9. Decision support systems

Jeremy C Wyatt DM FRCP

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A medical decision support system (DSS) is a computer program that provides reminders, advice or interpretation specific to a given patient at a particular time[1]. These systems differ from bibliographic or other search tools in their use of patient data to drive a 'reasoner' program that searches a knowledge base to assemble a tailored report. The differences are summarized in Table 1.

KINDS OF MEDICAL DECISION SUPPORT SYSTEM

Some DSSs are designed for use by the public—for example, a web-based cardiac risk calculator ([www.allhealth.com/sponsors/zocor/calculator.html]). Those for health professionals include an anticoagulant dosage calculator[2], an AIDS reminder system[3], and the tools used by NHS Direct nurses to triage 12 million cases per annum[4].

DSSs can also be embedded in medical instruments such as electrocardiographs[5] or lung function recorders[6]. Others are integrated into general-practice or hospital information systems, and these can issue not only routine reminders but also urgent alerts about test orders, laboratory results or possible drug interactions[3]. In one study such a system led to more rational test ordering and reduced inpatient length of stay by a day—though at the cost of requiring junior doctors to spend 6 minutes extra per patient per day ordering tests[7].

DO WE NEED DECISION SUPPORT SYSTEMS?

A first question is, do doctors *want* decision support? A survey of 403 Internet-literate UK doctors (41% general practitioners), all members of the Medix Internet service provider, showed that in one month 60% would use a Royal College guideline, 55% a flowchart and 39% a checklist but only 24% would use a computer-based decision support system; 33% would never use one. Are these doctors right to judge DSSs less acceptable than guidelines, flowcharts or checklists? One drawback of guidelines and flowcharts is their proliferation[8], while another is difficulty tracing the path of a patient at a given encounter, even if you have the right guideline. Van Wijk used a randomized trial to compare the ability of a computer-based standard 15-item checklist and a DSS-generated problem-specific list derived from national guidelines to reduce the number of tests ordered by 66 Dutch general practitioners[9]. For those GPs randomized to the standard list there was a 12% reduction in the number of tests per order form, but the reduction was 29% (2.4 times greater) with the problem-specific DSS. Overall, the DSS led to 20% fewer tests ordered per GP than the standard checklist. Thus, despite the reluctance of computer-literate doctors to use DSSs, these systems can be more effective than their preferred tools such as a paper or computer based checklist.

Table 1 **Factors distinguishing decision support systems from bibliographic and other search tools**

	Decision support systems	*Search tools*
Use	System automatically assembles context specific advice or reminder using patient data	User formulates a search string; system retrieves potentially relevant text; user sorts through results to find relevant material
Input	Patient data, suitably coded, often obtained direct from electronic patient record	Text search string and/or coded search terms entered by human user
Output	Dynamically constructed reminder or advice	A list of performed text chunks (e.g. abstracts) matching the search string
Knowledge base	Machine-readable facts, assembled by a knowledge engineer or clinician using a knowledge editor	Human-readable prose and coded index terms selected by librarians, entered by clerks
Smallest knowledge unit	Discrete medical fact (e.g. a drug indication)	Text 'chunk', a sentence to a whole chapter in length (e.g. an abstract)
Search process	Reasoner progam uses patient data to search knowledge base with predefined algorithms	Boolean search program matches search string against text or index terms, ranks results using a relevance score
Scope	Usually narrow—e.g. a single problem or disease	Wide—e.g. the journals covering one discipline

Knowledge Management Centre, University College London, 29/30 Tavistock Square, London WC1H 3EZ, UK
E-mail: jeremy.wyatt@ucl.ac.uk

Table 2 **How decision support systems (DSS) can overcome barriers at each stage in the clinical innovation process**

Stage (Ref 10)	*Barrier to innovation*	*Possible benefit from decision support system*
1. Predispose to innovation (staff unwilling to change)	Clinicians do not know about innovation	Might help when used as a learning tool
	Apathy	Installation might attract clinical interest and generate discussion
	Peer resistance	DSS might help in marketing
	Patient resistance	DSS might promote innovation to patients
	'We're too busy'	DSS could empower nurse practitioner to take on the new task, freeing medical time
	Conflicting financial interest	Unlikely to help
2. Enable innovation (staff willing, 'system' is against them)	Patient data not complete, poorly presented	DSS issues problem-specific checklist or reminder to record relevant data, preinterprets complex patient data, carries out automatic case finding
	Poor access to detailed knowledge	DSS as intelligent front end to literature, filtering knowledge according to current patient and problem
	Doctors find it hard to synthesize patient data and knowledge	DSS carries out complex calculation or logical reasoning to link relevant patient data and clinical knowledge
	Lack of skills	DSS might help when used as a learning or simulation tool
	Lack of space, drugs, equipment, money; medicolegal or other organizational problems	Unlikely to help
3. Reinforce innovation (staff need encouragement)	Forgetting	Reminders for clinicians (and patients)
	Mistakes caused by action slips, capture errors	Reminders and alerts to build a safe operating environment; preinterpreted patient data; problem-specific work-flow and record formats to lessen errors
	Diminished motivation over time	Reminders or alerts; DSS can help support others (e.g. nurse practitioners) to carry out routine tasks

An alternative analysis requires understanding of how DSSs might overcome barriers to clinical innovation (article 3). The PRECEDE model[10] suggests that, to innovate, we must first predispose doctors to change by informing them of the innovation, then enable them to change by providing the necessary resources, and finally reinforce the change. A wide range of techniques including DSSs are available to assist this process, but should only be applied after consideration of the personal and organizational barriers to change. Some barriers that can occur at each of the three innovation stages are listed in Table 2, with suggestions about how decision support systems might help overcome most of them: clearly, DSSs have the potential to assist at all three innovation stages, particularly when they are used to educate patients and clinicians, to support staff substitution or to enhance data capture and interpretation.

This leads on to the question, when do DSSs actually change doctors' decisions, actions and patient outcomes?

When do decision support systems work?

Friedman *et al.*[11] examined the influence of two commercial diagnostic DSSs on the decisions of 216 US doctors confronted with difficult case scenarios[11]. Overall, the correct diagnosis appeared on 40% of doctors' differential diagnosis lists pre-DSS and 45% post-DSS—an 11% increase in diagnostic accuracy. In 12% of cases, the DSS caused doctors to put the correct diagnosis on their list but in 6% it caused them to drop the correct diagnosis, giving a net gain of 6%. The net gain was largest for students (9%) and smallest for faculty (3%). The QMR system[12] produced a net gain of 8%, twice that of the ILIAD system (4.1%). Thus a DSS, if it is to improve performance substantially, needs to be well designed and to be used by relatively inexperienced doctors. On some occasions a DSS causes doctors to override their own correct decisions.

How often DSSs improve clinical decisions is less important than how often they lead to more appropriate actions and patient outcomes[1,13]. Hunt[14] systematically reviewed 68 randomized trials of DSSs from 1974 to 1997. Improvement was seen in 43 (66%) of the 65 trials with an endpoint of clinical performance and 6 (43%) of the 14 with an endpoint of patient outcome. Most interesting was the way in which the percentage of studies showing improvement varied according to the behaviour targeted:

- Diagnosis: 1 (20%) of 5 studies
- Drug dosing: 9 (60%) of 15 studies
- Active clinical care: 19 (73%) of 26 studies
- Preventive care: 14 (74%) of 19 studies.

This shows that the typical complex diagnostic DSS is rarely effective—perhaps because routine clinical practice poses few diagnostic challenges, because doctors already excel at diagnosis or because doctors pay little attention to what emerges from such systems. However, the simple reminder systems that advise on active or preventive care frequently do lead to improved actions. Despite many years of development, complex diagnostic systems seem a solution looking for a problem.

A further question is, how do DSSs compare with other innovation methods? Davis *et al.* reviewed 101 randomized trials of innovation methods, again checking how many led to improved clinical practice, with the following results[15]:

- Formal continuing education course: 1/7 (14%)
- Educational materials: 4/11 (36%)
- Audit and feedback: 10/24 (42%)
- Patient mediated (e.g. leaflets): 7/9 (78%)
- Reminders to clinicians (e.g. DSS): 22/26 (85%)
- Outreach visits: 7/7 (100%)
- Opinion leaders: 3/3 (100%)

This showed that simple reminder systems were more effective at improving clinical actions than continuing medical education, audit and feedback, mailed educational materials or patient-mediated interventions, but less effective than the typical methods used by the pharmaceutical industry. One concern about these results is that they came from a wide range of settings, so perhaps the DSSs were used on clinical practices that were easier to alter. The only rigorous way to determine whether DSSs are more effective than another innovation method is to conduct a comparison within a single study. However, there are very few within-study comparisons. I have already mentioned one showing that DSSs were more effective than a standard checklist for containing test orders[9]. In another trial, a DSS was compared with a DSS combined with a team intervention, for improvement of drug ordering[16]. The expensive team intervention brought no additional benefit.

One factor that will obviously influence the acceptability of a DSS, and also its effectiveness, is the source of its knowledge[17].

SOURCE OF KNOWLEDGE FOR A DECISION SUPPORT SYSTEM

All too often in the past the knowledge for DSSs has been acquired by a computer scientist or a knowledge engineer from a single expert—or even by browsing out-of-date narrative textbooks, with all their defects[18]. A handful of systems such as QMR[12] were constructed after informal literature reviews, while Preop was the first in which the knowledge engineering team used a critical appraisal process and tagged each fact in the knowledge base with its level of evidence[19]. A more recent example of a DSS based on reliable evidence is an ischaemic heart disease risk adviser used daily at a London teaching hospital[20]. The knowledge on which all advice is based derives from regression equations fitting the Framingham dataset.

With the growth of secondary literature such as Cochrane reviews and *Clinical Evidence*, it is now much easier for those building DSSs to assemble the knowledge base direct from relevant evidence. However, whether you are building a DSS or writing a practice guideline, the goal is to give advice rather than simply précis evidence. As well as the relevant evidence, therefore, makers of DSSs need to include information on such matters as preferences, policies and resource availability. If an evidence-based guideline already exists which has assimilated all this information, this makes the perfect starting-point for a DSS knowledge base (Figure 1).

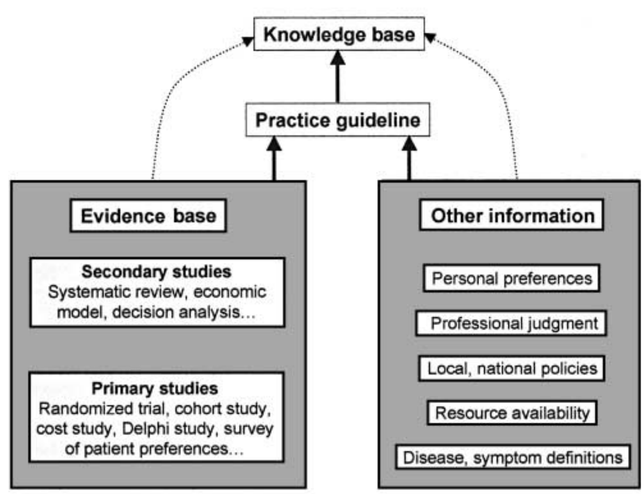

Figure 1 **The roles of evidence and other information in practice guidelines and decision support systems**

Box 1 **Some criteria for a clinically useful decision support system (adapted from Refs 17 and 26)**

The knowledge is based on the best evidence available (e.g. an evidence-based practice guideline or risk score)
The knowledge covers the problem in sufficient breadth and depth to allow sophisticated problem solving, advice and explanations
To ensure flexibility, the knowledge can be readily updated by a clinician without unexpected effects
To promote lifelong learning, the knowledge base links to related local and Internet material (images, practice guidelines...)
To make the system easy to use, most patient data are drawn from existing electronic sources
The performance of the entire system is validated against a suitable gold standard (Ref. 27)
The system improves clinical practice or patient outcomes in a rigorous study (Refs 1, 25)
The clinician is always in control, so can receive advice, browse the knowledge base, get help and explanations, try out 'what-if' scenarios and obtain a critique of the patient management plan
The system is easy to access—for example via the world wide web [e.g. the Heart Failure Program (Ref. 28) or an infective endocarditis advisor for developing countries (Ref. 29)]

CONCLUSIONS

DSSs are a seductive technology with the potential to lessen information overload and reduce clinical oversights. However, we should remember that there will often be more than one way to resolve a problem—medication errors, for example[21]. Although DSSs can help at each of the three main innovation stages, it would be wrong to conclude that they are always the correct solution[22].

One reason to think twice before developing or buying a DSS is that these systems do have important drawbacks. As with many information systems[23], there is a risk that an expensive, inflexible DSS will freeze an organization's policies and procedures at one historical moment. DSSs can also be unpredictable[24], needing rigorous evaluation[1,25] to ensure that they are indeed improving clinical practice. Few DSSs will be used unless most of the patient information can be drawn from other routine data sources in suitably coded form. This means that they require substantial infrastructure, in the form of networks, electronic patient records and ubiquitous terminals (which need to be used frequently if medical staff are to receive alerts and reminders promptly). For example, in the Safran study of outpatient reminders[3], the median time till doctors responded to a computer-generated alert was 11 days: the reason for this delay was they did not use the computer regularly. Box 1 lists some criteria for a clinically useful DSS.

DSSs also raise complex professional and medicolegal issues. For example, to avoid exposure to liability, every DSS must treat its user as a 'learned intermediary'[30]. Consequently, black-box reasoners such as neural networks are clinically dubious[31]. Lately, a GP was sued after prescribing antacids for an epilepsy patient; the antacids had precipitated a seizure, causing the patient's driving licence to be withdrawn. The GP had inferred that, because there had been no alert from his prescribing system, no hazard would arise. However, although the system 'knew' that antacids are contraindicated in epilepsy and that the patient was receiving phenytoin, it did not 'know' that phenytoin is an antiepileptic drug. It was thus unable to deduce that the patient had epilepsy and that antacids were contraindicated.

Currently, although DSSs work well in certain clinical niches, their overall cost-effectiveness compared with other innovation methods is unclear. It also remains to be seen whether the complex systems developed with advanced 'artificial intelligence' functions have greater impact, or are easier to maintain, than the simple reminder and algorithm systems already widely used in electronic patient records and for nurse triage.

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