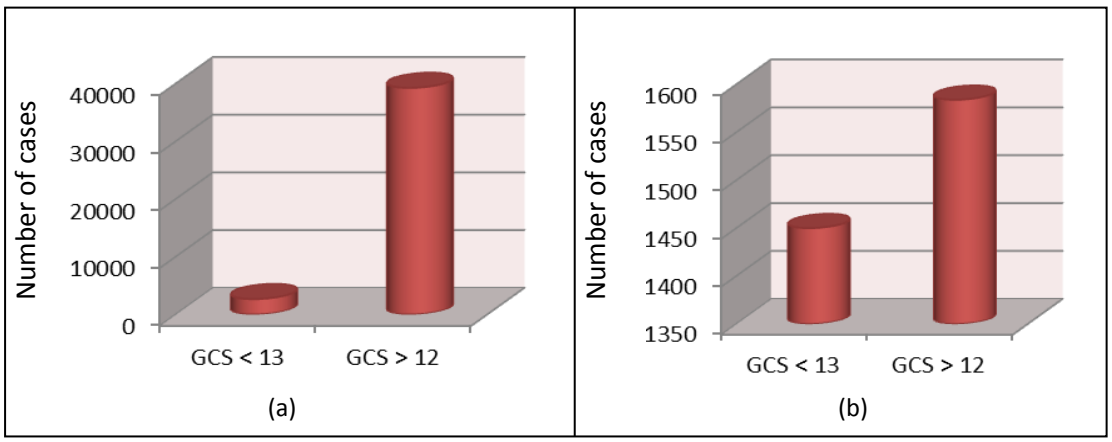


Figure 5-7 (a) GCS values (a) those that survived and (b) those that did not survive.

Figures 5-8a and b show the effects of pre-existing medical conditions (PMC) on the probability of survival for the cases that (a) survived and (b) those that did not survive. The value of PMC<1 indicates no pre-existing condition and PMC>0 indicates existence of at least one pre-existing medical condition such. The majority of those that survived did not have a pre-existing medical condition but the opposite is the case for those that did not. This shows PMC is an effective factor for predicting non-survivor cases.

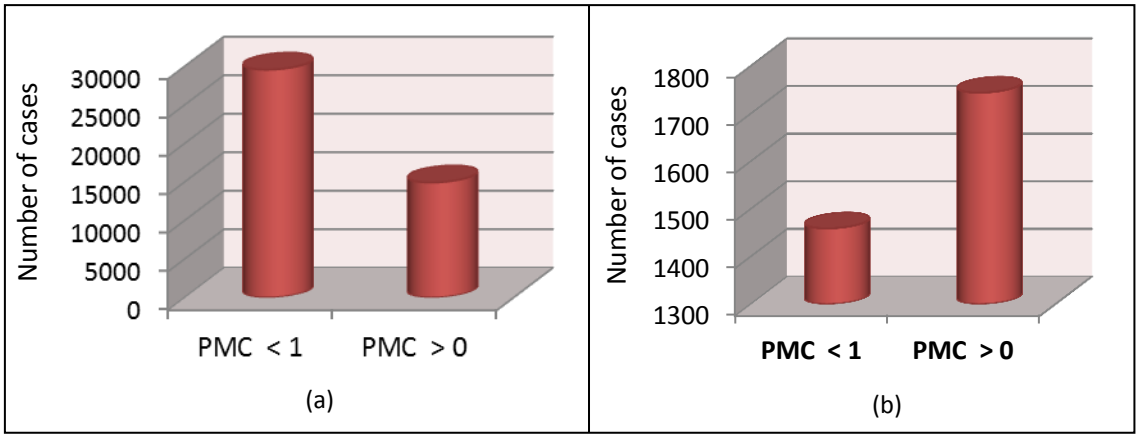


Figure 5-8 (a) The effect of pre-existing medical condition on (a) those that survived and (b) those that did not survive.

Figures 5-9a and b show the number of adult cases with emergency department respiratory rate in the healthy or normal range (considered as 12 to 20 breaths per minute) for cases (a) that survived and (b) those that did not survive. The proportion of cases with emergency department respiratory rate 12-20 breathes per minute (bpm) that did survive is much higher than the cases that did not. Therefore the respiratory rate is an important factor in determining the probability of survival.

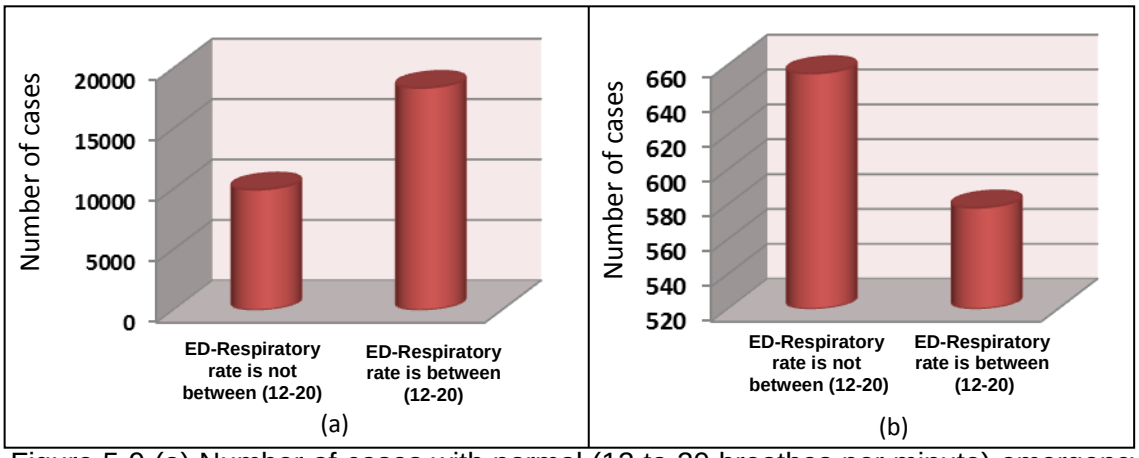


Figure 5-9 (a) Number of cases with normal (12 to 20 breathes per minute) emergency department respiratory rate (a) those that survived and (b) those that did not survive.

Figures 5-10 a and b show the effect of normal pulse rate (heart rate) on survival of adults. Pulse rate for healthy adults is typically between 60-100 beats per minute (bpm). In surviving cases (Fig.5-10a), a much higher proportion of individuals had normal pulse rate. Fig.5-10b shows the proportion of the individuals with a normal and abnormal emergency department pule rate for cases that did not survive is much closer than those that did survive. Consequently, PR has a slight effect in non-survivors.

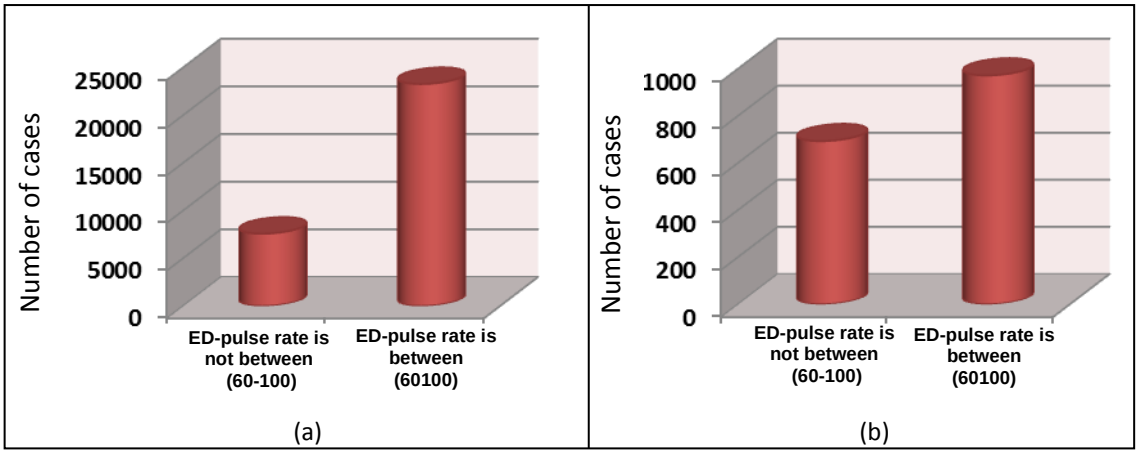


Figure 5-10 Effect of emergency department pulse (heart) rate on probability of survival in adults (a) survived cases (b) those that did not survive.

Blood pressure is one of the vital sign for medical examinations. Figures 5-11a and b show the number of adult cases with emergency department (ED) - Systolic blood pressure (SBP) in the normal range (90 to 140 mmHg) and outside this range for the cases that survived and (b) those that did not survive. The proportion of cases with SBP in the normal range is higher in individual that survived than those who not survive indicating this physiological measure in an important indicator of Ps.

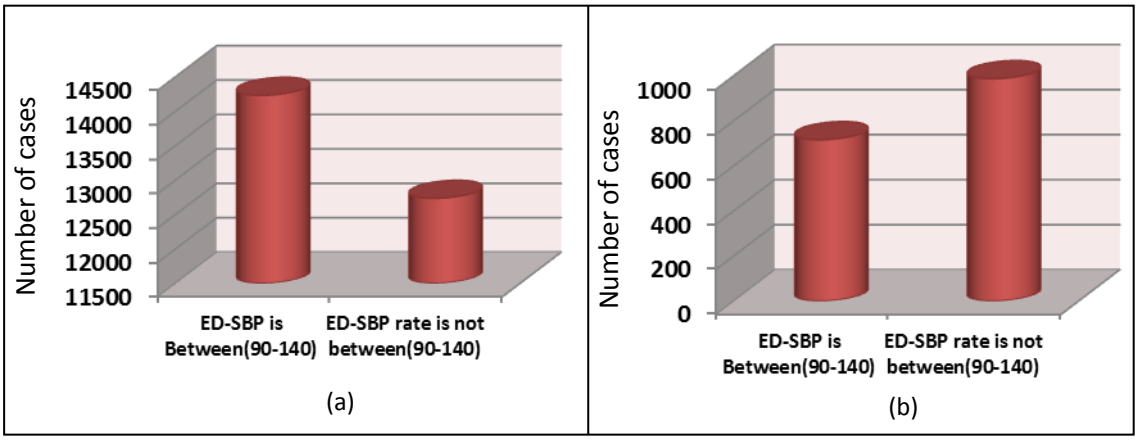


Figure 5-11 Impact of emergency department systolic blood pressure on probability of survival in adults (a) survived cases (b) those that did not survive.

5.3 Investigation of relationships and correlation between AIS body regions and with other factors for non-surviving.

Figure 5-12 shows the correlation between the traumas associated with the 8 body regions as defined in AIS standard for cases that did not survive. Head injuries occurred more often in combination with face and thorax injuries. Face injuries are more common with head injuries. Thorax injuries occur more often with head and abdomen injuries.

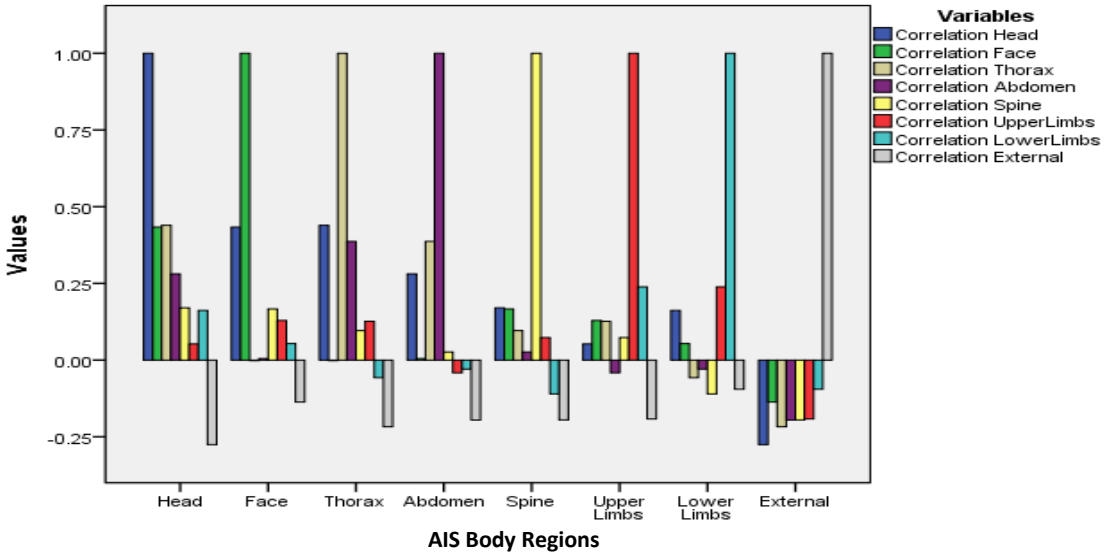


Figure 5-12 Correlation of trauma associated with the AIS defined body regions in cases that did not survive.

Figure 5-13 shows the AIS scores of the cases with joint head, thorax and lower limb injuries (i.e. the main body areas affected by trauma) that did not survive. The largest number of deaths is for head (AIS score =5), thorax (AIS score= 3) and lower limbs (AIS scores= 4 and 5) injuries.

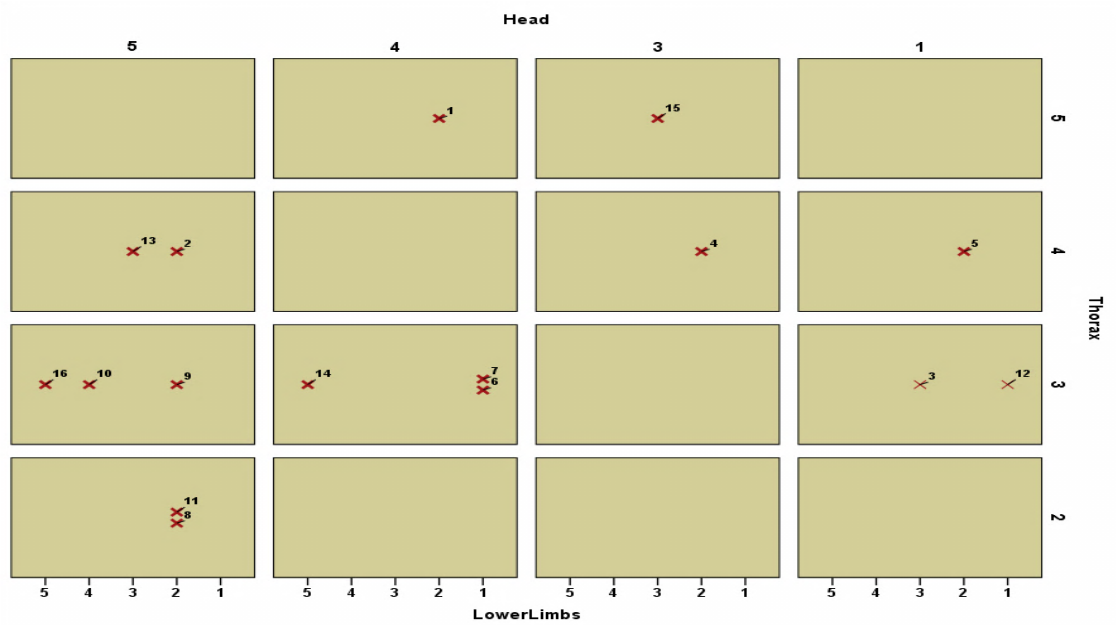


Figure 5-13 The interrelationship between trauma injuries associated with head, thorax, and lower limb cases that did not survive represented by AIS scores 1-5.

Figures 5-14a and b show boxplots indicating the relations between head injury only and thorax injury only for cases that did not survive. Both injury types have mainly AIS score= 5 but age ranges are different. Age ranges could have been obscured by the distribution of the specific cases in the data base that itself is influenced by the age distribution of the population in the UK.

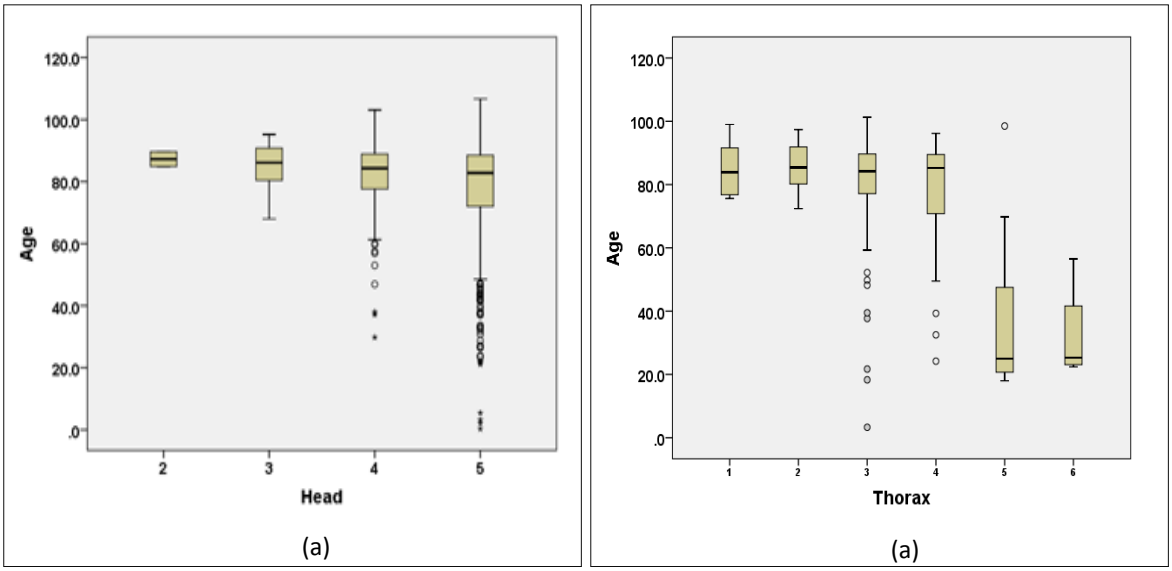


Figure 5-14 Box plots indicating the relationship between (a) head only injury and (b) thorax only injury for those that did not survive.

Figure 5-15 shows the interrelationship between age, GCS and head only injuries in cases that did not survive. Most cases are related head injuries AIS=5, ages around 64- 98 years and GCS=3-6 or 13 to 15. Most head injuries with AIS=4 had GCS values 13 to 15. As result of this AIS=5 and ages 64-98 are clearly significant factors in not survivors however with these GCS values 3 to 6 also has a big number of cases.

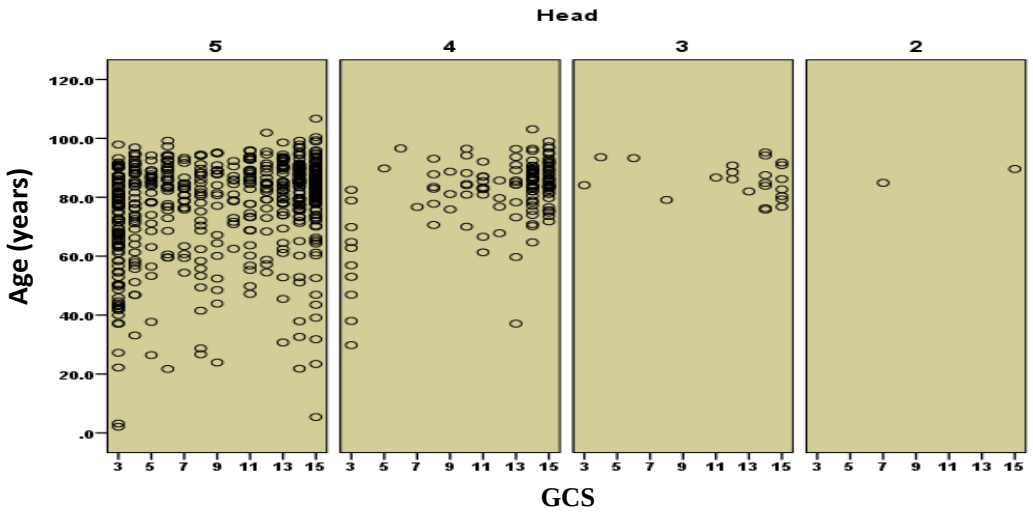


Figure 5-15 The interrelationship between GCS and head injuries in cases that did not survive.

Figure 5-16 shows analysis in Figure 5-15 extended with inclusion of gender. Gender is a more significant factor in determining the probability of survival in older subjects. A larger number of older (aged around 80 years) males have head injury than females. Age can be important in determining the probability of survival (Sammy et al., 2016).

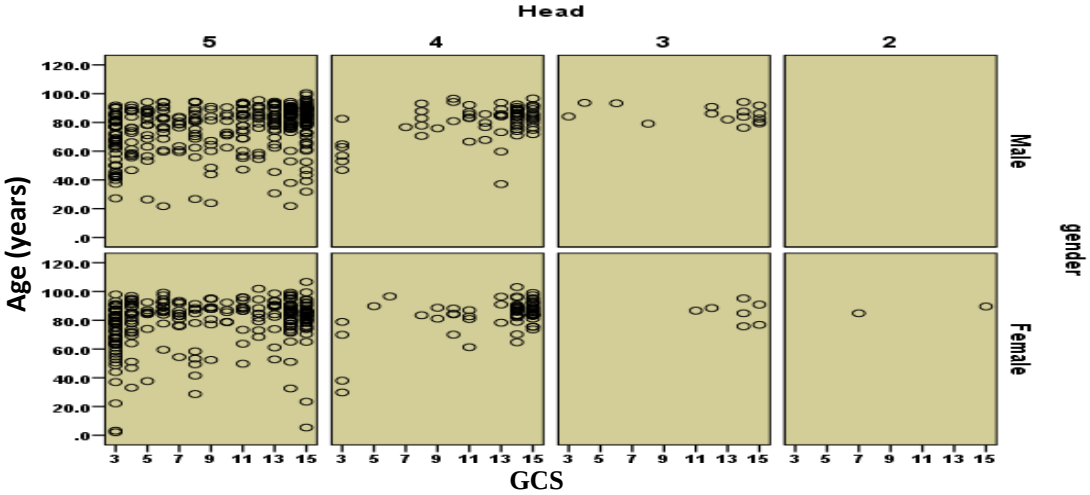


Figure 5-16 The interrelationship between GCS, head injury and age in cases that did not survive.

Figure 5-17 shows the relationships between trauma mechanisms, GCS, PMC and head only injury in cases that did not survive. Most cases that did not survive were associated with falls less than 2 meters, AIS scores= 4 and 5 and PMC values -1 to 15.

Figure 5-17 Relationship for GCS, PMC, injury mechanisms and head only injuries for cases that did not survive.

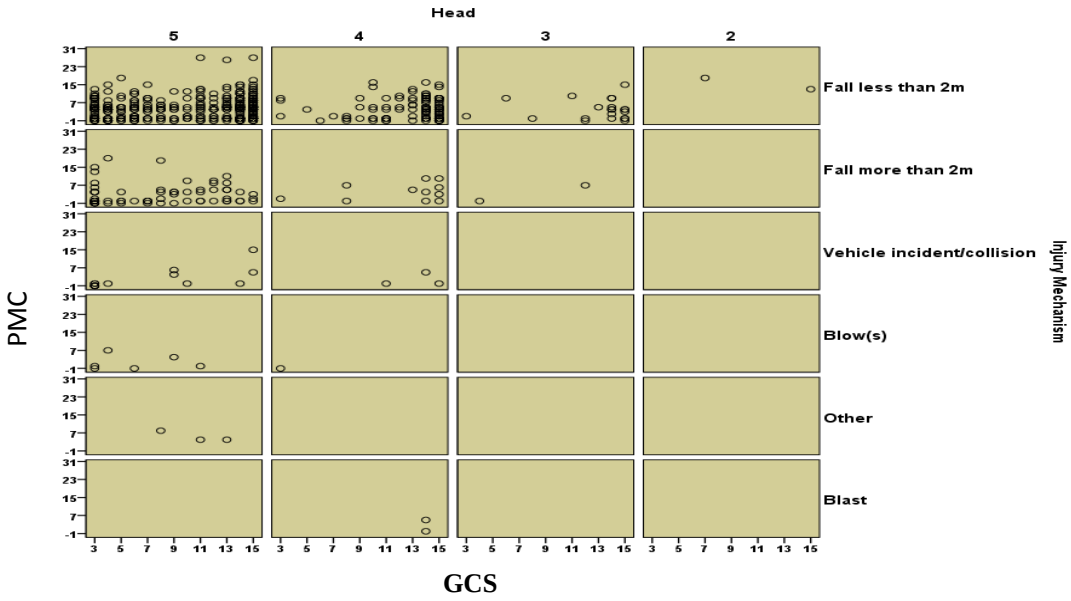


Figure 5-18 shows the relationships for intubation, GCS, head and face only injuries, and GCS in cases that did not survive. Most cases were associated with intubation and head injury AIS=5, face injuries AIS=2 and GCS=3 to 9.

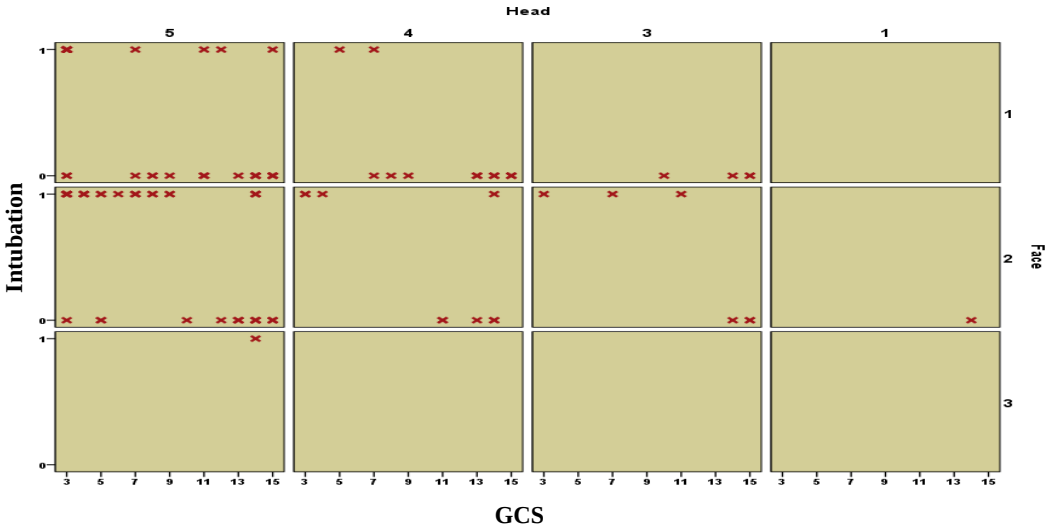


Figure 5-18 The relationships for intubation, GCS, head and face regions, and GCS in cases that did not survive.

Table 5-2 provides a summary the interrelationships between injuries associated with specific body regions and factors affecting the probability of survival (age, PMC, GCS and gender) in cases that did not survive. Both the number of cases and respective percentages are included.

Table 5-2 Overview of injury cases.

Body Regions	Total	Age		PMC		GCS		Gender	
		>54	<55	<=0	>0	<13	>=13	Male	Female
Head	811	745 (91.86%)	66 (8.14%)	289 (35.64%)	522 (64.36%)	402 (49.57%)	409 (50.43%)	362 (44.64%)	449 (55.36%)
Lower Limbs	347	335 (96.54%)	12 (3.46%)	105 (30.26%)	242 (69.74%)	9 (2.60%)	338 (97.40%)	119 (34.30%)	228 (65.70%)
Thorax	194	166 (85.57%)	28 (14.43%)	76 (39.18%)	118 (60.82%)	35 (18.04%)	159 (81.96%)	110 (56.70%)	84 (43.30%)
Head & Face	129	103 (79.84%)	26 (20.15%)	49 (37.98%)	70 (54.26%)	64 (49.61%)	62 (48.06%)	79 (61.24%)	50 (38.76%)
Head& Thorax & Lower limbs	16	11 (68.75%)	5 (31.25%)	10 (62.5%)	6 (37.5%)	12 (75.0%)	4 (25.0%)	7 (43.75)	9 (56.25%)

5.4 Chapter summary

A preliminary computational analysis of a number of important factors that influence the probability of survival in traumas was performed. The study highlighted some of the complexities associated with the manner traumas affect the probability of survival. This analysis will be built upon in the following chapters to develop models to predict the probability of survival and overcome some limitations of the existing probability survival prediction approaches. The main element of these models is their knowledge base that is derived from the TARN trauma data. This information leads us to create trauma knowledge representation and coding in following chapter. There is further statistical analysis in Appendix A.

Chapter 6 Trauma Knowledge Representation and Coding

6.1 Overview

In this chapter the development of the knowledge representation and coding methods are described. Traumatic brain injury (TBI) is the focus of this investigation. Trauma knowledge representation and coding were constructed based on four steps as illustrated in Figure 6-1. First is the knowledge representation and visualization of the TARN data and domain knowledge by using Tree Decision technique. This was followed by the investigation of the TARN data statistical analysis in order to distinguish between trauma characteristics that led to survivors or non-survivors with the view to obtain and determine interrelationship between injury factors and survival outcomes. Next step was the knowledge coding this was used as enhancement of IRCC operation part and FIS rule base that by a series of If-Then Statement.

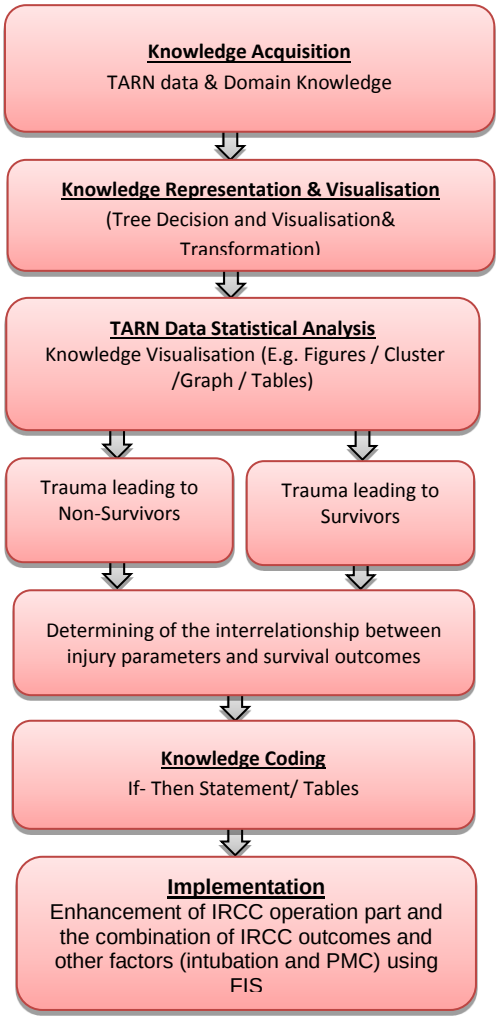


Figure 6-1 Planning of Knowledge representation and coding design overview.

6.2 Knowledge Representation and Visualisation

It is valuable to visualise the knowledge so that the interrelationships between the variables are better understood. Decision trees are a means of visualising knowledge. A design tree for visualising parameters considered for predicting trauma is shown in Figure 6-2.

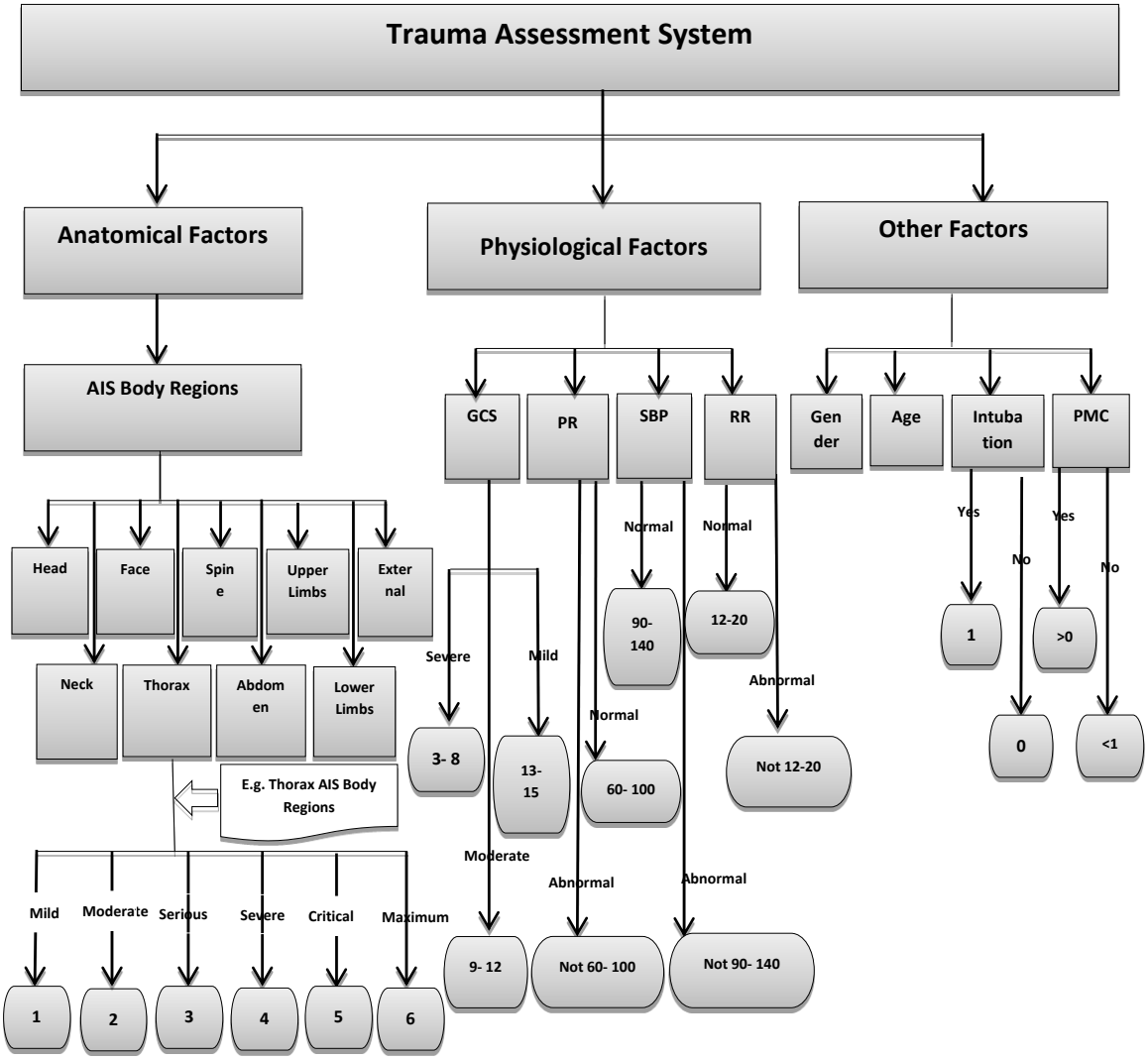


Figure 6-2 Decision tree for the trauma assessment system.

In this figure trauma assessment system is divided into three types. One is anatomy and has 9 AIS conformed body regions as described in (AAAM 2005, updating 2008). Physiological factors are (GCS, PR, SBP and RR) and every parameter has scores or ranges that are determined by medical experts. (The Royal Children's Hospital Melbourne, 2018; Andersen et al., 2016; Iain Wheatley 2018; Verdecchia et al., 2009). Finally, other factors are Gender, Age, Intubation and PMC.

6.3 Description of Data Used as Input to the Models for Predicting Probability of Survival

6.3.1 Overview

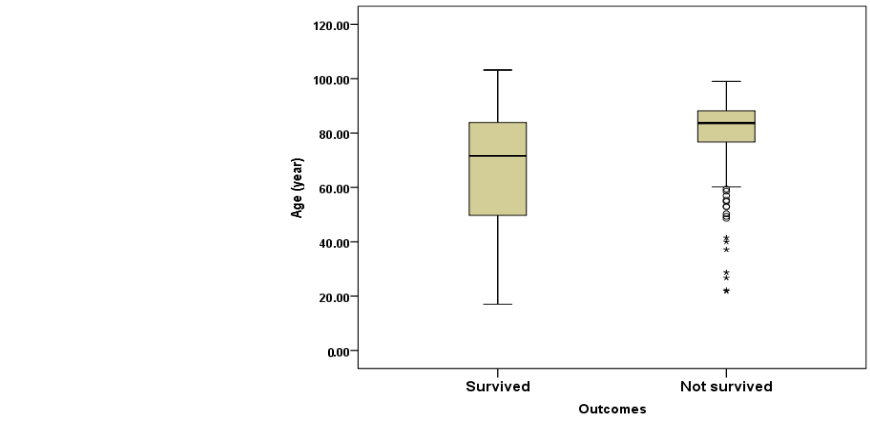
In this section the TARN data used as input to the models to predict probability of survival are described. The data were considered in three stages: (a) surviving cases and non survivors, (b) dividing the available cases into calibration and test sets, identification of relevant trauma parameters.

In this section trauma brain injuries (TBI) is chosen to be investigated as it was the main injury type in the dataset resulting in death. Table 6-1 provides the details of these cases consisting of their age, sec and numbers.

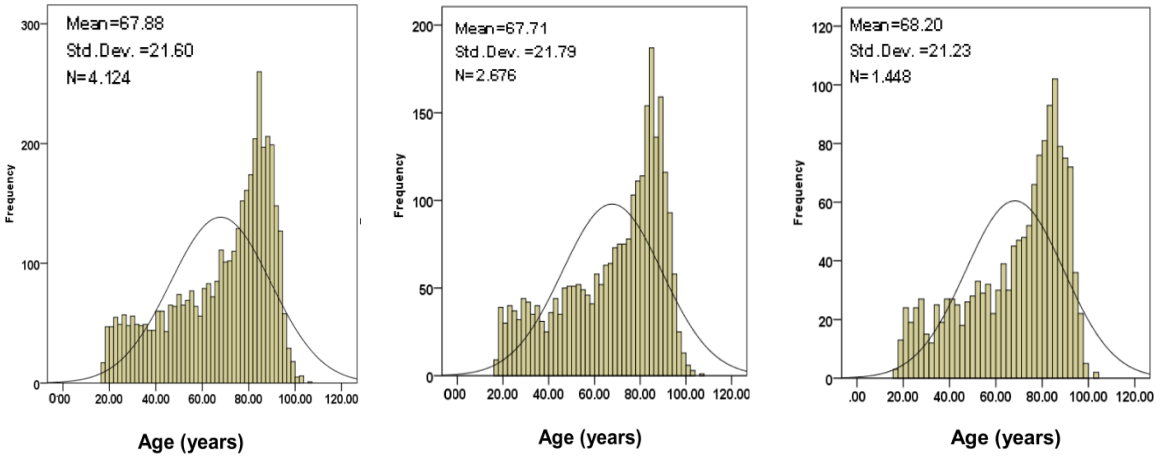
Table 6-1 Information summary for adult TBI cases (total 4124).

Gender		Age (Years)		Injury Outcomes	
Male	Female	Mean	Standard Deviation	Survivors	Not survivors
2488 (60.3%)	1636 (39.7%)	67.9	21.6	3553 (86.2%)	571 (13.8%)

The calibration data set contained approximately 2/3 of the cases (number = 2676) and the validation data set contained the remaining 1/3 subjects (number = 1448) Figure 6-3 shows details of the subjects' age. Figure 6-3a shows their age boxplots divided to survivors and non-survivors. The median of age (83.7 years) for no survivors is higher than survivors (71.6 years). Figure 6.3b shows the age distribution of all subjects. Figures 6-3c, d show the age distributions for survivors and non-survivors respectively.



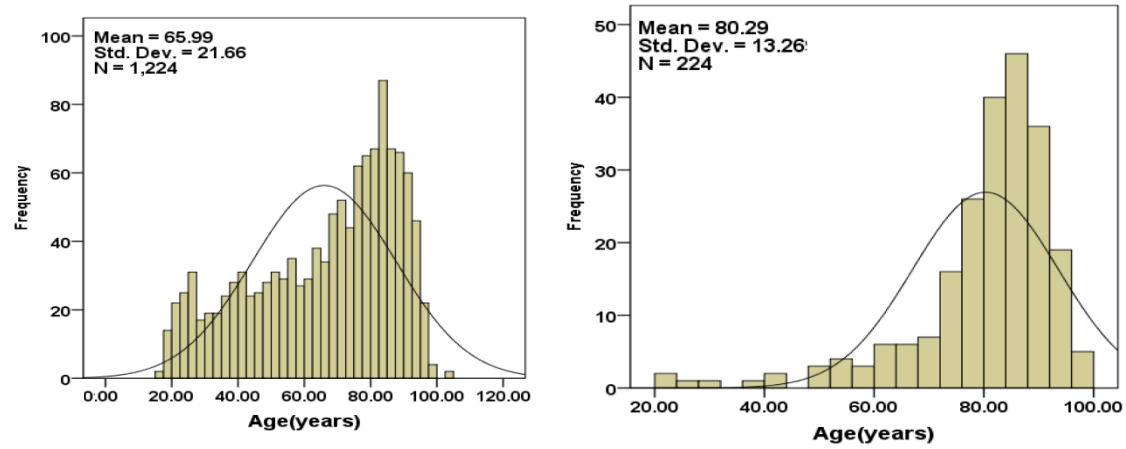
(a)



(b) (c) (d)

Figure 6-3 (a) shows the boxplots for the subjects' age divided into survivors and not survivors. (b) Shows the age distribution of all subjects, (c) the subjects included in the calibration and (d) those in the validation set.

Figures 6-4 a and 6-4 b show the age distributions of the subjects included in the validation set separated into survivors and not survivors respectively.



(a) (b)

Figure 6-4 (a) Age distributions of the subjects in the validation set for (a) survivors and (b) not survivors.

A summary statistics for subject's age included in the validation set is provided in Table 6-2.

Table 6-2 Age (in years) statistical summary for subjects in the validation set.

Parameter	All Subjects	Survivors	Not Survivors
	1448	1224	224
Mean	68.2	66.0	80.3
Median	75.1	71.6	83.7
Mode	87.5	87.5	85.7
Standard deviation	21.2	21.7	13.6
Variance	450.7	469.5	176.1
Range	86.2	86.2	77.2
Minimum	17.0	17.0	21.8
Maximum	103.2	103.2	99.0

6.3.2 Analysis of Trauma Parameters

The trauma parameters used as input to the developed models are analysed in this section. The parameters were AIS, GCS, pulse (heart) rate, respiratory rate and systolic blood pressure. In some analysis (described in later sections) the actual values of these parameters were not used. Instead their severities were used as input. The association of the actual values to their severities are provided in Table 6-3. (The Royal Children's Hospital Melbourne 2018; Andersen et al., 2016; Iain Wheatley 2018; Verdecchia et al., 2009). This categorization allocated the actual values of these parameters into predefined groupings, i.e., normal, abnormal mild, moderate severe. The reason for this operation was that the inter-class variations within the measured variables could be reduced and the results could be interpreted more specifically into severity types. However, the disadvantage of this categorization is that actual readings are replaced by their category types.

Table 6-3 Categorization of Glasgow coma score (GCS), pulse rate (PR, beats per minute, bpm), respiratory rate (RR, breaths per minute, bpm) and systolic blood pressure.

Measures	Range	Category	
GCS	Score 13–15	3 (Mild)	
	Score 9–12	2 (Moderate)	
	Score 3–8	1 (Severe)	
Pulse rate	60–100 bpm	Normal = 2	Abnormal = 1
Respiratory rate	12–20 bpm	Normal = 2	Abnormal = 1
Systolic blood pressure	90–140 mmHg	Normal = 2	Abnormal = 1

Table 6-4 provides an analysis of the relationship between trauma parameters (categorized according to Table 6-3) and the percentage survivors (number 1224 cases) and not survivors (number 224 cases) in the validation set. Considering the not survivors, 77.2% had AIS = 5, 37.1% were categorized as GCS =37.1 severe, 30.8% categorized as abnormal pulse rate, 26.8% were categorized as abnormal respiration rate and 71.4% were categorized as abnormal systolic blood pressure.

Table 6-4 Analysis of injury parameters in relation to cases that survived and those that had not survived.

Parameters Injury Grade		All Subjects	Survivors	Not Survivors
		1448	1224	224
AIS	2	12 (0.8%)	12 (1.0%)	0 (0.0%)
	3	159 (11.0%)	154 (12.6%)	5 (2.2%)
	4	597 (41.2%)	551 (45.0%)	46 (20.5%)
	5	680 (47.0%)	507 (41.4%)	173 (77.2%)
GCS (categorized)	1 (Severe)	147 (10.2%)	64 (5.2%)	83 (37.1%)
	2 (Moderate)	133 (9.2%)	98 (8.0%)	35 (15.6%)
	3 (Mild)	1168 (80.7%)	1062 (86.8%)	106 (47.3%)
PR (categorized)	1 (Abnormal)	338 (23.3%)	269 (22.0%)	69 (30.8%)
	2 (Normal)	1110 (76.7%)	955 (78.0%)	155 (69.2%)
RR (categorized)	1 (Abnormal)	236 (16.3%)	176 (14.4%)	60 (26.8%)
	2 (Normal)	1212 (83.7%)	1048 (85.6%)	164 (73.2%)
SBP (categorized)	1 (Abnormal)	762 (52.6%)	602 (49.2%)	160 (71.4%)
	2 (Normal)	686 (47.4%)	622 (50.8%)	64 (28.6%)

Table 6-5 provides the mean and standard deviation of AIS and categorized GCS, pulse rate (PR), respiratory rate (RR) and systolic blood pressure (SBP) for not surviving cases included in the validation set. The results from this table confirm the conclusion derived from Table 6-5 with regard to the particular significance of GCS, AIS and SBP. The mean (categorized) systolic blood pressure is close to the abnormal value while the mean GCS is close to moderate severity and AIS represent high injury severity.

Table 6-5 The mean and standard deviation of AIS and categorized Glasgow Comas Score GCS, PR, RR and SBP for not surviving cases included in the validation set.

Parameters	Mean	Standard Deviation
AIS	4.75	0.48
GCS (categorized)	2.10	0.92
PR (categorized)	1.69	0.46
RR (categorized)	1.73	0.44
SBP (categorized)	1.29	0.45

Figure 6-5 shows the interrelationship between AIS and categorized SBP (Figure 6-5a) and GCS and categorized SBP for not survivors included in the validation set. The figure indicates that great majority of cases with AIS = 5 had abnormal SBP. The relationship between GCS and systolic blood pressure is not as well defined as that for AIS and systolic blood pressure but it is seen that 1 abnormal in SBP is more associated with three levels in GCS.

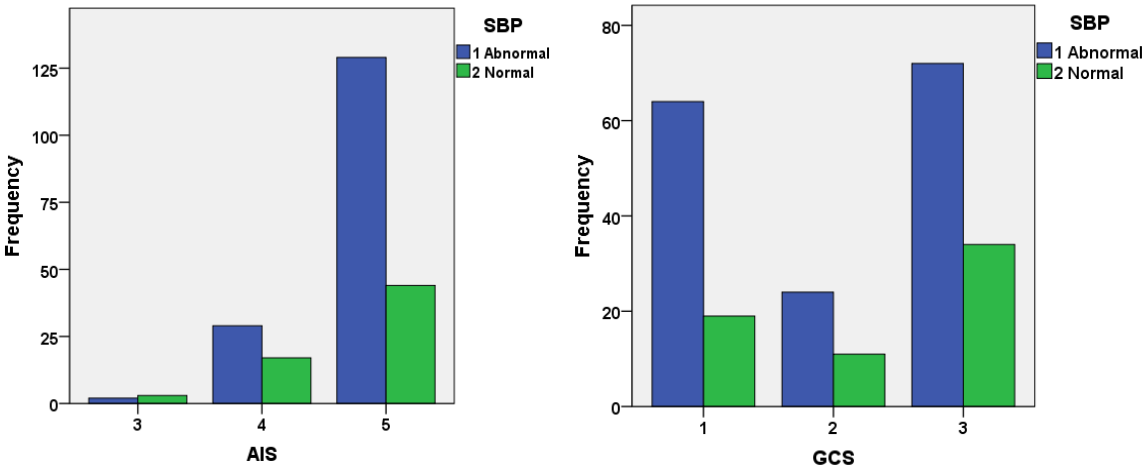


Figure 6-5 Relationship between (a) AIS and systolic blood pressure; (b) GCS and systolic blood pressure for not survivor's that were included in the validation set. Blue = abnormal category, Green = normal category.

6.3.3 Relationship between TBI AIS Code and GCS, SBP, RR, RP, Gender and Age for Enhancing IRCC Operation.

To establish the inter-relationships between AIS and GCS, SBP, RR and RP, the clustering information shown in Figure 6-6 was plotted. It showed the highest number of cases (total) 186 were associated with PR=2 (normal), RR =2(normal), SBP=1(abnormal), AIS=4 and GCS=3.

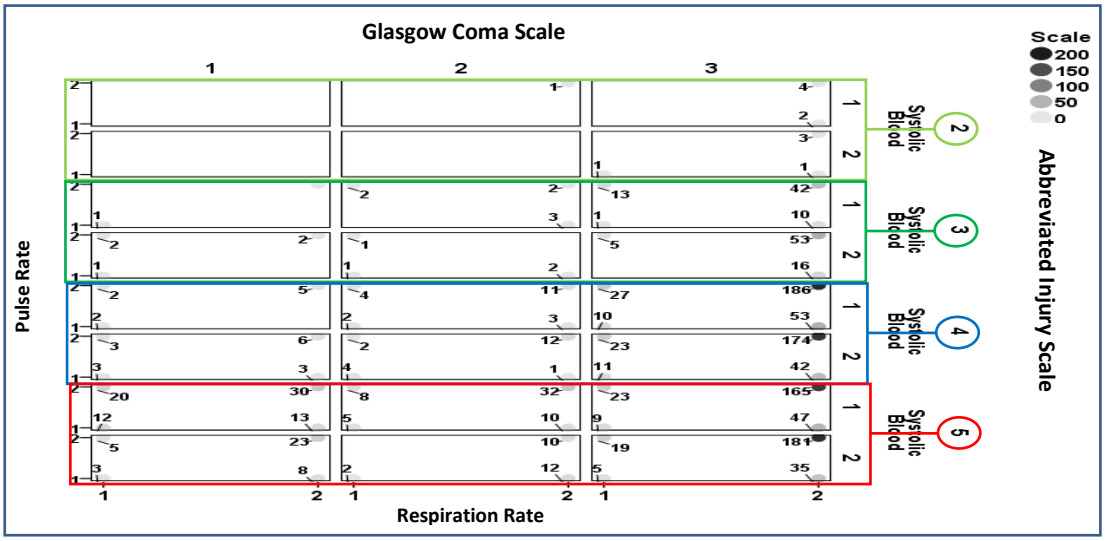


Figure 6-6 The inter-relationships between pulse rate, systolic blood pressure, GCS, AIS, and respiration rate. The values next to the circles indicate the number of associated cases. Larger values are highlighted by darker circles. Subjects are from the validation data set.

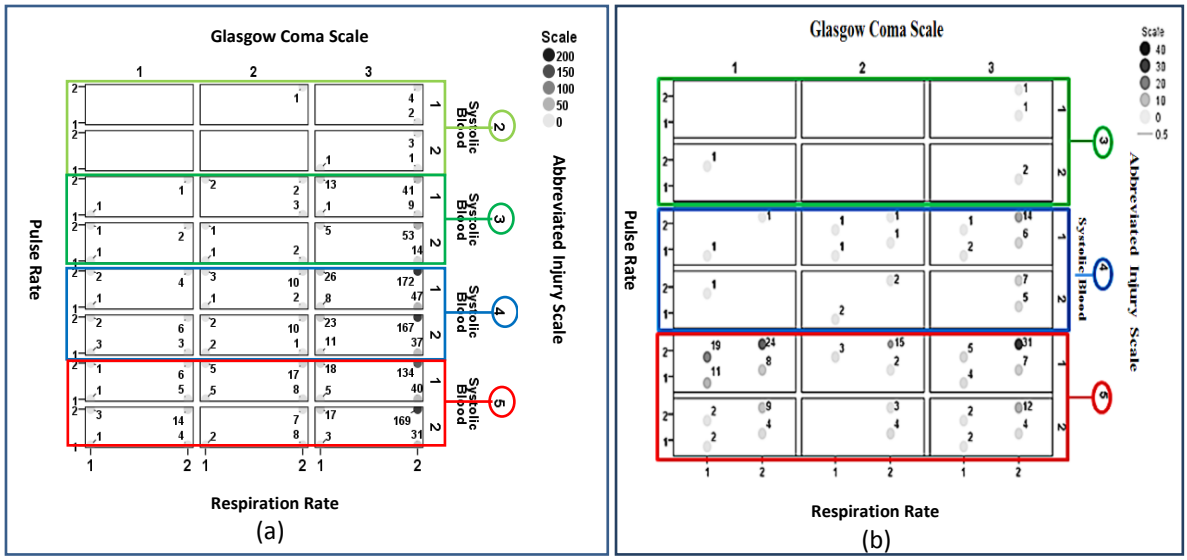


Figure 6-7 Inter-relations of trauma parameters separated into (a) survivors and (b) not survivors.

Figure 6-7 b shows the inter-relationships between pulse rate, systolic blood pressure, GCS, AIS, and respiration rate information for not survivors included in the validation set. A large cluster of cases appears for AIS = 5, GCS = 1 (categorized as severe injury) and systolic pressure = 1 (categorized abnormal).

Table 6-6 Analysis of injury patterns TBI included in the validation set (the patterns with relatively small number of cases are not shown). An x in the trauma parameter columns indicates abnormal or severe categorization for the related parameter.

No.	Injury Scenarios	All cases (Figure 6.7)	Survivors				Not survivors				Trauma Parameter				
			number of cases (Figure 6.8a)	Age Mean	Gender		Number of cases (Figure 6.8b)	Age Mean	Gender						
					M	F			M	F	PR	RR	SBP	AIS	GCS
1	X22143	186	172 (92.4%)	76	90	82	14 (7.4%)	89	8	6			x	x	
2	X22253	181	169 (93.3%)	63	121	48	12 (6.6%)	75	10	2				x	
3	X22243	174	167 (95.9%)	63	101	66	7 (4.1%)	87	4	3				x	
4	X22153	165	134 (81.2%)	70	87	47	31 (18.7%)	83	15	16			x	x	
5	X22233	53	53 (100.0%)	61	33	20	0 (0.0%)	/	/	/				x	
6	X12143	53	47 (88.6%)	69	29	18	6 (11.3%)	81	3	3	x		x	x	
7	X12153	47	40 (85.1%)	73	31	9	7 (14.8%)	86	6	1	x		x	x	
8	X22133	42	41(97.6%)	72	21	20	1(2.3%)	79	1	0			x	x	
9	X12243	42	37 (88.1%)	64	19	18	5 (11.9%)	89	4	1	x			x	
10	X12253	35	31 (88.5%)	58	24	7	4 (11.4%)	85	1	3	x			x	
11	X22152	32	17 (53.1%)	66	12	5	15(46.8%)	80	10	5			x	x	x
12	X22151	30	6 (20.0%)	62	6	0	24 (80.0%)	76	10	14			x	x	x
13	X21143	27	26 (96.2%)	74	12	15	1 (3.7%)	37	1	0		x	x	x	
14	X21243	23	23 (100.0%)	62	15	8	0 (0.0%)	/	/	/		x		x	
15	X21153	23	18 (78.2%)	72	10	8	5 (21.7%)	80	4	1		x	x	x	
16	X22251	23	14 (60.8%)	46	11	3	9 (39.1%)	68	3	6				x	x
17	X21151	20	1 (5.0%)	67	1	0	19 (95.0%)	80	11	8		x	x	x	x
18	X21253	19	17 (89.4%)	65	10	7	2 (10.5%)	88	1	1		x		x	
19	X12233	16	14(87.5%)	47	7	7	2(12.5%)	79	1	1	x			x	
20	X12151	13	5(38.46%)	54	3	2	8(61.5%)	82	5	3	x		x	x	x
21	X21133	13	13(100.0%)	67	7	6	0(0.0%)	/	/	/		x	x	x	
22	X11151	12	1(8.3%)	67	1	0	11(91.4%)	73	7	4	x	x	x	x	x
23	X12252	12	8(66.6%)	53	4	4	4(33.4%)	80	2	2	x			x	x
24	X22242	12	10(83.4%)	42	7	3	2(16.6%)	73	0	2				x	x
25	X22142	11	10(90.9%)	60	7	3	1(9.0%)	80	1	0			x	x	x
26	X11243	11	11(100.0%)	74	7	3	0(00.0%)	/	/	/	x	x		x	
27	X12152	10	8(80.0%)	68	5	3	2(20.0%)	77	1	1	x		x	x	x
28	X22252	10	7(70.0%)	49	6	1	3(30.0%)	86	2	1				x	x
29	X11143	10	8(80.0%)	75	5	3	2(20.0%)	87	1	1	x	x	x	x	
30	X12133	10	9(90.0%)	61	6	3	1(10.0%)	83	1	0	x		x	x	
31	X11153	9	5(55.5%)	69	4	1	4(44.4%)	83	3	1	x	x	x	x	
32	X12251	8	4(50.0%)	63	3	1	4(50.0%)	66	1	3	x			x	x
33	X21152	8	5(62.5%)	74	3	2	3(37.5%)	85	3	0		x	x	x	x
Total & Percentages		1340	1131	63.56	708	423	209	79.21	120	89					

Note: Xabcde: The subscript “a” represents pulse rate (categorized as 1 abnormal, 2 normal), “b” represents respiration rate (categorized as 1 abnormal, 2 normal), “c” represents systolic blood pressure (categorized as 1 abnormal, 2 normal), “d” represents AIS and “e” represents GCS (1: severe, 2: moderate and 3: mild).

Table 6-7 shows three colours in the trauma parameters column. Red represents AIS=5 (critical) or GCS=3 (severe), or abnormal in other parameters. Yellow represents AIS=4 (severe) or GCS=2 (moderate). Green represents AIS=3 (serious). Using the information from the table, the trauma cases with highest occurrence and their associated trauma parameters can be identified for both survivors and not survivors.

Table 6-7 Trauma scenarios and their associated trauma parameters for survivors.

No.	Scenarios' Numbers in Table 6.6	Injury Scenarios	Number of All Cases That (Figure 6.7)	survivors				Trauma Parameter				
				Number of cases (Figure 6.8a)	Age Mean (years)	Gender						
						M	F	RR	PR	SBP	AIS	GCS
1	5	X22233	53	53 (100.0%)	61	33	20				x	
2	14	X21243	23	23 (100.0%)	62	15	8	x			x	
3	21	X21133	13	13(100.0%)	67	7	6	x		x	x	
4	26	X11243	11	11(100.0%)	74	7	3	x	x		x	
5	8	X22133	42	41(97.6%)	72	21	20			x	x	
6	13	X21143	27	26 (96.2%)	74	12	15	x		x	x	
7	3	X22243	174	167 (95.9%)	63	101	66				x	
8	2	X22253	181	169 (93.3%)	63	121	48				x	
9	1	X22143	186	172 (92.4%)	76	90	82			x	x	
10	25	X22142	11	10(90.9%)	60	7	3			x	x	x
11	30	X12133	10	9(90.0%)	61	6	3		x	x	x	
12	18	X21253	19	17 (89.4%)	65	10	7	x			x	
13	6	X12143	53	47 (88.6%)	69	29	18		x	x	x	
14	10	X12253	35	31 (88.5%)	58	24	7		x		x	
15	9	X12243	42	37 (88.1%)	64	19	18		x		x	
16	19	X12233	16	14(87.5%)	47	7	7		x		x	
17	7	X12153	47	40 (85.1%)	73	31	9		x	x	x	
18	24	X22242	12	10(83.4%)	42	7	3				x	x
19	4	X22153	165	134 (81.2%)	70	87	47			x	x	
20	27	X12152	10	8(80.0%)	68	5	3		x	x	x	x
21	29	X11143	10	8(80.0%)	75	5	3	x	x	x	x	
22	15	X21153	23	18 (78.2%)	72	10	8	x		x	x	
23	28	X22252	10	7(70.0%)	49	6	1				x	x
24	23	X12252	12	8(66.6%)	53	4	4		x		x	x
			1185	493	66.7	664 (90.7%)	409 (90.6%)					

Table 6-7 presents 24 main scenarios for the survivors. The table is divided into three parts based on percentages of the trauma cases. The first 7 scenarios are above 95% of cases. It can be seen that in these 7 scenarios AIS <=4 and GCS is =3 (Mild). Therefore it is concluded that when AIS <=4 and GCS =3 then patients had more likelihood of survival even other factors were not normal. The second part is form scenarios number 8 to 19. It is noted that there is not any scenario with AIS=5 and GCS is 1. AIS=5 is repeated only five times. The majority of these scenarios had AIS=5 and GCS = 2 or AIS=5 and SBP= abnormal. These results indicate that when AIS <5, GCS =3 and SBP is normal then there is a higher likelihood of survival. This information is used in later section for knowledge coding.

Table 6-8 Nine significant scenarios from Table 6-6 related to not survivors.

No	Scenarios' Numbers in Table 6.6	Injury Scenarios	Number of All Cases That (Figure 6.7)	Not survivors				Trauma Parameter				
				Number of cases (Figure 6.8b)	Age Mean	Gender						
						M	F	RR	PR	SBP	AIS	GCS
1	17	X21151	20	19 (95.0%)	80	11	8	x		x	x	x
2	22	X11151	12	11(91.4%)	73	7	4	x	x	x	x	x
3	12	X22151	30	24 (80.0%)	76	10	14			x	x	x
4	20	X12151	13	8(61.5%)	82	5	3		x	x	x	x
5	23	X12251	8	4(50.0%)	66	1	3		x		x	x
6	11	X22152	32	15(46.8%)	80	10	5			x	x	x
7	31	X11153	9	4(44.4%)	83	3	1	x	x	x	x	
8	16	X22251	23	9 (39.1%)	68	3	6				x	x
9	32	X21152	8	3(37.5%)	85	3	0	x		x	x	x
			155	97	77.0	53 (51.9%)	44 (54.3%)					

Table 6-8 shows the highest percentages of scenarios of not survivors. The first four scenarios are greater than 50% of the overall cases. They have AIS=5, GCS=1 (severe) and SBP=1 (abnormal). Likewise, RR is abnormal in two first scenarios. All scenarios in this table have AIS = 5 and they are also associated with severe or moderate values for GCS and abnormal values for SBP. The average age of the subjects is 77.0 years. In terms of Gender, female cases are 54.3% while male cases are 51.9%. This information is also used in later section for knowledge coding.

6.3.4 Investigation of the Relationships between AIS and Intubation and PMC for FIS

There were 16589 trauma cases with PMC consisting of which14844 were survivors and 1745 were not survivors. Table 6-9 shows the PMCs and the number of cases involved for all body regions. The PMC cases that result in a relatively larger number of deaths are highlighted as pink in Table 6-9. These four PMCs with TBI were chosen for further investigations. Figure 6-8 shows the interrelationships between those four PMCs, AIS, GCS and average age for not survivors. The average of GCS and AIS scores are highlighted as red in Figure 6-8.

Table 6-9 PMC information for the cases studied.

No.	PMC	Number of all cases	Number and percentage of survivors	Number and percentage of not survivors
1	Hypertension	3464	3088 (89.1%)	376 (10.9%)
2	Diabetes mellitus (Type 2 / noninsulin dependent)	1584	1393 (87.9%)	191 (12.1%)
3	Alcohol abuse	991	915 (92.3%)	76 (7.7%)
4	Thyroid disease	750	680 (90.7%)	70 (9.3%)
5	Dementia	649	551 (84.9%)	98 (15.1%)
6	COPD	630	558 (88.6%)	72 (11.4%)
7	Hypercholesterolaemia	587	527 (89.8%)	60 (10.2%)
8	Depression	582	549 (94.3%)	33 (5.7%)
9	Diabetes mellitus (Type 1 / insulin dependent)	555	496 (89.4%)	59 (10.6%)
10	Stroke/CVA/TIA	487	420 (86.2%)	67 (13.8%)
11	Asthma	486	451 (92.8%)	35 (7.2%)
12	Other Heart disease	448	404 (90.2%)	44 (9.8%)
13	Other	366	327 (89.3%)	39 (10.7%)
14	Crohn's disease/Colitis/Diverticular	308	280 (90.9%)	28 (9.1%)
15	Osteoarthritis	274	257 (93.8%)	17 (6.2%)
16	Epilepsy	255	237 (92.9%)	18 (7.1%)
		12416	**11133 (89.6%)**	**1283 (10.3%)**

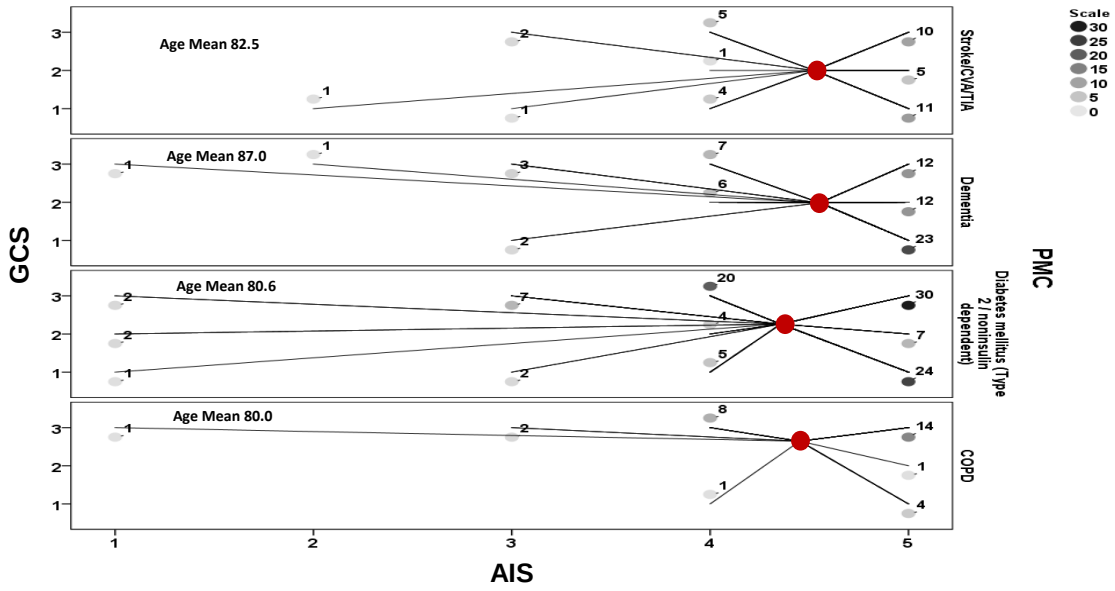


Figure 6-8 The interrelationships between PMC, AIS, GCS and average age for TBI not survivors.

In terms of average values (red circles) for GCS and AIS scores that were associated with Cerebrovascular Accident/Transient Ischemic Attack (stroke/ CVA/TIA), PMC is about 2.2 for GCS, 4.5 for AIS and age is 82.5 years. Whereas, Chronic Obstructive Pulmonary Disease (COPD) PMC relates to mean age of 80.0 years, about 2.8 for GCS and 4.4 for AIS code. This information is used in later part for knowledge coding. The number of trauma cases with intubations for survivors and not survivors are provided in Table 6-10. The number of cases with intubation for survivors and not survivors are 1511 and 755 respectively.

Table 6-10 Number of cases with intubation and their mean age.

Trauma cases with Intubation	Number of cases	Mean Age (years)
Survivors	1511	45.8
Not survivors	775	58.3

Figure 6-9 shows the interrelations between AIS, GCS and intubation. This indicate intubation factor is more pronounce for AIS scores 4 and 5 and GCS=1.

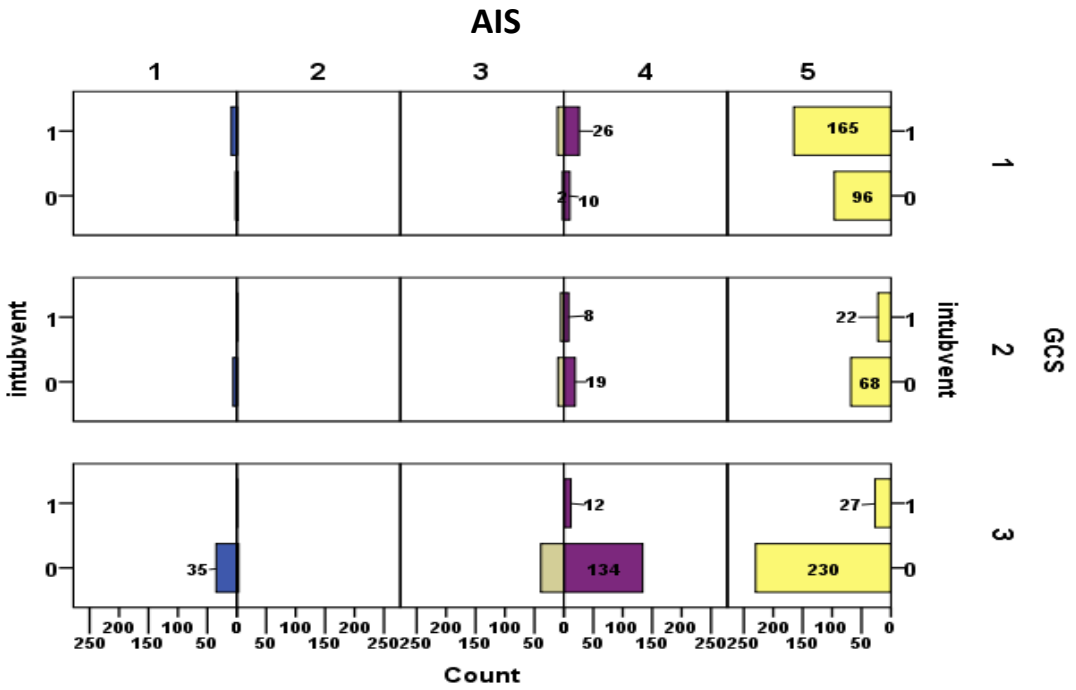


Figure 6-9 Interrelationships between AIS, GCS and intubation.

6.4 Knowledge Coding

In this section, knowledge coding is described. The coding is used as part of IRCC method to improve its performance for predicting probability of survival and FIS rules base. Firstly, knowledge coding incorporating TBI AIS code, GCS, RP, RR, SBP, Age and Gender for enhancement IRCC operation.

The knowledge coding is an extension of IRCC operation to further improve their predication accuracy. Table 6-11 indicates the IF-THEN rules for survivors developed as part of this knowledge coding. These rules were derived from the information provided in Table 6-7.

Table 6-11 IF-THEN rules for survivors derived from the information provided in Table 6.7

Injury Scenarios Based on Table 6-7	**If-Then Statement**
X22233 X21243 X21133 X11243 X22133 X21143 X22243	1) If (AIS>=4, GCS = 3 and Age < 73) Then P=98%
X22253	2) If (AIS =5 and Age < 73) Then P=93%
X22143	3) If (AIS =4, SBP=1 and Age < 73) Then P=92%
X22142 X22242	4) If (AIS =4, GCS=2, SBP=1 and Age < 73) Then P=87%
X12133	5) If (AIS =3, SBP=1, PR=1 and Age < 73) Then P=90%
X21253	6) If (AIS =5, RR=1 and Age < 73) Then P=89%
X12143	7) If (AIS =4, SBP=1, RR=1 and Age < 73) Then P=88%
X12253 X12243	8) If (AIS =5, 4, RR=1 and Age < 73) Then P=88%
X12153 X22153	9) If (AIS =5, SBP=1, RR=1 and Age < 73) Then P=84%
X12152	10) If (AIS =5, GCS=2, SBP =1, RR=1 Age < 73) Then P=80%
X11143	11) If (AIS =4, SBP =1, PR =1, RR=1 and Age < 73) Then P=80%
X21153	12) If (AIS =5, SBP =1, PR =1 and Age < 73) Then P=78%
X22252	13) If (AIS =5, GCS =2, Age < 73) Then P=70%
X12252	14) If (AIS =5, GCS =2, RR =1 and Age < 73) Then P=66%

A number of scenarios were combined in Table 6-11 because of their associations and to reduce the number of rules.

The knowledge base coded as IF-THEN Statement for not survivors are provided in Table 6-12. These were derived from Table 6-8.

Table 6-12 IF-THEN rules for not survivors derived from the information provided in Table 6-8

Injury Scenarios Based on Table 6-8	If-Then Statement
X21151 X11151	1) If (AIS=5, GCS=1, SBP=1, PR=1, RR=1, Age >=73,PR=1 and Gender= female) Then P= -93% 2) If (AIS=5, GCS=1, SBP=1, PR=1, RR=1, Age >=73, PR=1 and Gender= male) Then P=-90%
X22151 X12151	3) If (AIS=5, GCS=1, SBP=1, PR=1 , Age >=73 and Gender= female) Then P=-70% 4) If (AIS=5, GCS=1, SBP=1, PR=1, , Age >=73 and Gender= male) Then P=-67%
X12251	5) If (AIS=5, GCS=1, PR=1, Age >=73 and Gender= female) P=-50% 6) If (AIS=5, GCS=1, PR =1, Age >=73 and Gender= male) P=-48%
X22152	7) If (AIS=5, GCS=2, SBP =1 , Age >=73 and Gender= female) Then P=-46% 8) If (AIS=5, GCS=2, SBP =1, Age >=73 and Gender= male) Then P=-44%
X11153	9) If (AIS=5, SBP=1, RR =1, PR=1, Age >=73 and Gender= female) Then P=-44% 10) If (AIS=5, SBP=1, RR =1, PR=1, Age >=73 and Gender= male) Then P=-42%
X22251	11) If (AIS=5, GCS=1 and Age >=73 and Gender= female) Then P=-39% 12) If (AIS=5, GCS=1 and Age >=73 and Gender= male) Then P=-36%
X21152	13) If (AIS=5, GCS=2, SBP=1, RR=1 and Age >=73 and Gender= female) Then PS%=-37 14) If (AIS=5, GCS=2, SBP=1, RR=1 and Age >=73 and Gender= male) Then PS%=-34

Secondly, knowledge coding associated with PMC and Intubation for integration of IRCC with FIS. Table 66-13 shows the knowledge coding associated with intubation and PMC. These were derived from Tables 6-9 and 6-10 and Figures 6-8 and 6-9.

Table 6-13 knowledge coding associated with intubation and PMC

No.	PMC	PMC If statement based on Table 6-9 and Fig 6-8	Intubation=yes If statement based on Table 6-10 and Fig 6-9	PMC and Intubation combining weights
1	Stroke/CVA/TIA	If AIS>=4, GCS<=12 and Age>=82 Then x=0.13	If AIS>=4, GCS<=6 and Age>=58 Then x= 0.677	If AIS>=4, GCS<=9 and Age>=70 then x= 0.805
2	Dementia	If AIS>=4, GCS<=12 and Age>=87 Then x=0.15		If AIS>=4, GCS<=9 and Age>=72 then x= 0.825
3	Diabetes mellitus (Type 2 / noninsulin dependent)	If AIS>=4 and Age>=80 Then x=0.12		If AIS>=4, GCS<=9 and Age>=69 then x= 0.795
4	COPD	If AIS>=4 and Age>=80 Then x=0.11		If AIS>=4, GCS<=9 and Age>=69 then x= 0.785

6.5 Integration of IRCC with FIS

Integration of IRCC with FIS required deciding on the type and number of membership functions and determining the extent of the overlap between them. These are explained in the next section.

6.5.1 FIS Development for incorporation to IRCC

The method developing the fuzzy inference system that accommodated the rules for PMC and intubation is explained in this section. This FIS was combined with the IRCC to improve the accuracy of predicting probability of survival.

Gaussian 2 membership function used to fuzzify the inputs and defuzzify the output. This type of membership function provided flexibility to represent the inputs and output. It is a smooth curve derived from two Gaussian membership functions (Zheng et al,. 2011).

To aggregate the rules, each rule was applied to the corresponding membership function and the minimum of the membership function was mapped into associated output membership function. The output fuzzy set from the implication process for each rule was combined together via the aggregation process to produce the output fuzzy set. The FIS output was obtained from the aggregation of the output fuzzy set using the centroid scheme. The centroid method returns the centre of area under the curve of the aggregated output values using equation (Al-Sbou et al, 2006) (6.1).

$$Y = \sum_{i=1}^{m} y_i \times \mu_i / \sum_{i=1}^{m} \mu_i \qquad 6\text{-}1$$

where m is the number of fuzzy sets obtained after implication, y_i is the centroid of fuzzy region *i*, and μ_i is the output membership value.

There were 5 membership functions for input to the FIS. These were labelled as categories 1-5. In order to determine the boundary between them, the IRCC results were plotted as shown in Figure 6-10. The boundaries were then decided by determining the maximum and minimum points on the plot. The membership functions are shown in Figure 6-11.

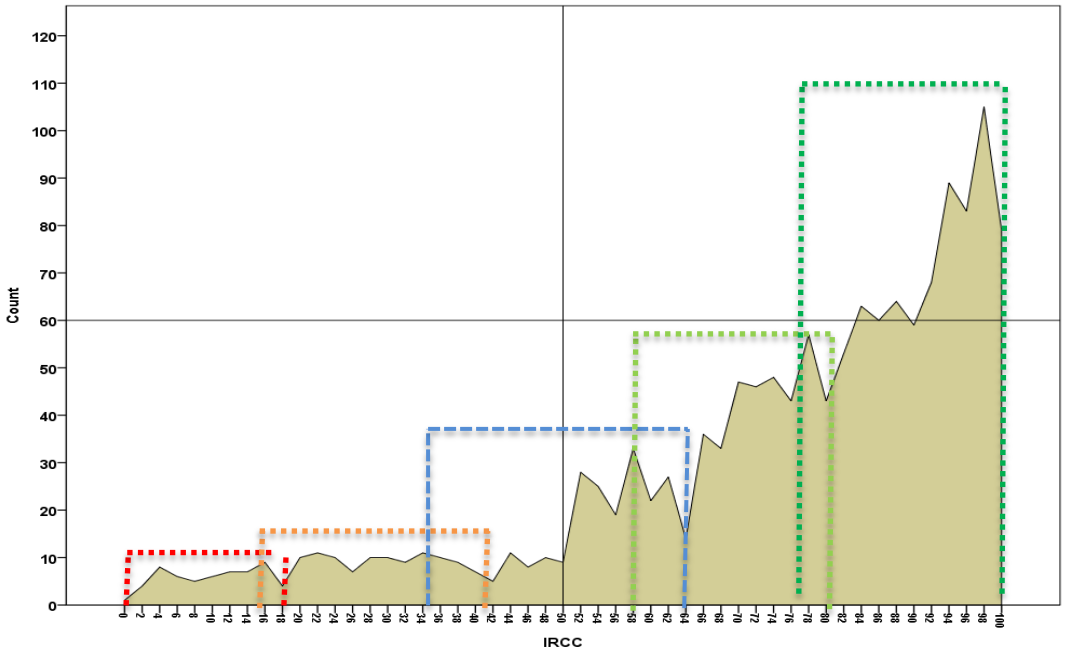


Figure 6-10 Demonstration of IRCC outcomes.

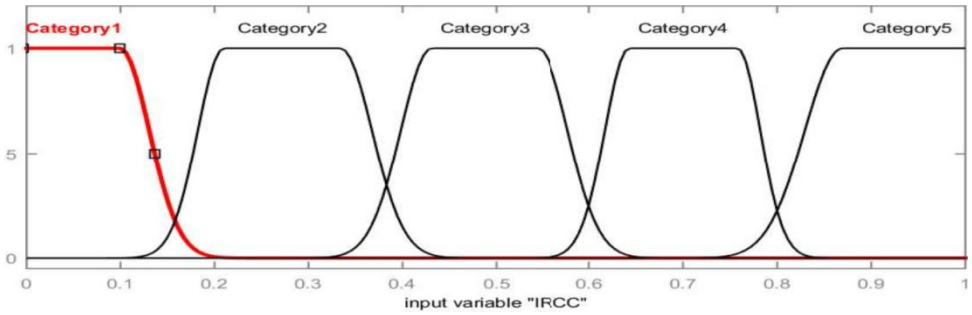


Figure 6-11 IRCC outcomes input membership functions.

Figure 6-12 shows input membership functions associated with intubation and PMC and intubation. They are 4 membership functions representing both PMC and intubation, intubation only, unspecified and PMC only based on Table 6-13. Unspecified refers to cases with related information were not available.

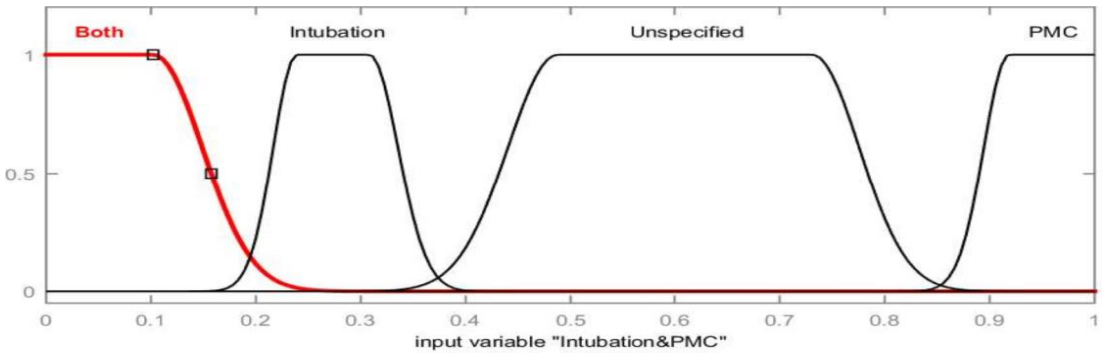


Figure 6-12 Membership functions for intubation and PMC.

Table 6-14 shows the approach used to integrate IRCC output with PMC and intubation to obtain the FIS output. This information was then used to obtain the associated FIS output membership functions shown in Figure 6-13.

Table 6-14: Setting up of the FIS rules for PMC and intubation for associated with IRCC output.

No	Rules to combine IRCC output with PMC and intubation	System output function				
		Level1	Level2	Level3	Level4	Level5
1	IRCC is Category1 & Contributing factors is Both	√				
2	IRCC is Category1 & Contributing factors is Intubation	√				
3	IRCC is Category1 & Contributing factors is PMC	√				
4	IRCC is Category 2 & Contributing factors is Both	√				
5	IRCC is Category 2 & Contributing factors is Intubation	√				
6	IRCC is Category 2& Contributing factors is PMC	√				
7	IRCC is Category 3 & Contributing factors is Both	√				
8	IRCC is Category 3 & Contributing factors is Intubation		√			
9	IRCC is Category 3 & Contributing factors is PMC		√			
10	IRCC is Category 4 & Contributing factors is Both	√				
11	IRCC is Category 4 & Contributing factors is Intubation		√			
12	IRCC is Category 4 & Contributing factors is PMC			√		
13	IRCC is Category 5 & Contributing factors is Both		√			
14	IRCC is Category 5& Contributing factors is Intubation			√		
15	IRCC is Category 5 & Contributing factors is PMC				√	

Figure 6-13 shows FIS output membership functions it has five levels based on Table 6.14.

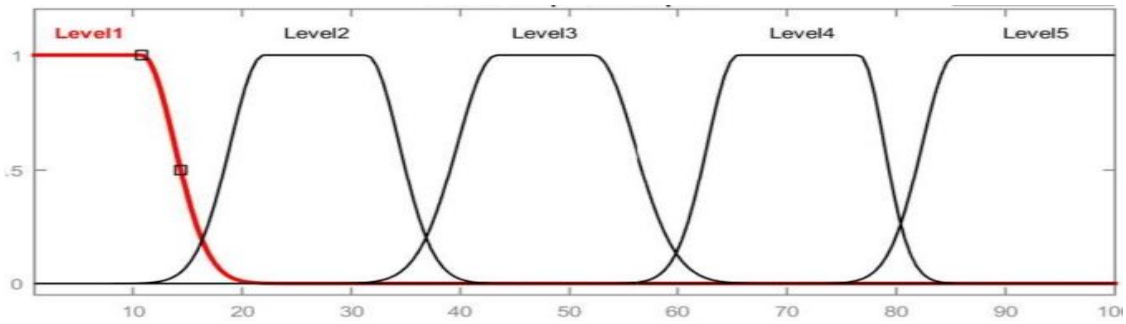


Figure 6-13 FIS output membership functions.

6.6 Chapter summary

Results of the analyzing the trauma parameters used as input to the models for predicting the probability of survival was provided in this chapter.

These results indicated that AIS, GCS, systolic blood pressure and age are particularly sensitive for differentiating between survivors and not survivors. The procedure for developing the FIS rules, the FIS membership functions and the manner the IRCC output was integrated with the FIS are also explained in this chapter.

Chapter 7 Probability of Survival Estimation Methods

7.1 Introduction

In this chapter the operations and the results for the three methods (PSD, IRCC and combing IRCC with FL) for determining probability of survival are explained and their merits and limitations are analyzed against the exiting Ps14 method. The study mainly evaluated the performance of the methods for determining the probability of survival in adult subjects with traumatic brain injuries as TBI represented most trauma cases. A number of other body regions were also included in the analyses but the numbers associated with them were much smaller. In this chapter two probabilities of survival models were developed. One was based on Bayesian statistics that accommodated PSD and the other was a novel approach called IRCC. There were 4124 TBI cases (age: mean = 67.9 years, standard deviation = 21.6 years). In total, 86.2% of cases were survivors and 13.8% of cases were not survivors. The parameters considered for input to PSD and IRCC were age, AIS, GCS, PR, SBP and RR. PSD was used as the statistical method while IRCC is an iterative method. These two models were calibrated on randomly selected, roughly 2/3 (number 2676), of the trauma cases and their performances were validated on the remaining cases (number 1448, i.e. validation dataset). The effectiveness of the two models in determining the probability of survival was compared with Ps14 method that uses regression operation to predict probability of survival Ps14 is the method developed by the Trauma and Research Audit Network. Fuzzy inference system was further adopted as part of IRCC to further improve its operation.

7.2 PSD Model

PSD required the prior probability for not survivors to be specified as part of its operation (prior probability for survival = 1- prior probability for not survival). To determine the most suitable value for this prior probability, prior probability values between 0 and 1 were experimented and for each value the percentage correct identifications for the survivors and not survivors for the calibration (training) dataset were determined. Figure 7-1 shows the plot of these results. The plots indicated that the highest identification accuracy was for prior

probability equal to 0.27 and this value was chosen for the rest of the analysis (only a section centered on 0.27 is shown in the figure).

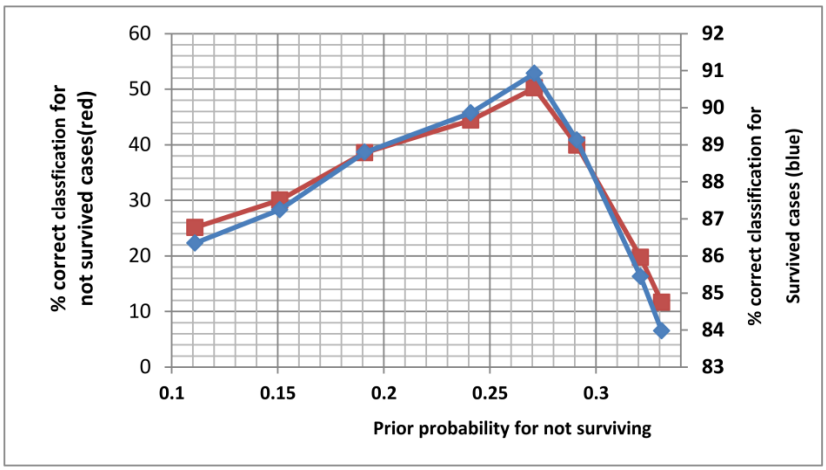


Figure 7-1 The relationship between the prior probability of not survivors and the associated percentage correct identification for the survivors (blue plot) and not survivors (red plot).

Figure 7-2 shows the interrelationships between pulse rate, systolic blood pressure, GCS, AIS, and respiration rate information for non-surviving cases included in the validation set. A large cluster of cases appears for AIS = 5, GCS = 1 (categorized as severe injury) and systolic pressure = 1 (categorized abnormal).

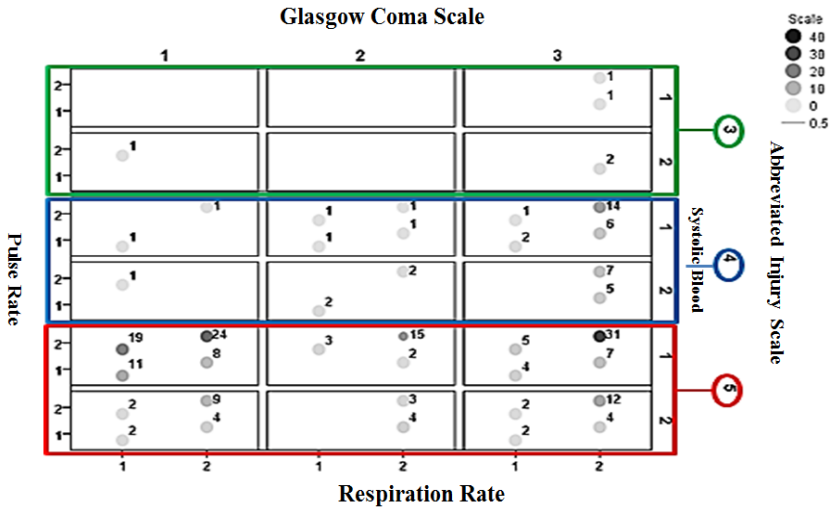
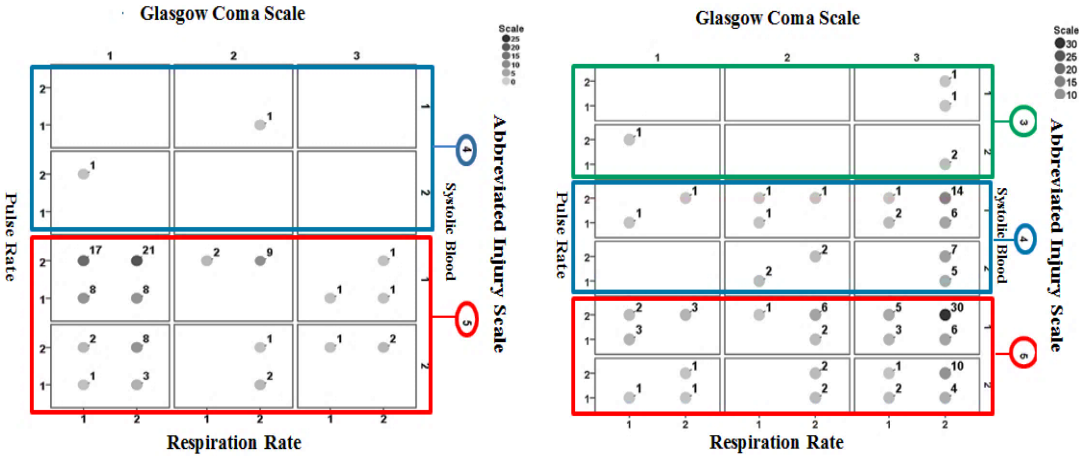


Figure 7-2 The interrelationships between injury parameters for non-surviving cases.

The values next to the circles indicate the number of associated cases. Larger values are highlighted by darker circles. Subjects are from the validation data set.

Figure 7-3 shows the identification results using Ps14 for not survivors included in the validation dataset. Figure 7.3a is for those correctly identified and Figure 7.3b is

for cases misidentified. A large proportion of correctly identified cases are associated with AIS = 5, GCS = 1 (categorized as severe injury) and a large proportion of misidentified cases are associated with AIS = 5 and 4, GCS = 3 (categorized as mild injury).



(a) (b)

Figure 7-3 Identification results for Ps14 for non-surviving cases in the validation dataset: (a) correctly identified cases (b) misidentified cases. The values next to the circles indicate the number of associated cases.

Figure 7-4 shows the identification results obtained using PSD for not survivors included in the validation dataset. Figure 7-4a is for those correctly identified and Figure 7-4b is for those misidentified. Results consistent to those from Ps14 are observed where a larger proportion of correctly identified cases are associated with AIS = 4 and 5, GCS = 1 and 2 (categorized as severe and moderate injury) and a large proportion of misidentified cases are associated with AIS = 5, GCS = 3 (categorized as mild injury).

Table 7.1 provides an analysis of injury patterns and performance of PSD and Ps14 in identifying non-surviving cases included validation dataset. An X in the last 5 columns of the table indicates the associated parameter is categorized as abnormal, serious injury (for AIS 3 to 5) or as severe injury (for GCS). The table shows that in some injury patterns Ps14 has performed better than PSD and vice versus. For example, the injury pattern resulting with the largest number of non-surviving cases (i.e., 31 cases, expressed as X22153) is associated with pulse rate = 2 (categorized as normal category), respiration rate = 2 (categorized as normal category), systolic blood pressure = 1 (categorized as abnormal category), AIS = 5 (critical) and GCS = 3 (categorized as mild injury). Only one of the associated

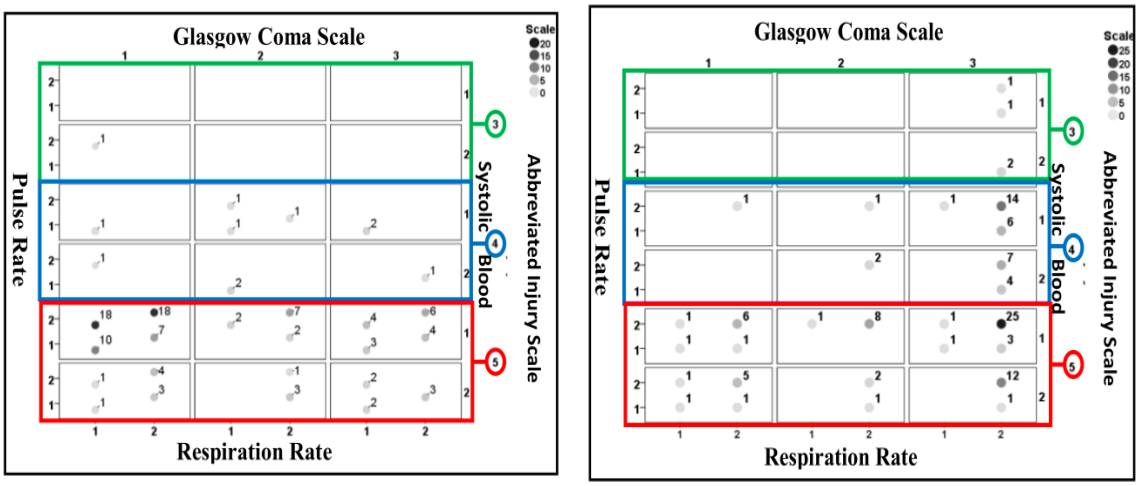
cases has been correctly identified by Ps14 however 6 were correctly identified by PSD. There were 24 cases associated with the injury pattern X22151. For this injury pattern pulse rate = 2 (categorized as normal category), respiration rate = 2 (categorized as normal category), systolic blood pressure = 1 (categorized as abnormal category), AIS = 5 (critical) and GCS = 1 (categorized as severe injury). Ps14 has performed better than PSD by correctly identifying from 21 out of 24 cases while PSD identified 18 cases correctly. For some injury patterns the identification accuracy for PSD and Ps14 was 0%. An example for this is injury pattern X22143. This is associated with pattern pulse rate = 2 (categorized as normal category), respiration rate = 2 (categorized as normal category), systolic blood pressure = 1 (categorized as abnormal category), AIS = 4, and GCS = 3 (categorized as mild injury). The reason why PSD and Ps14 performance differ or in some injury patterns they fail to identify the outcome correctly requires further investigation.

Table 7.2 compares the results obtained using PSD and Ps14 to determine the probability of survival in cases included in the validation dataset. The inputs to PSD were AIS, GCS, age, systolic blood pressure, respiration rate and pulse rate. Ps14 correctly identified 97.4% of survivors and 40.2% of the not survivors. However PSD correctly identified 90.8% of the survivors and 50.0% of not survivors. These results indicate the main difference between the two methods relates to their abilities to identify the not survivors.

Figures 7-5 a, b provide a further analysis of the results in Table 7-2. The figures indicate the number of survivors and not -survivors correctly identified by Ps14 and PSD and the overlap in the number of cases correctly identified by both methods.

The results in Table 7-2 are taken further by considering the effect of age on the performance of PSD and Ps14. The cases included in the validation that did not survive were divided into two groups (i) those aged between 17 years and 65 years and (ii) those aged above 65 years. Age 65 was considered as the boundary as criteria for immediate CT scan of the head in adults with traumatic brain injury include age more than 65 years and some loss of consciousness or amnesia since the injury (Moppett 2007). In the Canadian CT Head-Rules traumatic head injury patients aged 65 are classed as high risk that warrant a CT of the head (Janich et al., 2016). The results obtained are shown in Table 7-3. PSD has higher identification accuracy for both age groups as compared with Ps14. Comparing the

identification results for the two age groups; the performance of both models is influenced by the considered age ranges. Ps14 has been more accurate for cases aged above 65 years than those between 17–65 years. PSD on the other hand has been much more accurate for cases aged 17–65 years as compared with those aged over 65 years.



(a) (b)

Figure7-4. Identification results for PSD for not survivors included in the validation dataset. (a) Correctly identified cases (b) misidentified cases. The values next to the circles indicate the number of associated cases.

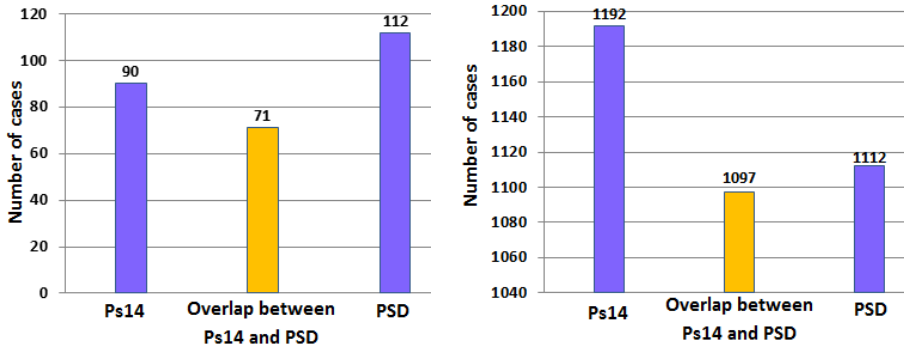
Table 7-1 Analysis of injury patterns for not survivors included in the validation set (the patterns with relatively small number of cases are not shown). An x in the trauma parameter columns indicates abnormal or severe categorization for the related parameter.

Injury Scenarios	Number of Cases That Did Not Survive (Figure 7-2)	Number of Cases Correctly Identified by Ps14 (Figure 7-3a)	Number of Cases Correctly Identified by PSD (Figure 7-4a)	Trauma Parameter				
				PR	RR	SBP	AIS	GCS
X22153	31	1 (3.2%)	6 (19.4%)			x	x	
X22151	24	21 (87.5%)	18 (75.0%)			x	x	x
X21151	19	17 (89.5%)	18 (94.7%)			x	x	x
X22152	15	9 (60.0%)	7 (46.7%)			x	x	x
X22143	14	0 (0.0%)	0 (0.0%)			x	x	
X22253	12	2 (16.7%)	0 (0.0%)				x	
X11151	11	8 (72.7%)	10 (90.9%)	x	x	x	x	x
X22251	9	8 (88.9%)	4 (44.4%)	x			x	
X12151	8	8 (100.0%)	7 (87.5%)			x	x	x
X21243	7	0 (0.0%)	0 (0.0%)	x			x	
X12153	7	1 (14.3%)	4 (57.1%)	x		x	x	
X12143	6	0 (0.0%)	0 (0.0%)	x		x	x	
X12243	5	0 (0.0%)	1 (20.0%)	x			x	
X21153	5	0 (0.0%)	4 (80.0%)		x	x	x	
X11153	4	1 (25.0%)	3 (75.0%)	x	x	x	x	
X12251	4	3 (75.0%)	3 (75.0%)	x			x	x
X12252	4	2 (50.0%)	3 (75.0%)	x			x	x
X12253	4	0 (0.0%)	3 (75.0%)	x			x	

7.2.1 Results and Discussion of Ps14 Method and PSD Model

Table 7-2: Comparison of PSD and Ps14 to predict probability of survival for cases in the validation set (when probability value was greater than or equal to 0.5, the subject was classed as surviving and when probability value was less than 0.5, the subject was classed as not surviving).

Number of Cases		Ps14		PSD	
Survived	Did not survive	Survived	Did not survive	Survived	Did not survive
1224	224	1192 (97.4%)	90 (40.2%)	1112 (90.8%)	112 (50.0%)



(a) (b)

Figure7-5 The number of cases in the validation set correctly identified by Ps14 and PSD (a) non-surviving cases; (b) surviving cases. The middle bar indicates the overlap in correct identification of cases by both Ps14 and PSD.

Table 7-3 Performance comparison of PSD and Ps14 based on age groups for not surviving cases in the validation dataset.

Total Number of TBI Cases Based on Age Range		Ps14 Prediction Accuracy				PSD Prediction Accuracy			
Age (Years)	Age (Years)	Identified Correctly		Misidentified		Identified Correctly		Misidentified	
17–65	≥66	17–65	≥66	17–65	≥66	17–65	≥66	17–65	≥66
26	198	6	83	20	115	21	89	5	109
		(26.0%)	(41.9%)	(76.2%)	(58.0%)	(80.7%)	(44.9%)	(19.3%)	(55.0%)

In order to explore the effects of respiration rate, systolic blood pressure and pulse rate on the accuracy of PSD in identifying the cases included in the validation set, each parameter was separately excluded and PSD identification accuracy was determined. The results are summarized in Table 7-4. The use of GCS and AIS on their own sharply reduced the effectiveness of PSD, resulting in 55.1% and 31.3% correct identification of the survivors and not survivors respectively. Inclusion of the age with AIS and GCS significantly improved the PSD performance resulting in 82.4% and 65.2% correct identification for the survivors and not survivors respectively. The inclusion of systolic blood pressure with age, AIS and GCS

resulted in 83.3% and 64.3% correct identification of survivors and not survivors respectively (Saleh et al., 2018).

Table 7-4 Illustration of the effect of age, PR, SBP and RR on PSD performance in identifying surviving and not-surviving cases included in the validation set.

Number of Cases in the Validation Set		Correct PSD Identification Using AIS and GCS Only		Correct PSD Identification Using AIS and GCS with Age Only		Correct PSD Identification Using AIS, GCS, Age and SBP		Correct PSD Identification Using AIS, GCS, PR, SBP, RR and Age	
Survived	Did not survive	Survived	Did not survive	Survived	Did not survive	Survived	Did not survive	Survived	Did not survive
1224	224	675 (55.1%)	70 (31.3%)	1008 (82.4%)	146 (65.2%)	1019 (83.3%)	144 (64.3%)	1112 (90.8%)	112 (50.0%)

The study evaluated the performance of PSD in determining the probability of survival in adult subjects with TBI. It highlighted some complexities in determining the probability of survival. An issue is related to the interrelationships of injury parameters and other factors such as age, pre-existing medical conditions that can influence the probability of survival (Saleh et al., 2017). AIS, GCS, age, respiration rate, pulse rate and systolic blood pressure play an important role in determining the probability of survival in TBI cases.

7.3 IRCC Model

IRCC is an iterative classification method developed to predict probability of survival. The calibration and evaluation of this model were based on the same data used for PSD and Ps14. This allowed the performance of models to be compared. About 2/3 (number 2676) randomly selected cases were used for calibration and is the remaining 1/3 (number 1448) of the cases were used for evaluation of the method. The trauma parameters used as input to the IRCC were mapped from their original ranges to a range of 0 and 1 by using

$$normaised\ value = \frac{actual\ value - Minimum\ of\ the\ values}{Maximum\ of\ values - \min imum\ of\ values} \qquad 7\text{-}1$$

In order to determine the optimum number of iterations and group size, these two parameters were varied and the prediction outcome for the calibration data set was determined. The results are plotted in Figure 7-6. This indicated that 50 iterations with group size of 6 provided highest predication accuracy and were selected for the remaining analysis.

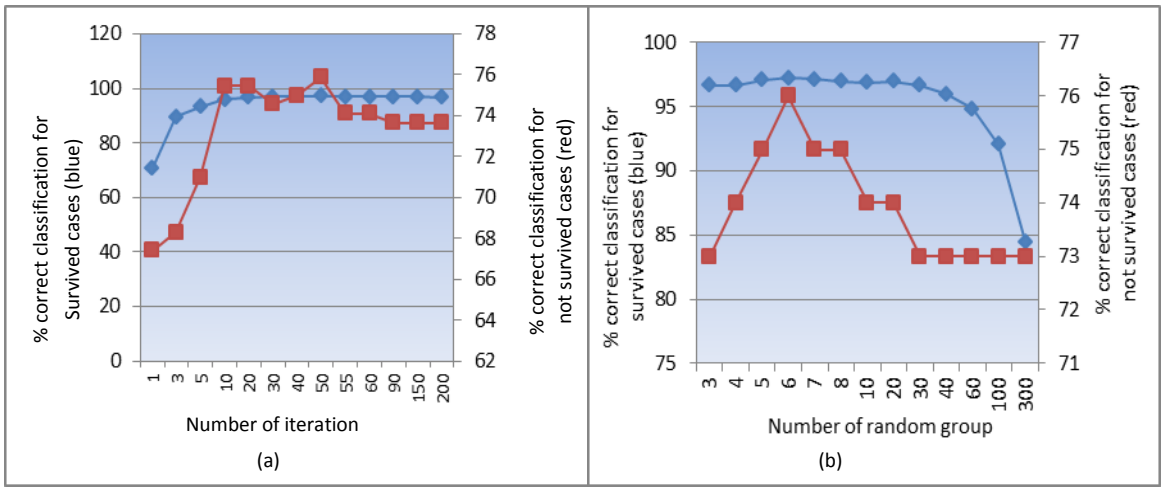


Figure 7-6 The number of IRCC iteration (a) for surviving and non-surviving cases; (b) number of random groups.

Figure 7-7 shows the interrelationship between GCS, AIS, PR and RR for not survivors. In the following sections the performance of IRCC for determining the probability of survival for TBI based on the validation set is described. Figure 7-8a and b show the IRCC prediction results for not survivors correctly identified and misidentified respectively. Not survivors are included in the analysis as the investigations from previous sections indicated that they are harder to identify as compared to the survivors.

A large proportion of correctly identified cases are associated with AIS = 5, GCS = 1, 2 and 3 (categorized as severe, moderate and mild injury) and a large proportion of misidentified cases are associated with AIS = 4, GCS = 3 (categorized as mild injury).

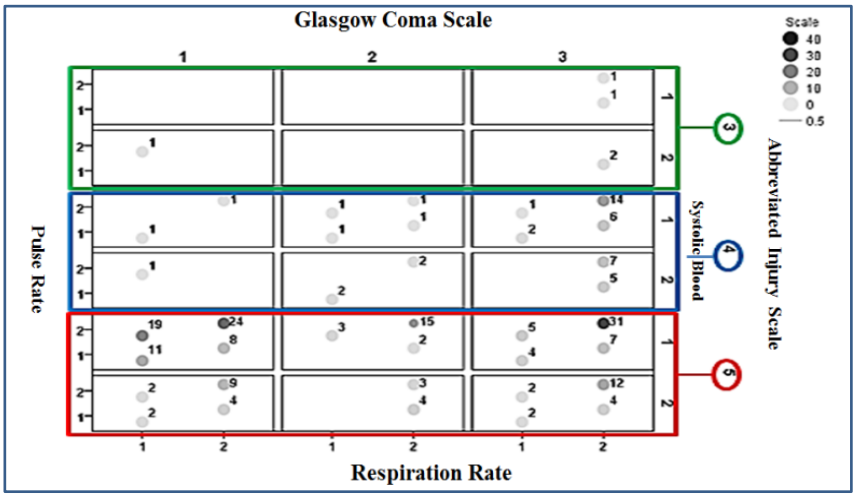


Figure 7-7 The interrelationships between pulse rate, systolic blood pressure, GCS, AIS, and respiration rate information for not survivors.

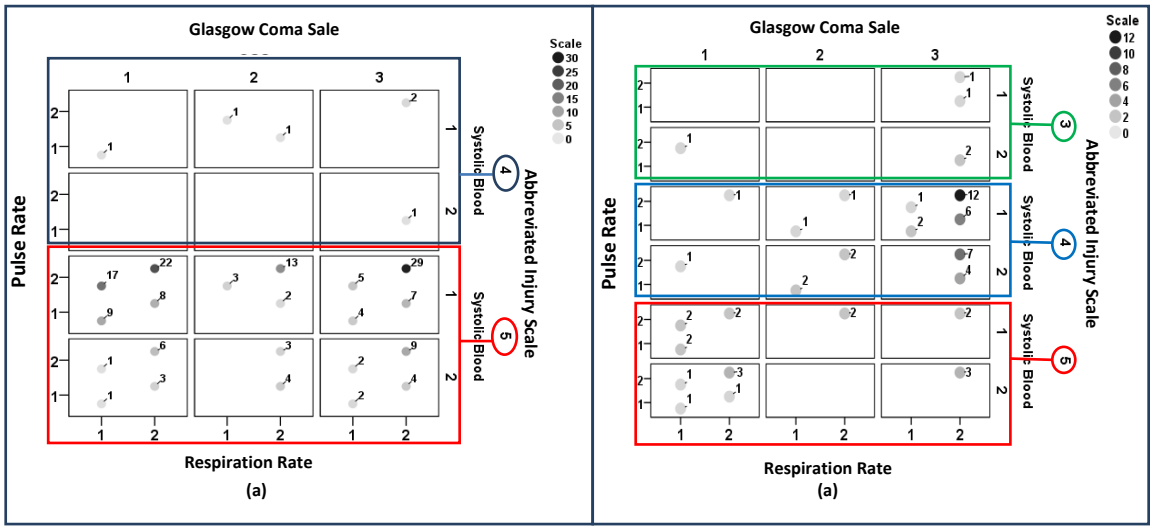


Figure 7-8 Prediction results for IRCC for not survivors cases: (a) correctly identified (b) misidentified

Table 7-5 Shows relates the IRCC not survivors classification results from Figures 7-8a and b to the trauma scenarios.

Table 7-5 Analysis of IRCC classification for injury patterns for TBI non-surviving cases included in the validation set (the patterns with relatively small number of cases are not shown). An x in the trauma parameter columns indicates abnormal or severe categorization for the related parameter.

No.	Injury Scenarios	Number of not survivors (Figure 7.7)	Number of not survivors identified correctly (Figure 7.8a)	Number of not survivors misidentified (Figure 7.8b)	Trauma Parameter				
					PR	RR	SBP	AIS	GCS
1	X22153	31	29 (93.5%)	2 (6.4%)			x	x	
2	X22151	24	22 (91.6%)	2 (8.3%)			x	x	x
3	X21151	19	17(89.4%)	2 (10.6%)		x	x	x	x
4	X22152	15	13 (86.6%)	2(13.3%)			x	x	x
6	X22143	14	2 (14.3%)	8 (85.7%)			x	x	
7	X22253	12	9(75.0%)	3 (25.0%)				x	
8	X11151	11	9(81.8%)	2(18.2%)	x	x	x	x	x
9	X22251	9	6 (66.6%)	3 (33.3%)				x	x
10	X12151	8	8(100.0%)	0(00.0%)	x		x	x	x
11	X12153	7	7(100.0%)	0 (0.0%)	x		x	x	
12	X22243	7	0 (00.0%)	7 (100.0%)				x	
13	X12143	6	6 (100.0%)	0 (00.0%)	x		x	x	
14	X12243	5	1 (20.0%)	4 (80.0%)	x			x	
15	X21153	5	5(100.0%)	0 (00.0%)		x	x	x	
16	X12253	4	4 (100.0%)	0 (00.0%)	x			x	
17	X12252	4	4(100.0%)	0(00.0%)	x			x	x
18	X11153	4	4(100.0%)	0(00.0%)	x	x	x	x	
19	X12251	4	3(75.0%)	1(25.0%)	x			x	x

In Table 7-5 the rows identified as pink colour are associated with the three highest misclassified scenarios. The table shows that those scenarios are associated with AIS = 4 (severe) and GCS =3 (categorized as mild injury). However, IRCC has performed better when AIS=5 (critical) and GCS = 1, 2 (categorized as severe or moderate injury) or systolic blood pressure = 1 (categorized as abnormal category). For instance, the injury pattern resulting with the largest number of those who were classified correctly for non-surviving cases (i.e., 29 cases, expressed as X22153) is associated with systolic blood pressure = 1 (categorized as abnormal category) and AIS = 5 (critical).

7.3.1 Results of Ps14 Method and IRCC Model

Table 7-6 provides the IRCC results and IRCC uses enhancement IRCC operation part and a comparison with Ps14. When the probability value was greater than or equal to 50%, the subject was classed as survivors and when probability value was less than 50%, the subject was classed as not survivors

Table 7-6 IRCC results combined with the enhancement IRCC operation part and a comparison with Ps14.

Number of Cases		**Ps14**		**IRCC without enhancement IRCC operation part**		**IRCC**	
Survived	**Did not survive**	**Survived**	**Did not survive**	**Survived**	**Did not survive**	**Survived**	**Did not survive**
1224	224	1192 (97.4%)	90 (40.2%)	967 (79. 0%)	160 (71.4%)	1190 (97. 2%)	170 (75.9%)

The probability of survival prediction accuracy for IRCC is higher than Ps14 for not survivors and lower nor survivors. However, after integrating enhancement IRCC operation as part of IRCC, its performance for survivors improved from 71.4% to 75.9%, in order to investigate the consistency of the results, different random validations cases from the same dataset were chosen. The results are included in Table 7-7. For all cases IRCC with enhancement IRCC operation part performed better than IRCC on its own.

Table 7-7 Performance of IRCC based on different random validation cases from the same data set.

Validation set	All TBI cases		IRCC	
	Survived	Did not survive	Survived	Did not survive
a	1224	224	1190 (97. 2%)	170 (75.9%)
b	1289	194	1249 (96.8%)	146 (74.7%)
c	1255	192	1206 (96.1%)	151 (78.6%)

7.3.2 Discussion and Comparison of Ps14 and IRCC Outcomes.

In this section the performance of IRCC in comparison with Ps14 is investigated in more detail. The prediction threshold is 0.5 (or 50%) i.e. if probability is greater 0.5 (50%) the individual is considered as survivor otherwise not survivor. Figures 7-9a and 7-9b show both methods have similarities in the manner they predict probability of survival for survivors (green peaks) but for not survivors they have distinct performance (blue peaks). Ps14 correct prediction relates to number of cases between 88% and 100% while for IRCC this is between 50% and 100%. The plot shows greater number of correct prediction by IRCC as compared with Ps14.

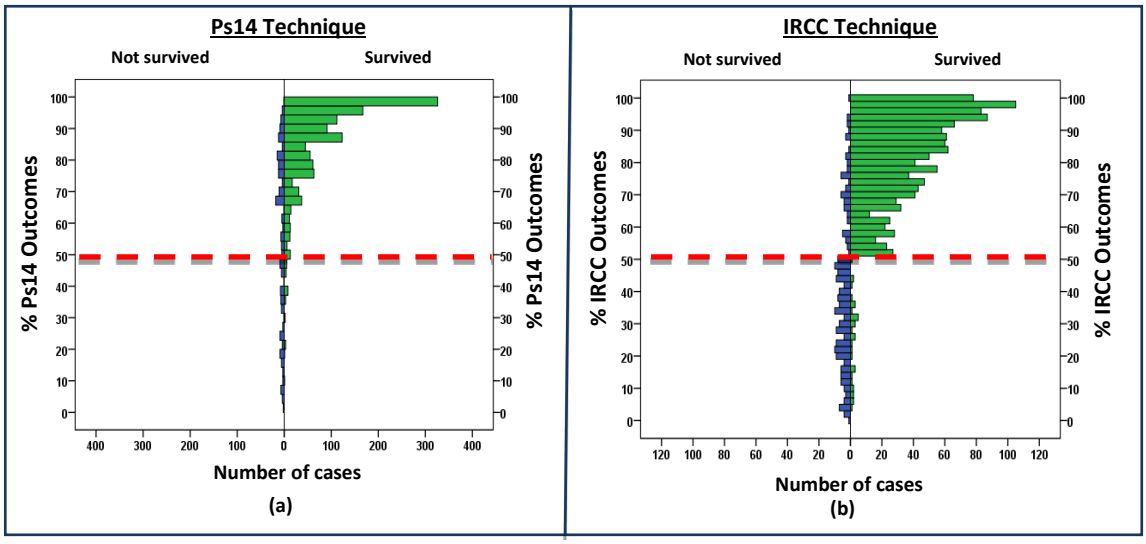


Figure 7-9 The distribution for IRCC and Ps14 results (a) Ps14 and (b) IRCC. The red line is the boundary for survivors and not survivors considered as 50%.

Figure 7-10 provides the Bland-Altman plot with horizontal axis as the mean prediction from Ps14 and IRCC and vertical axis is the difference of their outcomes for survivors and not survivors. The red and green lines represent the region of agreement. Green line is the mean difference plus 1.96 standard deviation and red line is mean difference minus -1.96 standard deviation. Most

results for the two methods are with this boundary. Blue line is mean difference (value= 7.50) of two techniques.

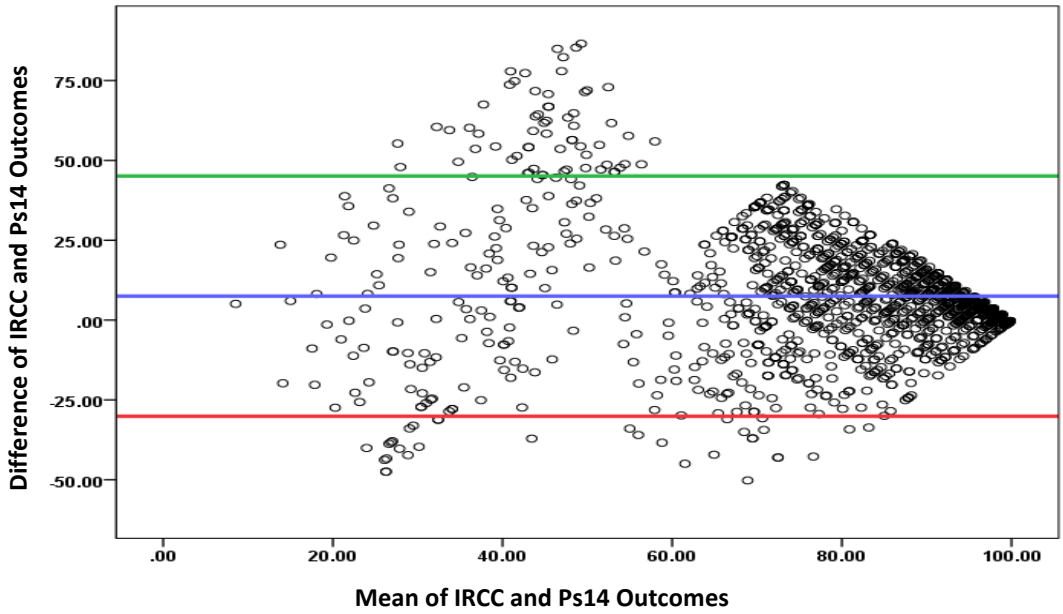


Figure 7-10 Bland Altman plot for IRCC and Ps14 outcomes for survivors and not survivors.

Figure 7-10 shows the concentration of differences is between -27 and 47. This range is the most significant in predicting probability of survival and will be explored further in the following sections.

Figure 7-11(a-b) show regression plots to compare IRCC and Ps14 results. This plot shows the extent of probability of survival agreement between IRCC and Ps14. The two methods had closer agreement with regard to the survivors than not survivors. The blue lines in Figure 7-11 (b) is median of two methods for not -survivors. The median for IRCC is 42 and for Ps14 is 62. Interquartile range of IRCC is between 25 and 56 whereas for Ps14 is from 36 to 80. These indicate that a larger number of not survivors were predicted by IRCC as compared to Ps14 and therefore IRCC performed better than Ps14 for not survivors.

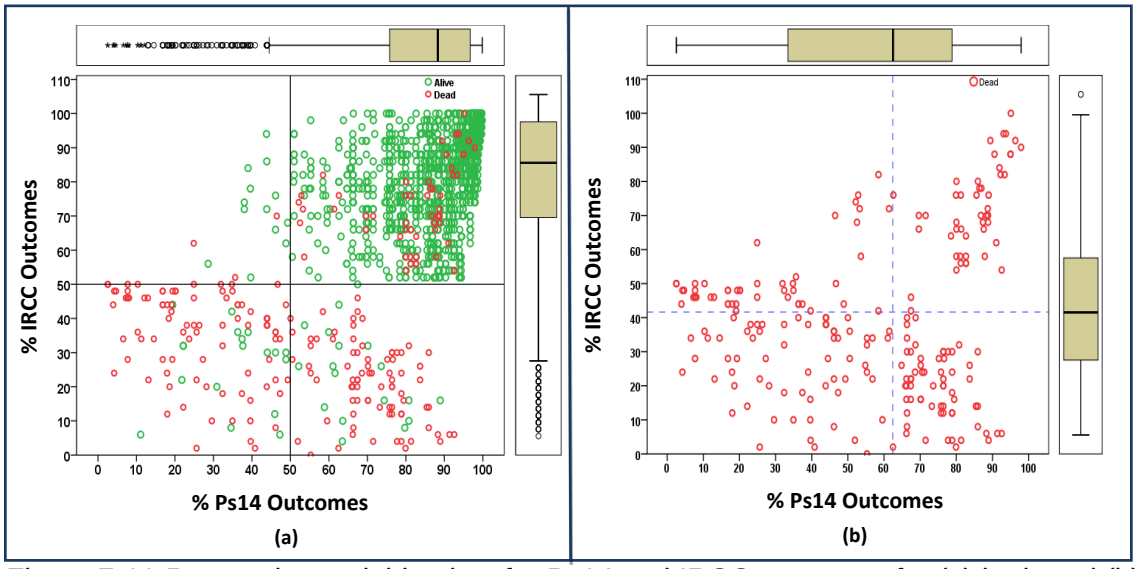


Figure 7-11 Regression variable plots for Ps14 and IRCC outcomes for (a) both and (b) not survived cases (green circles are survival cases and red those are not) considered as 50%.

Association of AIS and prediction accuracy for Ps14 and IRCC for not survivors is provided in Figures 7-12 (a) 7-12(b) respectively. It can be seen that there is a significant difference between two techniques when AIS=2 or 3 they are not significantly different for AIS equal to 4 and 5. The incorrect prediction by Ps14 is mainly associated with AIS scores 4 and 5 whereas IRCC showed a significantly larger number of correct prediction for these two scores for not survivors.

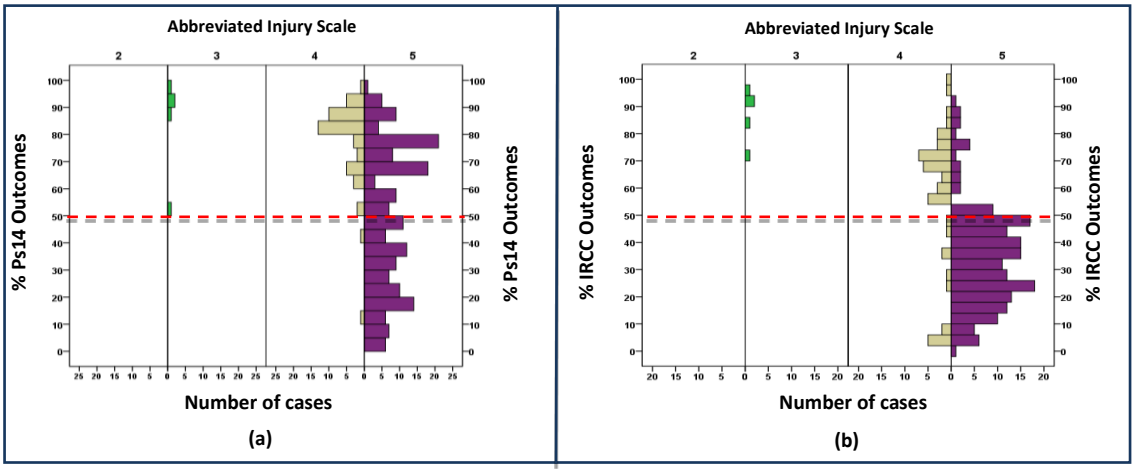


Figure 7-12 Association of AIS and prediction accuracy for (a) Ps14 and (b) IRCC for not survivors considered as 50% (burble columns are number of cases with AIS=5(critical) and brown those are AIS=4).

Figure 7-13(a-b) Shows a number of not survivors that had GCS= 2 and 3 (categorized as moderate and mild trauma) were identified as survivors while IRCC had higher identification accuracy for both scores as compared with Ps14.

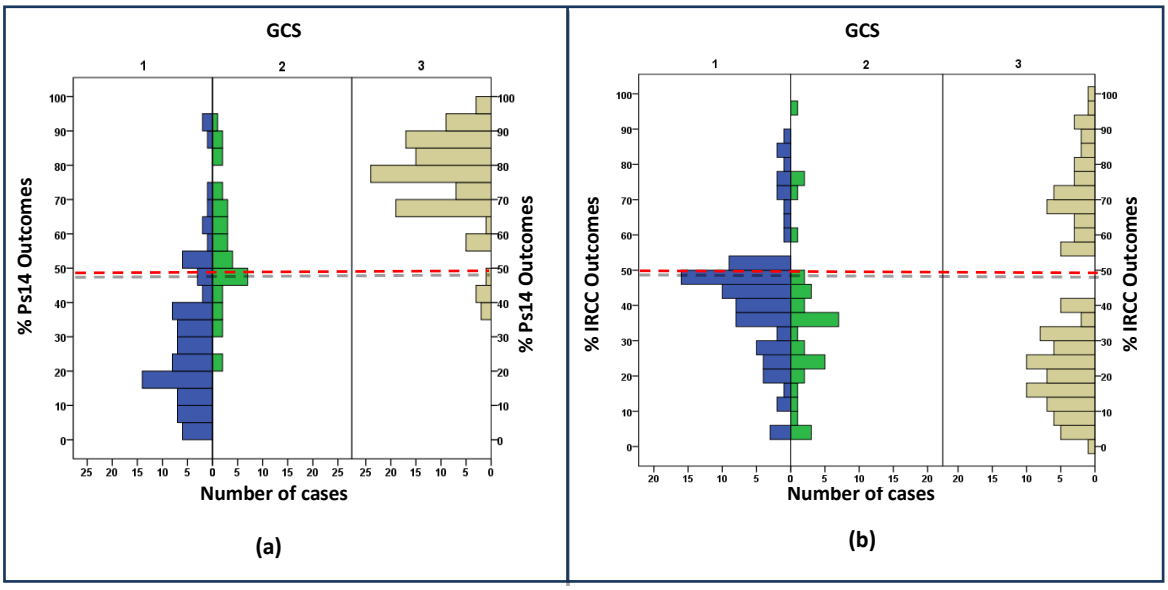


Figure 7-13 Association of GCS and prediction accuracy for (a) Ps14 and (b) IRCC for not survivors considered as 50%. (blue columns are number of cases with GCS=1(severe), green those are GCS=2 (moderate) and yellow those are GCS=3(mild).

Figure 7-14 shows the manner age relates to the survival probability prediction for not survivors obtained using the IRCC and Ps14. It indicates that larger number not survivors correctly identified by the IRCC (triangles) as compared with Ps14 (stars) as they appear under the 0.5 threshold (50%). of triangle shapes are classified correctly < 50 by IRCC technique. Ps14 was especially less sensitive for cases aged 73 years or older.

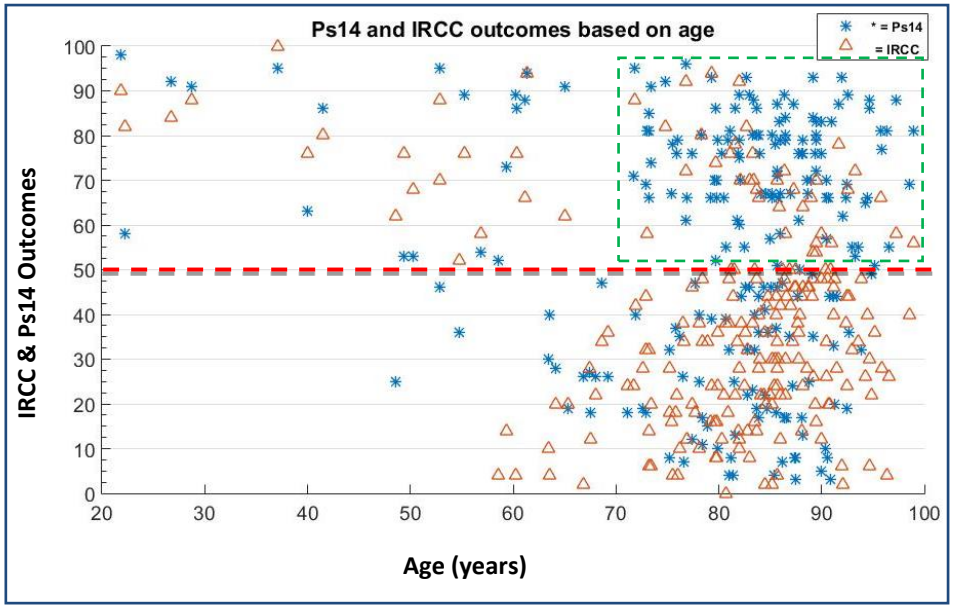


Figure 7-14 Association of age with probability of survival prediction for IRCC and Ps14 for not survivors. Stars represent Ps14 and triangles represent IRCC. Threshold for decision is 0.5 (50%), i.e. when probability less than 0.5 (50), case is recognised as not survivor.

In summary, Ps14 was not as accurate in predicting the probability of survival when AIS=4 or 5 and GCS=2 or 3. It was also less accurate for cases who aged more than 73. IRCC was overall more accurate than Ps14. Therefore IRCC was chosen for further developments in this study.

7.3.3 Comparison of Probability of Survival Predication Capability of Ps14, IRCC and PSD by Considering Different Body Regions

Table 7-8 provides a summary of a comparison of Ps14, IRCC and PSD for predicting probability of survival for trauma associated with different body regions. The data used are the validation set. When the method's output was larger or equal to 50% threshold (corresponding to probability = 0.5), the individual was considered as survivor otherwise as not survivor. The traumas are for head injury only, head and face, head and chest and head and head chest and face. Considering the overall accuracy of probability of survival for not survivors, IRCC performed better than Ps14 and PSD. In Table 7-8, the green rows represent body region injuries other than the head, i.e. the first row is for TBI. For TBI IRCC with knowledge code was used (as discussed in Chapter 6). However, for other injuries (highlighted green in the table), IRCC without knowledge coding was used. For other body regions, prediction for not survivors remain better

than PSD and Ps14. However, for survivors its predication accuracy is lower as it did not accommodate knowledge coding. The accommodation of knowledge coding is left for further work.

Table 7-8 provides a summary of a comparison of Ps14, IRCC and PSD for predicting probability of survival for trauma associated with different body regions.

Body Regions	All subjects		Ps14		PSD		IRCC	
	Survivor	not survivor	Survivor	Not survivor	Survivor	Not Survivor	Survivor	Not Survivor
Head injury only	1224	224	1192 (97.3%)	90 (40.1%)	1112 (90.8%)	112 (50.0%)	1190 (97. 2%)	170 (75.9%)
Head & Face injury	992	118	945 (95.26%)	50 (42.37%)	913 (92.03%)	55 (46.26%)	900 (90.7%)	93 (78.8%)
Head & Chest injury	375	74	350 (93.33%)	46 (62.16%)	331 (88.26%)	50 (75.56%)	315 (84.0%)	57 (77.0%)
Head & Face & Chest Injury	112	17	96 (85.71%)	9 (52.96%)	103 (91.71%)	13 (76.47%)	95 (84.8%)	16 (94.1%)

7.4 Development of a User Interface for Probability of Survival Predication

In this section a user interface to allow clinicians enter the trauma information is developed. This is linked to IRCC combined with FIS to determine the probability of survival.

7.4.1 Development of Trauma Scoring System Interface

The purpose of this interface is to allow clinician indicate the trauma and based on the information AIS code is produced. Due to copyright nature of AIS, this interface is not fully developed and only a basic prototype for demonstration resulted from the work. The interface will not be taken further and will not in any way medically or otherwise deployed without prior consultation and agreement from the authorities responsible for AIS. Figure 7-15 shows a typical AIS menu list from this interface that indicates selected traumas and associated AIS code.

	Specific Anatomic Structure	AIS Code	AIS Scale
2	**Injuries to the Face** NFS	200099	9
3	- Died of facial injury without further substantiation of injurie	200999	9
4	Penetrating injury NFS	216000	1
5	minor; superficial	216002	1
6	with tissue loss >25cm^2	216004	2
7	with blood loss >20% by volume	216006	3
8	massive destruction of whole face including both eyes	216008	4
9	**Skin/subcutaneous/muscle** NFS	210099	1
10	- abrasion	210202	1
11	- contusion; hematoma	210402	1
12	- laceration NFS	210600	1

Figure 7-15 A section of AIS injury description and associated codes based on AAAM dictionary.

Figure 7-16 shows the actual user interface. Help feature is included to allow clinician query about trauma types.

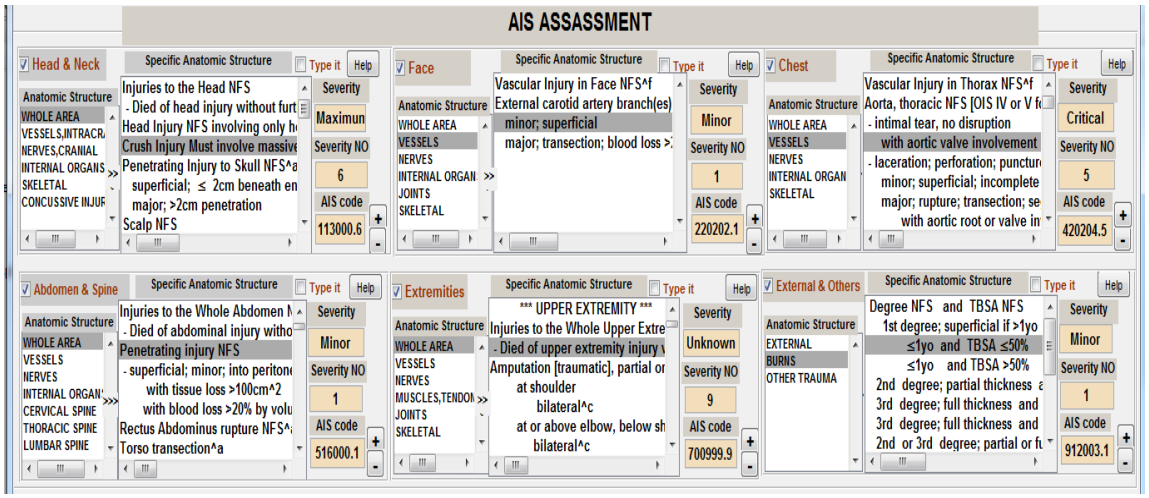


Figure 7-16 Graphic user interface.

Figure 7-17 shows an example of the manner the interface can be used.

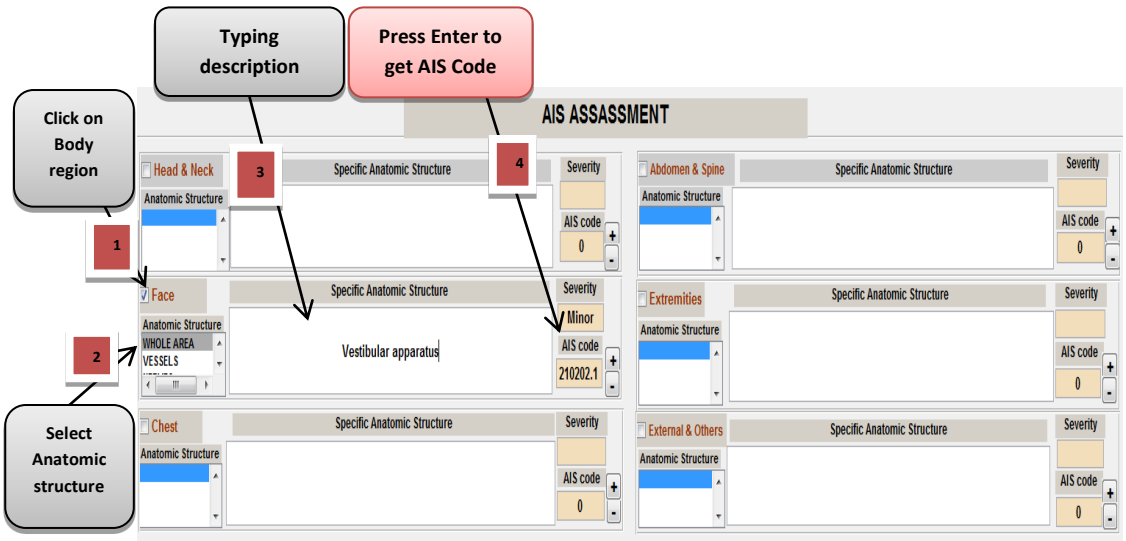


Figure 7-17 Interface to generate AIS code

In Figure 7-18 the user interface is linked to probability of survival method of IRCC incorporating FIS. The user interface allows the injuries to be selected and the probability of survival is then indicated. The user interface has a feature that allows the data to be saved for later study.

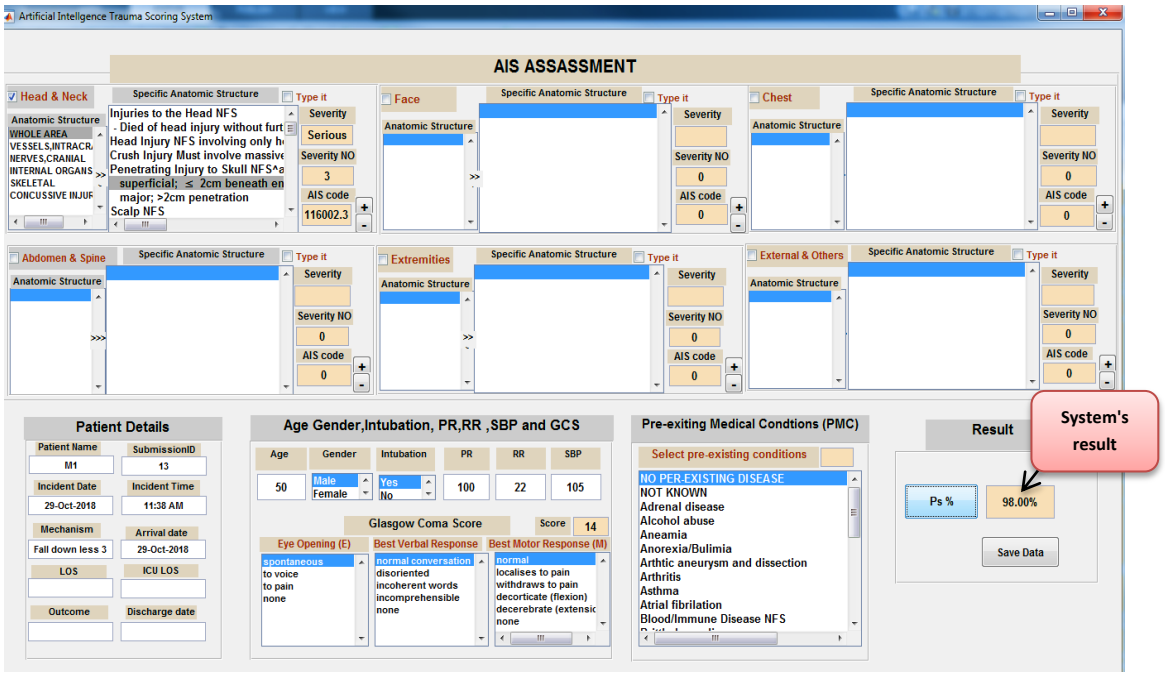


Figure 7-18 Determining probability of survival (Ps) Interface.

Figure 7-19 shows samples of TBI trauma cases and the determined probability of survival obtained using the method obtained using either with IRCC on its own or IRCC with FIS. The figure indicates the patient ID, his/her age, Gender, AIS code, GCS, PR, RR, SBP, Intubation, PMC and %Ps. Green highlighted rows are associated with IRCC with FIS and the remaining cases are for IRCC on its own.

Artificial Intellegece System to Predict Trauma Outcomes

				AIS Body Region Severity Code														
Patient Name	SubmissionID	Age	Sex	Head	Neck	Face	Chest	Abdomen	Spine	Extremities	External	Others	GCS	PR	RR	SBP	Intubation	PMC	% Ps
Subject_1	41970	79	Female	116004.5	0	0	0	0	0	0	0	0	15	98	17	183	0	0	42.50%
Subject_2	15438	56	Male	161008.4	0	0	0	0	0	0	0	0	15	61	17	156	0	0	94.00%
Subject_3	4117	56	Male	140683.5	0	0	0	0	0	0	0	0	13	102	15	160	0	0	84.20%
Subject_4	20057	41	Male	150202.3	0	0	0	0	0	0	0	0	13	89	17	129	1	0	98.30%
Subject_5	31986	68	Male	120402.5	0	0	0	0	0	0	0	0	3	58	10	194	1	0	22.78%
Subject_6	49136	92	Male	120205.4	0	0	0	0	0	0	0	0	14	148	24	132	0	Stroke/CVA/TIA	56.00%
Subject_7	2893	90	Male	120406.5	0	0	0	0	0	0	0	0	3	100	28	180	0	COPD	8.00%
Subject_8	48844	82	Female	140204.5	0	0	0	0	0	0	0	0	14	117	17	121	1	Stroke/CVA/TIA	42.00%
Subject_9	6472	89	Male	121005.5	0	0	0	0	0	0	0	0	9	90	18	199	1	Stroke/CVA/TIA	10.00%

Figure 7-19 Examples cases for related TBI and determined probability of survival. For the head injury, GCS, PR, RR, SBP, intubation and PMC status (1=exist, 0=does not exist)

7.6 Chapter summary

In this chapter, the results obtained using PSD and IRCC models for predicting probability of survival are explained. A prototype interface for demonstration was also provided. The results indicate that IRCC can determine the probability of survival more accurately compared PSD and PS14.

Chapter 8 Conclusions and Further work

8.1 Conclusions

Based upon the findings from the review of trauma scoring systems and a description of the various techniques adopted in this research as presented in Chapters two and three respectively; the detailed methodological framework described in Chapter four; the investigation of interrelation between trauma parameters and survival outcomes presented in Chapter five; trauma knowledge representation and coding presented in Chapter six; and the rigorous analysis of the probability of survival estimation methods presented in Chapter seven, the summary of conclusions and key findings from the numerous analysis carried out during the course of the activities which stems from this research are presented in this chapter. Also presented in this chapter are a summary of the original contributions to knowledge made by this work to research and scholarship, the limitation of the research and an outline of possible future extension of the current research.

To reiterate, the primary aim of this research is to develop and evaluate improved methods of determining probability of survival in traumas. Specific objectives include (i) a detailed analysis of the trauma cases from the available TARN database with the view to ascertain the interrelationships between a number of trauma parameters including age, gender, respiration rate, systolic blood pressure, pulse rate, abbreviated injury scale Glasgow coma score, pre-existing medical conditions and intubation with the probability of survival; (ii) development of improved methods for the prediction of probability of survival based on the information derived from the TARN database; (iii) critical evaluation of the methods developed in objective two against each other and against Ps14 for different with the main focus on traumatic brain injury (TBI). Against this backdrop, the achievement of the research aim could be said to have been met as a result of the following research activities and numerous analysis that have been conducted as highlighted in the succeeding sections.

8.2 Summary of Models Developed and the Approach for their Evaluation

Three methods for predicting probability of survival were developed and their performances were evaluated against Ps14. One employed predictive statistical

diagnosis (PSD) that is based on Bayesian approach. The second was a novel approach termed Iterative Random Comparison Classification (IRCC). The third method incorporated fuzzy inference system (FIS) with the IRCC. The PSD and IRCC used respiration rate, age, systolic blood pressure (SBP), pulse rate (RR), Gender, Glasgow Coma Scale (GCS) and abbreviated injury scale (AIS). The IRCC combined with FIS further accommodated the intubation and pre-existing medical condition (PMC).

8.2.1 Analysis of Trauma Cases

The analysis of trauma cases revolved valuable information related to the interrelationships between trauma parameters (age, Gender, RR, SBP, PR, AIS and GCS, PMC and Intubation) with the trauma outcomes, i.e. survivors and not survivors. The main focus of this analysis was on TBI as it represented the majority of cases in the available data base although several other body regions were also considered. For TBI there were 4124 trauma cases (2488 males, i.e. 60.3% and 1636 female cases, i.e. 39.7%). Their mean age was 67.9 years (standard deviation=21.6 years). From this population, 86.2 % (number=3553) were survivors and 13.8% (number=571) were not survivors. It was found all these parameters are important in determining probability of survival. The investigation consider of each parameter individually as well as combination of parameters jointly on the probability of survival. A variety of techniques were utilised for these investigations that included distribution analysis, clustering and statistical analysis. Detailed discussions of findings are included in chapter 5.

8.2.2 Trauma Knowledge Representation and Coding

Knowledge representations in the forms such as tree diagrams, flow charts, box plots and cluster diagrams were developed. These assisted the knowledge coding that took the form of a number of IF-THEN statements relating to the trauma parameters to the outcomes (survivors and not survivors). The developed knowledge representation and coding schemes lead to the successful development of the fuzzy inference system that was integrated with IRCC improve its performance. By using FIS the developed system was able to include two parameters Intubation and PMC this is in case the patient had related information. As result of this developed system became more

sophisticated to cover all considerable parameters. The details of the related schemes are included in chapter 6.

8.2.3 Development of Methods to Predict Probability of Survival

Three methods to predict probability survival in trauma were developed and the performances were evaluated against each other as well as Ps14. The first method was PSD that is based on Bayesian statistics. The second method was IRCC that works by randomly selecting a subgroup of trauma cases from each outcome (survivors and not survivors), determines the distance of their mean to the trauma case being considered and repeating this process for predefined number of iterations to be able to obtain probability of survival. The third method based on combining IRCC and FIS and incorporated PMC and intubation. PMC and intubation were not included in all three methods as only a subset of cases had related information. The focus of the study was on TBI, although a number of other body sections were also considered. For TBI, the IRCC performed best amongst all methods including Ps14. It predicted survivors and not survivors with 97.2% and 75.9% accuracies respectively. The details of the related investigations are included in chapter 7.

8.2.4 Graphic User Interface for Predicting the Ps

A user graphic interface for the Ps was developed that can assist clinicians enter trauma parameters and obtain the percentage of probability of survival. This is a prototype and could save clinicians time.

8.3 Summary of Original Contributions to Knowledge

8.3.1 A Detailed Analysis of Trauma Parameters

The parameters taken into consideration include age, gender, respiration rate, systolic blood pressure, pulse rate, abbreviated injury scale, Glasgow coma score, pre-existing medical conditions, and intubation. All parameters were used for the evaluation of the probability of survival in TBI, with each of them indicating high level of significance towards the overall determination of the probability of survival. The investigations indicated the manner AIS and GCS values for different body regions relate to the probability of survival.

8.3.2 Proposition of three Methods for the Effective Prediction of Probability of Survival for TBI

The first method is based on a statistical Bayesian method known as PSD. The second was a novel method referred to as IRCC, which employs a randomly selected group of cases with predefined group size as part of its operation and by iterative repeating the process, determine the probability of survival. The third method developed is a combination of IRCC with FIS to accommodate PMC and intubation information. The use of FIS required careful knowledge representation and knowledge coding.

8.3.3 Critical Evaluation of the Methods Developed

The methods developed were evaluated against each other and against Ps14 for different traumas. Other body regions such as head and face were also included in the evaluation but the focus of the study was on TBI given that it constituted the main fatalities in the available database. The main challenge for all methods was to improve prediction for non-survivors as compared with the existing Ps14 method, which already had a high accuracy for the survivors. The three methods proposed in this study managed to significantly improve the probability of prediction for non-survivors. For example for TBI, there were 1224 survivors and 224 non-survivors. The predicted accuracy for not survivors for Ps14, PSD and IRCC were 40.1%, 50.0% and 75.9%. The predictive accuracies for Ps14, PSD and IRCC for survivors were 97.3% 90.8% and 97.2%.

8.4 Further Work

Although significant progress was made in this study toward developing improved methods for predicting probability of survival, nevertheless there remain several areas for further exploration.

- The knowledge representation and coding can be extended to for example a larger number of body parts.
- A valuable trauma parameter is fragility. The value of this for the cases included in this study was not available but in future this may be accommodated and its influence in improving the accuracy of the

prediction methods can be determined. Frailty can be related to age (e.g. very young and very old) as well as health detrition as a result of various medical conditions.

- Inclusion of larger number of trauma cases in particular not survivors.
- Analysis of duration of stay in hospital to establish whether this affected probability of survival.
- Comparison of IRCC and TARN Ps17 outcomes for determining the probability of survival. At the time of this study Ps14 was available.
- Use of artificial neural networks and deep learning to predict probability of survival could be explored. Machine leaning using neural networks could be valuable as they can model complex processes and non-linear systems effectively however their black-box behaviour may be a concern in some medical fields.
- In this study only adults were included as the number of available children trauma cases is not sufficiently large.
- It will be very helpful if the developed methods are validated and evaluated in clinicians in the medical field. This can provide very valuable feedback to improve the developed schemes.

References

AAAM, A.I.S. (2005, Updating 2008). Association for the advancement of automotive medicine. *Barrington*, IL.

Abdul Aziz, S. and Parthiban, J. (2006), Fuzzy Logic, [Online] Last access on 08 March 2013 at URL:
http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/sbaa/report.fuzzysets.html

Aho, A. V., and Corasick, M. J. (1975). Efficient string matching: an aid to bibliographic search. *Communications of the ACM*, 18(6), pp. 333-340.

Aitchison, J., & Dunsmore, I. R. (1980). Statistical prediction analysis. CUP Archive.

Aitchison, J., Habbema, J. D. F., & Kay, J. W. (1977). A critical comparison of two methods of statistical discrimination. *Applied Statistics*, pp.15-25.

Allen, R. and Smith, D., (2001). Neuro-fuzzy closed-loop control of depth of anaesthesia. *Artificial Intelligence in Medicine*, 21(1), pp. 185-191.

Al-Sbou, Y., Saatchi, R., Al-khayatt, S., and Strachan, R. (2006), Quality of service assessment of multimedia traffic over wireless Ad hoc networks, International Symposium on Communication Systems, *Networks and Digital Signal Processing (CSNDSP)*, pp. 129-133.

Al-Sbou, Y. A. (2006). Quality of service assessment and analysis of wireless multimedia networks (Doctoral dissertation, Sheffield Hallam University,).

Alonso, S. K. (2014). eMathTeacher: Mamdani's Fuzzy Inference Method.

Al West, T., Rivara, F. P., Cummings, P., Jurkovich, G. J., & Maier, R. V. (2000). Harborview assessment for risk of mortality: an improved measure of injury severity on the basis of ICD-9-CM. *Journal of Trauma and Acute Care Surgery*, 49(3), pp. 530-541.

Andersen, L. W., Kim, W. Y., Chase, M., Mortensen, S. J., Moskowitz, A., Novack, V., ... & Donnino, M. W. (2016). The prevalence and significance of abnormal vital signs prior to in-hospital cardiac arrest. *Resuscitation*, 98, pp. 112-117.

Arshdeep, K., Amrit, K. (2012), Comparison of mamdani-type and sugeno-type fuzzy inference systems for air conditioning system, *International Journal of Soft Computing and Engineering (IJSCE)*, vol. 2, Issue 2, pp. 323 -325.

Baker, S. P., o'Neill, B., Haddon Jr, W., & Long, W. B. (1974). The injury severity score: a method for describing patients with multiple injuries and evaluating emergency care. *Journal of Trauma and Acute Care Surgery*, 14(3), pp. 187-196.

Cabré, L., Mancebo, J., Solsona, J. F., Saura, P., Gich, I., Blanch, L., ... & Bioethics Working Group of the SEMICYUC. (2005). Multicenter study of the multiple organ dysfunction syndrome in intensive care units: the usefulness of Sequential Organ

Failure Assessment scores in decision making. *Intensive care medicine*, 31(7), pp. 927-933.

Chawda, M. N., Hildebrand, F., Pape, H. C., & Giannoudis, P. V. (2004). Predicting outcome after multiple trauma: which scoring system? . *Injury*, 35(4), pp. 347-358.

Champion, H., (2002). Trauma scoring. *Scandinavian journal of surgery*, 91(1), pp. 12-22.

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. *Journal of Trauma and Acute Care Surgery*, 29(5), pp. 623-629.

Cirstea, M., Dinu, A., Khor, J., and McCormick, M. (2002), Neural and fuzzy logic control of drives and power systems. Oxford.

Clarke, J. R., Cebula, D. P., & Webber, B. L. (1988). Artificial intelligence: a computerized decision aid for trauma. *The Journal of trauma*, 28(8), pp.1250-1254.

Deitch, E. A. (1992). Multiple organ failure. Pathophysiology and potential future therapy. *Annals of surgery*, 216(2), pp. 117.

Dillon, B., Wang, W., & Bouamra, O. (2006). A comparison study of the injury score models. *European Journal of Trauma*, 32(6), pp. 538-547.

Elkfafi, M., Shieh, J., Linkens, D. and Peacock, J., (1997). Intelligent signal processing of evoked potentials for anaesthesia monitoring and control. *IEE Proceedings-Control Theory and Applications*, 144(4), pp. 354-364.

Fani‐Salek, M. H., Totten, V. Y., & Terezakis, S. A. (1999). Trauma scoring systems explained. *Emergency Medicine*, 11(3), pp.155-166.

Gennarelli, T. A., & Wodzin, E. (2006). AIS 2005: a contemporary injury scale. *Injury*, 37(12), pp. 1083-1091.

Gilboy, N., Tanabe, T., Travers, D., & Rosenau, A. M. (2011). Emergency Severity Index (ESI): A triage tool for emergency department. Rockville, MD: Agency for Healthcare Research and Quality. Retrieved from http://www. ahrq. gov/professionals/systems/hospital/esi/esi1.

Glance, L. G., Osler, T. M., Mukamel, D. B., Meredith, W., Wagner, J., & Dick, A. W. (2009). TMPM–ICD9: A trauma mortality prediction model based on ICD-9-CM codes. *Annals of surgery*, 249(6), pp.1032-1039.

Goris, R. J. A., te Boekhorst, T. P., Nuytinck, J. K., & Gimbrère, J. S. (1985). Multiple-organ failure: generalized autodestructive inflammation?. *Archives of Surgery*, 120(10), pp. 1109-1115.

Güler, I., Tunca, A., & Gülbandilar, E. (2008). Detection of traumatic brain injuries using fuzzy logic algorithm. *Expert Systems with Applications*, 34(2), pp. 1312-1317.

Güler, İ., Hardalaç, F. and Barişçi, N., (2002). Application of FFT analyzed cardiac Doppler signals to fuzzy algorithm. *Computers in biology and medicine*, 32(6), pp. 435-444.

Health and Safety Executive. (2012). [online]. Last accessed 23 06 2012 at: http://www.hse.gov.uk/statistics/at-a-glance.pdf

Haman, A, and Geogranas, N (2008) Comparison of mamdani and sugeno fuzzy inference systems for evaluating the quality of experienceof hapto-audio-visual applications, *IEEE International Workshop on Haptic Audio Visual Environments and their Applications (HAVE)*, pp. 87-92.

Haykin, S. S., Haykin, S. S., Haykin, S. S., & Haykin, S. S. (2009). Neural networks and learning machines (vol. 3). Upper Saddle River: Pearson.

Holmes, J.F., Palchak, M.J., Macfarlane, T. and Kuppermann, N., (2005). Performance of the pediatric Glasgow Coma Scale in children with blunt head trauma. *Academic Emergency Medicine*, 12(9), pp. 814-819.

Iain Wheatley (2018). Respiratory rate 3: how to take an accurate measurement. *Nursing* 114; 7, pp. 21-22.

Jantzen, J., (1998) Design of Fuzzy Controllers. Technical report, University of Denmark, Department of Automation, vol: 236.

Janich, K., Nguyen, H. S., Patel, M., Shabani, S., Montoure, A., & Doan, N. (2016). Management of adult traumatic brain injury: A review. J. *Trauma Treat*, 5.

Kentala, E., Pyykkö, I., Laurikkala, J. and Juhola, M., (1999). Discovering diagnostic rules from a neurotologic database with genetic algorithms. Annals of Otology, *Rhinology & Laryngology*, 108(10), pp. 948-954.

Khoukhi, L., and Cherkaoui, S. (2008) Experimenting with fuzzy logic for qos management in mobile ad hoc networks. *IJCSNS International Journal of Computer Science and Network Security*, 8(8), pp. 372-386.

Kim, Y., (2012). Injury severity scoring systems: a review of application to practice. Nursing in critical care, 17(3), pp. 138-150.

Klir, J. and Yuan, B. (1995) fuzzy sets and fuzzy logic: theory and applications. Prentice Hall Inc. *ISBN*: 0131011715.

Kondo, Y., Abe, T., Kohshi, K., Tokuda, Y., Cook, E. F., & Kukita, I. (2011). Revised trauma scoring system to predict in-hospital mortality in the emergency department: Glasgow Coma Scale, Age, and Systolic Blood Pressure score. *Critical care*, 15(4), R191.

Kuwabara, K., Matsuda, S., Fushimi, K., Ishikawa, K. B., Horiguchi, H., & Fujimori, K. (2010). Probability of survival, early critical care process, and resource use in trauma patients. *The American journal of emergency medicine*, 28(6), pp. 673-681.

Laytin, A. D., Dicker, R. A., Gerdin, M., Roy, N., Sarang, B., Kumar, V., & Juillard, C. (2017). Comparing traditional and novel injury scoring systems in a US level-I trauma center: an opportunity for improved injury surveillance in low-and middle-income countries. *journal of surgical research*, pp. 215, 60-66.

Le Gall, J. R., Lemeshow, S., & Saulnier, F. (1993). A new simplified acute physiology score (SAPS II) based on a European/North American multicenter study. *Jama*, 270(24), pp. 2957-2963.

Le Gall, J. R., Klar, J., Lemeshow, S., Saulnier, F., Alberti, C., Artigas, A., & Teres, D. (1996). The logistic organ dysfunction system: a new way to assess organ dysfunction in the intensive care unit. Jama, 276(10), pp. 802-810.

Lefering, R. (2002), "Trauma scpre systems for quality assessment", *European Journal of Trauma*, no.2, vol.28, pp.52-63.

Liu, N. T., Holcomb, J. B., Wade, C. E., Batchinsky, A. I., Cancio, L. C., Darrah, M. I., & Salinas, J. (2014). Development and validation of a machine learning algorithm and hybrid system to predict the need for life-saving interventions in trauma patients. *Medical & biological engineering & computing*, 52(2), pp.193-203.

Madane, A., & Thakore, D. (2012). An approach for extracting the keyword using frequency and distance of the word calculations. *International Journal of Soft Computing and Engineering (IJSCE)*, pp. 2(3).

Man, D. W. K., Poon, W. S., & Lam, C. (2013). The effectiveness of artificial intelligent 3-D virtual reality vocational problem-solving training in enhancing employment opportunities for people with traumatic brain injury. *Brain injury*, 27(9), pp. 1016-1025.

MEDAL MILITARY MEDICINE, (2010-last update) , The Trauma Index. Available: http://www.mymedal.org/index.php?n=Military.290109 [10/07, 2015].

Meredith, W., Rutledge, R., Hansen, A. R., Oller, D. W., Thomason, M., Cunningham, P., & Baker, C. C. (1995). Field triage of trauma patients based upon the ability to follow commands: a study in 29,573 injured patients. *Journal of Trauma and Acute Care Surgery*, 38(1), pp. 129-135.

Moon, J. H., Seo, B. R., Jang, J. W., Lee, J. K., & Moon, H. S. (2013). Evaluation of probability of survival using trauma and injury severity score method in severe neurotrauma patients. *Journal of Korean Neurosurgical Society*, 54(1), pp. 42.

Moppett, I. K. (2007). Traumatic brain injury: assessment, resuscitation and early management. *British Journal of Anaesthesia*, 99(1), pp. 18-31.

Mullins, R.J. (1999), " A historical perspective of trauma system development in the United States", *J Trauma*, vol.47, no.3, pp.1-11.

Muyeen, S. M., and Al-Durra, A (2013) modeling and control strategies of fuzzy logic controlled inverter system for grid interconnected variable speed wind generator, *IEEE System Journal*, issue 99, pp. 1-8.

Naoum-Sawaya, J., Ghaddar, B. (2005) A fuzzy logic approach for adjusting the contention window size in IEEE 802.11e wireless ad hoc networks. *International Symposium on Communication, Control, and Single Processing (ISCCSP)*. pp. 1-4.

NHS England. (2018). [online]. Last accessed 08 12 2018 at: https://www.england.nhs.uk/blog/frailty/

Nyström, P. O. (1998). The systemic inflammatory response syndrome: definitions and aetiology. *The Journal of antimicrobial chemotherapy*, 41(suppl_1), pp.1-7.

Olsson, T., Terent, A., & Lind, L. (2004). Rapid Emergency Medicine Score can predict long-term mortality in nonsurgical emergency department patients. *Academic Emergency Medicine*, 11(10), pp. 1008-1013.

Osler, T., Baker, S. P., & Long, W. (1997). A modification of the injury severity score that both improves accuracy and simplifies scoring. *Journal of Trauma and Acute Care Surgery*, 43(6), pp. 922-926.

Schluter, P. J. (2011). The trauma and injury severity score (TRISS) revised. *Injury*, 42(1), pp. 90-96.

Pang, N., & Lai, Z. D. (2012, August). Signature word extracting research based on web metadata. In *Instrumentation & Measurement, Sensor Network and Automation (IMSNA), 2012 International Symposium on* (vol. 2, pp. 506-508). IEEE.

Pang, B. C., Kuralmani, V., Joshi, R., Hongli, Y., Lee, K. K., Ang, B. T., ... & Ng, I. (2007). Hybrid outcome prediction model for severe traumatic brain injury. *Journal of neurotrauma*, 24(1), pp.136-146.

Patient, (2015-last) update, Trauma Triage and Scoring. Available: http://patient.info/doctor/trauma-triage-and-scoring [10/15, 2015].

Pearl, A., Bar-or, R. and Bar-or, D., (2008). An artificial neural network derived trauma outcome prediction score as an aid to triage for non-clinicians. *Studies in health technology and informatics*, 136, pp. 253.

Pedia Content Solutions Pvt. Ltd.(2015), Network planning center, guangdong power grid applies for patent on intelligent extracting method for engineering characteristic indexes in paragraph contents of word document of transmission and transformation project,

http://lcproxy.shu.ac.uk/login?url=http://search.proquest.com.lcproxy.shu.ac.uk/docview/1757896427?accountid=13827, [11/05 , 2016]

Pike, I., Khalil, M., Yanchar, N. L., Tamim, H., Nathens, A. B., & Macpherson, A. K. (2017). Establishing an injury indicator for severe paediatric injury. *Injury prevention*, 23(2), pp.118-123.

Reith, F. C., Lingsma, H. F., Gabbe, B. J., Lecky, F. E., Roberts, I., & Maas, A. I. (2017). Differential effects of the Glasgow Coma Scale Score and its components: An analysis of 54,069 patients with traumatic brain injury. *Injury*, 48(9), pp.1932-1943.

Rhee, K. J., Fisher, C. J., & Willitis, N. H. (1987). The rapid acute physiology score. *The American journal of emergency medicine*, 5(4), pp. 278-282.

Ross (1995) Fuzzy logic with engineering applications. McGraw-Hill, USA. *ISBN* 007-pp. 113637-1.

Saleh, M., Saatchi, R., Lecky, F., & Burke, D. (2018). Predictive statistical diagnosis to determine the probability of survival in adult subjects with traumatic brain injury. *Technologies*, 6(2), pp. 41.

Saleh, M., Saatchi, R., & Burke, D. (2017). Analysis of the influence of trauma injury factors on the probability of survival. *International journal of biology and biomedical engineering*, 11, pp. 88-96.

Saleh, M., Saatchi, R., Burke, D., & Lecky, F. (2017, August). Computational analysis of factors affecting the probability of survival in trauma injuries. In Mathematics and Computers in Sciences and in Industry (MCSI), 2017 *Fourth International Conference on* (pp. 114-118). IEEE.

Sammy, I., Lecky, F., Sutton, A., Leaviss, J., & O'Cathain, A. (2016). Factors affecting mortality in older trauma patients—A systematic review and meta-analysis. *Injury*, 47(6), pp. 1170-1183.

Schluter, P. J. (2011). The trauma and injury severity score (TRISS) revised. *Injury*, 42(1), pp. 90-96.

Shah, P. K., Perez-Iratxeta, C., Bork, P., and Andrade, M. A. (2003). Information extraction from full text scientific articles: Where are the keywords?. *BMC bioinformatics*, 4(1), pp. 1.

Siritongtaworn, P., & Opasanon, S. (2009). The use of trauma score-injury severity score (TRISS) at Siriraj Hospital: How accurate is it?. *Medical journal of the Medical Association of Thailand*, 92(8), pp. 1016.

Stevenson, M., Segui-Gomez, M., Lescohier, I., Di Scala, C. and Mcdonald-Smith, G., (2001). An overview of the injury severity score and the new injury severity score. Injury prevention : *journal of the International Society for Child and Adolescent Injury Prevention*, 7(1), pp. pp. 10-13.

Saraireh, M. Saatchi, R. Al-Khayatt, S. and Strachan, R. (2008) "Assessment and improvement of quality of service using fuzzy logic and hybrid genetic-fuzzy approaches", *ACM*., vol 27, issue 2-3, pp. 95–111, ISSN:0269-2821.

Tanabe, P., Gimbel, R., Yarnold, P.R., Kyriacou, D.N. and Adams, J.G., (2004). reliability and validity of scores on the emergency severity index version 3. *Academic Emergency Medicine*, 11(1), pp. 59-65.

Tanabe, P., Gimbel, R., Yarnold, P. R., & Adams, J. G. (2004). The Emergency Severity Index (version 3) 5-level triage system scores predict ED resource consumption. *Journal of Emergency Nursing*, 30(1), pp. 22-29.

Tepas, J. J., Mollitt, D. L., Talbert, J. L., & Bryant, M. (1987). The pediatric trauma score as a predictor of injury severity in the injured child. *Journal of pediatric surgery*, 22(1), pp. 14-18.

The Royal Children's Hospital Melbourne. Normal ranges for physiological variables. Availableonline: https://www.rch.org.au/clinicalguide/guideline_index/Normal_Ranges_for_Physiological_Variables (accessed on 05 April 2018).

Ting, D. S. W., Cheung, C. Y. L., Lim, G., Tan, G. S. W., Quang, N. D., Gan, A., ... & Wong, E. Y. M. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. Jama, 318(22), pp.2211-2223.

Trauma Audit and Research Network, (November 2014-last update), Improvements in the Probability of Survival Model. Available: https://www.tarn.ac.uk/Content.aspx?ca=4&c=3515 [13/04, 2015]. last accessed 17/05/2017

Tohira, H., Jacobs, I., Mountain, D., Gibson, N., & Yeo, A. (2012). Systematic review of predictive performance of injury severity scoring tools. *Scandinavian journal of trauma, resuscitation and emergency medicine*, 20(1), pp. 63.

Verdecchia, P., Staessen, J. A., Angeli, F., De Simone, G., Achilli, A., Ganau, A., ... & Reboldi, G. (2009). Usual versus tight control of systolic blood pressure in non-diabetic patients with hypertension (Cardio-Sis): an open-label randomised trial. *The Lancet*, 374(9689), pp. 525-533.

Walter, L. C., Brand, R. J., Counsell, S. R., Palmer, R. M., Landefeld, C. S., Fortinsky, R. H., & Covinsky, K. E. (2001). Development and validation of a prognostic index for 1-year mortality in older adults after hospitalization. *Jama*, 285(23), pp. 2987-2994.

Wisner, D.H. (1992), "History and current status of trauma scoring system", *Arch. Surg*. vol. 127, pp. 111–117.

Wong, T. Y., & Bressler, N. M. (2016). Artificial intelligence with deep learning technology looks into diabetic retinopathy screening. *Jama*, 316(22), pp.2366-2367.

Wuerz, R.C., Travers, D., Gilboy, N., Eitel, D.R., Rosenau, A. and Yazhari, R., (2001). Implementation and refinement of the emergency severity index. *Academic Emergency Medicine*, 8(2), pp. 170-176.

Xian-Jiang, H., and Zhong-Hua, Y. (2012, November). A research on multi-feature word-level paraphrase extracting system based on context. In Multimedia Information Networking and Security (MINES), *2012 IEEE Fourth International Conference on*, pp. 441-444.

Yager, R. R., Zadeh, L. A., Kosko, B., & Grossberg, S. (1994). *Fuzzy sets, neural networks, and soft computing* (No. 006.33 F8).

Yamamoto, M., and Morooka, C. K. (2005). Dynamic positioning system of semi-submersible platform using fuzzy control. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 27(4), pp. 449-455.

Zallen, G., Offner, P. J., Moore, E. E., Blackwell, J., Ciesla, D. J., Gabriel, J., & Silliman, C. C. (1999). Age of transfused blood is an independent risk factor for postinjury multiple organ failure. *The American journal of surgery*, 178(6), pp. 570-572.

Zheng, H., Jiang, B., & Lu, H. (2011). An adaptive neural-fuzzy inference system (ANFIS) for detection of bruises on Chinese bayberry (Myrica rubra) based on fractal dimension and RGB intensity color. *Journal of food engineering*, 104(4), pp. 663-667.

Appendix A: Extra Work of Statistical Analysis

The highest score of GCS for Eye is N=4, Verbal is N=5 and Motor is N=6.

Table A.1 of Comparison of Eye - Verbal - Motor components for not survived

(Eye-Verbal- Motor) as single factor	Total number of single factor	Combining two factors	Total number of Combining two factors
(Eye) <=2-N-N	2	(Eye-Verbal) (<=2-<=3-N)	13
(Verbal) N-<=3-N	14	(Eye- Motor) (<=3-N-<=4)	7
(Motor) N-N-<=4	2	(Verbal- Motor) (N-<=3-<=4)	38

Table A.2 of Comparison of Eye - Verbal - Motor components for survived

(Eye-Verbal- Motor) as single factor	Total number of single factor	Combining two factors	Total number of Combining two factors
(Eye) <=2-N-N	14	(Eye-Verbal) (<=2-<=3-N)	143
(Verbal) N-<=3-N	70	(Eye- Motor) (<=2-N-<=4)	17
(Motor) N-N-<=4	11	(Verbal- Motor) (N-<=3-<=4)	117

Table A.3 of statistical analysis of age (years) range for all cases.

Age(years) range	Total number Of all cases	Total number of survival cases	Total number of not survival cases
18-38	5095 (21.35%)	4881 (22.11%)	214 (12.71%)
45-65	8153 (34.17%)	7886 (35.57%)	267 (15.85%)
75-95	10611 (44.47%)	9408 (42.43%)	1203 (71.43%)

Table A.4 of statistical analysis of age (years) range based on Gender.

Age(years) range	Total number of male survival cases	Total number of male not survival cases	Non-surviving female % remarks
18-38	3794 (77.73%)	161 (75.24%)	(24.76%) ↓
45-65	4774 (60.54%)	182 (68.16%)	(31.84%) ↓
75-95	3185 (33.85%)	589 (48.96%)	(51.40%) ↑

Table A.5 of statistical analysis of Gender, RR, SBP and PR.

Head Injury	Male		Female		Male		Female		Male		Female	
	RR 12-20	RR Not 12-20	RR 12-20	RR Not 12-20	SBP 90-140	SBP Not 90-140	SBP 90-140	SBP Not 90-140	PR 60-100	PR Not 60-100	PR 60-100	PR Not 60-100
Survived	1059 % 69.57	463 % 30.42	694 % 69.81	300 % 30.18	841 % 51.65	787 % 48.34	436 % 41.36	618 % 54.63	1281 % 79.36	333 % 20.63	857 % 80.92	202 % 19.07
Not survived	122 % 58.37	87 % 41.62	82 % 50.30	81 % 49.69	79 % 33.19	159 % 66.80	50 % 25.64	148 % 74.35	176 % 73.94	62 % 26.05	148 % 75.12	49 % 24.87

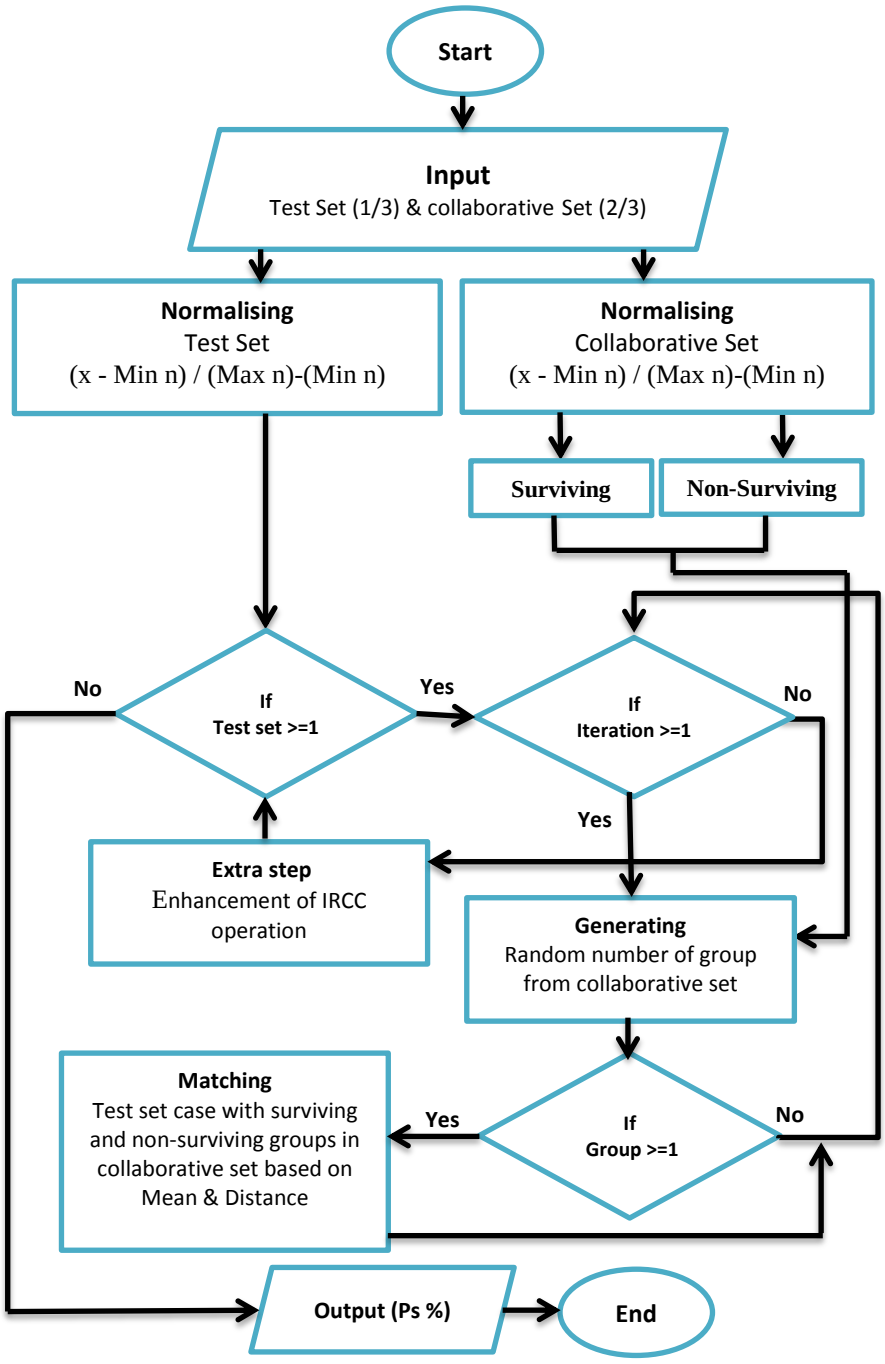


Figure A.1 IRCC flow chart.

Appendix B: SHU Ethics Approval

Dear Reza,

Thanks for these. We can now take both of these to be fully approve and will file the documents you have sent.

Regards,
Alison

From: Adam, Alison
Sent: 23 September 2015 14:07
To: Saatchi, Reza
Cc: ACES Research Ethics Committee (FREC)
Subject: Research ethics approvals

Dear Reza,

As you attended the FREC meetings last week you know of the outcomes of your students' research applications but here they are for the record.

Regards,
Alison

- Mohammed Salah

  Subject Title: Artificial Intelligent Methods for Prediction of Trauma Outcome for Emergency Department Patients

  outcome of the Committee's discussion

  Approved - Subject to the following:

  1. The end date on the SHUREC2A form is corrected.

  2. A copy of the NHS letter that confirms no NHS Ethical Approval is required is supplied to ACES FREC.

Professor Alison Adam
Cultural, Communication & Computing Research Institute
Sheffield Hallam University
Cantor Building
153 Arundel Street
Sheffield, S1 2NU

a.adam@shu.ac.uk

Appendix C: Use Agreement between TARN and SHU

CONFIDENTIAL

DATA TRANSFER AND USE AGREEMENT

THIS AGREEMENT is made the 2016 by and between

The University of Manchester with a business address at Oxford Road, Manchester, United Kingdom ("University")

and **Sheffield Hallam University** with a business address of City Campus, Howard Street, Sheffield S1 1WB ("the Recipient");

each a "Party" and collectively the "Parties"

WHEREAS University is a leading UK teaching and research institution and holds data in the Trauma Audit and Research Network ("TARN"); and

WHEREAS the Recipient has an interest in access to such TARN Data; and

WHEREAS the University is prepared to allow the Recipient access to certain TARN Data to enable a specific research project; and

WHEREAS the Parties wish to clarify their respective rights and obligations in respect of the Recipient's use of such TARN Data and each Party's use of the Results of such research project through entry into this Agreement.

NOW THEREFORE in consideration of the mutual promises and covenants set forth herein, and intending to be legally bound, the Parties agree as follows:

1. Definitions

1.1 "Purpose" shall mean use by the Recipient for academic research purposes in the specific research project detailed in Exhibit A and no other purpose.

1.2 "Principal Investigator" shall mean the representative(s) of the Recipient named in Exhibit A responsible for the conduct of the research project.

1.3 "Results" shall mean the results relating to the research performed by the Recipient using the TARN Data including without limitation all analyses, calculations, algorithms and meta-data irrespective of format.

1.4 "TARN Data" shall mean the proprietary data of the University requested by the Recipient for the Purpose and collected from participants in TARN and held at the University together with any additional information made available relating thereto.

2. Transfer of Data to the Recipient

The University will provide the TARN Data to the Recipient as soon as reasonably possible following execution of this Agreement. Thereafter the University may transfer such further TARN Data to the Recipient as the Parties may agree in writing and any such additional data shall be deemed TARN Data and subject to the terms

of this Agreement. Data will be transferred to the Principal Investigator by the University representative responsible for the care of the TARN Data.

3. Treatment of Data by the Recipient

3.1 The Principal Investigator will be responsible for receipt of the TARN Data and upholding the University's obligations in respect of the TARN Data. Notwithstanding the foregoing, the Recipient agrees to maintain TARN Data disclosed or transferred to the Recipient by or on behalf of the University as confidential data with the same degree of care it holds its own confidential data.

3.2 The Recipient will mark and store the TARN Data in such a manner that it is at all times traceable as proprietary to the University. The Recipient will keep the TARN Data secure using password protection as a minimum and preferably data encryption. The Recipient will not store the TARN Data on a laptop, disc, external drive or any other temporary media.

3.3 The Recipient will not use TARN Data or cause the same to be used except for the Purpose. The Recipient will disclose such TARN Data only to its directors, officers, employees, faculty, and researchers directly concerned with carrying out the Purpose subject to the Recipient having in place with such persons obligations no less strict than those set out herein and remaining fully liable for any breach by such persons. The Recipient will neither disclose the TARN Data to any third party nor use such TARN Data for any other purpose without the prior written consent of the University.

3.4 Each Party shall comply with the Data Protection Act 1998 ("the 1998 Act") and any other applicable data protection legislation. Both parties agree to use all reasonable efforts to assist each other to comply with the 1998 Act. For the avoidance of doubt, this includes providing the other with reasonable assistance in complying with subject access requests served under Section 7 of the 1998 Act and consulting with the other prior to the disclosure of any personal data created in connection with the conduct or performance of the Purpose in relation to such requests.

4. Exceptions.

The Recipient's obligations of nondisclosure and the limitations upon its right to use the TARN Data shall not apply to the extent that the Recipient can demonstrate that TARN Data: (a) was in its possession prior to the time of disclosure without obligation to the University; or (b) is or becomes public knowledge through no fault or omission of the Recipient; or (c) is obtained by the Recipient from a third party under no obligation of confidentiality to the University; or (d) if the Recipient is requested or ordered to disclose TARN Data in connection with a legal or administrative proceeding, the Recipient will give the University prompt notice of such request. The University may seek an appropriate protective order or other remedy or waive compliance with the provisions of this Agreement or both. If the University seeks a protective order or other remedy, the Recipient will cooperate with the University, at the University's expense. To the extent the University fails to obtain a protective order or waive compliance with the relevant provisions of this Agreement, the Recipient will disclose only that portion of the TARN Data which its legal counsel determines the Recipient is required to disclose.

5. Ownership of Results and License.

Results of the Purpose will be owned by the Recipient. The Recipient will keep the University reasonably updated with progress of the research project and will supply all Results to the University in a timely manner. The University will be entitled to receive all raw data contained in the Results. The Recipient grants to the University, without fee or payment of any kind, a perpetual, worldwide, non-exclusive, fully sublicensable, license to use the Results for internal teaching and research.

6. Publication.

Notwithstanding the other provisions of this Agreement, it is the desire of both Parties for Results to be published as appropriate. The Recipient may publish the Results, will detail the source(s) of data used, and to the extent that the University has made any significant contribution to the Results the Recipient will include pertinent University personnel as joint authors in accordance with accepted scientific publication practice. The University shall have the right to review all publications which refer in any manner to the Results prior to publication by the Recipient. The Recipient will send relevant manuscripts to the University for review prior to publication. The University will have up to thirty (30) days to review each manuscript ("Review Period") and will have the right to delete any University confidential information from such manuscript. The Recipient will be free to publish at the end of the Review Period.

7. Retention of Rights in the TARN Data.

All intellectual property rights in the TARN Data shall remain the property of the University at all times. Nothing in this Agreement shall be construed as granting any license to TARN Data or the University's other intellectual property rights unless otherwise expressly set out under this Agreement. .

8. No Further Obligation.

University is disclosing TARN Data to Recipient on the express understanding that neither Party will be obligated to enter into any further agreements relating to the subject matter hereof, and unless and until any final definitive agreement with respect to the above subject matter is agreed between the Parties, the Parties will not have any obligation to the other Party except under this Agreement or any other definitive written agreement already entered into with respect to the subject matter.

9. Limited Representations and Warranties.

9.1 The University represents that the TARN Data has been derived and supplied in accordance with all applicable laws, rules and regulations.

9.2 Each Party represents to the other, to the extent that it supplies to the other Party, uses itself, or permits the other Party to use, data it has obtained from a third party to perform this Agreement that it has all required permissions, licenses and consents from such third party to do so.

9.3 The Recipient warrants it will conduct the permitted research using the TARN Data and any third party data in accordance with all applicable laws, rules and regulations; and save for the express warranties set forth in this Agreement, no representations, undertakings or warranties, whether express or implied, are made or given by either Party including without limitation (i) as to the accuracy,

completeness, or fitness for a particular purpose of the TARN Data; or (ii) the Results or their freedom from infringement of any third party intellectual property rights.

10. Term and Termination.

This Agreement will terminate on 4th October 2020 or until the permitted research has been completed whichever is sooner. Either Party may terminate this Agreement without cause on giving the other not less than thirty (30) days written notice. Those sections intending to survive expiry or earlier termination of this Agreement will survive.

11. Return or removal of TARN Data.

Upon the written request of the University at any time or upon 12 months following publication of the Results (whichever is sooner), the Recipient will promptly return all TARN Data then in its possession or control and all copies of it save that the Recipient will not be required to surrender or destroy any computer files stored securely by the Recipient, its business units and Affiliates that are created during automatic system back-up or retained for legal purposes by the legal division of the Recipient. The Recipient will certify to the University that all electronic copies other than those required as above have been deleted, and that all paper copies have been destroyed.

12. General

Headings. Headings are provided for convenience only and do not affect the construction or interpretation of this Agreement.

No Waiver. No waiver shall be binding unless in writing and signed by the Party making such waiver. A waiver made on one occasion shall not be deemed a waiver on any other or subsequent occasion. All rights of the Parties are cumulative.

Authority. Each Party represents to the other that it has the full authority to enter into this Agreement. Each Party represents to the other that it is entering into this Agreement as principal not agent. Each signatory represents that they have the full authority to bind their respective company or organization to the terms of this Agreement.

Entire Agreement and Variation. This Agreement sets forth the entire agreement between the Parties as to its subject matter and supersedes all prior discussions, understandings, or verbal agreements (if any) in relation thereto all of which are replaced in their entirety by the terms of this Agreement. Notwithstanding the foregoing, this Agreement shall not supersede or vary any other definitive written agreements already executed between the Parties. None of the terms of this Agreement shall be amended except in a writing signed by each Party.

Counterparts and Execution. This Agreement may be executed in two or more counterparts each of which is separate but when taken together shall constitute one and the same instrument.

No Third Party Rights. No third party, including without limitation any director, officer, employee, agent or consultant of either Party or their respective Affiliates or business units shall have or acquire any rights under this Agreement.

Existence of Agreement. The Recipient, its students, researchers, directors, officers, employees, agents and consultants will not disclose or publicly announce the existence of this Agreement, its terms, or any activities contemplated under it, without the prior written consent of the University. Notwithstanding the foregoing, such restriction will not act to prevent any disclosure by the Recipient as required by law or a regulatory authority, or to any potential lender or acquirer for the purpose of pursuing the specific transaction subject to obligations of confidentiality.

Assignment. Neither Party may assign this Agreement, in whole or in part, without the prior written consent of the other Party.

Governing Law. This Agreement shall, in all respects, be construed and governed in accordance with the laws of England and Wales.

IN WITNESS WHEREOF the Parties have caused this Agreement to be executed by the hands of their duly authorized representatives as of the day and date first written above.

The Recipient

Signed: .....

Print Name: JOE RENNIE

Position: Deputy Registrar

The University of Manchester

Signed: .....

Print Name: .....

Position: .....

Director of TARN

Signed: .....

Print Name: .....

Position: .....

Exhibit A

[1] **Purpose of the Agreement:** The purpose of agreement is for Sheffield Hallam University to receive and use anonymised patients' trauma data from "The Trauma Audit and Research Network (TARN)" within the agreed guidelines.

[2] **Need for the Data:** The data is needed for a PhD study, the details of which are explained below. The data shall only be used for the PhD study.

[3] **PhD Study's Details:** The objectives of the study are to

i. Investigate and develop ways that could improve the assessment of the injury severity. There are a number of standards, such as the Abbreviated Injury Scale (AIS). These indicate the relative risks of treatment to life. However, these have some shortcomings with regards to their accuracy. These standards and their limitations are explained in a number of articles such as (Chawsa et al., 2004) (Lefering, 2002), (Orhon et al., 2002), (Rennie and Brady, 2007) and (Senkowski and McKenney, 1999).

ii. Develop means to determine the probability or likelihood of a patient survival following an injury.

iii. Critically evaluate the developed approaches.

[4] **Research Student:** The PhD student name is Mr Mohammed Saleh (date of birth 24/09/1982). He is registered as a PhD full-time student at Sheffield Hallam University. His official study start date is 05/Oct/2015 and his study's regulatory end date is 04/Oct/2019. He is a Libyan national and his PhD study is sponsored by the Government of Libya.

[5] **Supervisory Arrangement:** The PhD student's principal supervisor is Dr Reza Saatchi, a Reader at Sheffield Hallam University who has about 25 years research experience. Dr Reza Saatchi takes responsibility with regard to the conduct of this study and is the Principal Investigator for the purposes of the Data Transfer and Use Agreement. The study is supported by co-supervisors, Professor Derek Burke (Medical Director, Sheffield Children Hospital, SCH) and Professor Fiona Lecky (Clinical Professor of Emergency Medicine, University of Sheffield, UoS).

[6] **The Trauma Audit and Research Network (TARN):** *A brief description of TARN is: " Established 25 years ago by a small group of collaborators, the Trauma Audit and Research Network (TARN) is now recognised as the UK's national clinical audit for traumatic injury and holds the largest trauma registry in Europe. Based at Salford Royal NHS Foundation Trust, TARN's role is to support hospitals by providing evidence of the standards of care through the analysis of key process measures and case-mix adjusted outcomes."* [http://emj.bmj.com/content/32/12/966.full]

[7] The link to TARN official site is: https://www.tarn.ac.uk/

[8] **The TARN Data:** The TARN Data shall be provided in anonymised electronic form on a secure disk or secure memory storage. It will be in a spread sheet form with a number of columns. Each row of the data sheet represents a patient's trauma injury description divided into columns. The columns typically include information such as Abbreviated Injury Scale (AIS) scores and codes, injury severity score, descriptions of the nature of injury and injury outcome (lived /died) etc.

[9] **Manner the TARN Data Shall be Stored at Sheffield Hallam University:** Although the TARN Data are anonymised and it is not possible to relate them to individual patients, nevertheless, they are highly confidential and their storage needs to be secure. Therefore they will be stored on the University's networked Research Store for all master copies and, if any derivative of the TARN Data is also confidential, they also will be kept on the same storage facility. Data is backed up automatically on a daily basis, and can be fully recovered in the case of accidental loss. All backups are securely kept on two remote locations for a period of 90 days. The TARN Data will not be downloaded onto laptops, memory sticks or other similar portable devices.

[10] **Access to the TARN Data at Sheffield Hallam University:** Access to the data folders created for the purpose of this study shall be restricted to researchers working on the project. At project close down relevant data relating to this project will be securely archived, and all TARN Data will be deleted from the Research Store.

[11] **Safeguard Measures:** The PhD student prior to accessing the TARN Data will be required to

i. Undergo appropriate training with regard to handling of confidential data,
ii. Sign the Data Transfer and Use Agreement between SHU and the University of Manchester. He will also be updated with regards his role and responsibilities by his main supervisor.

Reference

Chowda, M.N., Hilderbrand, F., Pape, H.C. and Giannoudis, P.V. (2004), "Predicting outcome after multiple trauma: which scoring system", Injury, Int. J. care Injured, vol.34, pages 347-358.

Lefering, R. (2002), Trauma score systems for quality assessment", European Journal of Trauma, vol.28, no.2, pages 52-63.

Orhon, R., Eren, S.H., Karadayi, S., Korkmaz, I, Coskun, A., Eren, M., Katrancioglu, N. (2014) "Comparison of trauma scores for predicting mortality and morbidity on trauma patients", Ulus Travma Cerrahi Derg, vol.20, no.4, pages 258-264

Rennie, C.P. and Brady, P.C. (2007), "Advances in Injury Severity Coding", Journal of Emergency Nursing, vol.33, no.2, pages 179-181.

Senkowski, C.K. and McKenney, M. G. (1999), "Trauma scoring systems: a review", American College of Surgeons (published by Elsevier Science Inc.), vol.189, no.5, pages 491-503.