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Article

Composite and Wearable Sensor Kit for Location Aware Healthcare Monitoring and Real-Time Trauma Scoring for Survival Prediction.

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Abstract: With the advances in microfabrication of analogue front-end devices, embedded system technology, data acquisition and signal processing, it has now become possible to device a composite health status monitoring kit that can measure vital signs and other physiological parameters pertaining to human health non-invasively and in real time. Traditionally, this was possible only in a hospitalized or ambulatory environment; however, patients or individuals subject to monitoring may suffer from a traumatic experience or may suffer injury at any time and at any location. The research focussed on developing a composite, wearable healthcare monitoring kit that can perform real-time trauma scoring and can calculate measures used for prediction of survival. In addition, location information could be transmitted with the physiological data and trauma scores, as telemetry data, and could be logged into electronic health records using standard coding schemes. Such system can enable emergency response and critical healthcare teams to prepare for medical treatment well in time, as in case of cardiac arrests or severe injuries. Vital signs and physiological parameters were used to calculate trauma scores (NEWS, RTS, TRISS) and Prediction of Survival (Ps). The signals from various sensors were denoised, filtered to remove motion artefacts using level 5 stationary wavelet transform and 'sym4' wavelet, which yielded signal-to-noise ratio of 27.83dB. Physionet, MIMIC II Numerics database was used to calculate NEWS and RTS scores and to generate correlation and regression models using the vital signs/physiological parameters for a clinical class of patients with respiratory failure and admitted to Intensive Care Unit (ICU). Parameters such as Age, Heart Rate, Systolic BP, Respiratory Rate and SpO2 as predictors to Ps, showed significant positive regression of 93% at $p<0.001$. NEWS and RTS scores showed no significant correlation ($r = 0.25$, $p<0.001$) amongst themselves, however together NEWS and RTS showed significant correlation with Ps (blunt) ($r = 0.70$, $p<0.001$). RTS and Ps (blunt) scores showed some correlation ($r = 0.63$, $p<0.001$) and NEWS score showed significant correlation ($r = 0.79$, $p<0.001$) with Ps (blunt) scores. GPS system was built into the kit to locate the individual and to calculate shortest path to the nearest healthcare centre using QGIS Network Analysis tool. The physiological parameters from the sensors, along with the calculated trauma scores were encoded according to a standard Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT) coding system and International code of Diseases (ICD) codes and the trauma information was logged to Electronic Health Records (EHR) using Fast Health Interoperability Resources (FHIR) servers. FHIR servers provided interoperable web services to log the event information in real time. It could be concluded that analytical models trained on existing datasets can help in analysing a traumatic experience or an injury and the information can be logged using a standard telemetry protocol as a telemedicine initiative. These scores enable the healthcare service providers to estimate the extent of trauma and prepare for medical emergency procedures ahead of time, which is quite critical in general and military healthcare.

Keywords: Wearable Healthcare kit; Composite IoT sensors; Trauma Scoring; TRISS; Prediction of Survival Ps; NEWS; RTS; HL7 FHIR; SNOMED-CT; Location Aware Healthcare kit; GIS GPS Healthcare kit; Physionet MIMIC II Trauma Scoring

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1. Introduction

Vital signs are useful in detecting or monitoring medical problems. Vital signs can be measured in a medical setting, at home, at the site of a medical emergency, or elsewhere. [1] With more and more wearable kits that have become easily available, manual intervention in healthcare monitoring has been reduced in many hospital and prehospital settings. With increasing number of miniaturized Internet of Things (IoT) devices, Analogue Front-End (AFE) modules and Digital Signal Processing (DSP) devices that have surfaced recently, vital signs and other physiological parameters can be easily measured non-invasively; and the readings can be analysed in a networked environment to provide a managed health monitoring system. [2] Increasing use of machine learning algorithms and neural networks on vital signs data can determine deterioration of health in a patient and can help predict health status ahead of time in order to prepare for emergency. [3] Several hospitals and healthcare service providers use standard trauma scoring mechanisms to ascertain or at least estimate patient health, though these are restricted to hospital or ambulatory settings. Scoring measures such as National Early Warning Score (NEWS), Glasgow Coma Scale (GCS), Injury Severity Score (ISS), Trauma and Injury Severity Score (TRISS) and Simplified Acute Physiologic Score (SAPS) II/III have been successfully used to identify high health risks and the extent of trauma in patients Intensive Care Unit (ICU) settings. [4] [5] These scores in turn can estimate Probability of Survival (Ps) in a patient and can help critical care team to prepare for emergency procedures ahead of time, though due to limitations in the size of equipment this has remained restricted to hospitalized settings.

This research begins with literature review on various wearable monitoring equipment used in healthcare emphasizing on the need of a composite sensor kit. An individual sensor module, e.g. Electrocardiogram (ECG) module can only measure biopotential, a composite sensor; however, with additional modules like Pulse Oximeter (SpO2), Hall Effect Sensor other physiological parameters from a human subject can be measured simultaneously. These readings, collectively, can be used to calculate trauma scores in real-time and can be used to estimate prediction of survival in patients. They can also be used to study correlations and regressions amongst themselves, and can be used to develop other statistical models for further analysis.

The readings taken from the human subjects are in time series format, have noise, and motion artefacts. In order to perform accurate waveform and statistical analysis, the data should be clean and accurate. The research subsequently illustrates use of data acquisition, filtering, smoothing and quantization- error removal techniques to extract the portion of the signal that is error free. MATLAB environment and SPSS statistical tools have largely been used for waveform and statistical analysis. Physionet MIMIC II Numerics database was used to develop correlation and regression models. The NEWS, RTS and TRISS scores were found quite useful in estimating Probability of Survival in patients. Following trauma scores calculations, adding location awareness features to the sensor kit has been illustrated using Quantum GIS and Global Positioning System (GPS) tools and techniques.

For a composite healthcare monitoring kit to be useful to patients as well as the healthcare service providers, the readings and trauma scoring have to be transmitted to the healthcare service providers using a standard telemetry protocol. Furthermore, the readings and the trauma experience has to be encoded in a standard coding system that is widely acceptable within the medical community. Health Level 7 (HL7) based Fast Health Interoperability Resources (FHIR) interoperable software components have been used to encode the events related to trauma as observations that can be logged to the electronic health record databases in real-time. The research demonstrates the use of FHIR servers, [6] the development and generation of trauma event context and observation models for EHR interoperability.

There has been a focus on remote health monitoring systems based on Internet of Things (IoT) technology and the concept is being accepted and adopted by private and public healthcare service providers. This has resulted in reducing healthcare costs, and at the same time improve healthcare for aging patients and patients with chronic diseases. It also assists in reducing the accommodation requirements in the hospitals and private health care providers. This continuously monitored information, however, would have limitations in terms of diagnosis if there were no emergency

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related trauma scores available to the critical care team ahead of time. The methods section also demonstrates calculating the shortest route from the subject's current position to the nearest healthcare provider using GIS tools and techniques. The research endeavours to bridge this gap between the monitoring, diagnosis and timely treatment in trauma related events. The IoT based healthcare system results in an architecture with sensing and analytical IoT devices, ubiquitous sensor networks, standard coded data distribution, FHIR servers and incident response systems.

1.1. Literature Review

1.1.1. Physiological Parameters for Health Status Determination:

Vital signs have been widely used as performance indicators of a person's health. The four main vital signs that are routinely monitored by health care providers are Body temperature, Pulse rate/heart rate, Respiration rate (rate of breathing), Blood pressure (Non-invasive Systolic) [7] [8]

The normal body temperature of a person varies depending on gender; recent activity person has been engaged in along with food and fluid consumption, the time of the day, and in women, the stage of the menstrual cycle. Normal body temperature can range from 97.8 degrees F (or Fahrenheit, equivalent to 36.5 degrees C, or Celsius) to 99 degrees F (37.2 degrees C) for an average healthy adult. A person's body temperature can be taken in any of the following ways:

- Orally: A traditional glass, mercury thermometer is generally used, or the digital thermometers with an electronic probe.
- Rectally: Temperatures measured rectally tend to be 0.5 to 0.7 degrees F higher than when taken by mouth, though type of measurement is only case specific.
- Axillary: Temperatures under the arm are measured using a glass or digital thermometer and these measurements can be 0.3 to 0.4 degrees F lower than mouth measurements.
- By ear: A special thermometer is used to measure temperature in eardrums which represents temperature of internal organs and can vary according to age groups and may differ by as much as 1 - 1.5 degrees Celsius. Normal body temperatures show large variations and the same applies to increased temperatures in fever. [9]
- By skin: A thermistor thermometer or an infrared thermometer for skin temperature have been found to be quite reliable and more portable as compared to the traditional mercury based thermometers. [10]

The pulse rate is a measure of the heart rate or the heart beats per minute. As the heart pumps blood in and out of the body the action puts pressure on the arteries, which could be felt as pulse. Taking a pulse on the wrist measures the heart rate and can indicate heart rhythm and health. The normal pulse for healthy adults ranges from 60 to 100 beats per minute. The pulse rate can fluctuate and may increase with exercise, illness, injury, and emotions. The heart rate and pulse rate are technically different though it is the heart beats that cause the pulse, so for analytical purposes the heart rate can be used just as much as the pulse rate. Pulse rate however can use used in heart rate variability measurement. [11]

The respiration rate is the number of breaths taken by a person per minute. It is usually measured when a person is at rest, sometimes in supine position and simply involves counting the number of breaths for one minute. Respiration rates also vary and can increase with fever, sickness, and with other medical conditions that influence respiration. Normal respiration rates for an adult person in resting position range from 12 to 20 breaths per minute and may depend on age. Traditionally, in intensive care units and ambulatory settings, Spirometer has been used to measure respiration rate; however, there has been a range of modern respiration rate sensing devices that have emerged even in consumer market which are non-invasive in nature. [12] This research uses an example citing the use of Hall Effect sensor to measure respiration rate. The expansion of chest during respiration can be measured by implementing and calibrating a Hall Effect sensor worn by the individual. This assembly makes the respiratory sensing possible even during normal activities like

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driving. Thus, all the sensors mentioned in this research are ubiquitous, wearable, and accurate as compared to the traditionally used sensing devices and manual interventions. [13]

Blood pressure is the force of the blood pressurizing the artery walls during contraction and relaxation of the heart. Each time the heart beats, it pumps blood into the arteries, resulting in increase and peak in blood pressure as the heart contracts and when the heart relaxes, the blood pressure falls. Two measures have been traditionally recorded when measuring blood pressure using an instrument called sphygmomanometer. The higher measure called the systolic pressure refers to the arterial pressure when the heart contracts and pumps blood through the body. The lower measure called the diastolic pressure refers to the arterial pressure due to the heart when it comes to rest and gets filled with blood. Both the systolic and diastolic pressures are recorded as "mm Hg" (millimeters of mercury). The sphygmomanometer consists of an inflatable rubber cuff and a wrap around the arm and which affects the levels in a column of mercury next to a calibrated scale, which enables measurement of systolic and diastolic blood pressure by increasing and gradually releasing the pressure in the inflatable cuff. There have been modern blood pressure measuring kits that measure blood pressure digitally and these are widely being used for self-measurements. This research revolves around using modern state of the art measuring methods and means and modern wearable sensing devices for measuring vital signs. [14] High blood pressure (or hypertension) increases the risk of cardiac arrest, heart failure, and stroke and its measurement is used as an important vital sign. Blood pressure can be categorized as normal, elevated, or stage 1 or stage 2 high blood pressure: Normal blood pressure is systolic of less than 120 and diastolic of less than 80 and generally recorded as 120/80. The elevated blood pressure is systolic with range 120 to 129 and diastolic less than 80. Stage I hypertension: Systolic BP range 130-39 or Diastolic BP range 80-89 mm Hg, Stage II hypertension: Systolic BP >= 140 or Diastolic BP >= 90 mm Hg Pulse Oximetry though not usually considered as a vital sign, it can be a very important measure to ascertain an individual's health status and hence is considered as the fifth vital sign. [15]

Experiments to determine the use of pulse oximetry as a vital sign have been conducted in the past for example in an emergency in geriatric assessment using pulse oximetry to measure oxygen saturation in geriatric patients, which led to, improved diagnosis and treatment. [15] Gas measurements in blood provide critical information regarding oxygenation, ventilation, and acid-base concentration in blood; however, these measurements are not frequent. It is well known that oxygenation can change very quickly, and in absence of continuous oxygenation measurements, these changes may go undetected until it is too late. Pulse oximeters measure blood oxygen saturation continuously and noninvasively using SpO2 sensors. The blood-oxygen saturation indicates the haemoglobin concentration, due to haemoglobin affinity to oxygen, in the arterial blood, which gets saturated with oxygen. The reading may be referred to as SaO2 and the term SpO2 can be used instead. In healthy adults, the saturation range can vary from 94% to 100%. The SpO2 sensor has a pair of light-emitting diodes (LED) and a photodiode on a probe element that is clipped to the patient's body (usually a fingertip or an earlobe). The Red LED has wavelength of 660 nm, the other is an infrared element with wavelength of 910 nm. Absorptions on each wavelength differs significantly with changes in oxygenated and deoxygenated concentrations of blood, therefore from the difference of the absorption due to red and infrared light the oxy/deoxyhemoglobin ratio can be calculated. As the amount of blood in the capillaries depends on the actual blood pressure on the capillary wall (due to heartbeats), the heartbeat rate can be measured as well with the Pulse Oximeter.

1.1.2. Injury severity and trauma scoring for prediction of survival based on physiological parameters:

The scoring measures such as National Early Warning Score (NEWS), Glasgow Coma Scale (GCS), Injury Severity Score (ISS), Trauma and Injury Severity Score (TRISS), Simplified Acute Physiologic Score (SAPS) II/III and Probability of Survival (Ps) have been successfully used to identify

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high health risks in patients that have suffered injury, trauma and have been admitted to Intensive Care Unit (ICU). [4] [5]

The NEWS score is based on an aggregate scoring system in which a score is calculated using physiological measurements, recorded in routine check-up in hospital or prehospital settings. Six simple physiological parameters used for NEWS calculations are, respiration rate, oxygen saturation, systolic blood pressure, pulse rate, level of consciousness or confusion and body temperature. In case the patient is in confused state of mind or disoriented, where the patient may respond to the questions, but is confused, the score of 3 or 4 is assigned to GCS scale. The normal GCS score equals 5 for verbal response. NEWS scoring takes GCS score into consideration and in case of trauma GCS scores can be very low which can affect NEWS scoring. A score is allocated to each measured parameter, with the magnitude reflecting how the parameter varies from the normal values. These act as weights to each measured parameter. Two additional points are added for people requiring supplemental oxygen to maintain oxygen saturation in blood. There is also AVPU score (Alert, Voice, Pain, Unresponsive) that can be added to the calculation depending on the alertness of the patient.

Interpretation of NEWS score: A low score (NEWS 1–4) would ideally require assessment by a competent registered nurse who would further decide how often clinical monitoring would be required and if the case should be referred to next level of diagnosis. A medium score (ie NEWS of 5–6 or a RED score) would prompt an urgent review by a clinician skilled with relevant competencies in the assessment of the kind of illness the patient is suffering from which is usually a ward-based doctor or acute team nurse who would further assess the patient's health and if required refer to critical-care team. A RED score refers to an extreme condition in one of the physiological parameter (e.g. score of 3 on the NEWS chart in any one physiological parameter). A high NEWS score (NEWS ≥7) should prompt emergency assessment by a critical care staff with critical-care skills and competencies and in such cases the patient has to be transferred to a higher critical care settings for diagnosis and treatment. [4] [5] [16]

The use of physiologic scoring systems for identifying high-risk patients for mortality detection has been considered using Acute Physiology and Chronic Health Evaluation II (APACHE II) and Simplified Acute Physiologic Score (SAPS II) models and is currently used in a large number of hospitals worldwide. Although, these scores are not very exact or perfect, these do enable in estimating health status of a patient who has had recent episode of trauma or similar condition.

Patients brought to the accidents and emergency wards may have suffered multiple injuries in which case the Injury Severity Scores are used to assess the trauma levels. Such patients who have been injured may have one or multiple injuries and the Injury Severity Score (ISS) is an anatomical scoring method that provides estimates and measures of the overall severity of injured patients. All injuries are assigned an Abbreviated Injury Scale (AIS) score and the codes of injuries have been derived from an internationally recognised and accepted dictionary that describes over 2000 injuries and ranges from 1 (minor injury) to 6 (an extreme life threatening injury). Patients with multiple injuries are scored by adding the squares of the three injuries with highest AIS scores in predetermined regions of the body and in the order of severity of injuries. This is the ISS score, which can range from 1 to 75 and a score of 75 represents an extreme condition. The maximum score is 75 (25+25+25) as maximum severity is 5 for each anatomical part. By convention, a patient with an AIS 6 in one body region is given an ISS of 75. The injury severity score is non-linear and scores 9 and 16 are common and scores, 14 and 22 unusual. Abbreviated Injury Scale (AIS) grades are 0 - no injury, 1 – minor, 2 – moderate, 3 - severe (not life-threatening), 4 - severe (life-threatening, survival probable), 5 - severe (critical, survival uncertain), 6 - maximal, possibly fatal.

The ISS > 15 has been associated with mortality of 10%. Advantage of using ISS is that it uses anatomic areas of injury to help in formulating a prediction of survival though at the same time is difficult to calculate this during initial evaluation when the patient arrives at the emergency ward and during resuscitation. In addition, it is difficult to predict outcomes for patients with severe single body area injury, though the New Injury Severity Score (NISS), which takes three highest scores regardless of anatomic area, overcomes this deficit. [17] [18]. The injury severity scoring can be classified as following:

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Physiologic: Revised Trauma Score (RTS), Acute Physiology and Chronic Health Evaluation (APACHE), Emergency Trauma Score

Anatomic: Abbreviated Injury Scale (AIS), Injury Severity Score (ISS), New Injury Severity Score (NISS)

Combined: Trauma Injury Severity Score (TRISS), A Severity Characterization of Trauma (ASCOT) and International Classification of Diseases Injury Severity Score (ICISS)

In the Methods section, these scores have been calculated and discussed along with severity levels associated with these scores. Statistical scores associated with these scores have been compared and analytical results have been presented. The correlation and regression scores between NEWS and RTS scores have been studied and later discussed. The measurements of the physiological parameters associated with these trauma scores have been measured in real time and the scores have been calculated and presented in real time.

In calculation of Injury Severity, the Trauma and Injury Severity Score (TRISS) [19] remains the most commonly used tool for benchmarking trauma fatality outcome. The predictive power of TRISS could be substantially improved by re-classifying the measured physiological parameters and altering the coefficients for environmental conditions, demographics or situations (e.g. combat). Despite some variations in the scoring mechanism in TRISS, it remains a largely used model. Despite the influence of demographics and environmental conditions on the patients, the TRISS model is still applicable to majority of cases. Anatomic injury, age, injury mechanism and pre-injury comorbidity are well-founded predictors of trauma outcome and for calculating TRISS score. Statistical prediction models may have some inaccuracies though these may be due to inaccurate calibration and inaccuracy due to applications of these models with influence of environmental conditions. [20]

Early warning scores have largely been used in cardiac emergencies as these patients along with other fatal injuries require medical attention and lead to emergent incident response. [7] Recognizing early signs of clinical deterioration of patients is thought to improve patient treatment outcomes by employing early warning scoring and can predict a patient's rate of deterioration. The Early Warning System (EWS) scores and the impact of EWS outcomes were studied on 48-hour mortality rate, for respiratory failure and cardiac arrest patients. It was found that the early warning system scores perform well for predicting cardiac arrest and death within 48 hours although the impact on health outcomes and utilization of resources for treatments remain uncertain. For ailments like cardiac arrests early warning scoring mechanisms become relevant and applicable as these patients may enter trauma any time and the healthcare service providers need to prepare ahead of time in readiness to attend this trauma. [21]

Even in patients admitted to ICU and facing deterioration of health, physiological parameters such as pulse rate, blood pressure, temperature and respiratory rate could be used to assess mortality and the serious adverse events (SAEs) such as cardiac arrest could be prevented. The Early Warning Score (EWS) is a scoring system, which assists with the detection of physiological changes and may help identify patients in risk of further deterioration. [22] In cardiac ailments, reduced heart rate (HR) is an established predictor of trauma and further mortality. However, the relationship between the predictors and trauma scoring is poorly understood hence it becomes important to establish the relationship between heart rate variability and trauma scores. [23]

The importance of using injury severity, comorbidity and prediction of survival scores becomes paramount in military operations when troops engaged in combat may require medical attention. The situation aggravates when the location of the troops is not known and a soldier requires medical attention when the time frames of arrival to base camps is uncertain. In such cases, predicting survival and measures related to injury severity scores become very important and the wearable vital signs and physiological measurement kits that can calculate and perform further analysis becomes crucial. [24]

The Trauma and Injury Severity Score (TRISS) methodology has been used in both the UK and US Military trauma registries. The method relies on dividing casualties according to survival probability (penetrating (Ps_penetrating) or blunt (Ps_blunt)), though uses different weighing mechanisms based on experiences in combat related environment. The UK Military Joint Theatre

Trauma Registry (JTTR) and US military use the same scoring mechanism with some variations in coefficients for soldiers injured in explosions. This study aimed to use the UK Military JTTR to calculate new TRISS coefficients for contemporary battlefield casualties injured by either gunshot or explosive mechanisms. The secondary aim of this study was to apply the revised TRISS coefficients to examine the survival trends of UK casualties from recent military conflicts. Such systems and early warning scoring kits can be very useful to forces deployed in combat zones where the scores can be calculated in real time in an event of an emergency. [25] The composite sensor kit in this research enables in measuring the physiological parameters that can determine the injury and trauma scores.

Traumatic cardiac arrest (TCA) is a precursor to traumatic death, but data on military outcomes are limited. A study was performed with a particular focus on survival rates and injury patterns. Data included mechanism of injury, Injury Severity Score (ISS), Abbreviated Injury Scale (AIS) for each body part and survival to deployed field hospital discharge. About 424 TCA patients were identified during the study period; median age was 23 years and with a median ISS score of 45. The most prevalent body region with a severe AIS injury was the head, followed by the lower limbs, thorax and abdomen. Haemorrhage, abdominal and lower limb injury was associated with survival; traumatic brain injury was associated with death. This study had shown that short-term prediction of survival from TCA in a military population was 10.6%. It was concluded that with appropriate and aggressive early scores management, survival could still be potentially predicted in military. [26]

Similarly, heart patients may have cardiac arrest, episodes of arrhythmia while they remain engaged in day-to-day activities, and there is uncertainty of time and locations of these patients. [27] In such cases, early warning signs and survival predictions can help in preparing for medical emergencies. [28] The objective of this study was to propose new adjustments to the Trauma and Injury Severity Score (TRISS) equation and compare their performances with the original TRISS for the study of prediction of survival. It was observed that despite the adjustments to the coefficients for physiological parameters measured the overall accuracy of about 89%.

These studies emphasize the importance of using trauma scores in predicting mortality and in calculating probability of survival in injuries and trauma situations.

1.1.3. Integration of Electronic Health Records with Injury and Trauma scores and Location Awareness:

Injuries and disease can be classified according to International Classification of Diseases (ICD) classification codes and can be used with clinical classification codes like Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT), Logical Observation Identifiers Names and Codes (LOINC). [29] [30] Injury can be described in two ways using ICD-10: (1) external cause of injury and (2) the nature of the injury. As an example of ICD coding, if death and causes of death for a particular patient has to be coded according to ICD-10 then External Cause of injury and Nature of Injury has to be determined. External Cause codes describe the mechanism or cause of the injury (e.g., motor vehicle crash) and the manner or intent of the injury (e.g., unintentional). The Nature of Injury codes describe the body region or site of the injury (e.g., hip) and the diagnosis (e.g., fracture). [31] [32] The ICD Injury matrices are frameworks designed to organize ICD coded injury data into meaningful groupings agreed upon by the global medical community. The matrices were developed specifically to facilitate national and international comparability in the presentation of injury statistics. [33]

Once the early warning and trauma scores have been calculated the Electronic Health Records (EHR) with the public health care service provider can be updated using ICD and SNOMED/LOINC classification codes using Health Level 7 (HL7) standards. Fast Health Interoperability Resources FHIR is an HL7 standard that provides interoperability specifications for web services and EHR databases. [34]

A very important application for wearable IoT healthcare monitoring devices is to be able to locate the individual when the trauma related events take place. With the availability of low cost wearable Global Positioning System (GPS) and Global System for Mobile communication / General Packet Radio Service (GSM/GPRS) receivers, which can be embedded into the wearable kits, such a provision can made available. The GPS receiver can provide the location specific information and the

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composite sensor can provide physiological information and trauma scores. This composite payload can be transmitted to the healthcare service provider and enable them to get ready for emergency. It can also help the ambulance critical care team can get ready for the emergency procedures while they are on their way to the incident location. Several GPS/GNSS systems already exist in mobile service vans tracking systems. E.g., an efficient vehicle tracking system has been implemented for tracking the movement of vehicles using a Smartphone application with a microcontroller interfaced with GPS/GNSS technology to track location in real time. The vehicle tracking system used the GPS module to get geographic coordinates at regular time intervals. The system used Google Maps API to display the vehicle on the map in the Smartphone application and could estimate the distance and time for the vehicle to arrive at a given destination. [35]

1.2. Problems and Challenges

1.2.1. Obtaining Vital Signs from Composite Sensor Kit

The most important aspect of any bio-medical device is data acquisition and techniques involved in signal filtering, smoothing and signal processing whilst making sure that no information has been lost in acquiring samples. In the Methods section, the hardware and the software used to obtain vital signs readings from human subjects has been discussed. The parameters like sampling frequency, the filtering (pass bands) parameters have to be set making sure that the required amplitude peaks have been captured whilst making sure that the outliers have been detected and eliminated. Another important aspect in bio-medical instrumentation is removal of motion artefacts and noise due to muscular movements and the effect of environmental conditions on the sensors.

The Blood Pressure (BP) and the Respiratory Rate (RR) can be calculated from the readings from ECG and SpO2 sensors using the Pulse Transit Time (PTT), Pulse Arrival Time (PAT), and Pulse Delay Time (PDT). (Source: https://www.heartisans.com) These are estimated Blood Pressure values, which can be used in the absence of proper digital Blood Pressure kits. The external BP sensor kits can provide accurate blood pressure readings, though it may not be possible to integrate and synchronize these readings with the ECG and SpO2 sensor readings. Since the readings from the individual sensors have to be sampled in a single sweep and timestamped, it is important that all the sensors be synchronized. The RR and BP calculated using the PTT can be accurate and may serve as a good starting point. The RR and BP can then be used as features extracted from the waveforms and can be used for further statistical analysis and for trauma values calculations. [36] [37]

1.2.2. Integrating Trauma and Injury Scores with Electronic Health Records.

The calculation of trauma and injury scores may not be adequate to address emergency response, the trauma information should be transmitted to the healthcare repository in real time and incident response should be generated by the sensor kit itself. The problem however is that the description of the injury has to conform to a standard coding system recognized by the healthcare service provider's information systems. E.g., if the processed heart rate readings from the ECG sensors identify arrhythmia then this event has to be logged into the EHR records according to a standard coding system. The methods section describes standard coding scheme and a sandbox server that conforms to the EHR standards accepted worldwide. In methods section a FHIR server implementation has been discussed and a sample observation of RTS trauma score encapsulated in XML format is shown in Table 3.

1.2.3. Location Awareness to trigger Real time Incident Response

In order to implement a prompt and real time incident response it was required to use GPS/GNSS and the Geographical Information Systems (GIS) tools to locate the nearest healthcare service provider. One such tool is Quantum GIS (QGIS), which is an open source software, that can align and map geographical maps to GPS coordinates. In methods section it has been used to create layers of information covering a geographical area. E.g., an area with contours for plains at same altitude, areas in a map that have same demographic information about healthcare centres in vicinity.

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This information was modelled as layers and was overlaid over the GPS coordinates. The tool can be used to load road and rail routes information into the environment and can be used to identify the shortest path between two points in a network based on either distance or time. [38]

2. Materials and Methods

2.1. Composite Sensor Kit for Real-time Multiparameter Physiological Data Acquisition

The raw ECG signals from human bodies have noise due to motion artefacts and baseline wandering. The motion artefact could be removed using the stationary wavelet transform level 5 decomposition and 'sym4' wavelet in MATLAB Stationary Wavelet Transform tool. The signal was further smoothed using Savitzky-Golay filter with order=3 and frame length = 51. Alternatively, the baseline wandering [39] along with motion artefacts could be removed by using Chebyshev Type II filter order = 2, sampling frequency = 1024, with passband (Wp) between 1Hz and 100Hz, stopband (Ws) between 0.5Hz to 100Hz according to code expressions (1).

```
[n,Ws] = cheb2ord(Wp,Ws,1,150); % Filter Order
[z,p,k] = cheby2(n,Rs,Ws); % Filter Design
[sosbp,gbp] = zp2sos(z,p,k);                                          (1)
filtered_signal = filtfilt(sosbp, gbp, ecgsig); % Filter Signal
%Source: matlabcentral/answers/364788-ecg-signal-artifact-removing
```

The Composite sensor kit captures signals in real time from all the sensor modules from Microelectronica: The Mickroe Click sensor modules being:

1. ECG 2 Click
2. Heart Rate 4 (SpO2) Click module
3. Mikrobus Beaglebone cape
4. Respiratory Rate and Blood Pressure Calculations

1) ECG 2 Click board from Mikroelektronika (Source: https://www.mikroe.com/ecg-2-click) is an ECG (or EKG) sensor break-out board that measures the electrical biopotential activity of the heart through electrodes attached (glued/taped) to the skin. The board requires a target Microcontroller Unit (MCU) with at least a 10-bit ADC (preferably powered from an external battery). The ECG sensor is connected to three electrodes, which are glued to left shoulder, right shoulder, and to the left side of the abdomen (below the heart). The fourth, if available can be glued to the left leg. ECG (Electrocardiography) is a method used to monitor heart health status. An ECG scanner connects a number of electrodes to different parts of the patient's body, and measures the biopotential on the skin. This electrical activity is then plotted on a graph, and this graph helps diagnose different heart diseases. Once the data is acquired, amplified and filtered, it is sent to one analog pin of an analog front-end device, the ADS1194/6/8 from Texas Instruments. The MCU in the analog front end then reads this analog data, converts it to digital data, which presents the value of the electrical activity of the heart at that particular moment. The signal is further subjected to digital signal processing and data analysis techniques to extract heart rate, pulse rate and ECG waveform related features. Average heart beat rate in a normal and healthy individual may vary from 60 to 100 beats per minute. The ADS1194/6/8 is a family of multichannel, simultaneous sampling, 16-bit, delta-sigma analog-to-digital converters (ADCs) with a built-in programmable gain amplifier (PGA), internal reference, and an onboard oscillator. The ADS1194/6/8 has an input multiplexer per channel that can be used for leadoff detection. Additionally, one of the input channels can be selected for right leg drive (RLD) output signal. Leadoff detection can be implemented using a pull-up/pull-down resistor or an excitation current sink/source.

2) The Heart Rate 4 (SpO2) Click module (Source: https://www.mikroe.com/heart-rate-4-click) hosts a MAX30101 high-sensitivity pulse oximeter from Maxim Integrated. It has been designed to run on either 3.3V or 5V power supply and communicates with the target MCU over I2C interface.

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The MAX30101 is an integrated pulse oximetry and heart rate monitor module. It includes internal LEDs, photodetectors, and optical elements and can remove noise by low ambient light rejection. The MAX30101 integrates red, green, and IR (infrared) LED drivers to modulate LED pulses for SpO2 and HR measurements. About, 0-50mA of LED current can be achieved using an appropriate power supply. Along with a proximity sensor to save power, the MAX30101 has an on-chip temperature sensor for calibrating the temperature dependence of the SpO2 subsystem.

As a principle, it is known that the oxygen-saturated blood absorbs light differently than unsaturated blood. Pulse oximeters measure the oxygen saturation giving an indication of the percentage of hemoglobin concentration in blood that is saturated with oxygen. In a healthy adult, these readings can range from 94% to 100%. Since oxygen-saturated blood absorbs more infrared light than red light, and unsaturated blood the opposite, the SpO2 readings are calculated by the comparison of the amount of absorption of these two types of light as quantified by the current generated by the photodetectors. The click board connector has to be clipped to a finger for measurement.

3) Mikrobus Beaglebone cape (Source: https://www.mikroe.com/beaglebone-mikrobus-cape) is an extension board for Beaglebone Black (Texas Instuments Sitara™ AM335x ARM Cortex-A8 processor), the popular low-cost development platform running Linux. This extension board has sockets to connect Click boards to add functionalities like GPS, WiFi, Bluetooth and the boards discussed above. The pinout consists of SPI, UART and I2C bus and six additional pins (PWM, Interrupt, Analog input, Reset and Chip select), and two power (+3.3V and 5V) pins. The extension board also has an EEPROM module for storing pin configuration data.

4) Respiratory Rate and Blood Pressure Calculations

Breathing rate (BR) or the Respiratory Rate (RR) is a key physiological parameter used in a calculating trauma scores and it is still widely measured by counting breaths manually. Quite a few algorithm have been proposed to estimate RR from the electrocardiogram (ECG) and pulse oximetry (Photoplethysmogram, PPG) signals. These RR non-invasive methods of RR estimation are applicable in both healthcare and fitness monitoring. [40]

The RR can also be calculated using Physionet WFDB library using the EDR (ECG Derived Respiration) utility and the derived value has high correlation to the measured values as found by the authors of the library. [60] Since the ECG waveforms are available, RR can be calculated from the ECG waveform itself. The EDR utility is a C program and can be compiled on any GNU/Unix/Linux platforms.

Blood Pressure (BP) is also an important vital sign sued in trauma scoring and in absence of an integrated sensor, there are challenges due to measure BP and remove motion artefacts. Researchers have tried to overcome this challenge by analyzing oscillometric pulses after amplitude modulation and amplification of the ECG signal. [41] The pulse transit time (PTT) can also be used for BP estimation. A prototype was developed and tested, which achieved mean absolute difference of less than ‘5’ mmHg for estimating BP, with the reference Omron BP monitor. It could be hypothesized that in the absence of RR and BP sensors that could be readily integrated with the composite wearable sensor kit; the estimated values of RR and BP derived from ECG waveforms could be used to calculate the trauma and injury scores.

PTT can be measured as the time interval between the R-peak in an ECG wave and a characteristic point at predetermined thresholds of the PPG signal in the same cardiac cycle. [42] By using PTT Systolic Blood Pressure (SBP) can be calculated as follows:

$$SBP = 4.8008600358 \times 10^4 \times PTT + 1.308532932$$

For the purpose of calculation of trauma scores and prediction of survival, and to study the relationship amongst them, a dataset containing sampled physiological parameters was required. Physionet is a widely used repository of such databases and MIMIC II Numerics (vital signs) dataset was used for this purpose.

2.2. Physionet MIMIC II database for statistical analysis

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The Multiparameter Intelligent Monitoring in Intensive Care (MIMIC II) Waveform Database is one of the two MIMIC II Databases. The Waveform Database contains several thousands of records of time series digitized physiological waveforms and simultaneously recorded Numerics (vital signs) signals of physiologic measurements. Some records also contain alarm annotations and signal quality indexes. The Waveforms could be visualized online or by using a WAVE toolkit. [43] The waveforms can also be read using WaveForm DataBase (WFDB) tool from Physionet and can be visualized in a MATLAB application. [44] [45]

Physionet is a widely used resource for complex Physiologic Signals, which was created for Research Resources of the National Institutes of Health (NIH), to instigate the study of cardiovascular and other complex biomedical signals. The interdependent components: **PhysioBank** is an archive of digital recordings of physiological signals and related clinical data. It includes databases of multiparameter cardiology, neurology, and other biomedical signals from healthy subjects and from patients with a variety of major and minor conditions, including life-threatening arrhythmias, neurological disorders, and aging. **PhysioToolkit** is a library of open-source software for physiological signal processing and analysis. There are annotations which highlight and detect physiologically significant events using statistical methods and nonlinear dynamics. There is also a library that can help in providing interactive display and characterization of signals, creation of new databases, and simulation of physiological phenomenon for further evaluation. **Physionet** is an on-line network for the dissemination and exchange recorded signals and open-source software for analysing them. There is free electronic access to PhysioBank data from PhysioToolkit software via the World Wide Web (http://www.physionet.org).

WFDB is a major component in the PhysioToolkit and has about 75 applications for signal processing and automated analysis. The WAVE software is used for viewing, annotation, and interactive analysis of the waveform. WFDB library [46] is a set of functions (subroutines) for reading and writing files in the formats used by PhysioBank databases. The library is LGPLed, and can be compiled using all major standard C/C++ compilers running under all versions of UNIX, MS-DOS, MS-Windows, the Macintosh OS, and VMS. Optionally, the WFDB library allows access over the internet which allows applications linked with the WFDB library to view or analyse data without the need to download entire records or to store them locally. WAVE is an interactive graphical environment for visualizing sets of digitized signals with optional annotations. WAVE has been built using the WFDB library and can run on all major operating systems. WAVE can enable fast display of waveforms and annotations and fast access to a portion of a waveform record, forward and backward access and searches for annotation patterns, graphical annotation editing, superimposed display, execution of signal-processing and analysis programs on the recorded waveforms.

For the current research experiment and data analysis the MIMIC II waveform and Numerics database was used. The database contains physiologic signals and vital signs in time series format captured from patient monitors for tens of thousands of Intensive Care Unit (ICU) patients. Data were collected from a variety of ICU admissions varying from (medical, surgical, coronary care, and neonatal) related admissions. The MIMIC II Clinical Database contains clinical data from bedside monitors and written notes taken by doctors and nurses. The MIMIC II Waveform Database includes records of high-resolution physiologic waveforms and minute-by-minute numeric (vital signs) time series (trends) of physiologic measurements. Waveform Database records are matched to corresponding Clinical Database.

The database is widely used for biomedical data analysis research because the records from the database form an intensive care unit research database and automated techniques have been applied to collate diagnostic and therapeutic data from a large, diverse population of adult patients admitted to intensive care unit patients. The data analysis and clinical research information can be used to develop resources to evaluate new clinical decision support systems and monitoring algorithms. The information in the corresponding clinical database consists of laboratory data, therapeutic and treatment related data, medication and ventilator settings, nursing progress notes, discharge summaries, radiology reports, ICD-9 notes and in relevant cases high-resolution vital sign trends and waveforms. Data complies with Health Insurance Portability and Accountability Act standards. [47]

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MIMIC-III ('Medical Information Mart for Intensive Care') which largely relates to MIMIC II, is a large database (more than 68000 subjects) which consists of information related to patients admitted to critical care units at a large tertiary care hospital. The clinical data includes vital signs, medications, laboratory measurements, observations and notes charted by care providers, fluid balance, procedure codes, and diagnostic codes, imaging reports, hospital length of stay, survival data, and more. The database is being used widely by academic and research institutions engaged in quality improvement initiatives, and in higher education coursework. [48]

Recorded waveforms and Numerics include one or more ECG signals, and often include arterial blood pressure (ABP) waveforms, fingertip Photoplethysmogram (PPG) signals, and respiration rate signal, with additional waveforms depending on the patient condition being monitored. Numerics (vital signs + physiological signals) typically include heart and respiration rates, SpO2, and systolic, mean, and diastolic blood pressure. Recording lengths also vary from a few days in to several weeks long.

Waveform Signals in MIMIC II/III were captured at 125 samples/second and consist of a few or more from the following signals [45] [47] [48]:

- ECG (electrocardiographic) waveforms include: AVF, AVL, AVR, I, II, III, MCL, MCL 1-V (unspecified precordial lead), V1, and V2
- BP (continuous blood pressure) waveforms include: ABP: arterial blood pressure (invasive, from one of the radial arteries) ART: arterial blood pressure (invasive, from the other radial artery) CPP: cerebral perfusion pressure CVP: central venous pressure FAP: femoral artery pressure ICP: intracranial pressure LAP: left atrial pressure PAP: pulmonary arterial pressure RAP: right atrial pressure UAP: uterine arterial pressure UVP: uterine venous pressure PLETH: uncalibrated raw output of fingertip plethysmograph RESP: uncalibrated respiration waveform, estimated from thoracic impedance.

The Numerics/Trends signals in MIMIC II/III were sampled at the rate of: 1 sample/second or 1 sample/minute. Some of the Numerics, such as temperature and cardiac output, were recalculated at irregular intervals and heart rate and systolic/mean/diastolic blood pressure, if recalculated, were recorded per sample. The following signals could be found in the MIMIC Numerics database [47] [48]:

BP (systolic, diastolic, and mean): AOBP (automated office blood pressure) NBP (non-invasive arterial blood pressure) PAWP (pulmonary artery wedge pressure) CO: cardiac output CO2: carbon dioxide HR: heart rate RR: Respiration rate SpO2: oxygen saturation (from fingertip pulse oximeter) ST: ECG ST segment levels and Temperature

For calculating trauma and injury severity scores HR, RR, SysBP, SpO2 scores were used along with Age. The signals were read into MATLAB environment and were sampled at sampling interval of 1.024 seconds.

Clinical Database Categories of MIMIC II/III [47] [48] link into the corresponding waveform database and the clinical data consists of:

General - Patient demographics, hospital admissions & discharge dates, death dates (in or out of the hospital), ICD-9 codes. Physiological - Hourly vital sign metrics, SAPS/SOFA scores, ventilator settings.

Medications - IV meds, provider order entry data, etc.

Lab Tests - Chemistry, haematology, ABGs, imaging, etc.

Fluid Balance - Intake (solutions, blood, etc.) and output (urine, estimated blood loss, etc.).

Notes & Reports - Discharge summary, nursing progress notes, etc.; ECG, radiology and echo reports.

2.3. Trauma and Injury Severity Scoring for Probability of Survival Prediction

The MIMIC database was used to calculate trauma scores and was used to calculate survival prediction. Since the trauma scores were calculated using the vital signs (Numerics) and physiological parameters, it could be hypothesized that there may be a relationship between trauma

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scores, related physiological parameters and the prediction of survival. Statistical analysis was performed to derive significance values for this relationship. [49]

Once the relationship between the trauma and physiological parameter variables was confirmed, the readings from composite sensors was used to calculate trauma scores and prediction of survival in real time. This is imperative for patients under continuous monitoring for chronic illness as they may suffer from episode of trauma at any time. The theory can be extended even to mission critical experiments such as for troops deployed in a war zone or experts engaged in fire and accident rescue missions.

In order to perform multiparameter analysis using parameters like heart rate, pulse rate, temperature, oxygen saturation and respiratory rate sensor readings from multiple sensors were gathered and trauma related scores were calculated.

Initially NEWS calculations were performed using following variables:

- Respiratory Rate (breaths per minute) score
- Oxygen Saturation (%) score
- Any Supplemental Oxygen score (Yes/No)
- Temperature in °C (°F) scale
- Systolic BP score
- Heart Rate (beats per minute) score
- AVPU score (Alert, Voice, Pain, Unresponsive)

NEWS score = Respiratory Rate score + Oxygen Saturation (%) score + Supplemental Oxygen score + Systolic BP score + Temperature scale + Heart Rate score + AVPU score

It can be noted that all the scores required to calculate NEWS score could be obtained by the composite sensor kit.

Following this, Revised Trauma Score (RTS) was calculated using additional parameters. RTS however requires Glasgow Coma Scale (GCS) scores.

Glasgow Coma Scale quantifies severity of head injury using the motor/verbal responses and uses following variables:

Best Motor Response
- 6 - Obeys command
- 5 - Localizes pain
- 4 - Normal withdrawal (flexion)
- 3 - Abnormal withdrawal (flexion): decorticate
- 2 - Abnormal withdrawal (extension): de-cerebrate
- 1 - None (flaccid)

Best Verbal Response
- 5 - Oriented
- 4 - Confused conversation
- 3 - Inappropriate words
- 2 - Incomprehensible sounds
- 1 - None

Eye Opening
- 4 - Spontaneous
- 3 - To speech
- 2 - To pain
- 1 - None

Calculation

GCS = motor response + verbal response + eye opening

Revised Trauma Score (RTS) is the most widely used prehospital field triage tool and was calculated using following variables:

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Glasgow Coma Scale (GCS) score
Systolic blood pressure score
Respiratory rate score
Calculation:
RTS = Glasgow coma scale score + systolic blood pressure score + respiratory rate score
Interpretation
Lower score indicates higher severity
RTS < 4 proposed for transfer to critical trauma centre

Following NEWS and RTS, the Injury Severity Score (ISS) had to be calculated. ISS is the first scoring system to be based on anatomic criteria which defines injury severity for comparative purposes. It was assumed that ISS score be based on ICU admitted patients' readings so an Abbreviated Injury Scale (AIS) score of 4 (severe) was chosen resulting in ISS = 48.

Variables for ISS are generally based on scores of 9 anatomic regions in human body: head, face, neck, thorax, abdominal and pelvic contents, and spine (upper extremity, lower extremity, external)

Calculation
Abbreviated Injury Scale (AIS) grades
0 - No injury
1 - Minor
2 - Moderate
3 - Severe (not life-threatening)
4 - Severe (life-threatening, survival probable)
5 - Severe (critical, survival uncertain)
6 - Maximal, possibly fatal
ISS
ISS = sum of squares for the highest AIS grades in the three most severely injured ISS body regions
$ISS = A^2 + B^2 + C^2$, where A, B, C are the AIS scores of the three most severely injured ISS body regions
ISS scores range from 1 to 75
Single score of 6 on any AIS region results in automatic score of 75

For the NEWS and RTS calculations to be useful it is very imperative that probability of survival scores could be calculated. Trauma is measured using TRISS scores. An important aspect of measuring trauma is to calculate the probability of survival. The Probability of Survival (Ps) scores are measured as Ps blunt or Ps penetrating. Ps blunt indicate probability of survival if the patient has suffered internal injuries. Ps penetrating scores indicate the patient has suffered injuries which has resulted in outpour of blood. E.g., Ps penetrating would mean that a person has fallen, has bruises for example a soldier wounded in war. Ps scores along with TRISS scores give an indication of how serious the injuries have been. Similar experiment had been performed in the past and Logistic regression analyses were performed using the 412 cases with scores on all severity measures. A trauma injury severity score more than 11.13 indicated more than 95% probability of survival. [25] [61]

TRISS (TRauma Injury Severity Score) determines the Probability of Survival (Ps) score of a patient from the ISS and RTS using the following formulae:

$Ps = 1/(1 + e^b)$ where, $b = b0 + b1\ (RTS) + b2\ (ISS) + b3\ (Age)$ and, the coefficients b0=-0.4499, b1= 0.8085, b2= -0.0835, b3= -1.7430 (Source: trauma.org) for Ps (blunt) assuming patients suffered no external injury

This trauma injury severity score (TRISS) provides an estimate of Ps blunt and Ps penetrating trauma score based on patient's age, RTS and ISS results. It is possible to modify TRISS scores

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depending on the situation and environmental conditions and sample population under consideration by altering the TRISS coefficients. [50]

There are severity levels associated with NEWS and the RTS scores e.g. RTS less than 3 would mean that the probability of survival of the patient is almost nil or the patient is already dead. The RTS and NEWS scores along with probability of survival scores can be transmitted to the healthcare service provider in real time using commonly available telemetry communication medium and the Healthcare service providers can use these scores to ascertain the extent of injuries and/or trauma and can get ready with their emergency procedures. Such a mechanism can save valuable time whilst the patient is being taken to the emergency ward.

In order to demonstrate real time calculations of NEWS and RTS scores along with severity scores, the readings from heart rate ECG sensor and pulse oximetry sensor were gathered in real time. For calculating Respiratory Rate and Systolic Blood Pressure, ECG waveforms were used with Pulse Transit Time calculations. [40] [41]. The scores were calculated in real time. The probability of survival, Ps, score could then be calculated and could be displayed in real time. If the Ps scores start falling below 4 or start approaching 0, alarms could be raised indicating emergency. These scores could also be transmitted wirelessly over the Internet to the healthcare service provider. In the absence of human subjects under trauma or severe injury, MIMIC II Numerics records were used to demonstrate the working of the composite sensor kit.

Statistical analysis of the NEWS and RTS scores along with the probability of survival scores show that the NEWS and the RTS scores were correlated as shown in the results section. In addition, severity of injuries and resulting health status using NEWS and the RTS scores were calculated using the vital signs as parameters. Vital signs were used as individual and independent variables and NEWS and the RTS values were dependent variables as were the Ps blunt and Ps penetrating scores.

The vital signs and physiological parameters from Physionet, MIMIC II Numerics (*mimicdb/numerics*) database was used to calculate NEWS and RTS and to generate correlation and regression models using the vital signs/physiological parameters for a clinical class of patients with respiratory failure and admitted to Intensive Care Unit (ICU).

2.4. To Add Location Awareness to the Wearable Sensor Kit using GIS Application and GPS Module

"GPS Click" module from Mikroelectronika was used for adding geo-positioning functionality to the sensing kit. It hosts the '*u-blox*' LEA-6S GPS Receiver and positioning engine. The module has been designed to run on a 3.3V power supply and communicates with the target microcontroller through UART or I2C interface. It can also be connected to a PC over a serial USB connection. GPS click can simultaneously track up to 16 satellites while it is searching for new ones. GPS click is ideal for asset tracking, road positioning and navigation devices, public transportation and vehicle information systems. The module takes less than a second to get satellite signals and navigation data, and based on this information, fixed position was calculated. The click board is low power device and uses 121 mW in continuous mode, and only 36 mW in power saving mode. Following this, the device gets into a tracking mode. Different power modes (Maximum performance, Eco, Power Save) allow controlling the acquisition and tracking engines to balance between performance and power consumption. Once started the receiver in continuously deploys the acquisition engine to search for all satellites and when a position fix is obtained, the acquisition engine continues to be used to search for all visible satellites that are not being tracked. During the start, once a position can be calculated and the satellites are being tracked, the acquisition engine powers off resulting in significant power savings. Even if the acquisition engine is powered off, satellites continue to be acquired. Power Save Mode (PSM) allows a reduction in system power consumption by switching between acquisitions and tracking mechanism. [51]

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GPS position is obtained using a mechanism called 'triangulation'. [52] 24 satellites orbit the earth at 7000 mi (11265 km) per hour. These satellites transmit and broadcast a weak 50-watt signal from 12,000 mi (19312 km) away. Each transmission beacon contains information about the ID of the satellite, status information, date, time, and position data. With multiple satellites reporting, calculations of their paths relative to the GPS receiver can be performed and the position of the composite sensor kit hosting the GNSS receiver can be calculated. Change in position can give speed. The Incoming Data to the GPS receiver comes in the form of encoded messages. The format of this data is specified by the National Marine Electronics Association (NMEA) definitions and each complete line of transmission is called a 'sentence' and multiple sentence data is called a 'transmit'. Some of the sentences are: GLL - Lat/Lon data, GSA - Overall Satellite data, ZDA - Date and Time, WPL - Waypoint Location information, XTE - measured cross track error, RMB - recommended navigation data for GPS, GSV - Detailed Satellite data amongst others. Each one of these abbreviated sentences has specific information related to location. It may or may not be related to the maritime navigation receivers. GPS Click incoming data sentences can be parsed using a GPS Parser library released by Mikroelectronica called "Libstock GPS_Parser". [53] As characters (sentences) arrive from in the GPS receiver, these are buffered and the parser will detect when a complete sentence has been provided and the sentence gets broken down into respective elements to retrieve the required values such as position coordinates. The kind of information that can be extracted from the parser depends on what the GPS/GNSS receiver module. Almost all GPS GNSS modules on the market support the basic sentences, which are GGA, RMC, GSA, GSV, GLL, and VTG. These are the standard structures commonly used in an application and most information related to location, speed, direction, time, and navigation could be retrieved.

Most of GPS/GNSS receiving modules support the NMEA standards. Some features of the GPS modules are:

Sensitivity: This measurement determines GPS module coverage sensitivity when used in remote areas, or even indoors. The lower the sensitivity the lower is the signal strength. Low sensitivity numbers mean lower requirements for reception.

Acquisition Time: The application depends on both how and importantly when the GPS receiver receives its first location fix. The lower the acquisition times the faster the reports of accurate location. However, this comes at a cost of power. Low acquisition time means your receiver will be on for less time.

Power: For a portable application that can remain and come off the GNSS grid, power should be managed for both has both acquisition power requirement and active tracking power requirement and power saving modes have to be considered. Receivers with adaptive power saving or standby mode can help saving power.

GPS click module hosts the LEA-6 receiver from 'u-blox' with a small form factor. The u-blox 6 has been designed for low power consumption for commonly used satellite constellations (e.g. GLONASS, Galileo). Intelligent power management in GPS modules is a major breakthrough as these applications run 24x7 and require low power consumption. The modules are certified according to ISO 16750 for robust performance and harsh environmental conditions. [52] [53]

It is also possible to use the GPS coordinates to gather all the terrestrial and demographic information using a third-party library like RTKLIB. The GPS information only provides the location coordinate, though these have to be mapped and aligned according to the geographical mapping system. RTKLIB (OpenStreetMap) is an open source GNSS toolkit for performing precise positioning. It was possible to determine position, using GNSS receiver. The software supports all major satellite constellations (GPS, GLONASS, Galileo and others) and uses standard file exchange formats. The toolkit can be used on Windows and Linux platforms. [54] [55] A number of GPS receivers provided raw measurements (carrier phase and code pseudo range) which were compatible with RTKLIB. The library was then used to calculate precise positioning to centimeter-level accuracy positioning. The most affordable are the single frequency receivers. The dual frequency receivers are more expensive

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but have a higher accuracy, especially for baselines longer than about 50 km; the advantage is much less pronounced in sub-km baselines. [56]

It was required to use GPS coordinates information and use it with GIS tools to provide location information and use maps to locate the nearest healthcare service provider. Following steps were carried out to achieve this.

1. The Road graph plugin in QGIS was used for this task to load road layers for a geographical area in UK.
2. Using the coordinates of the healthcare service providers in the nearby area, these were overlaid as layers.
3. The start point layer became the current GPS coordinates and the end-point layers were the coordinates to the nearby healthcare service providers.
4. Then using the Network analysis tool in QGIS, shortest path to the nearest healthcare service provider was calculated and the Centre information was retrieved.
5. The shortest route to the Centre was traced according to the road graph-mapping layer.

The GIS data was provided by [57] In order to create the network, a few files were required. E.g. the "Roads" shapefile, the "Outdoor Rinks" shapefile, the "Water Bodies" shapefile and lastly the "Wards 2014" shapefile. By creating an area of interest (AOI), only relevant area was selected or clipped. Since GIS, databases can contain excess data, which may not be relevant for analysis. It is a good strategy to clip area under consideration, which can reduce processing times.

The Road Graph Plugin, which is a (GNU) C++ plugin for QGIS, was used to calculate the shortest path between current GPS location and the end point on a polyline layer that was the nearest on the path over the road network.

Following parameters were used by the plugin:

- Time Unit and Distance Unit: Hour and kilometer were used as defaults.
- Topology tolerance: To make two lines look as continuous, a topology tolerance was applied, for example 10m, which meant the lines could snap together to make single continuous roads. Default value of ‘0’ was used because it was assumed that a municipal dataset would not have any topological errors.
- Transportation Layer: Clipped Roads layer was created using QGIS.
- Direction field: These are the FLOW of direction related to transportation. For Forward direction, "FT", and "TF" for reverse direction was used. These abbreviations meant "From - To" and "To - From" respectively, meaning from a current location to a point on the road polyline.
- Speed limit value was chosen as 40 km/h.

Using GPS/GNSS based current position location and using Network Analysis tool to calculate shortest path between current location and an end-point, which could potentially be a Healthcare Centre. For calculating shortest path from within an application, following steps were carried out:

- To match geographical maps with GPS co-ordinates.
- To generate a Heatmap of roads traveled based on GPS track recordings.
- To download road map data from online repository of shapefiles and transform it into a network of roads
- To store the road network in a database
- To generate own records of journeys using a GPS tracking device log of route traversed
- To implement a map matching algorithm to match GPS track recordings to an existing road network using shapefiles

Matching GPS data against a map: A GPS receiver/logger captures a series of latitude and longitude coordinates over time and traces the path of someone moving from place to place. The GPS coordinates are recorded and stored according to the person’s movements. Commonly available GPS

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devices enable recording a journey taken on foot or by a vehicle by recording a series of coordinates. The GPS device does not know which roads on the route map were followed during the journey. Map matching is a process of taking a GPS recording of coordinates followed during a journey and matching it against a database of roads on road map to identify the set of roads that were used on a particular journey.

For the map-matching task, three artefacts were required:

1) An accurate GPS track recording of the journey containing a log of GPS coordinates which would identify the roads that were followed on the journey.

2) An accurate database of road maps mapped to global geographical coordinates.

3) A suitable algorithm to match the GPS coordinates against the road map database.

For the current task using GPS coordinates, a road map and a suitable algorithm, the Heatmap of commonly used roads to reach a potential healthcare centre was generated.

A set of road map data in shapefile format was downloaded from OpenStreetMap (OSM) (http://openstreetmap.org) and converted into a network of directed road segments. A collection of GPS traces for journey from start location to an end location was generated using OpenStreetMap GPS traces utility online, which were used to identify commonly traveled roads. The traces are normally exported in GPX file format. A GPS Heatmap based on commonly used roads from a start point to an end point and captured by GPS devices and available on OSM GPS traces was generated. OpenStreetMap (http://openstreetmap.org) is a widely used source of GIS/GPS data, and for road map data, www.geofabrik.de was used to download the relevant files in 'osm' format. In order to calculate the shortest path between two points, the starting and ending points were to be selected and the shortest available path between those two points would be automatically calculated and suggested in real time. The track data was made persistent in a SpatiaLite database and the Basemap was a GeoTIFF raster image downloaded from OSM. Along with track data and Basemap layers, additional layers to display temporary information on top of the map were created. The temporary information was: 1) the currently selected starting point obtained by current GPS coordinates from the GPS/GNSS receiver device. 2) The end point selected, which was the location of the healthcare centre. 3) The shortest available path between the two points traced using line geometry.

Obtaining the Basemap: The GeoTIFF raster image downloaded from OSM was passed through the GDAL utility in QGIS, which aligns the raster image and makes corrections according to GPS coordinates to generate a Basemap that can be used in an application.

Defining the map layers: A separate map layer was created for each of the following: 1) Basemap 2) Track 3) StartPoint 4) EndPoint 5) shortest path. The Basemap layer was overlaid with the tracklayer stored in the SpatiaLite database. The map layers could also display additional attribute information e.g. healthcare centre information stored in the database.

Defining the map renderers: Appropriate symbols and renderers from QGIS were used to draw the vector data onto the map. The Start Point and End Point actions allowed the user to set the start and end points in order to calculate the shortest path between these two points.

To calculate Find Shortest Path action: The QGIS network analysis library was used to perform the actual calculation to find the shortest path between the start and the end points. The shortest path algorithm was run on the tracklayer in the memory-based map layers (start point and end point).

2.5. FHIR Application for Composite Sensor Kit

Physiological parameters such as heart rate, oxygen saturation, and pulse rate can be modelled according to HL7 FHIR specifications as Observations and events of Trauma could be modelled as 'Assessment Scales'. The assessment scales, scoring systems or indexes are observations with specific characteristics. [58] They have severity-points calculations that can make a quantitative statement on the severity and prognosis of a disease or injury. The scores in FHIR context are used to convert 'soft' observations into 'hard' data and evidence. Typically, assessment scales combine the individual values into a total score, which can be calculated for a reference population. The assessment scale can either be a single value it can consist of several dozen values, which can be calculated using a complex

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mathematical calculation or statistical technique. According to SNOMED-CT classification, TRISS is an assessment scale with SCTID: 273886002 and RTS has SCTID: 273885003. (Source:http://browser.ihtsdotools.org). The entire context of Patient, Observations of physiological parameters and Assessment Scales can be encapsulated as a resource Bundle and can be uploaded to the FHIR sandbox server using RESTful Webservices.

In order to demonstrate real-time integration and interoperability of the sensor kit and EHR, a FHIR sandbox was developed that hosted the EHR functionality and the trauma episodes were modelled as FHIR resources of 'Bundles', 'Observations' and 'Assessment Scales'. The readings from the sensor kit were encapsulated as Observations and Trauma Scores were encapsulated as 'Assessment Scales' according to FHIR specifications. SMART on FHIR [6] is a well-known interoperability project with the distinctive goal of developing a platform to enable interoperability between the healthcare application and the FHIR servers. The project was called Substitutable Medical Applications and Reusable Technologies (SMART) and it adopted web standards application programming interface transport, authentication/authorization, user interface, and standard medically coded data. The system helped specify a clinical description of an ailment in a patient. SMART FHIR provides an interoperable interface to develop web services to integrate end user application with the FHIR servers.

3. Results and Discussion

3.1. Workflow from Data Acquisition to Location Tracking

3.1.1. Signal Processing of Physiological Parameters

The signals acquired from the vital signs sensors were filtered using signal processing utilities in MATLAB signal processing toolbox. MATLAB Coder tool could emit C programs for the corresponding MATLAB scripts for the target processor (Texas Instruments Sitara ARM Cortex A8), hosted in Beaglebone Black. The motion artefact were removed using the stationary wavelet transform level 5 decomposition and sym4 wavelet (code expression (2)) with MATLAB Stationary Wavelet Transform De-noising tool as shown in Figure 3. The Signal-Noise Ratio observed was 27.83dB. The maximal overlap discrete wavelet transform (MODWT) using *modwt* function in MATLAB could enhance the R-peaks in the ECG waveform acquired from the ECG sensor, which helped to reconstruct a frequency-localized version of the waveform using only the wavelet coefficients. The coefficients correspond to the approximate frequency passbands which could maximize QRS energy. The *findpeaks* function in MATLAB enabled in isolation of the R-peaks in the waveform for vital signs readings as seen in MATLAB code expression (2)

```
wtrans = modwt(ecgsig,5);
wtrec = zeros(size(wtrans));
wtrec(4:5,:) = wtrans (4:5,:);
y = imodwt(wtrec,'sym4');                                                    (2)
y = abs(y).^2;
[qrspeaks,locs] = findpeaks(y, tm,'MinPeakHeight', 0.1, 'MinPeakDistance',0.150);
```

It may have been possible to calculate the vital signs: Respiration Rate and Systolic Blood Pressure using the ECG waveforms without having to integrate additional sensors using the Pulse Time of Transit (PTT), as the ECG waveform for the MIMIC II Numerics record linked into the MIMIC II Waveform database. Since the objective was to calculate trauma measures for the trauma patients, vital signs from the Numerics record (033n) were used for statistical analysis. Samples from MIMIC II Numerics database for the patient (MIMIC Numerics Record = 033n) admitted to ICU for clinical class Respiratory Failure were used. The samples were known to be taken at the interval of 1.024 seconds. In order to demonstrate the filtering mechanism, samples from MIMIC II Numerics (Record

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033n) database were read into MATLAB. The samples were filtered using parameters set in MATLAB code expressions (3) using 4th order Kaiser Window:

```
%E.g. ecg033array(:,2) contained the Physiological samples for MIMIC II record 033n
Hd= designfilt('lowpassfir','FilterOrder',20,'CutoffFrequency',150,
'DesignMethod','window','Window',{@kaiser,4},'SampleRate',1024);          (3)
y1 = filter(Hd,ecg033array(:,2));
```

The filtering mechanism induces phase lag and in order to eliminate the lag, group delay had to be introduced according to expression (4)
Savitzky-Golay filter (sgolay) was used as a smoothing algorithm with order=3 and frame length = 51 as in expression (4)

```
fvtool(Hd,'Analysis','grpdelay');
sgf = sgolayfilt(ecg033array(:,2),3,51);                                   (4)
y1 = filtfilt(Hd,ecg033array(:,2));
```

The spectral image, Figure 2, of respiratory rate signal for the patient (MIMIC Numerics Record = 033n) admitted to ICU clearly showed two episodes of 'significant drop in respiratory rate', which agrees with the patient condition of Respiratory Rate Failure.

3.1.2. Correlation and Regression of Trauma Scores and their Predictors

In order to validate the hypothesis that there is a correlation between RTS, NEWS and the Ps blunt or Ps penetrating scores, the statistical analysis had to be performed with an existing dataset. The MIMIC 2 Numerics dataset hosted by Physionet was used to perform the statistical analysis. The dataset was cleaned to extract features relevant to the NEWS and the RTS calculations according to patients admitted to the ICU and belonging to a clinical class category "RESPIRATORY FAILURE". Once the vital signs samples of all the patients belonging to a clinical category was extracted, columns for each of the vital signs were used for statistical analysis. It was observed that since the patients were admitted into ICU wards, the NEWS and the RTS scores agreed with their health status. The NEWS and the RTS severity scores less than 4 indicated the patients were under severe trauma and this helped to accept the hypothesis. The MIMIC II database is widely accepted and some experiments of similar nature have been performed on the dataset so it can be used for trauma score calculations.

The vital signs and physiological parameters from Physionet, MIMIC II Numerics (mimicdb/numerics) database was used to calculate NEWS and RTS and to generate correlation and regression models using the vital signs/physiological parameters for a clinical class of patients with "respiratory failure" and admitted to Intensive Care Unit (ICU).

NEWS and RTS scores showed no significant correlation ($r = 0.25$, $p<0.001$) amongst themselves, however together NEWS and RTS showed significant correlation with Ps (blunt) ($r = 0.70$, $p<0.001$). RTS and Ps (blunt) scores showed some correlation ($r = 0.63$, $p<0.001$) and NEWS score showed significant correlation ($r = 0.79$, $p<0.001$) with Ps (blunt) scores as shown in Table 1.

Regression: Considering Age, Heart Rate, Systolic BP, Respiratory Rate and SpO2 as predictors to PsBlunt, the predictors showed significant positive R for regression at $F(5,368715) = 1098725$, $p<0.001$, total R.sqr = 93% as shown in Table 2.

Both RTS and NEWS that were considered as variables to predict Ps had significant positive relationship with R for Regression significant at $F(2, 368718) = 442679.9$, $p<0.001$, total $R^2 = 70\%$.

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There was no significant correlation between NEWS and RTS (r = 0.25, p<0.001) which was due to the limitations of the sample space belonging to a particular clinical class. An extensive regression analysis over the entire Numerics dataset would be necessary to establish an affirmative correlation between NEWS and RTS scores. There may not be higher degree of correlation between NEWS and RTS scores themselves, which was due to the sample space considered from a single 'clinical class' for analysis. If the most recent MIMIC II/III Numerics dataset, which has more than 68000 records where each record covers more than 72 hours, an affirmative and significant relationship between RTS and NEWS could potentially be observed.

There was, however, significant positive relationship between NEWS and PsBlunt (r=0.79, p=0.01) and moderate positive relationship between RTS and PsBlunt (r=0.63, p=0.01).

Correlation and Regression between Age, HeartRate, SpO2, SysBP and PsBlunt: There was positive significant relationship between Age (r=0.91, p=0.01), HeartRate (r=0.87, p=0.01) and SpO2 (r=0.94, p=0.01) with PsBlunt. There was weak positive relationship between SysBP (r=0.47, p=0.01) and Respiratory Rate (r=0.33, p=0.01) with PsBlunt.

With additional information related to blood chemistry using portable blood chemistry analysis kits it would be possible to predict mortality and probability of survival using Simplified Acute Physiology Score (SAPS II) scores, which is more precise score as it also considers blood chemistry and urine samples. The use of machines learning models can enhance the prediction accuracy as has been found in quite a few data analysis experiments that have used MIMIC II Numerics database as it contains the physiological parameters for NEWS, RTS calculations. MIMIC database has been used in several machine learning data analysis tasks and is a quite widely used database. Numerics records contain time series of vital signs sampled once per second or once per minute, containing measurements of systolic and diastolic blood pressure, or heart rate. Numerics records are stored in a format similar to the waveform records, but since the sampling rates are far lower, Numerics records are much smaller. Numerics data also contain annotations related to patient alerts and monitoring devices related alerts with other non-periodic data. E.g. electrode misplaced or device disconnected etc. Information about some of the ICU monitor alerts, in some cases with additional observations collected from other equipment sources. The format of additional observations is similar to annotation logs of the MIMIC II Clinical Database and each annotation links with a specific time interval in a waveform or Numerics record, and may optionally also link to a specific waveform signal or time series. The copies of the .alarms annotation files containing information about these alerts are linked to both waveform and Numerics records. Since MIMIC II database is combination of waveform and clinical database a QueryBuilder can be used to link waveform, Numerics (vital signs) and clinical information. Simple example SQL queries and the resulting data could be presented. MIMIC-II has also provided data for annual PhysioNet/Computing in Cardiology Challenges, including the 2012 Challenge "Predicting mortality of ICU Patients". [59] Since the relationship between risk of mortality in the ICU and physiological variables depends on sample space of the dataset, the prediction can be improved by using automated neural networks or data-mining approaches, to predict hospital mortality in ICU patients. [49]

3.1.2. Shortest Route Calculation Using GNSS/GIS algorithms

Calculating the shortest distance between two points is a very common spatial problem, which was solved using the Network Analysis tool in QGIS. The Road Graph plugin of QGIS with network analysis algorithms was used to calculate the shortest path distance or time by calculating cumulative cost between two points in a network. The plugin provides a measure of the cumulative cost based on length between two nodes of a network. Measurements took into consideration the first case, when the speed limit is the same for all the roads (edges of our network) or the second case, when the speed limit differs for some selected roads. The "Roads" and "Routes" information was downloaded from Geofabrik (www.geofabrik.de) repository in the form of shapefiles. The shortest path algorithm in Figure 4 showing distance of 4.15 km could be covered in 0.6 hours at 40 km/hr.

3.2. Figures, Tables and Schemes

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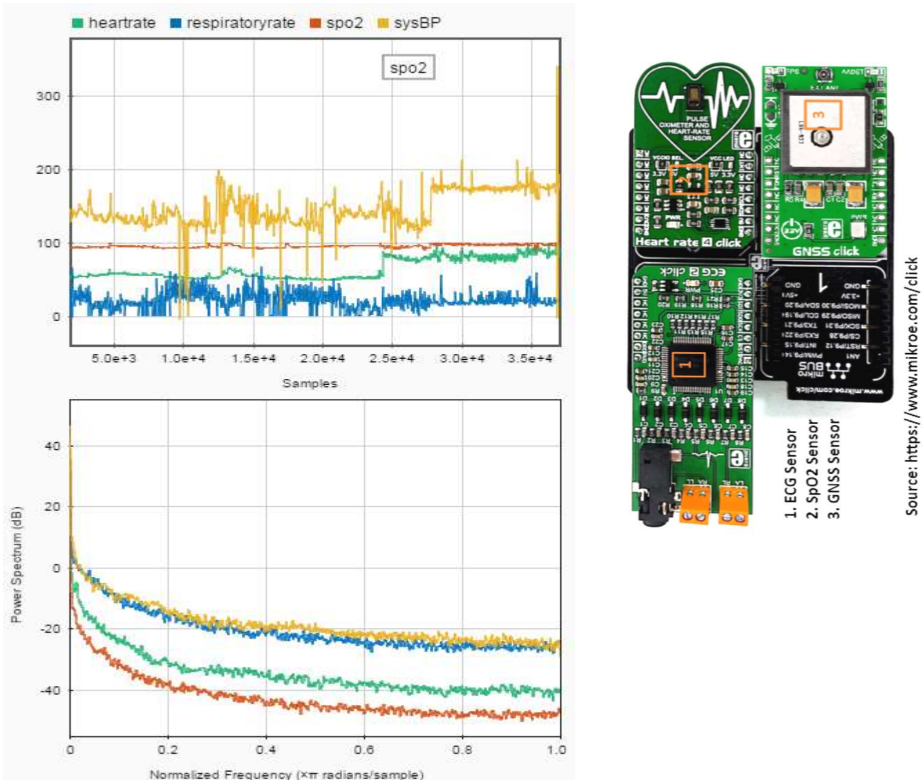


(a) (b)

Figure 1. The signal waveforms (a) for vital signs of Heart Rate, Respiratory Rate, SpO2, Systolic Blood Pressure for record 033n of MIMIC Numerics database. The power spectrum also shows cutoff at frequency of 0.25 (normalized in radians/sample). The composite sensor kit (b) showing the ECG sensor, SpO2 (pulse oximeter) and the GPS/GNSS (positioning) sensor boards to capture vital signs from human subjects.

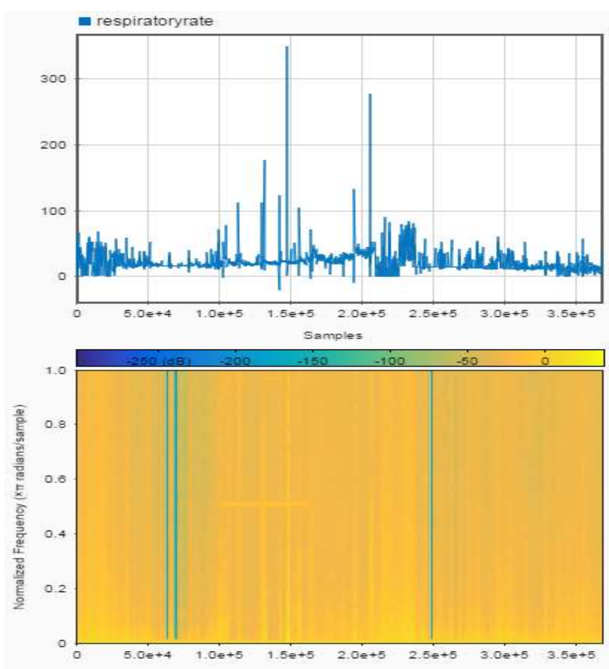


Figure 2. Spectral image of RR waveform clearly showing two episodes of Respiratory Rate Failure for the Record 033n in MIMIC Numerics database.

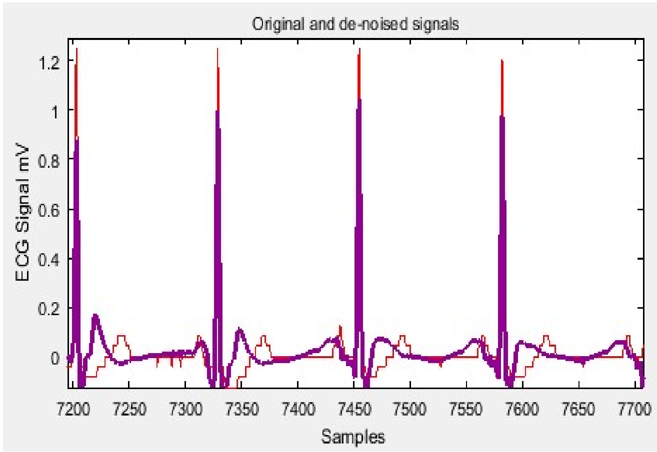
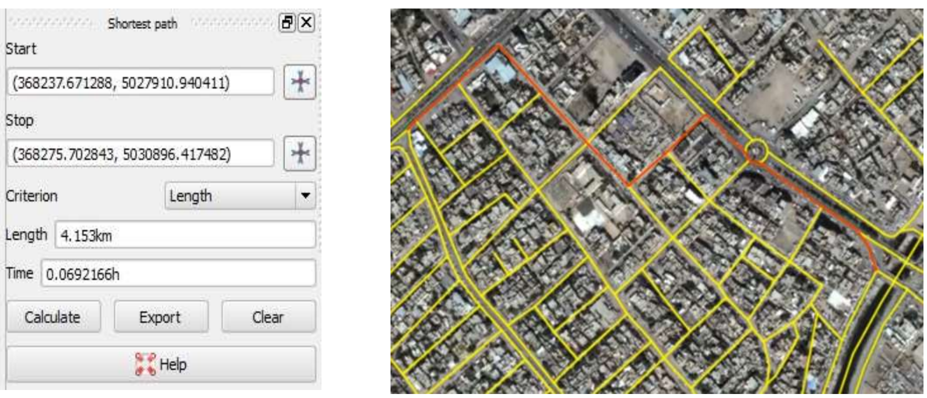


Figure 3. Noise removal in ECG signal using stationary wavelet transforms 1-D (MATLAB) using 'sym4' wavelet and level '5' decomposition. The ECG signal was used to derive Heart Rate and Arterial Blood Pressure using Physionet WFDB library.



(a) (b)

Figure 4. The shortest route algorithm using QGIS Network Analysis tool indicating shortest route between start and the end points.

Table 1: Correlation between Ps, NEWS and RTS scores

		PsBlunt	NEWS	RTS
PsBlunt	Pearson Correlation	1	.795**	.063**
	Sig. (2-tailed)		.000	.000
	N	368721	368721	368721
NEWS	Pearson Correlation	.795**	1	-.252**
	Sig. (2-tailed)	.000		.000
	N	368721	368721	368721
RTS	Pearson Correlation	.063**	-.252**	1
	Sig. (2-tailed)	.000	.000	
	N	368721	368721	368721

Correlation is significant at the 0.01 level (2-tailed).

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Table 2: Regression for Ps (Blunt) prediction

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.968[a]	.937	.937	.033065132300000

Predictors: (Constant), SpO2, RespiratoryRate, SysBP, HeartRate, Age

Table 3. FHIR Specific code to encapsulate an observation of RTS trauma score that can be uploaded as a Resource Bundle in XML or JSON format to FHIR Server sandbox

```
// Create a FHIR Observation object.
Observation observ= new Observation();
// Assign a randomly generated Universal ID (UUID).
 observ.setId(uuid)
// Set the Observation code according to a Coding System
// Coding System refers to RTS trauma score in SNOMED CT
observ.getCode()
    .addCoding()
    .setSystem("http://snomed.info/sct")
    .setCode("273885003")
    .setDisplay("RTS Trauma Assessment")
observ.setValue(
   new QuantityDt()
      .setValue(3)
// Set the Date and Time stamp for the observation
observ.setIssued(
     new InstantDt("2017-05-05T15:30:10+01:00"))
```

```
// The Observation upload request above generated the following
// response in XML or JSON format after observation is logged to
// FHIR Servers.
<Bundle xmlns="http://hl7.org/fhir">
 <id value="ddde128-e4e2-481ee-9acb3-c5eebc2ec5e0"/>
 <type value="transaction-response"/>
<entry>
     <response>
          <status value="201 Created"/>
          <location value="Observation/96728/_history/1"/>
          <etag value="1"/>
          <lastModified value="2017-05-05T15:30:10+01:00"/>
     </response>
 </entry>
</Bundle>
```

4. Conclusions

The research began with the questions and hypothesis of being able to calculate trauma scores for patients under trauma, using wearable sensor kits, non-invasively in real time and importantly, under no ambulatory or hospitalization settings. It was also hypothesized that given the vital signs plus physiological information about the patient and the corresponding trauma scores, prediction of survival scores could be estimated, which could help the critical care team at a remote location prepare for the emergency procedures. To enable such a system to function without key

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infrastructural changes, location information had to be garnered and the information payload had to be transmitted in real time and using standard telemetry protocols and clinical coding standards. The four main vital signs like temperature, pulse rate/heart rate, respiration rate (rate of breathing), blood pressure (Non-invasive Systolic) and oxygen saturation were adequate to calculate trauma scores and prediction of survival. [7] [8]

From the results obtained, stationary wavelet transform along with passband Chebyshev Type II order 2 filter, turned out effective in removing signal noise, motion artefacts and baseline wandering in ECG waveforms and yielding a better signal to noise ratio.

The respiration rate and blood pressure as vital signs were important physiological parameters and in the absence of a sensor that can directly and non-invasively measures these parameters, it was found that the ECG derived measures could be used. Respiratory rate was calculated using Physionet WFDB library using the EDR (ECG Derived Respiration) utility and the derived value has high correlation to the measured values as found by the authors of the library. [60] The EDR utility is a C program and can be compiled on any GNU/Unix/Linux platforms.

Blood Pressure (BP) is also an important vital sign used in trauma scoring and in absence of an integrated sensor; there were challenges in measuring BP and remove motion artefacts. [41] The pulse transit time (PTT), which requires synchronization of ECG and SpO2 sensor measurements, could have been used, though synchronization in two sensor readings may lead to inaccuracies. Besides, BP samples are not required as frequently as SpO2 or ECG samples, so an external BP monitor can be used.

Pulse oximetry as the fifth vital sign [15] was also used in calculating trauma scores and was required in trauma calculations and prediction of survival assessment. The pulse oximetry sensor can capture SpO2 readings non-invasively.

The correlation and regression scores between NEWS, RTS and Ps scores were studied and a high degree of regression was observed between NEWS and RTS taken together with Probability of Survival (Ps). There may not be higher degree of correlation between NEWS and RTS themselves, though this may have been due to the sample space considered from a single 'clinical class' for analysis. If the most recent MIMIC II/III Numerics dataset, which has more than 68000 records where each record covers more than 72 hours, an affirmative and significant relationship between RTS and NEWS could potentially be observed. This however, would require resources with higher computing power and storage.

In the calculations for injury severity scores, the Trauma and Injury Severity Score (TRISS) [19] remains the most commonly used tool for benchmarking trauma fatality outcome. The predictive power of TRISS could be substantially improved by re-classifying the measured parameters and by altering the coefficients for the sample space belonging to a particular clinical class. The TRISS scores form the basis for calculation of prediction of survival scores and for predicting mortality and estimating mortality rate.

Once the early warning and trauma scores were calculated the Electronic Health Records (EHR) with the public health care service provider could be updated using ICD and SNOMED/LOINC classification coding system using Health Level 7 (HL7) standards. Fast Health Interoperability Resources FHIR is an HL7 standard that provides interoperability specifications for web services and EHR databases and by modelling the trauma scores into FHIR 'Observations' and 'Bundles' of information payload the trauma specific information could be logged into EHR databases for future decision support and to prepare for emergency procedures ahead of time. [34]

It was observed that since the analysis was performed on datasets of patients that were admitted to the ICU wards, the NEWS score, the RTS scores and the prediction of survival scores agreed with their health status. The NEWS and the RTS severity scores less than 4 indicated the patients were under severe trauma and this helped to accept the hypothesis. The MIMIC II Numerics database is a widely accepted database and the trauma scoring hypothesis could be effectively tested with the datasets in the database as it contained all the vital signs required for calculating trauma scores.

A very important application for any wearable IoT healthcare monitoring kit is to be able to locate the individual when the trauma related events take place. With the availability of low cost

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wearable GPS/GNSS or the Global System for Mobile communication / General Packet Radio Service (GSM/GPRS) receivers, the location awareness could be embedded in the kit itself. The GPS receiver could provide the location specific information and the composite sensor could provide physiological information and the trauma scores. This composite payload could be transmitted to the healthcare service provider, which could enable them to get ready for emergency. With the preloaded GIS information, related to the rail and road routes and the traffic conditions, the shortest path/route between current location and the nearest healthcare centre could be calculated using QGIS network analysis tools. [38]

By putting the data acquisition, signal processing tools and techniques along with the trauma scoring and standard clinical coding practices together and by embedding location awareness into the composite healthcare monitoring kit, it could be concluded that a real time incident response system for trauma related events could be implemented. Such a system would prepare the critical care team in healthcare units to prepare for emergencies well ahead of time and can reduce the mortality rates for severe injuries and trauma.

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Conflicts of Interest:

"The authors declare no conflict of interest."

"The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results".

Appendix A

The appendix is an optional section that can contain details and data supplemental to the main text. For example, explanations of experimental details that would disrupt the flow of the main text, but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data is shown in the main text can be added here if brief, or as Supplementary data. Mathematical proofs of results not central to the paper can be added as an appendix.

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