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Decision Support Systems in Anesthesia, Emergency Medicine and Intensive Care Medicine

Thomas M. Hemmerling
McGill University
Canada

1. Introduction

Decision support systems (DSS) in the context of anesthesia, critical care and intensive care medicine consist of several components: the 'brain', which integrates a variety of input parameters and delivers as output various informative data which can help the physicians to perform better. They might be considered as 'automated textbooks' which by the use of a digitalized infrastructure not only deliver immediately all the necessary health care knowledge to the clinician but also has the capability of intelligently monitoring the actual health status of any given patient – 'smart monitoring'. It is obvious that in the context of anesthesia, critical – emergency – care and intensive care medicine, such systems are a vital backbone of medical care of the 21st century with a growing number of parameters, growing number of diseases, diagnostic possibilities and treatment options. Decision support systems have the potential to bridge the gap between the theoretical performance of a well trained physicians –who has spent a decade acquiring knowledge and a multitude of manual skills – and his or her actual performance in daily practice. This latter performance can be influenced by any given contextual condition, be it emotional, intellectual or behavioral pattern. What we define as 'clinical error' is influenced by several mistakes, one of the most prominent the impossibility to recall all diagnostic and therapeutic options any time for any patient – 'prospective recall failure'. Computerized information tools have been investigated for more than 2 decades and have been proven to be highly effective in a research environment.

However, especially in the specialties which are the object of this chapter, they have not been widely introduced into practice.

One of the problems is the clustering of information in modern healthcare facilities between hospital administrators, several laboratory or investigative units and health care providers. The complexity of modern diagnostic and therapeutic options is such that only the most complete coverage of all available patient information can deliver a most complete decision support for the clinician. A lack of standardization, immediate delivery of patient data due to inherent lag times of different working systems, make some of these systems inefficient in reality. Another problem is the 'user-friendliness' of these systems – the significant additional time necessary to 'feed' the data into the system, as well as the gradual integration of these decision support systems into the daily work pattern: accessibility of the

information in a most efficient way for a variety of health care providers with different technological and intellectual background is another problem. The widespread introduction of simple anesthesia information management systems (AIMS) into the daily practice, especially in North America – has also been impaired by shrinking health care budgets and administrative ignorance.

This chapter will focus on painting an outline of possible DSSs in anesthesia, critical care and intensive care medicine with a special attention on presenting a vision of what is needed for the future.

It is beyond the scope of this chapter to present all the research which has been done in designing and testing DSSs in these three specialties. It is tried to present exemplary case studies of DSSs which are not merely theoretical constructs but close to clinical usability. The examples used shall spur the reader's curiosity and show what is feasible in the context of modern health care systems, presenting both present challenges and future directions. At the end of this chapter, some recent review articles on the topic are added to instigate further reading.

2. Decision support systems

Decision support systems have been used in research and clinical studies in the fields of anesthesia, emergency medicine and intensive care medicine. It is beyond the scope of this chapter to present all studies and clinical applications; instead, the author tried to outline the characteristics of DSSs in all three specialties with specific examples highlighting the advantages of these systems as well as specific challenges.

2.1 Decision support systems in anesthesia

Anesthesia is characterized by being a specialty where more than 100 parameters have to be monitored constantly and rapid and appropriate action often defines the difference between good or adverse outcome. Anesthesiologists are often compared with pilots, and described as 'pilots of the human biosphere' (Hemmerling, 2010). Similar to pilots, they need to coordinate their monitoring with direct supervision of surgical progress and interact with health care providers from different background, nurses, anesthesia technicians and surgical team. Organizational accidents can easily develop in this environment (Reason, 2005); an example of a schematic development of an organizational accident is described in figure 1.
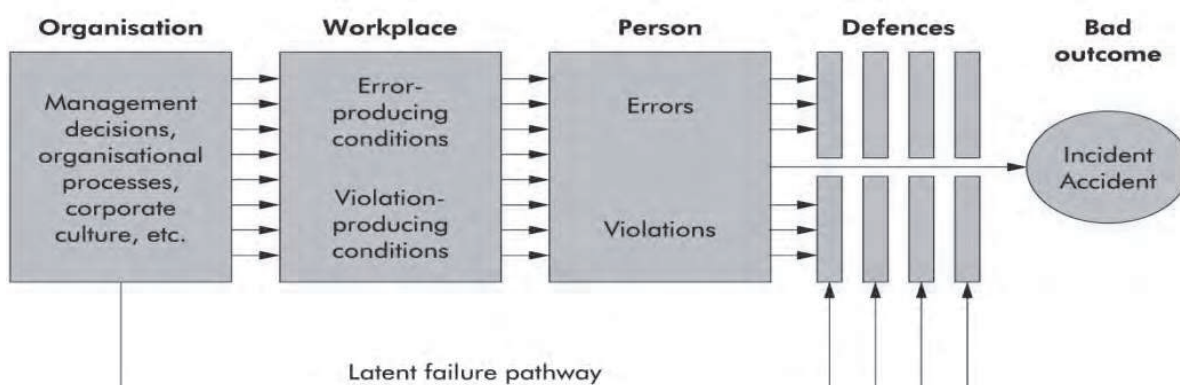

Fig. 1. Stages in the development of an organizational accident. (Reason, 2005)

Organizational deficits can be based on a specific culture, e.g. strictly hierarchical command structure, certain management decisions, e.g. organizational deficits in providing important drugs or devices or other forms of mistakes. The workplace can be faulted by lack of teamwork, communication issues, non-standardized or badly maintained equipment-or simply its absence – problems with proper drug labeling, delivery, OR scheduling or other planning deficits. All these deficits can lead to errors or violations of existing 'best evidence practice' with subsequent bad outcome.

As much as the various development stages of organizational accidents in anesthesia are common knowledge, as difficult is their analysis and efficient accident investigation. A possible model of efficient – in terms of avoiding subsequent bad outcome – accident investigation has long been presented (Eagle et al., 1992, Fig.2).
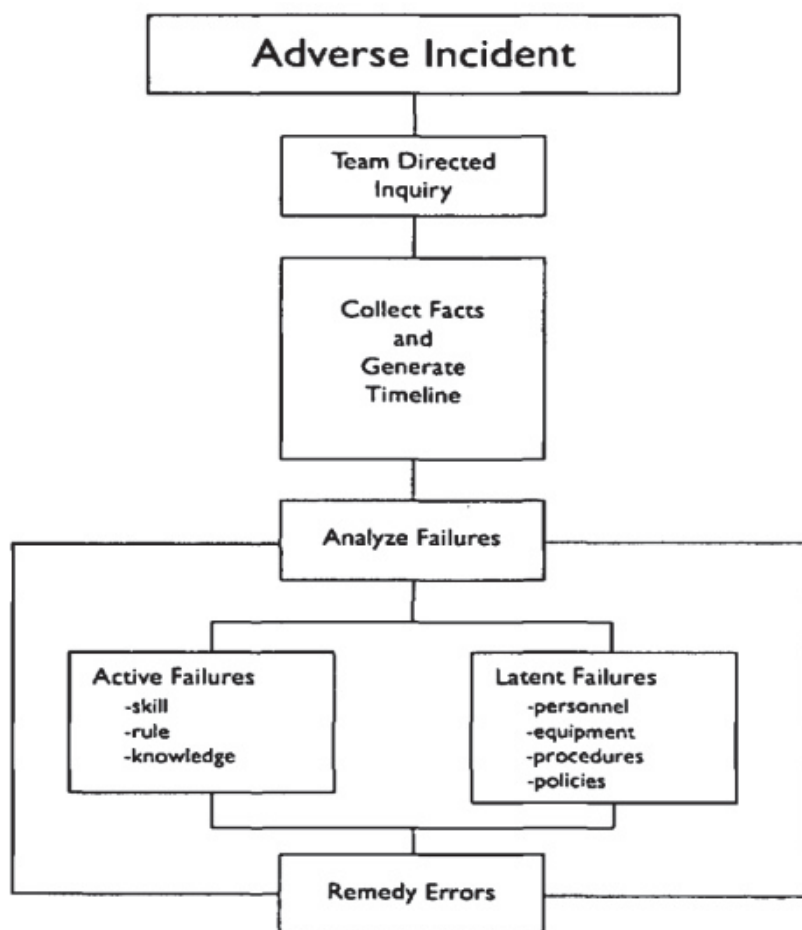

Fig. 2. A model of accident investigation. (Eagle et al., 1992)

Any adverse incident should therefore trigger a team-directed inquiry – any individualized search for mistakes will be doomed to fail. The correct establishment of both facts and timeline is the key for a successful analysis of the event. This will lead to the determination of both active failures, such as a lack of skill (e.g. intubation skill) and – more difficult to overcome – latent failures, such lack of equipment, wrongful procedures or policies. This can lead to better organizational DSS which allows to avoid bad outcome.

The influx of electronic data management systems – anesthesia information management systems (AIMS) – has helped to make this cascade of accident analysis readily available,

reliable and easy to use. The fact that less than 10% of North American hospitals have AIMS available is still a major setback for proper management of accidents and adverse events. However, recently, DSSs have been developed to extract events from the AIMSs for an improvement of quality of care, compliance to established best evidence practices and documentation of outcome, be it good or bad. However, the performance of the DSS is influenced by the timeliness of the data entry, the incidence of missing data and any possible query interval. These latencies of data entry can be caused by the simple absence of data entry, retroactive data entry – with the risk of data omission, data management delay within the AIMS or between the AIMS and any other database or clock differences. Any such latencies can influence the implementation of clinical or management workflows for improved outcome. (Epstein et al., 2009, Fig. 3)

Latency source	Explanation
Absence of user entry	Providers may not document the event.
Delayed (tardy) user entry	Providers typically document after the fact.
Processing delay by AIMS on the workstation	AIMS may not process entered events immediately, but on a schedule.
Processing delay writing to AIMS database	It can take time to traverse the network and then write to the database.
Data extraction from production database	Queries may not run against the production database, but against a copy of the database, updated periodically.
Rounding of times	AIMS may round times to the nearest minute when users adjust the time.
Clock synchronization	Perceived latency between workstation timestamps and database timestamps on the server may be a result of the clocks being different.

AIMS = anesthesia information management systems.

Fig. 3. Potential Sources of Latency in Decision Support Systems. (Epstein et al., 2009)

Anesthesiologists constantly demand smart alarms. One of the few monitoring systems which have a good track record as 'smart alarms' are pulse oximeters. Any anesthesiologist of some experience will be able to follow the different tonality of the pulse oximetric signal to detect various degrees of oxygen desaturations. However, for the majority of monitoring alarms, smart decision support or monitoring systems need to be developed. One example of a simple but effective DSS for tow of the most common adverse events during anesthesia – unstable blood pressure and light anesthesia – was presented in 2000 (Krol & Reich, 2000). When computerized algorithms were compared with subjective assessment by anesthesiologists, it was found that a 12% change of mean arterial pressure in comparison to the median of the mean arterial pressure of the previous 10-min interval can be used as indicating light anesthesia. Best agreement between computer readings and human assessment was achieved when the absolute value of the fractional change of the mean arterial pressure in between 2-min periods was used. (Fig.4)

It is not the objective of this chapter to reason whether changes in mean arterial pressure are indicative of 'light anesthesia'; this study simply shows that very simple computerization can be helpful to readily indicate anesthesiologists – in this case anesthesiologists following the paradigm that hemodynamic ability indicates an insufficient degree of anesthesia – a decision support in daily routine.

How can knowledge- and rule-based DSS be designed so that a maximum number of clinicians adhere to them and use them to improve outcome?

Design considerations have recently been presented (Dunsmuir et al., 2008): rule structures should be easy to understand, the process of knowledge authoring tooling should be intuitive, all decisions visible to everybody, and the user interface easy to use for everybody. Such a user interface is presented in figure 5 by Dunsmuir et al. (Dunsmuir et al., 2008) as a smart monitoring tool for hemodynamic adverse events in children undergoing anesthesia.
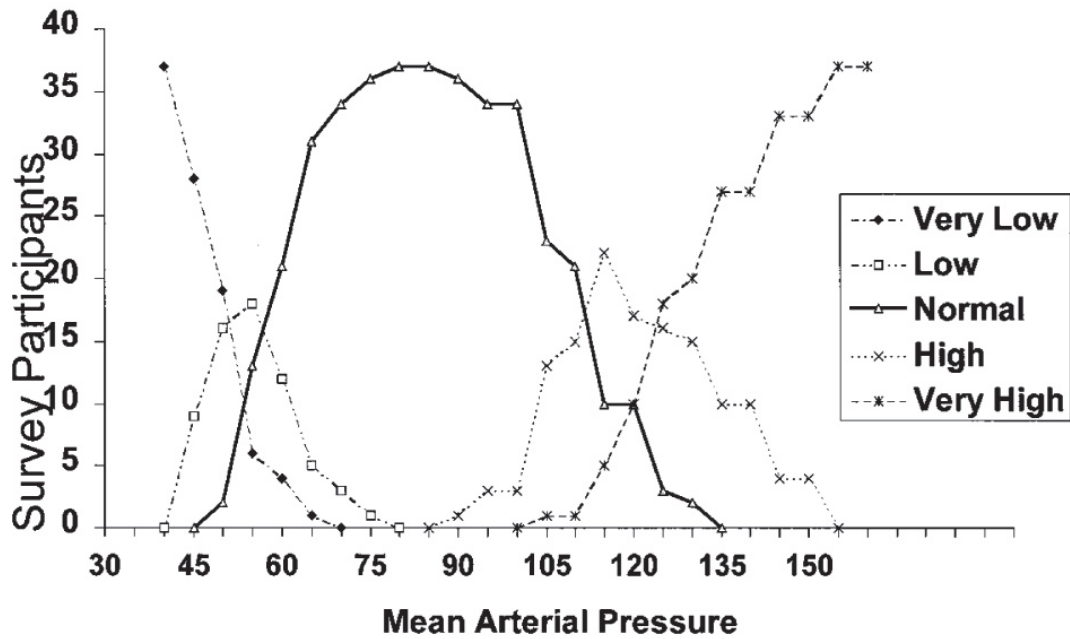
Fig. 4. Categorization of MAP by anesthesiologists. (Krol & Reich, 2000)
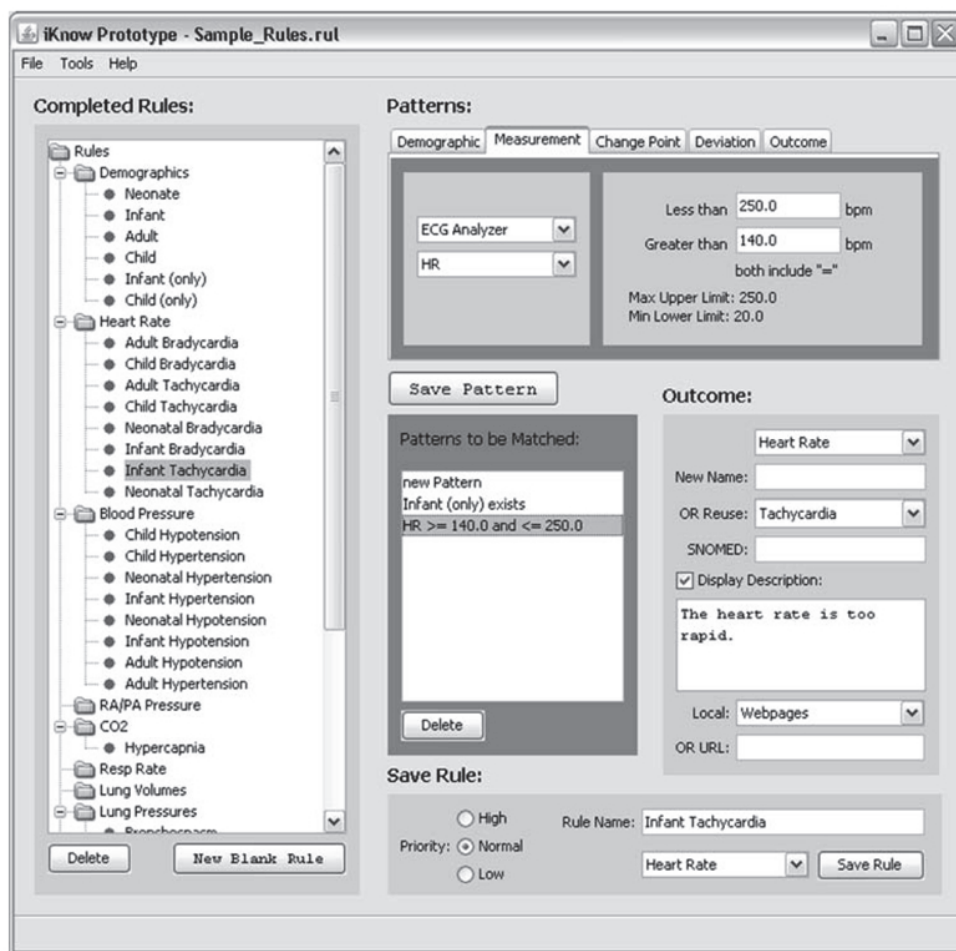

Fig. 5. The graphical user interface of the knowledge authoring tool. (Dunsmuir et al., 2008)

The importance of 'user feedback' is clearly demonstrated in this study. Some samples of results from a user questionnaire are presented and focus on 'user friendliness' of the interface more than a disagreement with the rules. (Fig. 6)

Statement	Median rating	Sample related comment
It was easy to learn to use this system	3.5	"Help sheet quite useful"
I believe I could become productive quickly using this system	2	"Quick learning curve"
The organization of the information on the system screens was clear	3	"The layout is nice but the boxes need to be labeled more intuitively"
Overall, I am satisfied with this system	3	"When using a system like this, I think when merging to be able to drag + drop rules into the new rule/outcome would be useful"

Fig. 6. Sample from PSSUQ results. (Dunsmuir et al., 2008)

The authors conclude that anesthesiologists can rapidly develop useful rules for use in a predefined clinical scenario (Dunsmuir et al., 2008). Using a fuzzy-logic evidence based expert diagnostic alarm system, similar success can be achieved for the diagnosis of intraoperative hypovolemia (Mirza et al., 2010). Its basic structure is depicted in Fig. 7.
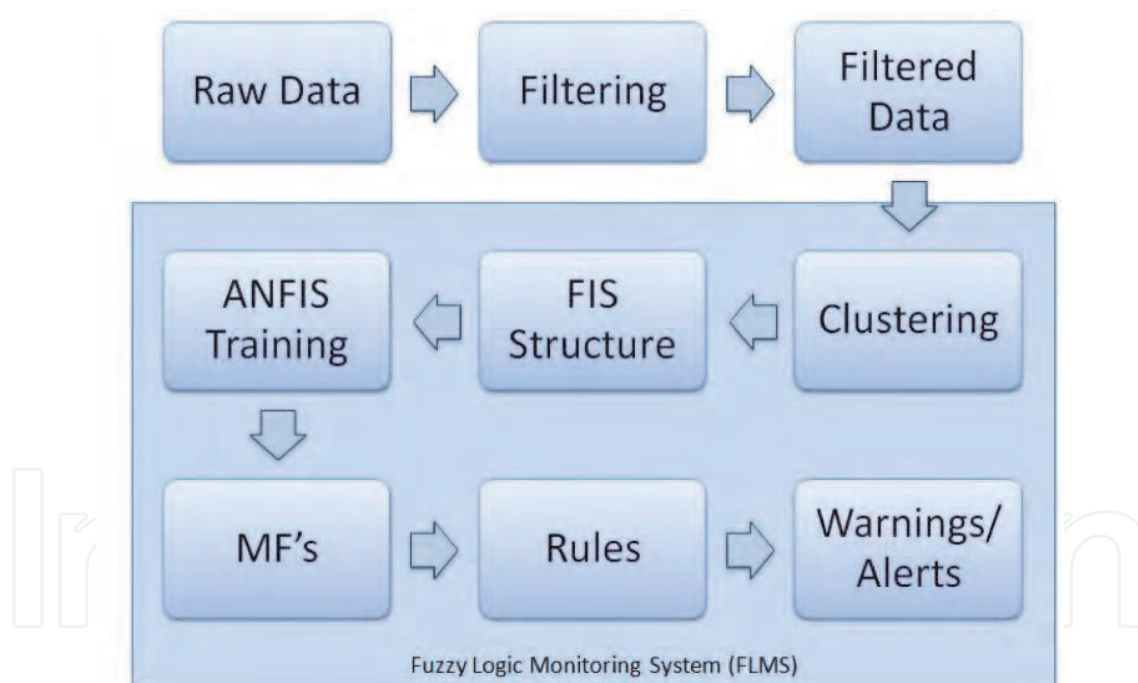

Fig. 7. Block diagram of the FLMS. ANFIS=Adaptive-Network-based Fuzzy Inference Systems ; FIS=fuzzy interference systems ; MF's=membership function. (Mirza et al., 2010)

An ideal scenario of anesthetic clinical practice almost implying the use of DSSs is the different PONV prevention strategies. The symbiosis of a clearly identified anesthetic problem – PONV - , clearly established guidelines – PONV guidelines – and the existence of several drug combinations make this an ideal work field for intelligent DSSs.
A recent study investigated the effect of such a DSS on guidelines adherence using an on-off design (Kooij et al., 2008). Fig. 8 presents the number of patients enrolled in this study.

	Control N (%)	Decision support N (%)	Post-DS N (%)	Significance
Prophylaxis indicated	373 (100)	871 (100)	321 (100)	
Prophylaxis prescribed?				P < 0.001
Yes	140 (38)	632 (73)	119 (37)	
No	233 (62)	239 (27)	202 (63)	
Total number of patients	1340 (100)	2715 (100)	1035 (100)	
Total prescribed	216 (16)	819 (30)	195 (19)	
Correctly	140 (10)	632 (23)	119 (12)	
Without indication	76 (6)	187 (7)	76 (7)	NS

NS = not significant.

Fig. 8. Scheduling Postoperative Nausea and Vomiting Prophylaxis. (Kooij et al., 2008)

However, this study shows as well that the use of DSS has no impact on 'changing the culture' of wrong-doing as an educational tool once it is withdrawn: although the DSS very significantly improved adherence to the PONV guidelines, guideline adherence decreased to the level before the DSS was used after its withdrawal. (Fig. 9)
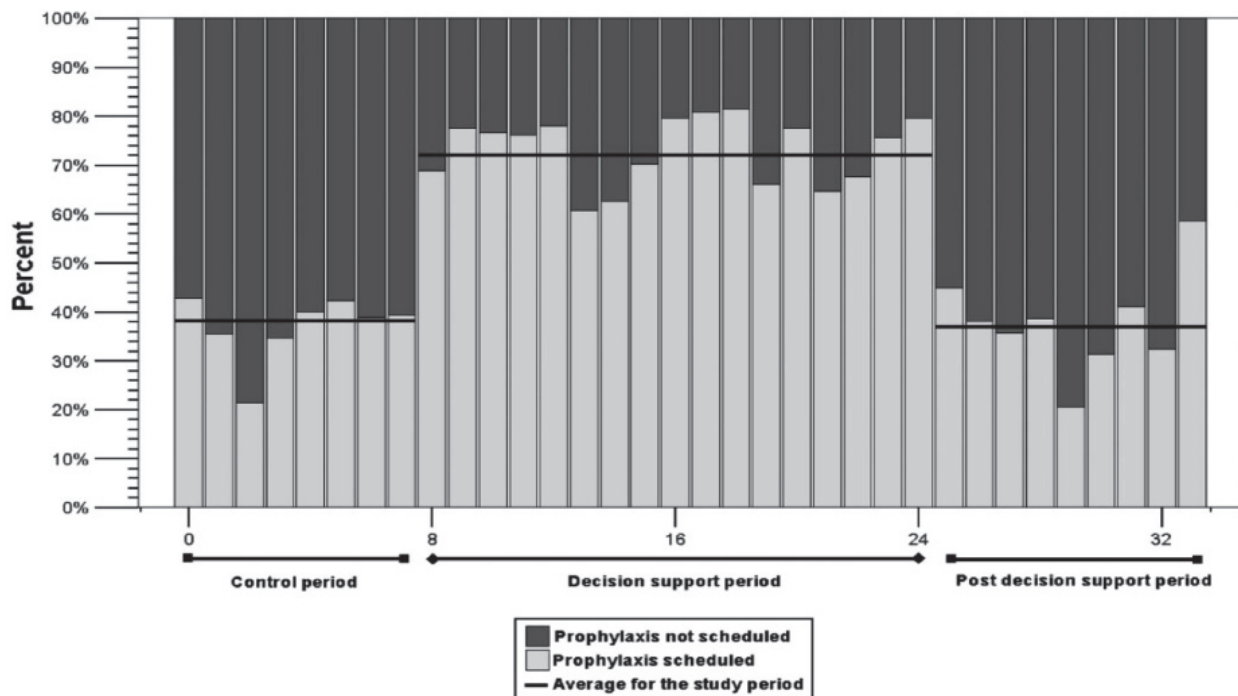

Fig. 9. Week by week analysis of all high risk patients. The bars show the percentage of high risk patients receiving postoperative nausea and vomiting prophylaxis prescribed. (Kooij et al., 2008)

Two studies have investigated the implementation of simple DSSs using an AIMS to improve adherence to proper antibiotic prophylaxis before surgery.

In one study (O'Reilly et al., 2006), a simple feedback system integrated in the AIMS was used to improve properly timed antibiotic prophylaxis provided by the anesthesiologist. (Fig.10)

Another group used the AIMS in combination with e-mail feedback of missed documentation, monthly summary reports and real-time electronic alerts to achieve a near 100% timely antibiotic prophylaxis; without filling out the antibiotic note, the AIMS anesthesia chart cannot be closed. (Nair et al., 2010)
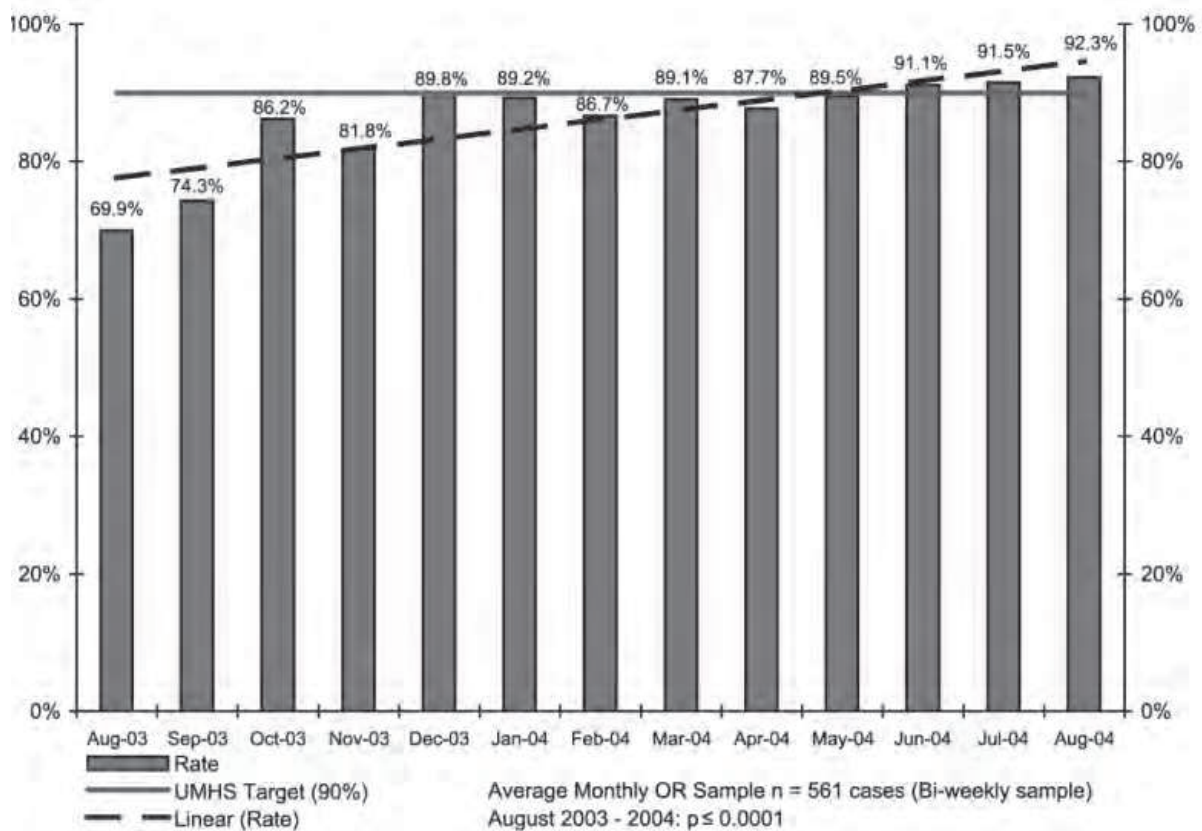
Fig. 10. Compliance with the timely administration of antibiotics gradually increased to about 92%. (O'Reilly et al., 2006)
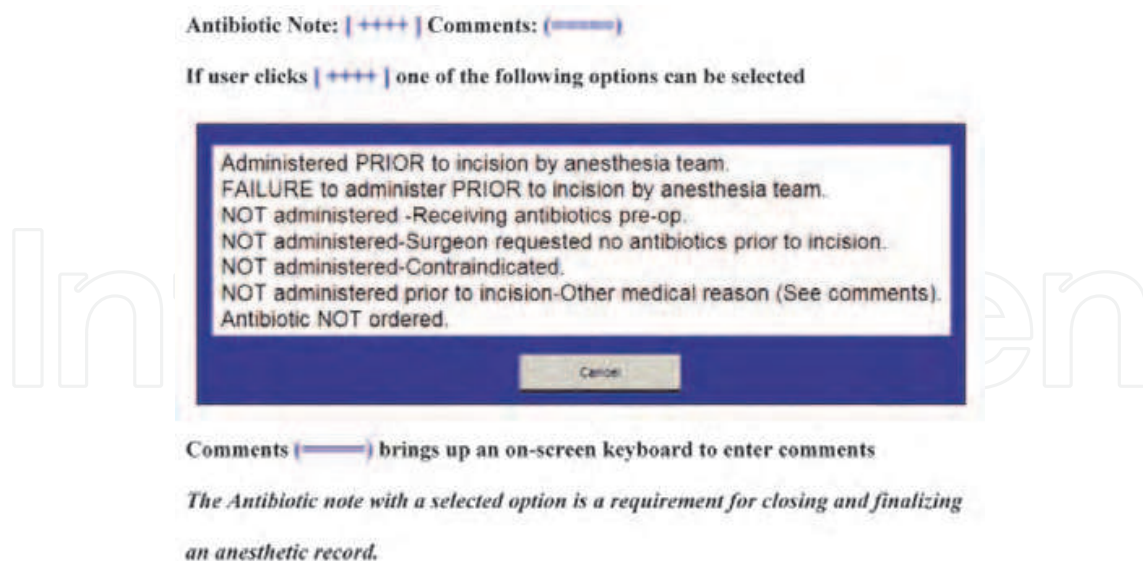

Fig. 11. Antibiotic compliance comment note options in AIMS (Anesthesia Information Management System). (Nair et al., 2010)

This was combined with 'smart messages". (Fig. 12) The user received messages which were displayed as a pop-up menu. These reminder messages are sent so that the users can see them before surgery starts and administer the antibiotic prophylaxis optimally timed for

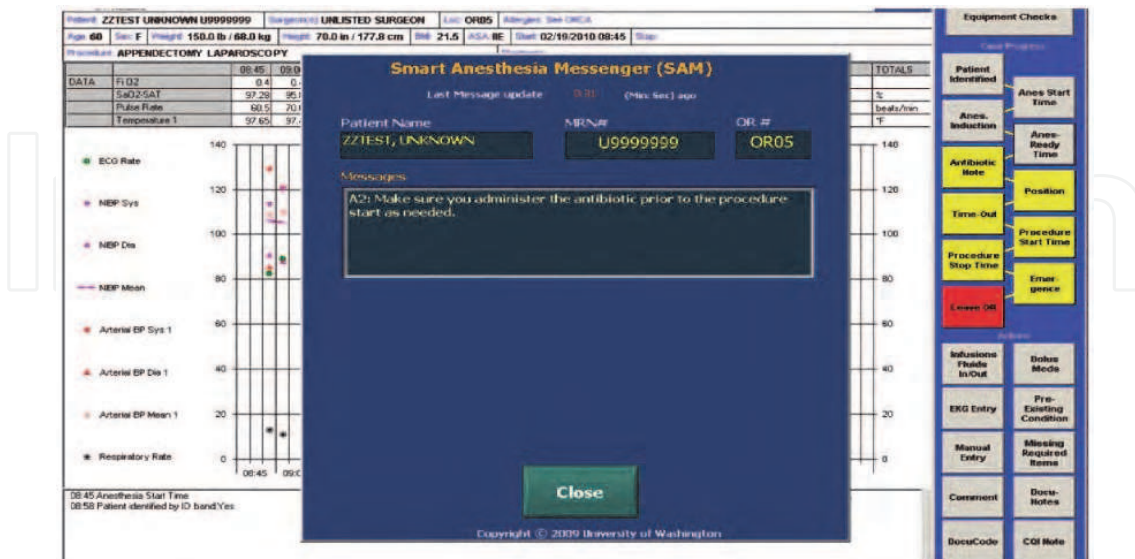effect. Messages also appear when administration of antibiotics are not documented or incomplete.

Fig. 12. Smart Anesthesia Messenger (SAM) alert screen overlaid on anesthesia information management system screen. (Nair et al., 2010)

In the course of the study period – june 2008 – jan 2010 – the weekly antibiotic compliance improved steadily, reaching a near 100% compliance at the end of step 4. (Fig. 13)
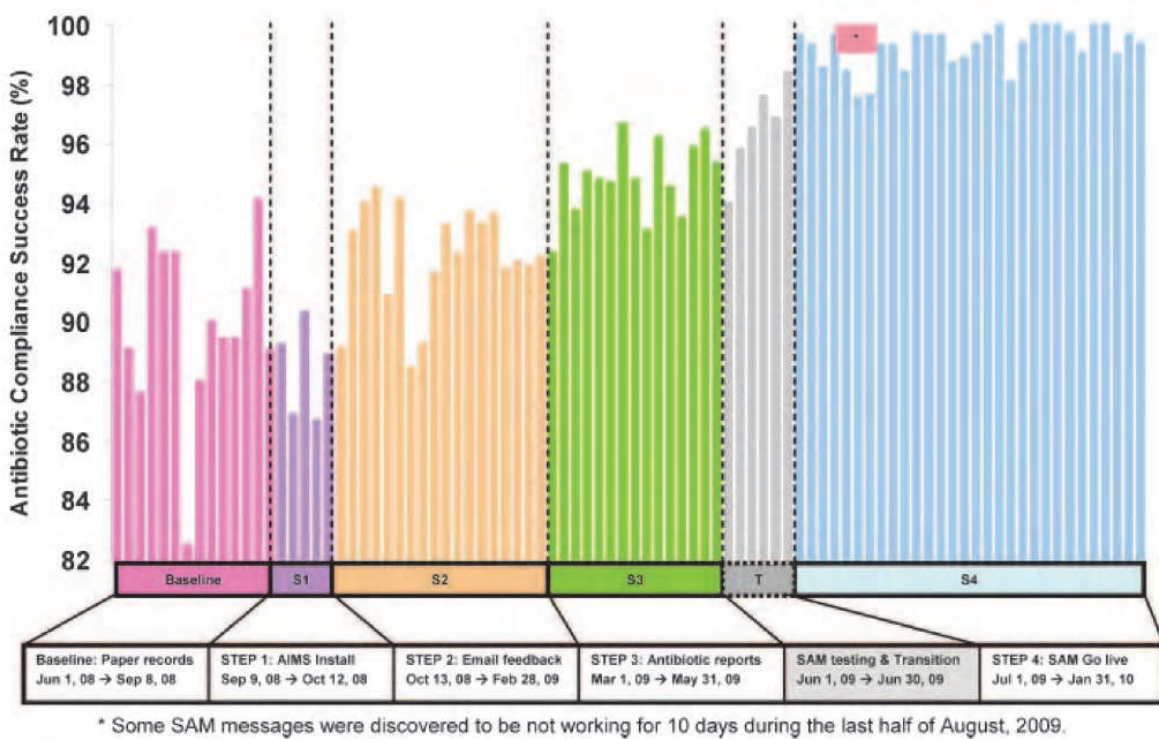

Fig. 13. Improvement in weekly antibiotic compliance success rate with each intervention. AIMS _ Anesthesia Information Management Systems; SAM _ Smart Anesthesia Messenger. (Nair et al., 2010)

Another example of an anesthetic DSS is the creation of an electronic algorithm for detecting insufficient depth of anesthesia based on computing different MAC values of volatile anesthetics with different intravenous sedative or hypnotic agents administered concomitantly. (Mashour et al, 2009).

The need for DSSs even for very simple anesthetic gestures, such as turning on the ventilator alarms after separation from cardiopulmonary bypass (which cardiac anesthesiologist has not forgotten this?), is demonstrated in a recent study (Eden et al., 2009). A simple electronic reminder as part of the AIMS (Fig. 14) improves significantly the incidence of alarm reactivation from 22% to 83%. (Fig. 15) At the end of the study period, there were significantly less electronic reminders and alarms were spontaneously reset after cardiopulmonary bypass.
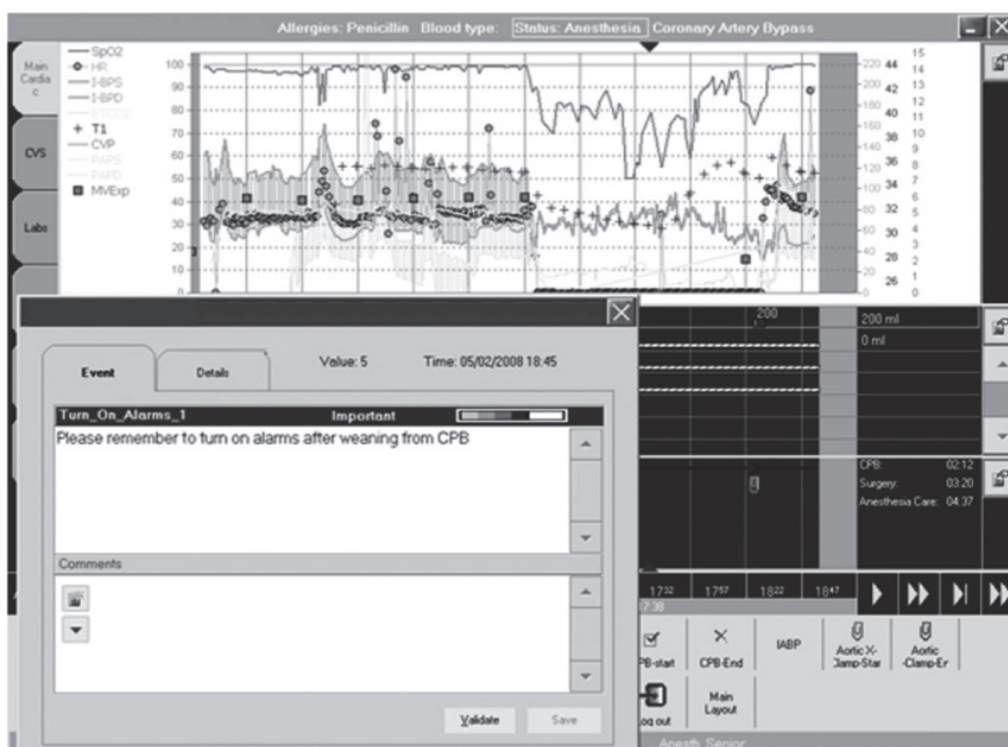

Fig. 14. The appearance of the electronic reminder on the anesthesia information management system main window. (Eden et al., 2009)

Characteristic	Stage I ($n = 304$)	Stage II ($n = 256$)	Stage III ($n = 435$)	P for trend
Alarm reactivation				
Yes	68 (22.4%)	160 (62.5%)	363 (83.4%)	$P<0.001$
No	236 (77.6%)	96 (37.5%)	72 (16.6%)	
No. of reminders per patient				
0	NA	60 (23.4%)	184 (42.3%)	$P<0.001$
1	NA	69 (27.0%)	162 (37.2%)	
2	NA	56 (21.9%)	62 (14.3%)	
3+	NA	71 (27.7%)	27 (6.2%)	

[a] Stage I = 5 mo before implementation.
Stage II = 5 mo after system introduction.
Stage III = Additional 8 mo follow-up, after the second educational meeting.
NA = not applicable.

Fig. 15. System Performance by Implementation Stage. (Eden et al., 2009)

However, these DSSs do not cover the actual administration of anesthetic agents, nor do they present different treatment options for adverse incidents. They mostly focus on the concept of smart monitoring, alarms for administering concomitant drugs, such as drugs for PONV prophylaxis or antibiotic prophylaxis, or alarms for insufficient depth of anesthesia or hemodynamic. They do not give several treatment options to the user – anesthesiologist. Recently, a hybrid system for conscious sedation with DSS was presented. (Hemmerling, STA abstract 2011). This system integrates closed loop sedation with a DSS, offering pop-up menus as smart alarms with several treatment advices for hemodynamic or respiratory adverse events, which need to be confirmed by the anesthetic team by clicking respective touch buttons on a touch screen. (Fig.16)
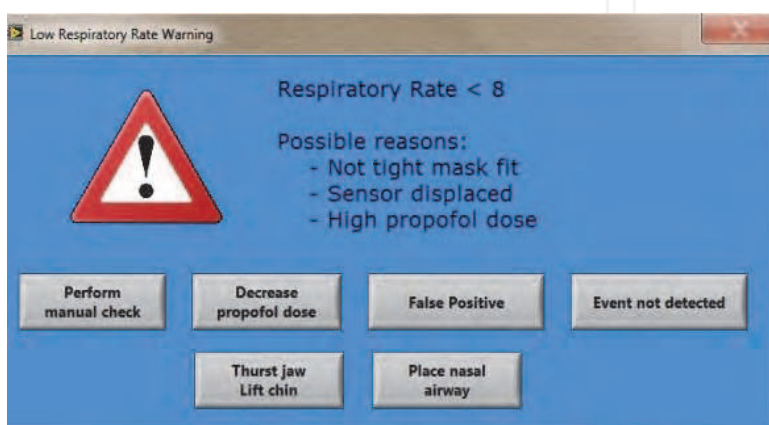

Fig. 16. Pop-up menu for respiratory rate critical event. (Hemmerling et al., 2011)

The DSS significantly improved the incidence of critical event detection as well as time between event occurrence and event recognition. (Fig. 17.)

	Protocol Group (N=50)	Control Group (N=50)	P
Events not detected (%)	0	25	*<0.0001 #<0.000
AVG Delay (s)	7.4±4.0	32.6±21.7	1
Critical events/h	5.6±4.1	7.4±5.1	#0.05
MAP /h	3.2±3.1	3.7±3.6	N.S.
RR/h	4.3±3.6	3.8±4.1	N.S.
HR/h	0.9±0.5	0.7±0.3	N.S.
Sat/h	1.6±1.1	2.2±2.4	N.S.

Fig. 17. Performance of anesthesiologists in detecting critical events. (Hemmerling et al., 2010)

The above presented examples show that DSSs can be created for perioperative use in anesthesia; whereas most research has focused on designing DSS as smart monitoring and alert systems, future research has to focus on combining purely 'Monitoring-DSS' to alerting several treatment options for providing anesthesia or treating critical events thus integrating best evidence based treatment options in modern DSSs.

2.2 Decision support system in emergency medicine

Decision support systems have long played a significant role in the management of emergency patients. Emergency medicine is driven by a combination of out-of-hospital and

in-hospital complex scenarios which pose logistical difficulties because of the following demands:

- rapid access to patients outside the hospital
- immediate care (both in diagnostics and treatment) by paramedical staff
- immediate link with logistical coordinators for transport organization
- acuteness of illness or trauma
- very often limited experience of health care providers as primary care
- resource management of both manpower and diagnostic tools
- single or mass casualties of primarily un-known trauma

The sheer combination of very often life-threatening illness or trauma with the need to rapidly diagnose and treat these pathologies is an ideal playing field for the implementation of computer-based decision support systems.

However, the studies are somewhat inconclusive: whereas DSSs have very successfully been implemented in the pre-hospital care system, making triage and organization far easier than without them, their implementation in the hospital based emergency care system is somewhat disappointing.

For the pre-hospital care system, the iRevive EMT application is a very good example of successful implementation of a DSS in a complex environment (Gaynor et al, 2005).

It is designed as a network of wireless, handheld computers, with wireless patient location and vital sign sensors, connected to an ambulance base station, and a central command center. (Fig. 18)
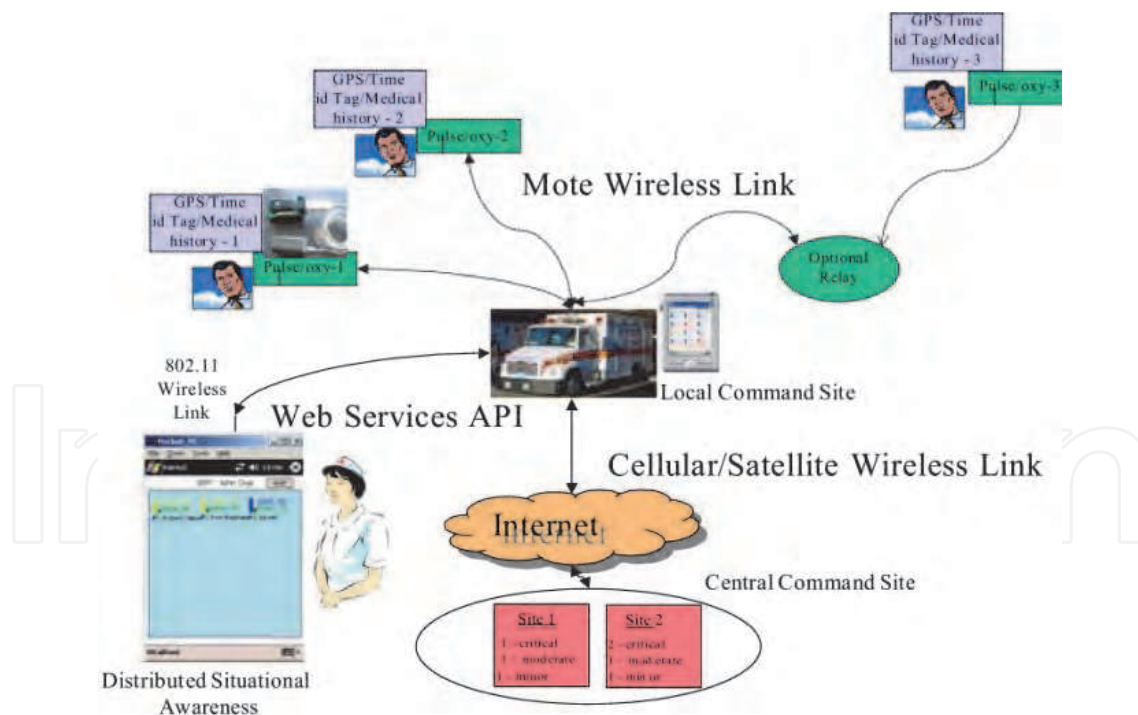

Fig. 18. iRevive System Architecture. (Gaynor et al, 2005).

It provides decision support at the site of the incident (pre-hospital), at local command centers, and at a central point of coordination. It is unique through its integration of vital sign parameters which are transmitted wirelessly. It is a key feature of emergency management in a pre-hospital setup to react not only to an initial patient conditions but

adjust management and triage towards possible dynamic changes in the patient's status: both elements are provided successfully by the iRevive structure as illustrated in Figure 19 (left side: stable condition, right side: vital sign changes)
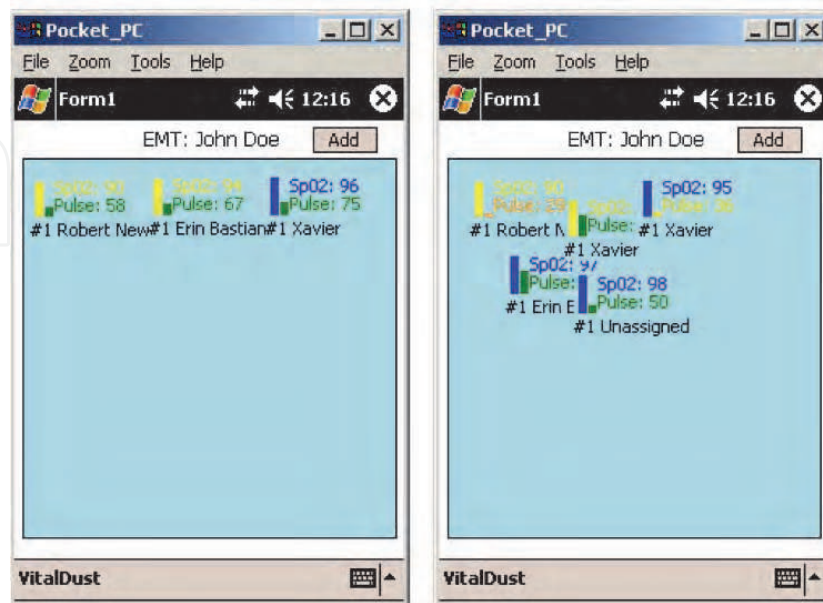

Fig. 19. Dynamic triage function in iRevive. (Gaynor et al, 2005).

A similar approach is presented by another Australian group for the in-hospital based emergency care management (Ceglowski et al, 2005). The task faced for the establishment of a DSS for the in-hospital based emergency department is illustrated in Fig. 20:
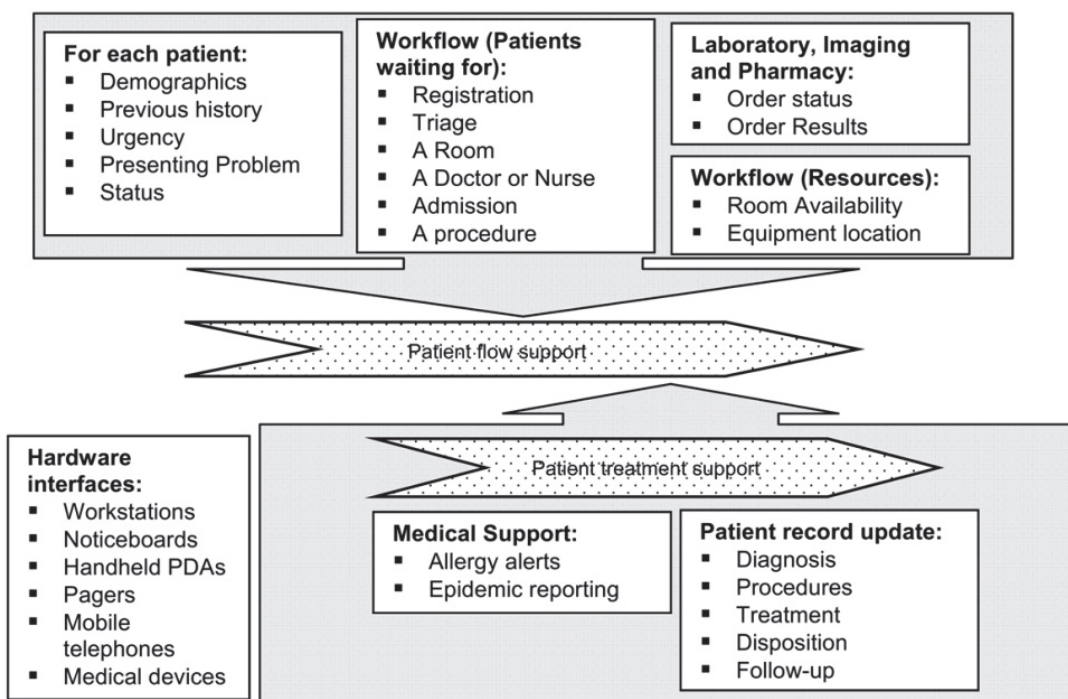

Fig. 20. EDIS support for emergency department patient flow (Ceglowski et al, 2005).

The combination of hardware interfaces, readily available through modern technologies, such as smart phones, and sophisticated software allow the modeling of a DSS, ready to help triage and improve the workflow of patients entering the emergency department.

However: how do these DSSs perform in a real-life setting?

Graber's study (Graber & VanScoy, 2003) has investigated the performance of a DSS in an emergency department. Whilst they could show that DSSs performed as well in this complex setup as in other medical fields, they also found a surprising under-performance of the DSS in comparison to the final human based emergency diagnosis: the final diagnosis was only found in 50 to 70% of the differential diagnosis, depending on which DSS was used, and only in approximately 30% of the time was the final diagnosis amongst the top 5 of the different diagnosis of the DSS. This means that its accuracy is not sufficient to allow to use it reliably at present. In addition, their use obviously takes considerable time, a key criticism when used in the emergency setting.

Similar results have been found when DSSs are used in the exemplary case of diagnosing a pulmonary embolism, which is always a difficult diagnosis to make: the characteristic element of this diagnostic setup – probability assessment based on several clinical and diagnostic tools rather than one single test confirming the diagnosis – should actually play in the hands of DSSs.

The study of Roy and another study of Drescher have looked at the performance of DSSs to diagnose pulmonary embolism. The first study (Roy et al, 2009) showed an improvement in the application of appropriate diagnostic strategies which was significantly better when a computer-based guidelines structure was used versus paper-based guidelines structure in a multi-centre study involving 20 centers and more than 1000 patients. (Fig. 21)

In the computer-based guidelines group, the same guidelines were used but on a handheld device into which the patients' parameters were entered: all clinical variables to derive a Geneva score, a probability score for pulmonary embolism are entered into the DSS. Then the DSS offers all necessary and available diagnostic tests to confirm or exclude the diagnosis of pulmonary embolism with probability thresholds. (Fig. 22)

This study clearly showed the superior performance of DSSs, which was confirmed for the same diagnostic setup by the second study (Drescher et al, 2010). However, the second study also showed one of the key problems of implementing DSSs in the context of in-hospital emergency departments: poor user (physician) acceptance. (Fig. 23)

The range of non-adherence to the DSS varied from 5% to 100% depending on the individual physician: only part of this non-adherence can be attributed to increased computer time in order to use the DSS. The authors state: 'emergency physicians attributed disbelief in its clinical utility and impatience with the time it required as the reasons for not following its recommendations or for opting out.'

Implementation of DSSs in the emergency medicine setting have been very successful for the preoperative environment; they can help make triage more efficient. Systems can help to provide better pre-hospital patient care.

In the in-hospital emergency medicine setting, the acceptance of DSSs is still limited: the significant amount of time necessary to enter all the data is one of the key aspects limiting their widespread use. However, the influence of human, emotional resentment towards the introduction of computer based decision-making cannot be excluded.

Appropriate Diagnostic Strategy Applied	Computer-Based Guidelines Group			Paper Guidelines Group			Adjusted Difference in Change (95% CI), percentage points*†	P Value
	Preintervention Period, n/n (%)‡	Intervention Period, n/n (%)‡	Adjusted Absolute Change, %*§	Preintervention Period, n/n (%)‡	Intervention Period, n/n (%)‡	Adjusted Absolute Change, %*§		
By posttest probability‖								
All diagnoses	108/460 (23.5)	378/694 (54.5)	30.2	109/532 (20.5)	245/951 (25.8)	10.9	19.3 (2.9 to 35.6)	0.023
Pulmonary embolism ruled out	63/381 (16.5)	306/581 (52.7)	33.5	62/435 (14.3)	138/768 (18.0)	7.1	26.4 (10.1 to 42.7)	0.003
Pulmonary embolism ruled in	45/79 (57.0)	72/113 (63.7)	10.7	47/97 (48.5)	107/183 (58.5)	14.4	-3.7 (-31.7 to 24.3)	0.78
All diagnoses with data inputted in real time (per-protocol analysis)	66/190 (34.7)	345/557 (61.9)	26.0	71/186 (38.2)	169/369 (45.8)	12.3	13.7 (-6.5 to 33.9)	0.171
By strict application of recommendations¶	59/460 (12.8)	287/694 (41.4)	25.7	60/532 (11.3)	162/951 (17.0)	8.5	17.1 (1.9 to 32.4)	0.030

* Adjusted for age, known heart failure, chronic lung disease, current anticoagulant treatment, previous thromboembolism, sex, palpation pain, and lower limb edema (see Methods).
† Difference in absolute change of appropriateness between the computer-based and paper guidelines groups.
‡ Fractions represent number of patients for whom appropriate strategy was applied over the total number of patients who received that diagnosis.
§ Adjusted absolute change in the frequency of appropriate pulmonary embolism diagnostic strategies between the preintervention and intervention periods.
‖ We considered a diagnostic strategy appropriate when the diagnostic criteria (clinical probability and the results of diagnostic tests) resulted in a posttest probability <5% for exclusion or >85% for confirmation (Table 1). We estimated intraclass correlation for all diagnoses to be 0.10 according to the Murray formula for binary outcomes.
¶ Appropriate diagnostic strategy according to strict application of recommendations was defined by using a table that summarized the validated strategies according to clinical probability level and diagnostic test results and assuming that a diagnostic work-up was inadequate when the clinical probability was not assessed or when additional unnecessary tests were performed (see Secondary Outcomes in Methods).

Fig. 21. Improvements in Application of Appropriate Diagnostic Strategy for Pulmonary Embolism (Roy et al, 2009).

Test Result	Clinical Probability of PE		
	Low (5%–15%)	Intermediate (15%–50%)	High (50%–85%)
Exclusion of PE			
Normal pulmonary angiography	Stop	Stop	Stop
Normal lung scan	Stop	Stop	Continue
Low-probability VQ scan	Stop	Continue	Continue
Negative quantitative ELISA D-dimer test result	Stop	Stop	Continue
Negative moderate-sensitivity D-dimer test result	Stop	Continue	Continue
Negative CT angiography	Stop	Continue	Continue
Negative multidetector CT angiography	Stop	Continue†	Continue
Negative CT or multidetector CT and negative proximal leg vein US	Stop	Stop	Continue
Confirmation of PE			
Pulmonary angiography showing PE	Stop	Stop	Stop
High-probability VQ scan	Continue	Stop	Stop
Positive CT or multidetector CT showing segmental or supra PE	Continue	Stop	Stop
Positive leg vein US showing proximal DVT	Continue	Stop	Stop
Echocardiography showing right ventricular dilatation	Continue	Continue	Stop

CT = computed tomography; DVT = deep venous thrombosis; ELISA = enzyme-linked immunosorbent assay; PE = pulmonary embolism; US = ultrasonography; VQ = ventilation–perfusion.

* Stop: Appropriate diagnostic criteria—stop testing. No further testing is required to exclude or to confirm PE. Continue: Inappropriate diagnostic criteria—continue testing. Further testing is required to rule in or rule out PE with confidence.

† Data that were not yet available at the beginning of the study suggest that PE can safely be excluded by negative multidetector spiral CT when the pretest probability is not high.

Fig. 22. Recommendations for Exclusion or Confirmation of PE on the Basis of Test Results, by Clinical Probability (Roy et al, 2009).

Emergency Physician	CT Angiography Not Recommended*	CT Angiography Ordered	CT Angiography Recommended†	CT Angiography Not Ordered	Total Number of Recommendations	Not Adherent With CDSS	Percentage of Decisions Not Adherent With CDSS
1	0	0	1	0	1	0	0
2	0	0	2	0	2	0	0
3	0	0	2	0	2	0	0
4	0	0	2	0	2	0	0
5	1	0	2	0	3	0	0
6	2	0	4	0	6	0	0
7	1	1	0	0	1	1	100
8	4	0	8	1	12	1	8.3
9	8	0	13	1	21	1	4.8
10	4	1	17	0	21	1	4.8
11	5	1	7	2	12	3	25
12	8	0	17	4	25	4	16
13	12	2	10	3	22	5	22.7
14	16	2	23	4	39	6	15.4
15	9	3	15	3	24	6	25
16	14	4	9	2	23	6	26
17	14	0	25	7	39	7	17.9
18	13	1	19	7	32	8	25
19	2	0	27	9	29	9	31

CDSS, computerized decision support system.
*Low pretest probability: Low Wells score and negative D-dimer result.
†High pretest probability: Wells score or positive D-dimer result and low Wells score.

Fig. 23. Adherence of individual emergency physicians to the clinical decision support system algorithm (Drescher et al, 2010).

2.3 Decision support systems in intensive care medicine

One of the most complex environments for physicians: there is an overload of parameters to watch, access to the patients can be limited, there is often a combination of very complex pathologies and the amount of technologies whose management needs mastering is significant. The main focus of initial DSSs in this setup is the idea of making all relevant patient data readily available.

Two of these systems shall initially be discussed here: the ACUDES system and the Rhea.

The ACUDES system (Palma et al, 2002) makes all patient data, be it clinical, based on monitoring or laboratory/investigative results available within the temporal context of relation to other data, trying to explain disease evolution, relationship between different abnormalities. ACUDES uses three modules, a temporal behavior model (TBM), the causal and temporal knowledge acquisition tool (CTKAT) and the diagnosis agent (DA). (Fig.24)

This combination allows the physician to have access to a knowledge data base (TBM) in a causal network, relating each abnormality with both a temporal evolution and a causality. The physician can mange, build, construct the data within the TBM – as long as any changes fit within the basic ontological structure of the system, thus avoiding any inconclusive data entry. The DA gives an explanatory framework from which diagnostic reasoning can be deducted.

The Rhea system (Metais et al, 2006) integrates a similar set of data as the ACUDES with the focus on iatrogenic adverse effects and nosocomial infections. At the time of writing the publication, 30 French hospitals participated in this project with more than 3000 patients' data set entered. The assembly of data serves to perform knowledge discovery for research purposes. Some of the proprieties which Rhea can deliver are the establishing of disease course models, alert rules depending on the individual patient's data and establishing procedural guidelines in order to decrease nosocomial infections. (Fig. 25)
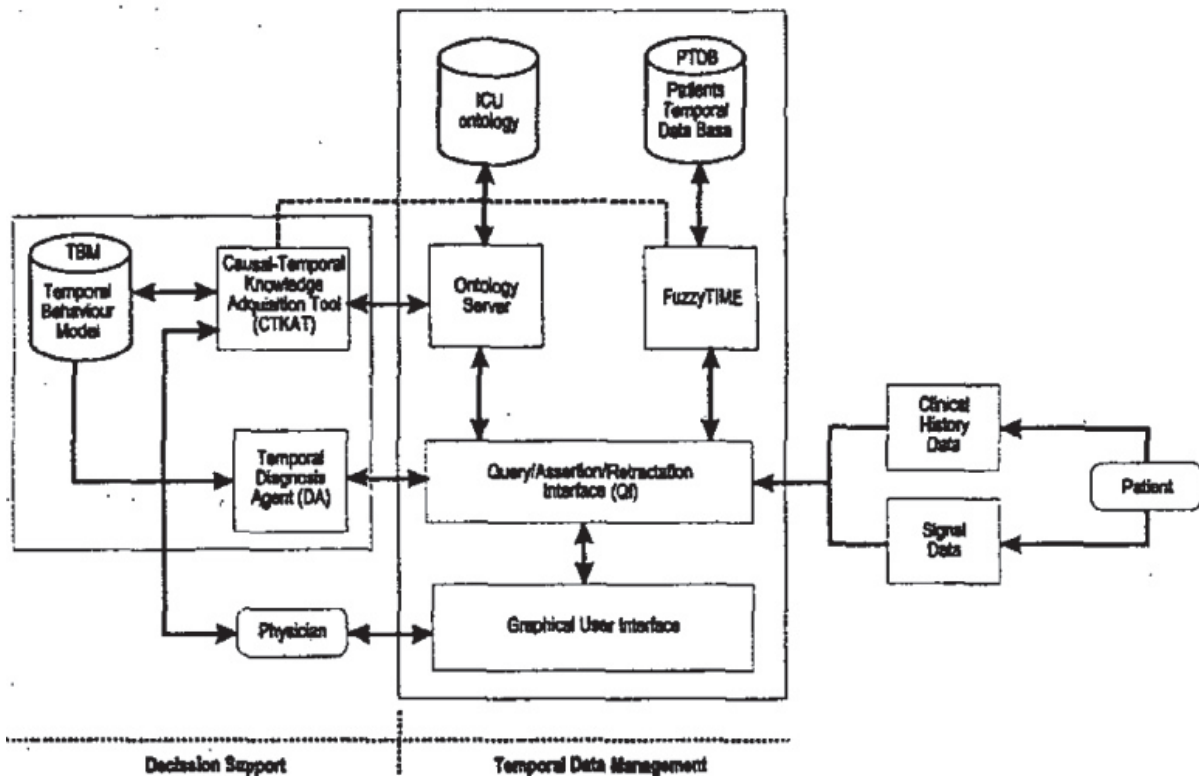
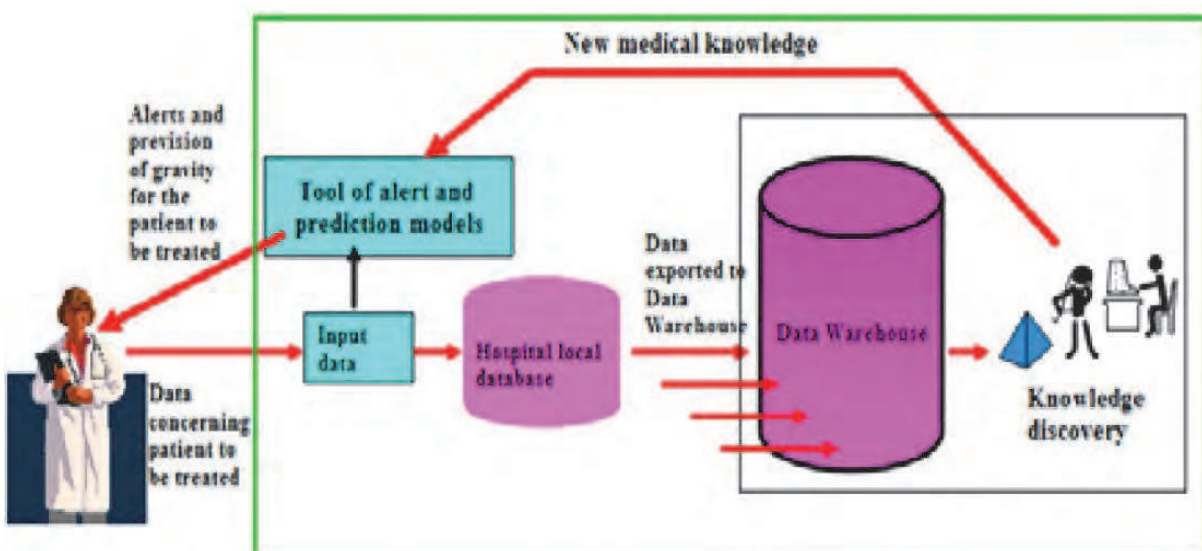Fig. 24. ACUDES General Architecture (Palma et al, 2002)

Fig. 25. General principle of Rhea project (Metais et al, 2006)

Each individual user can enter relevant data into the system at any time which renders the DSS 'dynamic' whilst making it available instantly to all users. (Fig. 26)

So far, Rhea has been solely used for biostatistical research; the increasing pressure on health care providers to audit safety and quality of their activities has led to the introduction

of these DSSs. However, these systems only provide actual 'decision support' with a significant lag time since they rely on studying data, auditing procedures and identifying possible shortcomings but do not provide an instantaneous help to the clinicians.
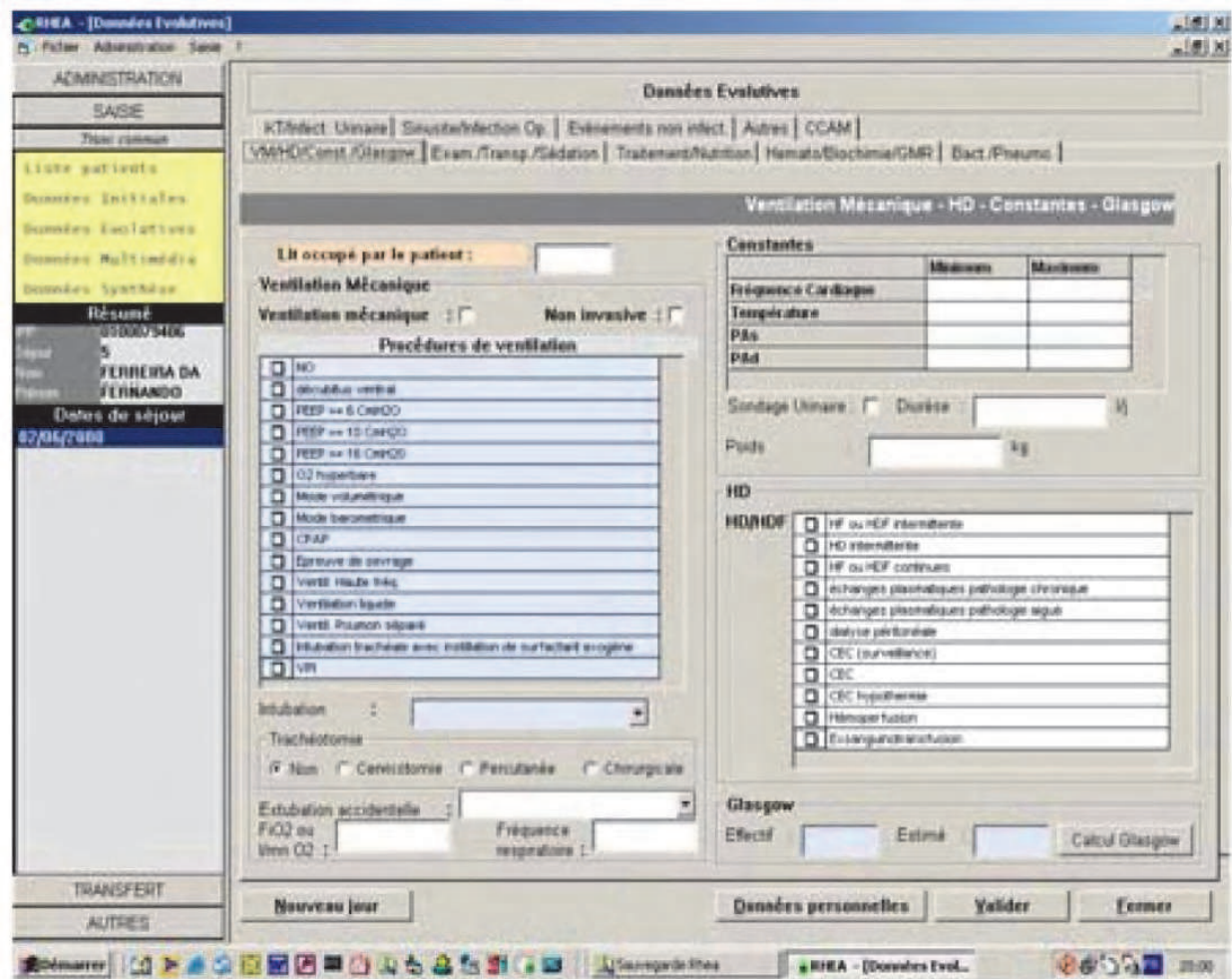
Fig. 26. Evolving data, tab "mechanical ventilation" (Metais et al, 2006)

The main area of DSSs in the field of intensive care medicine is a DSS for mechanical ventilation. Numerous systems have been developed and used for clinical trials. The fundamentals are outlines in a recent review of DSSs for mechanical ventilation (Tehrani & Roum, 2008, Fig. 27).

The efficacy of a DSS for mechanical ventilation is demonstrated in exemplary fashion by East's study (East et al, 1999) which was performed in 10 centers across the US. The use of DSS significantly reduced the overall morbidity in comparison to standard mechanical ventilation (Fig. 29) and a significant reduction in the incidence and degree of barotraumas. (Fig. 30)

In comparison to the poor efficacy of DSSs in in-hospital emergency medicine, the overall acceptance of these DSSs in this study was very good: 94% of the instructions were followed (out of 38546 instructions in total).

Might the high rate of DSS acceptance by the physician be a key to its success?

The main categories of DSSs for mechanical ventilation are outlined as follows (Fig. 28):
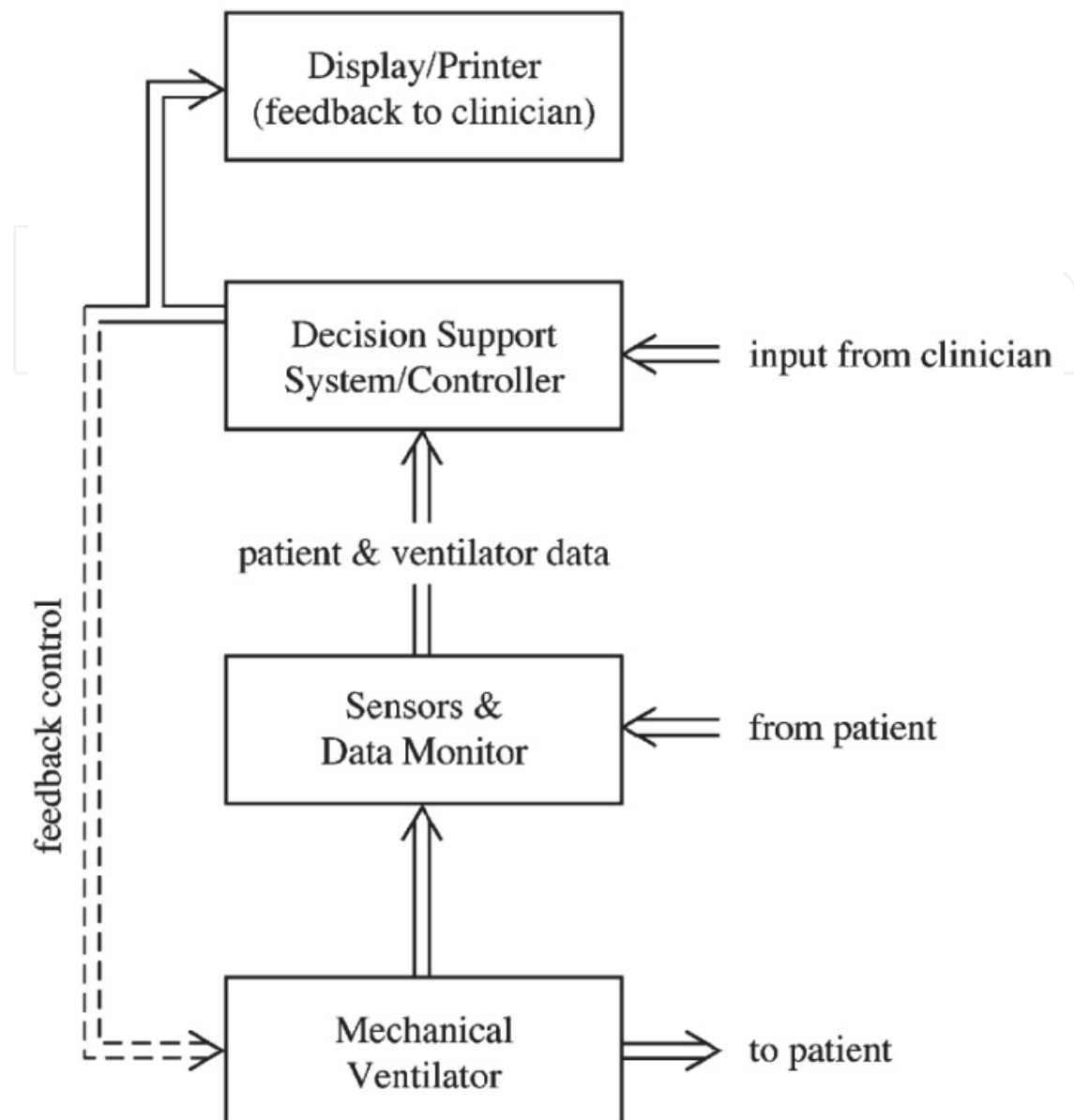
Fig. 27. Block diagram depiction of an IDSS for mechanical ventilation. The broken lines labeled as ''feedback control'' represent the automatic supply of control signals to the ventilator in case the system is used to control the ventilator in a closed-loop manner. (Tehrani & Roum, 2008).

Key characteristics	Available alternatives		
Basis structure	Rule-based	Model-based	Rule-based + model-based
Applicable ventilation modes	Pressure support (PS)	SIMV or IMV + PS	Multiple modes
Patient types	Adults	Neonates	ARDS patients
Optimized parameters	Blood gases	Weaning time	Blood gases and weaning time
Type of technology	Open-loop (advisory)	Closed-loop (automatic)	Open-loop + closed-loop

Fig. 28. Main categories of different IDSSs for mechanical ventilation (Tehrani & Roum, 2008).

Group	Survival	Age	MODS Score Mean	SEM	N
Control	died	<65	15.13	1.37	8
		≥65	16.59	0.70	22
	survived	<65	12.00	0.93	6
		≥65	11.58	0.44	57
Protocol	died	<65	14.88	1.63	8
		≥65	15.12	0.68	26
	survived	<65	11.42	1.30	12
		≥65	11.94	0.48	53

Fig. 29. The maximum daily MODS score in the protocol group and control group. (East et al, 1999)

Group	Baro	Barotrauma Score Mean	SEM	N
Control	non baro	0.73	0.20	59
	baro	3.56	0.36	32
Protocol	non baro	0.97	0.24	61
	baro	2.69	0.31	35

Fig. 30. Maximum daily barotraumas score of iatrogenic lung injury in the protocol group and control group. (East et al, 1999)

3. Conclusion

There are numerous examples of DSSs in the field of anesthesia, emergency medicine and intensive care medicine. The introduction of electronic anesthesia, ER or ICU management systems has been a key issue in these developments.

This chapter gives examples for design and smart alarm structure of DSSs in anesthesia. The introduction of DSSs in daily practice to assure following modern guidelines, as for PONV prophylaxis or proper antibiotic prophylaxis, is actually quite simple, and successful, depending on user compliance. Common areas of negligence and errors, such as turning on alarms after CPB, can be vastly improved by basic DSSs. Very few studies have looked at using DSSs in anesthesia delivery, but pop-up menus can be helpful to promote smart monitoring, alarms and help to treat critical events.

Emergency medicine is a particular arena where medical treatment needs to be coordinated between out-of-hospital and in-hospital treatment. Decision support systems provide the necessary logistical help in this complex environment. Their performance in a real life setting can be impaired by lack of compliance by physicians: however, this might be overcome with the more widespread introduction of these systems and the generational change of physicians, used to rely on technologies in their everyday life.

Decision support systems have long been introduced in intensive care medicine; complex ventilator settings are far easier to manage with DSSs than relying solely on human judgment.

Decision support systems have been studied for more than 2 decades in the fields of anesthesia, emergency medicine and intensive care medicine. They have an excellent track record for improving health care in the research setting; most of the studies have shown an

improvement in outcome, reduction of workload or better performance when DSSs assist health care providers. Before the widespread introduction of DSSs in these specialties, improvements in data entering and user interfaces need to be done.

There is no doubt that DSSs will in future healthcare systems be as common as computers in everyday life. All healthcare providers need to be ready for this.

4. Acknowledgement

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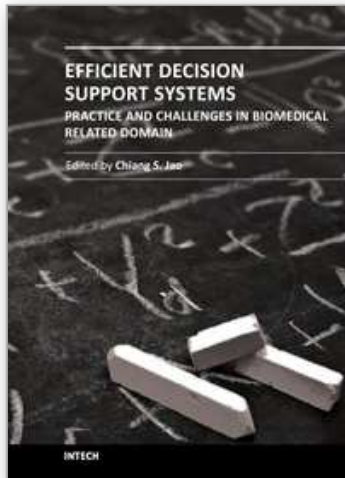
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