Computerized Decision Support System for Traumatic Brain Injury Management

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Abstract

Mortality and morbidity related to traumatic brain injury (TBI) present a major health care burden. Patients with severe TBI must be managed rapidly and efficiently to minimize secondary brain injury potentially leading to permanent sequelae. This is especially important in young patients, whose brain is still in development, making them particularly susceptible to secondary insults. The complexity of both brain injury pathophysiology and the intensive care unit environment makes the management of these patients challenging, with a risk of delayed response and/or patient instability contributing to worsened outcome. Computerized assistance in TBI appears likely to improve patient management, by helping clinicians quickly analyze and respond to ongoing clinical changes and optimizing patient status by guiding management. Currently, computerized decision support systems (CDSSs) do not feature continuous medical assistance with individualized treatment plans. This review presents new developments in CDSSs specialized in TBI. We also present the framework for future CDSSs needed to improve TBI management in real time, taking into account individual patient characteristics.

Keywords
- brain injury
- head trauma
- intensive care unit
- pediatric intensive care unit
- computerized decision support system
- neurocritical care

Introduction

Traumatic brain injury (TBI) is a major health problem.[1] These injuries can be sustained during motor vehicle accidents, falls, high-intensity sports, or projectile blasts to the head. TBI leads to 108 to 332 new intensive care admissions per 100,000 population every year.[2] Roughly 40% of those with severe TBI will succumb to their injuries, making it the first cause of mortality in adolescents and young adults.[2] Furthermore, children with severe TBI are at high risk of developing long-term sequelae, such as partial or complete palsy, coordination impairment, learning difficulties, social behavior disorder, and memory or language impairment. The impact of these comorbidities is heightened in children, limiting their social and academic development, and leading to decreased long-term economic contribution. In 2007, the lifetime cost per case of severe TBI was estimated at up to U.S. $400,000.[2]

Important progress has been made in the understanding of brain injury, but the pathophysiology of TBI remains extremely complex and difficult to operationalize at the bedside.[1] After the initial trauma, irreversible brain lesions occur immediately, known as primary lesions. In the following hours and days, the combination of patient instability with the acutely injured brain tends to generate additional lesions known as secondary lesions. To minimize the morbidity associated with TBI, the primary goal of critical care management in the first hours is to prevent the extension of these secondary injuries.[3] To achieve this, the patient's homeostasis is maintained with close monitoring of hemodynamic and respiratory functions, as well as hematologic and electrolyte balance.[4] In addition, multimodal cerebral monitoring is used

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to detect early warning signs including intracranial hypertension, brain ischemia, cerebral metabolic crisis, and loss of vascular autoregulation, which are associated with unfavorable outcome.[5,6] A precise analysis of brain status is fundamental to appropriately guide the treatment of these patients. Each treatment for intracranial hypertension has specific effects on brain equilibrium and can be harmful when used in inappropriate situations (e.g., hyperventilation lowers intracranial pressure (ICP) by decreasing cerebral blood flow, which can be harmful if cerebral perfusion is decreased or acceptable if hyperemia prevails).

The specific analysis of brain status is complex and requires a high level of expertise. Moreover, intensive care units (ICUs) are busy work environments, where an overwhelming amount of patient information needs to be processed quickly by the health care specialists to provide accurate clinical decisions.[7] This becomes critical in severe TBI cases, given the rapid and optimal management needed to minimize secondary brain injury and sequelae.

The Miller principle states that humans can only take into consideration two variables efficiently in their decision-making process, and that this capacity is fully lost when dealing with more than seven variables.[8] Considering this, and the abundant amount of data generated in the ICU, it is appropriate to consider that the use of computerized decision support systems (CDSSs) could be beneficial in assisting ICU physicians in the decision-making process. CDSSs have been shown to be helpful in the ICU, for instance in the context of mechanical ventilation weaning.[9] When applied to the management of TBI, the potential benefits of CDSSs may include (1) standardization and optimization of the management of TBI patients even when the expertise of the medical team varies (e.g., decisions are frequently taken by residents, especially during the nights), (2) decreasing the reaction time to a change in patient condition, (3) improving understanding of individual patient patterns in pathophysiology, and (4) reducing the workload of the medical team. A CDSS would be especially useful in hospitals lacking specialized neurological ICUs, as is the case for most pediatric ICUs.

In this article, we review the evidence regarding available CDSSs designed for improving the TBI management. We also propose some features that appear critical for future CDSS development, and finally discuss the perspectives that could be achieved using machine-learning techniques.

Data Acquisition System in ICU

To fully appreciate both the potential contribution and the complexity of CDSSs in the management of children with severe TBI, it is necessary to understand some aspects of the care of these patients. Unlike adults, the brain of young children is still undergoing development, which makes it particularly vulnerable to secondary insults following severe TBI.[4] Rapid and efficient management of the injury becomes essential to favor positive outcome and reduce sequelae. To do so, the medical team has to closely monitor the patient's condition and cerebral status. This task involves the monitoring of multiple physiological signals. Some of these are continuously acquired by different sensors and their values presented on physiological monitors—for example, mean arterial pressure, temperature, pulse oxymetry (SpO_2), end-tidal CO_2, ICP, brain tissue oxygenation ($PbtO_2$), continuous electroencephalography, while other variables are measured only intermittently (e.g., transcranial Doppler, cardiac echography). The temporal evolution of these data and correlation between them provide additional important information, such as the status of cerebral vascular autoregulation. In addition, laboratory test results and ongoing pharmacotherapy must also be considered in the evaluation. Overall, there is a tremendous amount of data, sometimes conflicting, that clinicians must prioritize, analyze, and manage in their clinical decision making. The physician's personal experience plays a large role in the filtering of information and their decision making.[10] Less experienced clinicians may be less comfortable dealing with an overload of data, potentially increasing the chances of error. In addition, unplanned rapid clinical deterioration requires prompt decision making around the clock, which can be problematic in a busy ICU. Other than the quantity of data in ICUs, its presentation to clinicians can also be a factor promoting errors. Text display in medical records can increase the probability of error in ICUs,[11] while properly designed graphical display methods have been shown to help the medical staff make faster and more accurate decisions,[12–14] and facilitate finding links between associated medical events.[15]

One of the main advantages of using a CDSS in a critical care environment is its ability to regroup different datasets under one interface, and to display them in an easily interpretable manner, avoiding additional information overload. The overall goal is to help clinicians rapidly draw a general portrait of the patient's clinical status. The quality and pertinence of information presentation plays a major role in problem solving,[16–21] and taking the physician's cognitive process[18,20] into account is therefore essential in the development of a CDSS. A clinician-centered designed CDSS would be easier to implement in an ICU, a key parameter for reducing human factor errors.[22,23]

To efficiently assist the clinician, a CDSS should be fed with all available data entering in the decision process. In the case of CDSS in critical care environment, where the assessment of the patient's state has to be made in real time, the system needs to continuously gather the most recent available data. The development of a database is an important step toward the implementation of CDSS, in particular during the design, calibration, validation, and auto-learning process. The creation of the database itself can represent a major challenge in the ICU due to the multiple possible types of entries (various monitors, ventilator, electronic pumps, laboratories, medical notes, pharmacy data, imaging, etc.). The data should be entered in the database at the highest sampling frequency supported by the equipment, to avoid losing valuable information.[24] This demands high storage and computational capacity, which can require high budget allocations.[25] Assuring the data security and validity, managing possible communication problems between medical devices from different manufacturers, and the choice of the data structure are all important considerations when developing a large-scale ICU database. The properly validated and annotated database becomes an important source of knowledge for the CDSS improvement. The database analysis by signal-processing techniques could lead to a better understanding of the TBI pathophysiology, and help develop and validate more robust mathematical models for the patient status analysis and the decision-making process.

The importance of physiological signal database for future research on complex pathophysiological pathways has led to several initiatives to make TBI-related data more accessible. The Brain Monitoring with Information Technology (BrainIT) project[26] is a European endeavor that aims to centralize TBI clinical data from different institutions, and make it research accessible to its members. The International Mission for Prognosis and Analysis of Clinical Trials in TBI (IMPACT) project[27] is a similar international collaborative group that promotes data sharing in the aim of developing TBI outcome predictors.

Computerized Clinical Support System in TBI

CDSSs have been used in the medical field for a long time. One of the first CDSSs implemented in the 1970s, the MYCIN system,[28] was used to identify the type of bacteria causing specific infections, and recommend the proper antimicrobial therapy. While this system used multiple pre-programmed medical rules to take the best decision possible, more recent CDSSs are now based on more intelligent and complex algorithms. Although not specifically designed for TBI, several systems have been developed for use in ICUs. Kamaleswaran et al[29] proposed a web-based platform that centralizes and analyzes physiological data, as well as electronic medical records in neonatal ICUs. Stylianides et al[30] developed a software that collects a database of vital signs in real time, by extracting from different medical devices. A customizable display of physiological signals facilitates interpretation and permits real-time annotations. The software also records the alarms produced by the medical devices and summarizes them on its own interface.

Of note, monitor-generated alarms are not always useful. They are mostly triggered by simple rules, usually when one physiologic signal exceeds a threshold. As a result, despite being frequently activated, they do not always reflect a medically relevant problem. They therefore tend to be ignored and can become an unnecessary source of stress for the medical team.[31] For this particular reason, one goal of CDSSs should be to avoid excessively frequent and irrelevant alerts. The integration of more sophisticated decision-making tools should result in more intelligent and clinically relevant alerts.[32]

In the specific context of TBI, a CDSS could facilitate the interpretation and diagnosis of very complex conditions, provide recommendations to improve the adherence to guidelines, and individualize patient management. A CDSS could also substantially reduce the intensivists' workload and increase their efficiency. For instance, determining optimal cerebral perfusion pressure (CPP) when managing a patient with severe TBI should take the patient's autoregulation status in account, which can be complex and time consuming. A CDSS can easily compute the brain's autoregulation coefficient (PRx), a validated indicator of autoregulation,[33,34] and rapidly provide clinically important recommendations regarding the adjustment of optimal CPP. Similarly, the automatic analysis of physiological signal time series can help identify specific patterns or predictors associated with outcome. For example, the variability of ICP is associated with long-term outcome in brain injury,[35] and a decrease in ICP approximate entropy is associated with a risk of intracranial hypertension.[36]

As listed in ►**Table 1**, a few CDSSs aiming to improve TBI management have been previously described. Wilson et al[37] have developed a CDSS specialized for neurological ICUs. Data from different sensors are gathered and processed, and alerts can be triggered based on pre-programmed medical rules. For example, an alert of high ICP in TBI would be activated when ICP exceeds 20 mm Hg, and CPP is below 60 mm Hg for more than 360 seconds. While this method produces more meaningful alerts compared with simple threshold triggering, it is limited to a specific problem (intracranial hypertension) and does not take into account other variables of the patient condition, which could influence the choice of the predetermined ICP and CPP targets (e.g., brain oxygenation or perfusion, autoregulation status).

iSyNCC is another CDSS developed for neuro-ICUs.[38] Its originality stems from its ability to predict the evolution of a physiological signal. This represents a step toward personalized treatment plans such as predicting the upcoming values of ICP over a short period of time to facilitate the anticipation of the problem (in time and in magnitude). It can also be used to compare the patient's response (after a treatment) to the predicted response, reflecting the patient's sensitivity to a treatment.

The ICM+ software developed by Smielewski et al[39] at the Cambridge University is widely used in the TBI field. Similarly to aforementioned systems, it collects physiological data in real time, displays them on a user-friendly interface, facilitating their analysis. Gomez et al[40] have also developed a toolbox for the analysis of TBI-related signals. This toolbox continuously calculates the PRx, mean velocity index (Mx), CPP, and the critical closing pressure. This software enables the calculation of monitoring indexes believed to individualize treatment; however, they do not provide any diagnostic evaluation or management recommendations.

Dora et al[41] developed a system that recommends medical treatment based on inputs. By considering the initial ICP, CPP, pupillary reaction, and the Glasgow score, the algorithm computes a list of 10 different treatments with associated certainty score. The algorithm is based on expert opinion and a probabilistic approach. Only 35% of recommendations were considered appropriate, likely because they were derived from limited baseline variables.

Wu et al[42] designed a modular CDSS that includes a TBI module. Based on real-time data processing, this system detects deviations from accepted guidelines for TBI management, and suggests treatment adaptation. The algorithm,

Table 1 Existing CDSSs developed for improving the management of patients with TBI in intensive care unit

Author	Year	Characteristics	Main strengths and limitations
Wilson et al[37]	2013	- Data gathered from different neurocritical care sensors in real time - Alarm activated by preprogrammed medical rules	Strength: improve the detection of intracranial hypertension with more meaningful alerts Limitations: limited to intracranial hypertension
Feng et al,[38] iSyNCC	2011	- Continuous data acquisition from neurocritical care medical devices - Prediction of physiological signal evolution	Strength: short-term prediction of signal evolution can facilitate anticipation Limitations: limited physiologic variables, no recommendation tool
Smielewski et al,[39] ICM+	2008	- Collects data in real time - Friendly interface facilitating signal analysis - Calculation of autoregulation parameters	Strength: facilitate the assessment of the precise brain status, including data from multimodal monitoring, favoring an individualized management Limitations: no comprehensive diagnostic classification, no recommendation for management
Gomez et al[40]	2010	- Real-time data collection and processing - Calculation of multiple indices regarding ICP, autoregulation status, perfusion status, CPP, and critical closing pressure	Strength: facilitate the assessment of the precise brain status, including data from multimodal monitoring, favoring an individualized management Limitations: no comprehensive diagnostic classification, no recommendation for management
Dora et al[41]	2001	- Recommends medical treatment based on initial ICP, CPP, pupils, and Glasgow coma score	Strength: management recommendations are available Limitations: limited quantity of variables entered in the system; the level of appropriateness of the recommendations is limited
Wu et al[42]	2009	- Real-time data acquisition and processing - Detects care deviation from medical guidelines - Suggests treatment adaptation based on ICP, CPP, and arterial blood pressure	Strength: management recommendations are available Limitations: limited quantity of variables entered in the system, recommendations not personalized based on a complete evaluation of the brain status

Abbreviations: CDSSs, computerized decision support systems; CPP, cerebral perfusion pressure; ICP, intracranial pressure; TBI, traumatic brain injury.

however, takes into account a limited quantity of variables (ICP, CPP, and arterial blood pressure), and does not adapt the recommendations to more complex pathophysiological patterns (in particular the status of brain perfusion and autoregulation), which are critical to individualize the management.

Other TBI-specific computerized algorithms have been designed to detect the severity of brain injury[43,44] or estimate patient prognosis.[45,46] Although they do not aim to optimize patient care, these tools could be useful as outcome prediction is difficult in the acute phase in ICU.

The development of more ambitious and integrative CDSSs in TBI is ongoing.[47] One project, coordinated by Moberg ICU solutions,[47] aims to facilitate the management of a patient with TBI from the time of injury, through transportation to the hospital and during its ICU stay. Similarly, the TBIcare project initiated in Europe several years ago is developing a CDSS that could provide personalized care to TBI, taking into account complex patient pathophysiological features.[48] Currently, no details or results have been published for either project.

Proposal of a CDSS in Severe TBI

Some important limitations of the systems presented earlier are the lack of specific diagnosis and recommendation capabilities; implementation of simple models using too few variables to achieve accurate results; and management recommendations that are absent, or limited to a few rules derived from guidelines for TBI care, without adaptation to the patient's specific condition. In accordance with recent international recommendations concerning the use of computer-aided monitoring systems in the neurocritical monitoring field,[32] we propose several characteristics that should be considered in the development of future CDSSs for the management of patients with TBI.

The medical management of patients with TBI has to be made on continuous basis. A real-time system connected to a dynamic database would be of great value, allowing the continuous evaluation of the patient-specific conditions, and the ability to compare one situation to a large database of previous similar conditions.

The primary role of a CDSS is to assist clinicians in their decision process, facilitating the identification and detection of specific conditions and providing them with appropriate clinical recommendations. To achieve a good acceptability, it is crucial that the CDSS algorithms take into account the clinician's cognitive clinical decision process. A rule-based system, with rules developed and widely accepted by medical specialists, should therefore be at the heart of the design. It will improve the understanding and trust in the CDSS, and facilitate its implementation in the ICU. The terminal user should also be able to adapt the algorithm rules or thresholds. It is also important that the system provides explanations and justifications regarding the diagnosis established and the suggested treatment, which would improve the acceptability of these outputs and favor the clinician training.

One major challenge in designing the rules is the understanding and replication of the decision-making process of clinicians. Clinical decisions are made based on scientific knowledge, experience, and intuition suggesting that the rules are not always strict and thresholds are not always fixed values. As such, fuzzy logic has proved to be a great tool in the design of expert systems,[49] and is well adapted for medical decisions.[50–52] The adaptability of implemented rules is also crucial to allow for inter-physician variability. One must also track the reasons why some decisions by the CDSS are denied by the clinician, to improve the CDSS recommendation process. Moreover, once a proper amount of validated data is recorded into the database, machine-learning tools will permit to reassess or recalibrate the rule basis. The CDSS should therefore be able to learn long term, based on patient behavior and clinician response to each of its decisions, to adjust the decision-making process accordingly.

To aid the medical staff in identifying the diagnostic step and consecutively adhere to the management recommendations, the CDSS should classify the state of the patient into a clearly designated category. For instance, the clinician should understand immediately if the TBI patient is in a controlled situation, or if the patient's brain seems at risk of ischemia, hyperhemia, and/or if a moderate or severe intracranial hypertension is present. By clearly assigning the brain pathophysiological condition, with the proper justification for this classification, the CDSS should more rapidly facilitate the recognition of complex condition, even by less trained physicians. This should also lead to a better acceptance of the recommendations, and reduce clinician stress, allowing them to focus on subtle details in critical situations. The prediction of the patient's ongoing clinical state will favor anticipatory rather than a posteriori reactions.

To facilitate the rapid interpretation by the medical team, the patient's status should be illustrated using specific and clear graphical display, exhibiting various pathophysiological conditions and the ongoing clinical state. This provides a visual indication of the dynamic evolution of the patient's state.

The validation of CDSS accuracy is a challenge. Retrospective patient data could be used to design and test the system. The data utilized to train the system algorithms should represent a wide range of conditions. Once the CDSS performances are validated on retrospective data against medical experts' decisions, prospective studies should evaluate the CDSS behavior in a real clinical environment. Finally, clinical trials should explore the impact of CDSS use on patient management, initially with simple objectives (e.g., percentage of adherence to guidelines) and subsequently with assessment of patient outcome.

Future Perspectives

As discussed in previous sections, the amount of data generated in ICUs is enormous. An initial challenge is centralizing and storing this information to provide an infrastructure for research. Big data mining is a very active field,[53] particularly pertinent for medical data in the ICU.[54–56] Data mining can help uncover links between variables, to help in the development of optimal strategies. Applying data mining techniques to well-structured TBI databases could generate a better understanding of complex brain conditions and aid in selecting the most significant variables to consider in TBI management. Furthermore, feature selection techniques such as genetic algorithms, frequently used in optimization problems, can be used to select, among several rules, the set of rules that provide the best accuracy. Forecasting of time series in physiological signals could also have major implication in the development of CDSS in TBI.[57–59] As previously stated, effective forecasted data would anticipate and accelerate the clinician's response, optimizing patient status for longer periods than conventional management.

In conclusion, CDSSs are crucial to improve the management of patients with TBI. CDSSs are still at an early stage in the field of TBI, but recent technologies should overcome the barriers and challenges of ICU environment, leading to the development of efficient systems. Collaboration between neurocritical care medical specialists, Information Technologies (IT) specialists, biomedical engineers, and companies is of outmost importance to prepare and validate optimal CDSS that will be reliable, efficient, and easy to implement. These future systems should have the power to decrease the impact of this major health problem on the patient, their family, and society.

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