Bilaga 4

Förstudierapport Stöd för rätt sjukskrivning

Omvärldsanalys

Clinical decision support systems and decision analysis in sickness certification practice: a meta-narrative review

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Inledning

Försäkringskassans prognoser visar att sjukskrivningarna ökar både i omfattning och längd. Sjukskrivning är en viktig del av vård och behandling, men forskning visar också att långvariga sjukskrivningar kan leda till sämre hälsa, ekonomi och relationer. Idén bakom projektet *Stöd för rätt sjukskrivning (SRS)* är att förbättra för alla inblandade i sjukskrivnings- och rehabiliteringsprocessen, inklusive individen själv.
Ett gemensamt IT-baserat bedömningsstöd ska kunna bidra med ett samlat kunskapsunderlag för att läkare ska kunna utfärda läkarintyg med större träffsäkerhet samt hjälpa hälso- och sjukvården och Försäkringskassan att identifiera individer som har behov av specifika eller samordnade insatser. Bedömningsstödet kan också i en framtid användas som ett stöd för arbetsgivare och av individen själv för att kunna ta en aktiv del i sin egen rehabilitering.

Under förstudiearbetet har projektet utrett förutsättningarna för att skapa ett sådant samlat bedömningsstöd för olika aktörer i sjukskrivnings- och rehabiliteringsprocessen. Huvudsyftet har varit att undersöka möjligheten att bättre utnyttja kunskap om prognosfaktorer som påverkar sjukskrivningen. Utifrån denna kunskap kan mer träffsäkra prediktioner ges om sjukskrivningslängd och omfattning för en enskild individ.

Projektet har finansierats via Socialdepartementet genom överenskommelsen mellan regeringen och SKL om en kvalitetssäker och effektiv sjukskrivningsprocess, den så kallade sjukskrivningsmiljarden. Försäkringskassan och Sveriges Kommuner och Landsting ansvarar gemensamt för projektet. Socialstyrelsen och andra intressenter är representerade i projektets styrgrupper och referensgrupper. Projektets utredningsarbete påbörjades i mars 2014 och slutredovisning sker i oktober 2015.

Förstudiearbetet har varit indelat i följande delområden:

- *Målarbetet* har tagit fram förslag på övergripande gemensamma nationella mål för sjukskrivningsområdet och effektmål för projektet.
- *Kunskapsanalysen* har sammanställt vetenskaplig och annan relevant och aktuell kunskap om sjukskrivning, prognosfaktorer och insatser.
- *Omvärldsanalysen* har inventerat liknande bedömningsstöd i världen för att se om det finns relevant kunskap att dra lärdom av.
- *Konceptutredningen* har utrett verksamhetsmässiga, tekniska och juridiska förutsättningar för att utveckla bedömningsstödet.

Utöver delområdena har projektövergripande arbete som styrning, ledning, uppföljning, kommunikation och kvalitetssäkring bedrivits.

Utredningsarbetet har utförts av en arbetsgrupp med bred kompetens och med stor samlad erfarenhet av nationella e-hälsoprojekt. Delar av utredningsarbetet har utförts av och med forskare och utredare från Karolinska Institutet, Lunds universitet och Linköpings universitet.

Denna rapport redovisar en del av förstudiens arbete. Förstudierapporten med en sammanfattning av hela resultatet går att beställa genom att mejla till cecilia.alfven@skl.se
Mer information om projektet *Stöd för rätt sjukskrivning* finns på SKL:s webbplats*:*
http://skl.se/halsasjukvard/sjukskrivningochrehabilitering/sjukskrivningsmiljarden/rattsjukskrivningstod.5229.html

Swedish summary

Syftet med omvärldsanalysen har varit att undersöka om det finns kunskaper, erfarenheter och framgångsfaktorer från andra liknande system i världen som går att återanvända i utvecklingen av ett bedömningsstöd för sjukskrivning.

Slutsatsen från omvärldsanalysen är att modellen för bedömningsstöd vid sjukskrivning som utvecklats inom SRS-projektet är ett bra och framsynt exempel på utveckling av e-hälsosystem, eftersom den bygger på en infrastruktur för patientinformation som är gemensam för alla sjukvårdsenheter och den utnyttjar integrationsfördelarna med ett heltäckande nationellt sjukförsäkringssystem. Erfarenheter från andra system är dock viktiga att ta med i det vidare arbetet för att bedömningsstödet ska bli en framgång och nå de effektmål projektet formulerat.

Analysen har gått igenom närmare 1 000 system från Europa, Nordamerika, Asien och Australien. Beslutsstödsystem har tillämpats med framgång inom sjukvården främst vid läkemedelsförskrivning och beslutsfattande om preventions- och rehabiliteringsåtgärder. De mest effektiva systemen är sammanbyggda i en gemensam infrastruktur med patientjournaler och laboratoriesystem. Exempel på sådana system som bygger på integrerade beslutstödsmoduler är de som används inom amerikanska privata sjukförsäkringskoncerner (eng. Health Maintenance Organizations (HMOs)) som tillhandahåller förebyggande hälsovårdstjänster, akutsjukvård och rehabilitering till den försäkrade.

I omvärldsanalysen, som byggt på information från sökningar i vetenskapliga databaser samt granskning av webbsidor och intervjuer, hittades inga utvärderingar av hur datorbaserade stöd för bedömning av sjukskrivningslängd fungerar när de tillämpas i praktiken. Det saknas också rent allmänt väl utförda utvärderingar av kliniska beslutsstödsystem inom sjukvården. Detta har lett till att omvärldsanalysen inte kan byggas på vetenskapliga utvärderingar av system som påminner om bedömningsstödet. Omvärldsanalysen kan däremot ge en översikt över vad som är beskrivet om liknande system som kan vara användbart att ta med sig in i fortsatt arbete med utredning och utveckling inom projektet.

De exempel på fungerande kliniska beslutsstödsystem som hittats kommer främst från sjukhus och läkarmottagningar inom amerikanska sjukförsäkringskoncerner, såsom Partner's Healthcare, Kaiser Permanente och Veterans'Affairs. Dessa system bygger på en gemensam och noggrant underhållen teknik för de sjukhus och mottagningar som ingår i koncernerna och är ofta först utvecklade tillsammans med forskare. Tillämpningarna av beslutsstöd inom dessa system omfattar ett vitt område, från diagnos till val av laboratorieundersökningar. Mest effektiva har de visat sig vara vid läkemedelsförskrivning samt vid planering av förebyggande program och rehabilitering för enskilda patienter. Utformningen av beslutsstöden varierar från varningar riktade till användaren om avvikelser från klinisk praxis till att systemet föreslår olika beslutsalternativ i en beslutsprocess. Liknande system, men med varierande integrationsgrad mellan beslutsstödet och den övriga informationsinfrastrukturen, finns även i Europa, Asien, och Australien. Dessa system är dock oftast begränsade till enskilda sjukhus eller tillämpningsområden.

Omvärldsanalysen har också sammanställt erfarenheter från användning av klinisk beslutsanalys, vilket innebär tillämpning av kvantitativa analysmetoder för att strukturera och åskådliggöra beslut om medicinska åtgärder. Klinisk beslutsanalys kan vara ett kraftfullt verktyg men kräver stor noggrannhet i val och utformning av metod. Till exempel får man ett dåligt resultat om man använder data som samlats in i andra sammanhang än där de används för prognoser. Det är också viktigt att utgå från nationella förhållanden och data när man utformar ett bedömningsstöd för

sjukskrivning. Omvärldsanalysen visar dessutom att en framgångsfaktor kan vara att även utveckla beslutshjälpmedel för patienter parallellt med att det utvecklas för hälso- och sjukvårdpersonal. Modern sjukvård bygger på att patienten medverkar i allt beslutsfattande som berör hens hälsa. Tillämpning av klinisk beslutsanalys vid rehabiliteringsplanering, där patientens prioriteringar och värderingar inte inkluderas, löper därför stor risk att leda till missvisande resultat.

Omvärldsanalysen visar också att det är nödvändigt att löpande utvärdera effektivitet och användbarhet för att undvika oönskade konsekvenser för patienterna och merkostnader i sjukförsäkrings- och sjukvårdssystemen. Erfarenheter från de långtidsuppföljningar som finns tillgängliga visar att systemen förlorar i effektivitet över tid om de inte uppdateras regelbundet, likaså att de fungerar sämre om de flyttas till miljöer med sämre tekniska resurser än där de utvecklats.

Som en praktisk grund för framtida beslutsstödsystemutveckling som bygger på tidigare vårderfarenhet finns det omfattande datavetenskaplig och matematisk forskning i lärande prediktiva modeller. Denna forskning är stadd i snabb utveckling vilket avspeglas av den breda variation i metodologi som de här undersökta systemen visar. Ett lärande beslutsstödsystem som utvecklas utifrån de senaste tekniska erfarenheterna måste lämna utrymme för att byta ut moduler både för lärande och härledning av ny kunskap när nya tekniker blir driftklara och för att kunna fatta adekvata tekniska beslut måste systemlösningarna utvärderas även tekniskt. Utvecklade beslutsstödsystem måste knäsättas i klinisk praxis för att bli användbar och balansera både känd vetenskaplig kunskap, klinisk erfarenhet och den invididuella situation som vårdgivaren bäst kan avgöra i mötet med patienten och patientens värderingar och attityder. De beslutsstöd som avses utvecklas måste utformas så att de passar in i vårdgivarens arbetsflöde.

Omvärldsanalysrapporten avslutas med en serie konkreta rekommendationer för införande av ett bedömningsstöd för sjukskrivning, baserat på genomgången av de system som behandlats i rapporten. De återges här i punktform i korthet:

1. Förankra projektet politiskt och se till att de aktörer som är berörda är överens om systemstrategi och framtida ansvarsfördelning.
2. Säkra projektets grund i förordningar och lagrum i frågor om ansvar, databehandling, personlig integritet och etik.
3. Prioritera utvecklingsprocessen efter de samhälleliga effekter de kan förväntas ge.
4. Mobilisera avnämare och användare.
5. Rekrytera en effektiv kvalitetsorienterad projektgrupp.
6. Formulera en operationaliserad och mätbar valideringsmodell enligt etablerad vetenskaplig standard.
7. Välj rehabiliteringsåtgärder med patientens prioriteringar i åtanke.
8. Använd systemutvecklingsprocesser enligt industriell standard.
9. För in systemlösningar kontinuerligt och utvärdera dem löpande i praxis.
10. Engagaera systemlösningarnas kommande kliniska användare genom en användarcentrerad utvecklingsprocess.
11. Informera marknadsför fördelar hos systemlösningarna till allmänheten.

Contents

Introduction

Sickness certification is an ongoing clinical decision-making practice aimed at suggesting an optimal sick leave and rehabilitation to individual patients (Timpka et al. 1995, Hensing et al. 1997). Just as selection of any other clinical action, the "best sickness certification decision" can be denoted as the choice that maximizes effectiveness and minimizes harm (Aleem et al. 2008). Nevertheless, when the supporting evidence is scant, decision-making depends on the subjective intuition of the physician and then may become unpredictable and non-reproducible (Banning 2008). Early in the new millennium, it was brought to the fore that health care delivered in industrialized nations often fell short of optimal, evidence based care. For instance, a nationwide audit found that US adults receive only about half of recommended care (McGlynn et al. 2003), and the US Institute of Medicine estimated that up to 98 000 US residents die each year as the result of preventable medical errors (Kohn et al. 1999). Similarly a retrospective study of hospital care in England found that 11% of admitted patients experienced adverse events, of which 48% were judged to be preventable and of which 8% led to death (Vincent et al. 2001). As a response to this situation, Evidence-based Medicine (EBM) was developed as a set of methodologies for making clinical decisions based on the best evidence (Rosenberg & Sackett 1996, Sackett 1998, Djulbegovic et al. 2000, Bae et al. 2013), expanded across the entire field of healthcare, and the concept of "evidence-based decision-making" has also been introduced (Dowie 1996, Teutsch & Berger 2005, Bates et al. 2003). By overcoming the complexity of the medical environment (Balla et al. 1989, Hamilton 2001, Galanter & Patel 2005, Thompson et al. 2004) and the uncertainty of clinical decisions (Beresford 1991, West & West 2002, Hu et al. 2004, Thornton et al. 1992), EBM is used to pursue qualitative improvements in healthcare (Bae 2014, Brazil et al. 2005, McCreery & Truelove 1991a, Myers & McCabe 2005) due to that decision-making is directly related to, for instance, the development of clinical treatment guidelines and drug prescriptions (Atkins 2007, Garrison et al. 2007).

One particular means used by healthcare organizations to address deficiencies in services provided to patients is clinical decision support systems (CDSSs), which provide practitioners with patient-specific assessments or recommendations to aid clinical decision making (Hunt et al. 1998). Such decision support may be delivered by a variety of means, e.g. manual or computer based systems that attach care reminders to the charts of patients needing specific preventive care services and computerized physician order entry systems that provide patient-specific recommendations as part of the order entry process. Early CDSSs have been shown to improve prescribing practices (Bennett & Glasziou 2003, Walton et al. 2001, Walton et al. 1999), reduce medication errors (Kaushal et al. 2003, Bates et al. 1999a), enhance the delivery of preventive care services (Shea et al. 1996, Balas et al. 2000), and improve adherence to recommended care standards (Hunt et al. 1998, Shiffman et al. 1999a). Compared with other approaches to improve practice, these systems have also generally been shown to be more effective and more likely to result in lasting improvements in clinical practice (Thomson et al. 2000, Hulscher et al. 2001, Oxman et al. 1995, Kupets & Covens 2001, Bero et al.

1998, Mandelblatt & Kanetsky 1995, Wensing & Grol 1994, Mandelblatt & Yabroff 1999, Stone et al. 2002, Weingarten et al. 2002). However, CDSSs may not always improve clinical practice. Relatively little sound scientific evidence is available to explain why systems succeed or fail (Kaplan 2001, Kanouse et al. 1995). Although some investigators have tried to identify the system features most important for improving clinical practice (Shiffman et al. 1999a, Wendt et al. 2000, Wetter 2002, Sim et al. 2001, Payne 2000, Shiffman et al. 1999b, Ash et al. 2003, Trivedi et al. 2002, Solberg et al. 2000, Bates et al. 2003, Centre for Health Informatics 2003), they have typically relied on the opinion of a limited number of experts, and none has combined a systematic literature search with quantitative meta-analysis.

The goal of the “Sickness Insurance Billion Program” in Sweden is to promote the establishement of an effective, safe, and high-quality sick leave process in the country. To achieve this, the assumption is that Swedish employees contained within the sickness insurance receive an individualized assessment and a personalized recommendation and action plan in association to an eventual sick leave. In the individualized assessment is an assessment of whether there is a need for specific and/or concerted action, or if there are such needs. The earlier in the process, individuals with such needs are identified, the sooner the right individual to get the right bet.

In the project “Support for the Right of Sick certification” (SRS) included in the “Sickness Insurance Billion Program”, the possibility for development of decision/evaluation support tools for practitioners involved in the sickness absence and rehabilitation process is investigated. As a part of the SRS project, this study set out to perform a meta-narrative analysis to identify factors that are of relevance when clinical decision support systems are introduced for improving clinical sickness certification practice. The purpose of the analysis is to bring knowledge, experience and "best practice" from similar decision support tools and systems used in other countries to the SRS project. The expected result of the analysis is a report that summarizes important experiences (opportunities and threats) from investigation, requirements gathering, development, pilot operation, deployment, operation and management of a similar decision support tools and systems.

The meta-narrative approach was chosen because it is suitable for not only addressing the question ‘what works?’, but also to elucidate a complex topic, highlighting the strengths and limitations of different research approaches to that topic (Mays et al. 2005). Meta-narrative analyses look at how particular research traditions have unfolded over time and shaped the kind of questions being asked and the methods used to answer them. They inspect the range of approaches to studying an issue, interpret and produce an account of the development of these separate ‘meta-narratives’ and then form an overarching meta-narrative summary. The principles of pragmatism, pluralism, historicity, contestation (conflicting data were examined to generate higher-order insights), reflexivity, and peer review were applied in the analysis (Wong et al. 2013).

Methods

A meta-narrative analysis (Wong et al. 2013) was conducted to assess scientific publications relevant for answering the analysis question, i.e. to bring knowledge, experience and "best practice" from decision support tools and systems used in other countries to the SRS project. Four steps were taken: an electronic literature search was done, papers were selected, data from these papers were extracted, and qualitative and semi-quantitative content analyses were conducted. For data extraction and analyses, researcher triangulation was used as a strategy for quality assurance. All steps were documented and managed electronically using a database.

PubMed and Scopus were used to search for eligible studies using search term combinations covering clinical decision support systems and decision analysis in sickness certification. The database searches were conducted between October 2014 and January 2015. To select papers for further analysis from the pool of search results, only publications in scientific journals and book chapters available in the English language were included. To describe the characteristics of the selected papers, information was documented regarding the main objective, the publication type, country, decision analysis or support method applied, and context of application.

In the next step, text passages, i.e. sentences or paragraphs containing key terms were extracted. If necessary, sentences before and after a statement containing the key terms were added to ensure that the meaning and context was not lost. Next, content analysis of the extracted text was performed. The meaning of the original text was condensed. The condensed statements contained as much information as necessary to adequately represent the meaning of the text in relation to the research aim, but were as short and simple as possible to enable straightforward processing. If the original text contained several pieces of information, then a separate condensed statement was created for each piece of information. To analyze the information contained in the papers, a coding scheme was developed inductively. Condensed statements could be labelled with more than one code. The creation of the condensed statements and their coding were carried out by one reviewer and rechecked by the others. Preliminary versions were compared and agreed upon, which resulted in final versions of the condensed statements and coding. The information was summarized qualitatively in tables and analyzed semi-quantitatively on the basis of the coding. Next analysis phase consisted of identifying the key dimensions of , providing a narrative account of the contribution of each dimension and explaining conflicting findings. The resulting narratives are presented narratively without quantitative pooling. In the last step, a wider research team and policy leaders with backgrounds in clinical medicine, social insurance medicine, public health, computer science, statistics, social sciences, and cognitive science were engaged in a process of testing the findings against their expectations and experience and their feedback was used to guide further reflection and analysis. The final report was compiled following this feedback.

Results

Analyses of the scientific and "grey" literature revealed no reports of CDSS use in the sickness certification context. Therefore, no corresponding narrative resulted from the analyses. Instead, two main narratives emerged, i.e. those retelling experiences from the use of decision analytic methods in the clinical sickness certification setting and those accouting for decision support system use in the clinical context, respectively. While numerous uses of decision analytic methods were included in the former narrative, no particular applications of decision support systems for sickness certification were included in the corresponding narrative. Both main narratives are concluded by listing challenges to be dealt with when implementing CDSS in sickness certification practice.

The clinical decision analysis and modeling narrative

Numerous clinical decisions are made on the basis of an estimated probability that a specific disease or condition is present (diagnostic setting) or a specific event will occur in the future (prognostic setting). Clinical decision analysis and modeling (CDAM) is used to denote formal predictions regarding diagnosis, prognosis or associated healthcare actions based on objectively quantitative indices (Table). In the diagnostic setting, the predicted probability that a particular disease is present can be used, e.g. to inform the referral of patients for further testing, to initiate treatment directly, or to reassure patients that a serious cause for their symptoms is unlikely. In the prognostic context, predictions can be used for planning lifestyle or therapeutic decisions on the basis of the risk for developing a particular outcome or state of health within a specific period (Moons et al. 2009, Steyerberg 2009, Wasson et al. 1985). In both the diagnostic and prognostic setting, probability estimates are commonly based on combining information from multiple predictors observed or measured from an individual (Moons et al. 2009, Steyerberg 2009, Riley et al. 2013, Steyerberg et al. 2013, Royston et al. 2009). Information from a single predictor is often insufficient to provide reliable estimates of diagnostic or prognostic probabilities or risks (Riley et al. 2013, Collins & Altman 2013). In a diagnostic model, multiple predictors (diagnostic test results) are combined to estimate the probability that a certain condition or disease is present (or absent) at the moment of prediction. They are developed from and to be used for individuals suspected of having that condition. In a prognostic model, multiple predictors are combined to estimate the probability of a particular outcome or event (for example, mortality, disease recurrence, complication, or therapy response) occurring in a certain period in the future. Prognostic models are developed and are to be used in individuals at risk for developing that outcome. They may be models for either ill or healthy individuals. For example, prognostic models include models to predict recurrence, complications, or death in a certain period after being diagnosed with a particular disease. But they may also include models for predicting the occurrence of an outcome in a certain period in individuals without a specific disease: for example, models to predict the risk for type 2 diabetes (Hippisley-Cox et al. 2009) or cardiovascular events (D'Agostino et al. 2008). The main difference between a diagnostic and prognostic prediction model is the concept of time. Diagnostic modeling studies are usually cross-sectional, whereas prognostic modeling studies are usually longitudinal. In this document, we refer to both diagnostic and prognostic prediction models as "prediction models," highlighting issues that are specific to either type of model.

Table Definitions of decision analysis (DA) and clinical decision analysis (CDA).

Decision Analysis

1. DA Is an explicit, normative and analytic approach to making decisions under uncertainty- provides a probabilistic framework for exploring difficult problems in non-deterministic domains (Wong et al. 1986).
2. DA is the application of explicit, quantitative methods to analyze decisions under conditions of uncertainty (Richardson &, Detsky 1995)

3. DA formalizes the decision process, highlights the factors that influence the decision, and applies mathematical rigour to quantify decision-making (Sonnenberg 2004).

Clinical Decision Analysis

1. CDA seeks to identify the optimal management strategy by modelling the uncertainty and risks entailed in the diagnosis, natural history, and treatment of a particular problem or disorder. (Doan et al. 1995).
2. CDA is a systematic method for making wise choices under just such circumstances. (Watts 1989).
3. CDA in a quantitative approach for dealing with the uncertainties inherent in many medical decisions, including decisions about genetic testing (McConnell & Goldstein 1999).
4. CDA is a quantitative by an ever increasing number of costly and confusing application of probability and utility theory to decision diagnostic tests and therapeutic interventions, decision-making under conditions of uncertainty (Sarasin 2001).
5. CDA is a quantitative approach to decision-making under conditions of uncertainty that can be applied to specific types of clinical problems ((Burd & Sonnenberg 2002).
6. CDA is a process whereby different treatment options are assessed systematically (Manarey et al. 2002).
7. CDA is a formal, mathematical approach to analyzing difficult decisions faced by clinical decision makers (i.e. patients, clinicians, policy-makers) (van der Velde 2005).
8. CDA is a formal, quantitative method for systematically comparing the benefits and harms of alternative clinical strategies under circumstances of uncertainty. (Elkin EB at al. 2006).
9. CDA is a tool that allows users to apply evidence-based medicine to make informed and objective clinical decisions when faced with complex situations. (Aleem et al. 2008; 42).
10. CDA is a simulation, model-based research technique in which investigators combine information from a variety of sources to create a mathematical model representing a clinical decision (O'Brien 2008).
11. CDA is the application of DA to a clinical or patient-based setting - is a technique that incorporates literature-derived probabilities with expert and patient preferences to result in an informed clinical decision. (Aleem et al. 2009).

McCreery & Truelove (1991a) have summarized five "families" of methodologies for decision analyses: (a) Bayes' theorem, (b) decision-tree design, (c) receiver-operating-characteristic curves, (d) sensitivity analysis, (e) utilities assessment. In 1976, Bear & Schneiderman (1976) suggested the terminology "clinical decision analysis" with the intention of applying the concept of decision analysis (DA), which had already been used in business and other social sciences, to the field of clinical practice. In order to understand the full meaning of the term CDAM, the term DA coined by Raiffa (1993) in 1968 should also be taken into regard. Watts (1989) proposed that CDAM should consist of six stages including cost analysis, whereas Sackett et al. (1991) proposed six stages including clinical practice.

Depending on the methodology used, the CDAM stages can be summarized as follows: (a) designing a decision tree showing all instances that can occur in a particular situation, (b) securing the likelihood and outcome utility values for each instance by conducting a literature search, (c) calculating the probabilities of cumulative expectation using the Bayesian theorem, and (d) performing a sensitivity analysis and assessing the variables needed for clinical decision-making.

Typical stages of the modelling process include design of the decision tree (Aleem et al. 2008, Hagen 1992, Podgorelec et al. 2002, Aleem et al. 2009, Detsky et al. 1997), debugging of logical errors in the designed tree (Krahn et al. 1997), calculation of the cumulative probability, and Monte Carlo simulation for the sensitivity analysis (Doan et al. 1995). The recent development of commercial software such as TreeAge Pro (website accessed November 2014) is making these processes easier. In parallel, the importance of the literature search to consolidate the appropriateness of the parameters used for the analysis is being emphasized (Aleem et al. 2008, Naglie et al. 1997). The latter is crucial since the meaning of the relevant values varies by country and time (Torrance 1987, Clancy & Cronin 2005). The cumulative expectation probabilities obtained by using a decision tree vary according to the input values of outcome utility and likelihood (Krahn et al. 1997). Consequently, by estimating the vulnerability (how much the outcomes change according to fluctuations in the input values) the ultimate objective was to reduce uncertainty in decision-making (Briggs 2000). In addition, sensitivity analysis could be used to elucidate the extent to which a given clinical situational variable affects the decision (Korah et al. 1999, van der Velde 2005, Graham & Detsky 2001, Hirai et al. 2001), so that these variables can be used as latent predictor variables for clinical prediction rules (CPR) (Huijbregts 2007, Cook 2008, Ingui & Rogers 2001, Vickers & Cronin 2010). Moreover, areas requiring future clinical research can be identified (Aoki et al. 2001), and logical systematic errors in the designed decision tree can be debugged (Krahn et al. 1997). Traditional n-way sensitivity analysis (Aoki et al. 2001, Hagen 1992) has been used as the statistical method for conducting a sensitivity analysis, but more recently, the Markov Chain Monte Carlo simulation methods (Aoki et al. 2001, Minelli et al. 2004, Naimark et al. 1997, Doubilet et al. 1985) has been mainly used.

After developing a prediction model, the performance of the model needs to be evaluates using other data than those employed for its definition (Collins et al. 2015). An external validation (Moons et al. 2012, Altman & Royston 2000) means that for each new individual patient providing data for the evaluation, outcome predictions are made using the original model and compared with the observed outcomes. External validation may use data collected in the original setting, typically using the same predictor and outcome definitions and measurements, but sampled from a later period (temporal or narrow validation); in another setting (Ioannidis & Khoury 2011), or even in other types of participants (Altman et al. 2009, Moons et al. 2012, Altman & Royston 2000, Justice et al. 1999, McGinn et al. 2000, Taylor et al. 2008). In case of poor performance (for example, systematic miscalibration), when evaluated in an external validation data set, the model can be updated or adjusted (for example, recalibrating or adding a new predictor) on the basis of the validation data set (Steyerberg 2009, Moons et al. 2012, Toll et al. 2008, Janssen et al. 2008). Randomly splitting a single data set into model

development and model validation data sets is frequently done to develop and validate a prediction model. However, this approach is a weak and inefficient form of internal validation, because not all available data are used to develop the model (Steyerberg et al. 2003, Steyerberg et al. 2001). This is sometimes, yet wrongly, believed to be a form of external validation. If the available development data set is sufficiently large, splitting by time and developing a model using data from one period and evaluating its performance using the data from the other period (temporal validation) is a stronger approach. With a single data set, temporal splitting and model validation can be considered intermediate between internal and external validation.

Clinical decision analysis in sickness certification

The CDAM use in the sickness certification setting, being performed with the aim of overcoming complexity and uncertainty in clinical decisions, can be broadly categorized into three areas.

The first area where CDAM can be used is to reveal the critical variables that need to be considered when making a decision about sickness certification n clinical settings (Naglie et al. 1997, Stockstill et al. 1992, McCreery & Truelove 1991b). This can be useful in decision-making not only for physicians, but also for sickness insurance organizations or decision-makers in healthcare administration (van der Velde 2005, Graham & Detsky 2001, Burd & Sonnenberg 2002). In 2007, a systematic review summarized the knowledge on which factors that are associated with continued sick leave among workers on sick leave for at least 6 weeks (Dekkers-Sanchez et al. 2008). Sixteen factors each associated with long-term sick leave were identified. Evidence, although limited, was found for the factors older age and history of sickness. All 16 factors were classified as predisposing factors for long-term sick leave. A later Dutch study set out to establish the structure of historical sickness absence that is associated with future sickness absence (Roelen et al. 2011). The number of days and episodes of sickness absence were ascertained for a total of 551 employees. Days of sickness absence in the past year predicted up to 15% of future days of sickness absence. Adding the sickness absence data of the past 2 or 3 years did not further increase the predictability of days of sickness absence. Episodes of sickness absence in the past year predicted up to 25% of future episodes of sickness absence. The predictability of episodes of sickness absence increased to 30% when the past 2 years of sickness absence were included in the regression model, but did not further increase when sickness absence of the past 3 years was included. It was concluded that employees who are more likely to have an above average sickness absence can be identified from their history of sickness absence in the past two years. In comparison, a study performed in a Primary Health Care setting in Sweden followed 943 sickness certified subjects for three years (von Celsing et al. 2012). The extent of previous sick leave, age, being on part-time sick leave, and having a psychiatric, musculoskeletal, cardiovascular, nervous disease, digestive system, or injury or poisoning diagnosis decreased the return to work rate, while being employed increased it. Marital status, sex, being born in Sweden, citizenship, and annual salary were in this study found to have no influence. In logistic regression analyses across follow-up time these variables altogether explained 88-90% of return to work variation.

True to its original purpose, the second area of CDAM use in sickness certification practice is to provide the care provider with objective evidence to make a judgment (Aleem et al. 2008, Sarasin 2001, Yentis 2006, Sisson et al. 1976, Richardson & Detsky 1995). Consistent and reproducible decision-making can reduce the misuse of medical resources caused by uncertainty, improve the patient-physician relationship (Bae 2014, Krahn et al. 1997, Kassirer et al. 1987), and lead to qualitative improvements in healthcare (Dolan 2001, Pauker & Kassirer 1987). An example of such CDAM applications for use in sickness certification practice is the Örebro Musculoskeletal Pain Screening Questionnaire (ÖMPSQ). The ÖMPSQ was developed as a tool to identify individuals at risk for long-term pain and disability among patients with acute or subacute neck pain or low back pain (NP/LBP) (Linton & Boersma 2003). It comprises 21 questions to be asked from the patient, covering areas ranging from pain experience to psychological and physical functioning and fear-avoidance beliefs. Five questions relate to work per se: sick leave, fear of reinjury due to work, expectations about future work ability, one item about heavy/monotonous work and one item about job satisfaction. The predictive ability of the ÖMPSQ concerning long-term sick leave, sickness presenteeism and disability pension during a follow-up time of 2 years has recently been evaluated (Bergström et al. 2014). The study population consisted of 195 employees seeking help due to NP/LBP at their occupational health service. The majority had experienced NP/LBP for more than a year but despite this long-standing pain, about half of the study group only had a week or less of sickness absenteeism. The predictive performance of the ÖMPSQ was found to vary from Area under the Receiver operating characteristic Curve (AUC) 0.67 to AUC 0.93, i.e. from less accurate for sickness presenteeism and registered sick leave during the second year of follow-up, to highly accurate for the prediction of disability pension. The ability to predict registered sick leave during the first year of follow up was moderately accurate. Regarding the performance of such prognostic tests, there is a tradeoff between the statistics sensitivity and specificity. Lowering the cutoff of one-dimensional predicition scales (with AUC < 1.0) decreases the proportion of false negatives, but increases the proportion of false positives. Whether a predictive instrument should have a high sensitivity or a high specificity depends on its use. In the rehabilitation setting, a high sensitivity will lead to a high proportion of patients referred to interventions, and due to the low specificity, not all of them may need a costly rehabilitation. For instance, in the case of the ÖMPSQ, a higher cutoff value would lead to high specificity and low sensitivity, while a lower cutoff value would lead to high sensitivity and low specificity. A meta-analysis (Sattelmayer et al. 2012) has evaluated how accurate the ÖMPSQ and the Acute Low Back Screening Questionnaire (ALBPSQ) (Linton & Halldén 1998) with fixed cutoffs can predict persistent consequences, such as sick leave (Sattelmayer et al. 2012). It was found that the summary scores of the ÖMPSQ or ALBPSQ were not optimal to identify individuals at risk of developing disability. Instead, the computation of an individual risk profile was recommended instead of the summary score.

Also recently, a Dutch study set out to develop and validate prediction models to identify employees at risk of high sickness absence (SA) (Roelen et al. 2013. Two prediction models were developed using self-rated health (SRH) and prior SA as predictors. SRH was measured by the categories excellent, good, fair and poor in a convenience sample of 535 hospital employees. Prior SA was retrieved from the

employer's register. The predictive performance of the models was assessed by logistic regression analysis with high vs. non-high SA days and SA episodes as outcome variables and by using bootstrapping techniques to validate the models. The overall performance as reflected in the Nagelkerke's pseudo R2 was 11.7% for the model identifying employees with high SA days and 31.8% for the model identifying employees with high SA episodes. The discriminative ability was AUC 0.73 (95% CI 0.67–0.81) for the model identifying employees with high SA days and AUC 0.83 (95% CI 0.78–0.88) for the model identifying employees with high SA episodes. The Hosmer–Lemeshow test showed acceptable calibration for both models. It was concluded tht the prediction models identified employees at risk of high SA, but need further external validation in other settings and working populations before applying them in public and occupational health research and care.

Another recent study, performed in Sweden, compared the predictive properties of traditional GP clinical assessments of return to work (RTW) in sickness certification practice, with those based on a multivariate analysis of potential determinants presented as nomograms for RTW (von Celsing et al. 2014). The study population included all patients that were sickness-certified during a certain time period in a Primary Health Care area, thus being reasonably representative for a Swedish sickness certified population. A manual model was analysed using proportional hazards regression (Cox's analysis), with RTW and the day from baseline when it occurred as dependent variables and high/low risk group assignment as the independent variable. A computer-based model was also based on the proportional hazards regression technique in its multivariate form. Significant determinants for RTW from a previous publication (von Celsing et al. 2012) were used, i.e. age, number of days of sick-leave during the year preceding baseline, sick-leave diagnosis, degree of sick-leave, and occupational status. RTW and the day from baseline when it occurred were entered as dependent variables. The sick-leave diagnoses were grouped as ICD-10 codes. The assessment showed a high agreement between actually occurring RTW and RTW according to the two analysis models, even though the computer-based one had a better precision (89% agreement) than the manual model (76%) and also provided more detailed information on the probability of RTW. Both models were stable over time, at least to day 180, when the majority of subjects had returned to work.

Most recently, the Dutch prognostic model developed for predictions of high SA in Dutch hospital workers (Roelen et al. 2013 has been validated in external settings. In addition, the prognostic model has been updated by adding person-, health-, and work-related variables. In a study aimed at predicting high SA in Danish eldercare, the added value of work environment variables to the models' risk discrimination was also investigated. It was found that the models underestimated the risk of high SA in eldercare workers and the SA episodes model had to be re-calibrated to the Danish data. Discrimination was practically useful for the re-calibrated SA episodes model, but not the SA days model. Physical workload improved the SA days model and psychosocial work factors, particularly the quality of leadership improved the SA episodes model. Another study performed among Norwegian nurses (Roelen et al. 2015), showed that the Dutch prognostic model under-estimated the risk of high SA also among Norwegian nurses. It is

hypothesized that this finding can be explaind by differences in the measurement of predictor variables as well as between country differences in societal systems for healthcare and sickness absence compensation. When the Dutch model was re-calibrated to the Norwegian data, it showed fair discrimination (AUC = 0.73), although a discriminative ability AUC C 0.75 is considered useful for practice. In an attempt to improve the prognostic model's discriminative ability, gender, marital status, BMI, physical activity, smoking, alcohol intake, job satisfaction, job demands, decision latitude, support at the workplace, and work-to-family spillover were added to the model. However, none of these variables improved the model's discriminative ability. Gender was the strongest person- related predictor of high SA.

By elucidating predictor variables, the sensitivity analysis can be useful and can be applied to utility analysis and cost analysis, as it reveals cases of insufficient evidence (Djulbegovic et al. 2000, Watts 1989, Graham & Detsky 2001, McCreery & Truelove 1991b, Burford et al. 2013, Burch et al. 2012).

CDA and modelling challenges

The fact that clinical decision makers need estimates of the health and economic consequences of their choices in sickness certification can be regarded as uncontended. However, to provide these estimates requires the integration of information from many sources, such as clinical trials, observational studies, databases, and expert opinion. This integration and the required calculations, including uncertainty analyses, are according to current best practice performed using a model—a formal framework that links the information, numerical inputs, and assumptions to yield the required outputs (Caro et al. 2012). The usefulness of CDAM has recently been emphasized (Black et al. (2011)), not the least because patients are able to access evidence through the internet as a basis for shared decisions. Nevertheless, several issues need to be considered when planning to apply CDAM methods in sickness certification practice.

Validation

As displayed in the TRIPOD statement (Collins et al. 2015), it is a strong consensus around that detailed care is required when interpreting the results of CDAM studies and applying them in clinical practice. Data from persons of different nationalities used for CDAM have limited generalizability (Clancy & Cronin 2005, Roelen et al. 2014, Roelen et al. 2015). In this regard, it can when applying CDAM in Swedish sickness certification practice be regarded as necessary to collect data from the Swedish sickness certification setting. If CDA is performed, efforts should be made to adhere to best practice principles, e.g. as suggested by Lurie & Sox (1999). It is disquieting that many decision analytic models undergo little or no validation. For instance, the recently issued Consolidated Health Economic Evaluation Reporting Standards (CHEERS) guidelines for reporting economic analyses do not even mention model validation as a requirement (Husereau et al. 2013). From this perspective, the recently published external evaluation of prediction models in the sickness absence context (Roelen et al. 2014, Roelen et al. 2015) are most encouraging.

Nonetheless, whether on behalf of industry or government agencies, it is worrisome if modelers can continue to construct models and use them to guide decisions that can affect the health and economy of thousands without checking the accuracy of their predictions. Unlike meteorological forecasts, there is no natural test—clinicians and patients will not find out if the predictions are accurate since there are no validation routines in place. A move toward multi-use models that are progressively validated over time would be one way to alleviating this problem (Afzali & Karnon 2011, Afzali et al. 2013). This scarcity of validation is certainly the greatest challenge facing decision-analytic modeling (Elliott & Popay 2000), also in the sickness certification context. The validation methods can use some development (particularly in terms of the statistical approach to comparisons and the delineation of what constitutes a noteworthy deviation), but surmounting the problem requires a concerted change in attitude and processes.

Patient values and shared decision-making

The patients' values must be reflected in decision-making regarding rehabilitation plans expressed in the sickness certification setting. CDA relates to the combined value of the available evidences, but EBM (Sackett et al. 1996, Barrat 2008, Tilburt 2008) emphasizes that the manner in which this evidence is interpreted and reflected in the decision depends on the experiences of the clinical team (Dans et al. 1998) and the preferences of the patient (Goetghebeur et al. 2008). In order to synthesize these three factors, Straus (Straus 2002) proposed the likelihood of being helped or harmed index. In this way, shared decisions (Godolphin 2009, Bate et al. 2012), meaning that decisions made together with the patient, are increasingly being demanded nowadays, and there is an emphasis on patient-centered clinical service (Barry & Edgman-Levitan 2012, Oshima Lee & Emanuel 2013). This is in line with the principles of medical ethics (ter Meulen 2005, Tannahill 2008, Berger et al. 2008) and can achieve the goal of restricting uncertainty in clinical treatment (Beresford 1991, Kass 2008, Légaré & Brouillette 2009).

Since the patient's opinion should be positively reflected in the decision-making, decision aids for patients should be developed (Légaré 2007, Stacey et al. 2008, Elwyn et al. 2011) in addition to increased CDA research. As seen in the various examples of decision aids described by O'Connor (2001), decision aids are instruments that help making a value-based decision in accordance with the patient's individual preferences but are different from educational material for patients (O'Connor 2007). Given that research has consistently shown that these instruments are helpful for patients (Roshanov et al. 2013, O'Connor et al. 2007, Liu et al. 2006), more decision aids in the rehabilitation area may well be developed.

Transparency

A natural compensation for the deficiencies in validation is for decision makers to insist that a model be ''transparent'' (presumably, so they can assess it themselves). Unfortunately, this demand is interpreted as the model having to be structured and displayed in such a way that it can be understood even by someone with no technical training or experience. Rather than increasing the credibility of the models, this may lead to their inappropriate simplification, and, paradoxically,

to even less validity. For example, an individual simulation was initially constructed for assessment of novel anticoagulants in atrial fibrillation that could handle the real complexities of using the older anticoagulants, including variations in the time in therapeutic range, treatment starts and stops, compliance, etc.. This model was discarded, however, in favor a simpler spreadsheet version that ignored the realities of actual anticoagulation ‘‘in the interest of simplicity and transparency’’. This drive toward transparency may introduce risks (Eddy 2006), because the expression ‘‘for simplicity’s sake’’ can be used as an excuse for allowing unrealistic assumptions. Modelers must therefore strive for sufficient accuracy to adequately address the problem at hand, with simplicity being an arbiter only among adequately accurate models. The TRIPOD standard for reporting must be followed both in full technical detail and in lay terms, so that the untrained decision maker can understand what has been done, while the expert can review replicate the model. Crucially, both reports must include details of the validation carried out. In addition, training and tools should be provided to decision makers to improve their ability to assess the validity of modeling results. A questionnaire to aid in this evaluation has been recently published (Caro et al. 2014) and related training materials are in preparation.

Structural uncertainty and assumptions

The estimates produced by decision-analytic models are inherently uncertain (Briggs et al. 2012), meaning that any given value cannot be taken as the definite result. This uncertainty arises from many sources, including the decisions and assumptions made in designing the model; the processing of data to provide inputs to the model; flawed understanding of the disease, the treatments, the health care and social insurance systems, etc.. It is, thus, inappropriate to produce a particular result and focus on this point estimate as if it were known to be the precise outcome, with no uncertainty. The biggest challenge in addressing uncertainty is posed by the elements that are grouped under ‘‘structural uncertainty’’ (Frederix et al. 2014). Any model is inevitably a simplification of reality, and assumptions are made in arriving at this simplified version. It is unclear how much departure from reality they introduce and whether alternative assumptions would do better or worse.

Table Structural assumptions with relevance for sickness certification modelling

1. Assumptions about the disease process. For example, the advance of cancer is often characterized in two states (Möller et al. 2011), disease-free and postprogression, instead of conceptualizing the ongoing changes in tumor volume, location, and so on (Habbema et al. 2006). Is the former sufficient to adequately inform the decision? These assumptions extend beyond the events and states that are included to how they are characterized (e.g., asthma exacerbation present/absent vs. degree of severity); how they relate to each other (e.g., does increase in body weight affect inflammation in a joint); how they change over time (e.g., relapses of multiple sclerosis are the same or become more severe with time); how they are managed (e.g., emergency percutaneous coronary intervention vs. medication); and what comorbidities exist (e.g., right heart failure in emphysema); in

other words, to virtually every aspect of illness that may affect the relevant health economic outcomes.

2. Assumptions about intervention effects. For example, the effect of anti-diabetic medications is often modeled in terms of short-term changes in glycosylated hemoglobin, but treatments often have effects on other metabolic parameters and body weight; and, in any case, interest is really in the long-term complications of diabetes, not in glycemia per se. Many structural choices are made in such a model. These extend to the undesired effects of medications (e.g., hypoglycemia) and the levels at which these are modeled. The behavior of patients (e.g., do they use treatment as directed?), clinicians (e.g., do they follow treatment guidelines?), caregivers (e.g., do they persist with home treatment or push for hospitalization?) and others can have a substantial impact on the disease and intervention effects. Thus, the degree to which these behaviors are incorporated in the model produces substantial structural uncertainty.
3. Assumptions about the modeled environment. This set of assumptions include, for instance, whether treatment is given in outpatient clinics or hospitals; the patients to be considered and how they are to be characterized; the health care and sickness insurance systems (e.g., will the impact of copays be considered. Underpinning the modeling of all these choices are equations that relate the various parts quantitatively.

Derivation of these associations introduces the need to make additional structural assumptions, e.g. regarding what functional form to be used, how factors should parameterized, how they are correlated, how time should be incorporated, and whether the effects are proportional over time. These choices often have to be based on short-term data from clinical trials that are extrapolated to much longer periods, up to lifetime. Yet, the disease and other components may very well differ in the longer term (e.g., the number of relapses in schizophrenia cannot be extrapolated from short- to long-term since the disease changes considerably with aging). Apart from time- dependent changes, basing the model on trial data introduces other structural assumptions, since those data are collected under unrealistic circumstances where the patient gets more medical attention, leading to better adherence and results. Then there are methodological choices about what to compare, which costs to include and at what level of detail, whether to allow changes in treatment, whether to model uptake of a new intervention in the market, whether to consider resource constraints, for how long to simulate the problem, and many other such aspects. Needless to say, even this abbreviated list of structural elements presents a daunting challenge, which we are just beginning to address with methods like model averaging (Price et al. 2011).

CDA model implementation

Once CDA model is designed, its implementation requires choosing software to house the inputs, carry out the calculations, and gather the results. Although this choice does not pose much of a challenge, there are plenty of options, and one need not depend on a single choice: inputs and outputs may use one program and calculations another. Sickness certification practice is composed of interacting

variables; therefore, CDAs need to include as many contextual factors as possible to deliver relevant support and information (Riedmann et al. 2011). Emerging international standards, such as HL7, are supposed to enable interoperability in health care; however, few information systems supporting are based on the HL7 (for an example exception see (Martinez-Garcia et al. (2013)). Simple implementations, such as basic spreadsheet software (e.g., Excel), has the advantage of widespread familiarity, but as the model grows in complexity, the spreadsheets rapidly become complex and difficult to follow and validate. Moreover, the nature of spreadsheet calculation algorithms makes this an inefficient approach for stochastic simulations. Often the software (or a selected few to choose among) have been stipulated by the evaluating authority, limiting the modeler's scope in selecting the tool best suited for the problem. Forcing modelers to use spreadsheets (driven by a desire, perhaps, to cater to reviewers demanding simplicity) leads to poor models, often filled with errors (Getsios et al. 2007). General programming languages (e.g., R, C++, Java, Visual Basic) offer flexibility and calculation efficiency but require much more effort to code the model and are much less transparent to users. Bespoke programs (e.g., TreeAge, Arena, Simul8) provide user-friendly development tools, transparency-aiding visualization, ease of use, and validated routines at the cost of reduced familiarity and greater expense. For individual simulations, an important challenge is selecting the number of individuals to simulate and how many times to replicate the model runs. This issue has to do with the degree of precision desired for the results and is driven by the uncertainty in the model. Algorithms exist for empirically optimizing these choices (Law 1983), but this remains an area that has been little explored in our field. All users of a model prefer short run times. Having to wait for results of a sensitivity analysis for hours or even days tends to cut down on the number of analyses run, which of course is bad from a decision-support point of view. Related to this problem of numbers to run is the need to ensure the model is programmed efficiently, while still ensuring quality and transparency. This is important because long run times foster hesitation to validate the model and make changes. Moreover, users may constrain their analyses and avoid exploration of the possible results. This consideration also affects the selection of software for the model. One option to address this issue for users is to pre-run many scenarios and store them in a library. Instead of forcing the user to run each scenario each time, the user interface can present the appropriate set of results, considerably shortening the answer time for the vast majority of questions. Of course, if a scenario is not ''pre-baked'', it still has to be run, taking the full model execution time.

The clinical decision support system (CDSS) narrative

CDSSs are in the context of eHealth technologies clinical information systems that integrate clinical and demographic patient information to provide support for decision making by clinicians. In other words, a CDSS can be seen as a CDA application embedded in and provided to users through an IT-based information system. These systems have highly variable levels of sophistication and configurability with regards to inputs (patient specific data), knowledge bases, inference mechanisms (logic), and outputs. They issue certain alerts or prompts, which can take either an active (requiring the user to act on them) or passive (without requiring the user to act on them) form. CDSSs can be integrated or interface with other systems or stand alone. The fundamental impact of these decision support systems is expected to be improved clinical decision making. This improvement should lead to improved practitioner performance in care activities, such as provision of preventive care, diagnosis, disease management), and also enhancement of the ways in which these care activities are delivered, e.g., more evidence-based or guideline adherent decisions). These systems should also be able to help address disparities in care by facilitating standardisation, especially when part of an Electronic Health Record (EHR), Picture Archiving and Communication System (PACS), or ePrescribing system. Improved practitioner performance should result in a variety of beneficial impacts depending on the care activity targeted (e.g., increased immunisation rates, reduced resource utilisation, more timely diagnosis) or better disease control. Obviously, in situations where practitioner's performance is directly related to patient outcomes, then these too should improve. The CDSS narrative is reported in the segments evaluation outcomes, success features, and main remaining challenges.

Evaluation outcomes

Clinical Outcomes - morbidity

Morbidity outcomes assessed with regard to CDSS use include hospitalizations, Apgar scores, surgical site infections, cardiovascular events, colorectal cancer, deep venous thrombosis, and hypoglycemia events (Bright et al. 2012). Topics addressed include diagnosis (Kline et al. 2009, Paul et al. 2006, Holt et al. 2006, Holt et al. 2010, Hamilton et al. 2004), pharmacotherapy (Cavalcanti et al. 2009, Zanetti et al. 2003, McDonald CJ et al. 1984, Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Heidenreich et al. 2007, Gilutz et al. 2009, Brier et al. 2010), chronic disease management (McCowan et al. 2001, McDonald et al. 1984, Roumie et al. 2006, Ansari et al. 2003, Tierney et al. 2005, Tierney et al. 2003, Gilutz et al. 2009, Khan et al. 2010, Maclean et al. 2009, Murray et al. 2004, Subramanian et al. 2004), laboratory test ordering (McDonald et al. 1984, Sequist et al. 2009), immunizations (McDonald et al. 1984, McDonald et al. 1992), preventive care (Kucher et al. 2005, McDonald et al. 1984, Gilutz et al. 2009, Holt et al. 2006, Holt et al. 2010, Sequist et al. 2009), and discharge planning (Graumlich et al. 2009a, Graumlich et al. 2009b). Approximately 50% of the studies have been performed in an academic setting. Many studies evaluated locally developed interventions implemented in the ambulatory environment. Typical interventions were automatically delivered, system-initiated recommendations provided synchronously at the point of care to enable decision making during the health

care provider–patient encounter. Three such interventions required a mandatory response (that is, required that the user respond to the given recommendation, whether that response was to accept or dismiss the recommendation or to modify the user's action) (McDonald et al. 1992, Zanetti et al. 2003, Sequist et al. 2009). Comparators included usual care or no CDSS and the same CDSS with additional features. Limitations included short follow-up, low statistical power to detect important differences, and the potential for contamination of providers in control groups that improved because of knowledge of interventions. Meta-analysis of these heterogeneous studies (n=16) suggested that CDSSs improved morbidity outcomes (relative risk, 0.88 [95% CI, 0.80 to 0.96]) (moderate evidence). Most studies were good quality, and many of the interventions were evaluated in multiple institutions. However, the interventions were often paper-based or standalone systems implemented in academic or Veterans Affairs settings.

Clinical Outcomes - mortality
Seven studies (McDonald et al. 1992, Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Brier et al. 2010, Kuperman et al. 1999, McGregor et al. 2006) reported mortality outcomes. Issues addressed included diagnosis (Paul et al. 2006), pharmacotherapy (Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Brier et al. 2010, McGregor et al. 2006), chronic disease management (Roumie et al. 2006, Ansari et al. 2003), preventing deep venous thrombosis (McDonald et al. 1992), and detecting and notifying clinicians of critical laboratory values (Kuperman et al. 1999). Most CDSSs were locally developed and integrated into a computerized physician order entry (CPOE) or electronic health record (EHR) system and had system-initiated recommendations delivered synchronously at the point of care that did not require a clinician response. Interventions were evaluated against usual care or no CDSS, except for 2 studies (Roumie et al. 2006, Ansari et al. 2003) that compared the same intervention with additional features. Limitations included small sample size, duration shorter than 1 year, and possible contamination of control providers. Meta-analysis of these heterogeneous studies (n=6) suggested no significant effect of CDSSs on mortality, although CIs were wide (odds ratio [OR], 0.79 [CI, 0.54 to 1.15]) (low evidence). However, two studies reported a significant reduction in mortality with use of CDSSs (Roumie et al. 2006, Ansari et al. 2003). Most studies were conducted in a single academic or Veterans Affairs setting with a comprehensive, well established health IT infrastructure.

Clinical Outcomes - adverse events
Five studies assessed the effectiveness of CDSSs in reducing or preventing adverse events (Graumlich et al. 2009a, Graumlich et al. 2009b, Kuperman et al. 1999, McGregor et al. 2006, Fihn et al. 1994, Gurwitz et al. 2008). Studies were mostly implemented in an academic, inpatient setting. Studies evaluated the effect of these interventions to improve the timing of warfarin therapy (Fihn et al. 1994), improve discharge planning (Graumlich et al. 2009a, Graumlich et al. 2009b), prevent adverse drug events (Gurwitz et al. 2008), detect critical laboratory values (Kuperman et al. 1999), and detect potentially inappropriate or inadequate antimicrobial therapy (McGregor et al. 2006). Typical interventions were locally developed, were integrated into a CPOE or an EHR system, and automatically delivered system-imitated recommendations in real time to enable decision making during the provider– patient encounter. Only 1 study clearly required a

mandatory response (Kuperman et al. 1999). All of the CDSSs were evaluated against usual care or no CDSS. Limitations included evaluation at a single institution, evaluation periods less than 1 year, and potential improvement in physician performance because of their knowledge of the intervention. Meta-analysis of these heterogeneous studies estimated a relative risk of 1.01 (CI, 0.90 to 1.14), and neither this summary nor any individual studies demonstrated a significant effect (low evidence). Most studies were good quality, and 2 were conducted at multiple sites; however, these interventions primarily contained locally developed knowledge, and results may not be generalizable to nonteaching settings.

Health Care Process Measures - Preventive Care Services
Forty-three studies examined the effect of CDSSs on the rates of ordering or completing recommended preventive care services (McDonald et al. 1992, McDonald et al. 1984, Tierney et al. 2003, Gilutz et al. 2009, McDonald et al. 1992, Sequist et al. 2009, Apkon et al. 2005, Bertoni et al. 2009, Burack et al. 1998, Burack et al. 2003, Cannon & Allen 2000, Demakis et al. 2000, Dexter et al. 2001, Dexter et al. 2004, Eccles et al. 2002, Frank et al. 2004, Fretheim et al. 2006a, Fretheim et al. 2006b, Litzelman et al. 1993, McDowell et al. 1986, McDowell et al. 1989b, Overhage et al. 1996, Price 2005, Taylor et al. 1999, Unrod et al. 2007, Dykes et al. 2010, Chambers et al. 1989, Burack & Gimotty 1997, Burack et al. 1994, Fiks et al. 2009, Flanagan et al. 1999, Fordham et al. 1990, McPhee et al. 1989, Gill et al. 2009, Hobbs et al. 1996, Holbrook et al. 2009, Kenealy et al. 2005, Lobach & Hammond 1994, Ornstein et al. 1991, Peterson et al. 2008, Reeve et al. 2008, Rosser et al. 1992, Rosser et al. 1991, Sequist et al. 2005, Tierney et al. 1986, van Wyk et al. 2008). Most studies were conducted in the academic or ambulatory environment. Topics addressed included diagnosis (Apkon et al. 2005, Cannon & Allen 2000, Dykes et al. 2010, Hobbs et al. 1996, van Wyk et al. 2008), pharmacotherapy (McDonald et al. 1984, Gilutz et al. 2009, Dexter et al. 2001, Fretheim et al. 2006a, Fretheim et al. 2006b, Gill et al. 2009, Reeve et al. 2008, Sequist et al. 2005), chronic disease management (McDonald et al. 1984, Tierney et al. 2005, Gilutz et al. 2009, Apkon et al. 2005, Bertoni et al. 2009, Demakis et al. 2000, Eccles et al. 2002, Gill et al. 2009, Holbrook et al. 2009, Lobach & Hammond 1994, Peterson et al. 2008), laboratory test ordering (McDonald et al. 1984, Sequist et al. 2009, Litzelman et al. 1993, Taylor et al. 1999, Gill et al. 2009, Hobbs et al. 1996, Lobach & Hammond 1994, Ornstein et al. 1991, Sequist et al. 2005, Tierney et al. 1986), preventive care (McDonald et al. 1992, McDonald et al. 1984, Gilutz et al. 2009, Sequist et al. 2009, Apkon et al. 2005, Burack et al. 1998, Demakis et al. 2000, Frank et al. 2004, Fretheim et al. 2006a, Fretheim et al. 2006b, Litzelman et al. 1993, McDowell et al. 1986, McDowell et al. 1989b, Overhage et al. 1996, Price 2005, Taylor et al. 1999, Dykes et al. 2010, Chambers et al. 1989, Burack & Gimotty 1997, Burack et al. 1994, Fordham et al. 1990, McPhee et al. 1989, Gill et al. 2009, Hobbs et al. 1996, Kenealy et al. 2005, Lobach & Hammond 1994, Ornstein et al. 1991, Rosser et al. 1991, Sequist et al. 2005, Tierney et al. 1986, van Wyk et al. 2008), immunizations (McDonald et al. 1984, McDonald et al. 1992, Demakis et al. 2000, Dexter et al. 2001, Dexter et al. 2004, Frank et al. 2004, McDowell et al. 1986, Fiks et al. 2009, Flanagan et al. 1999, Rosser et al. 1992, Rosser et al. 1991, Tierney et al. 1986), and initiating discussions with patients (Taylor et al. 1999, Unrod et al. 2007, Holbrook et al. 2009). Most interventions were locally developed, paperbased, or standalone

systems and automatically delivered recommendations in real time to enable decision making during the health care provider–patient encounter. Only 7 of the interventions required a mandatory response (McDonald et al. 1992, Sequist et al. 2009, Cannon & Allen 2000, Dexter et al. 2001) or justification (Burack & Gimotty 1997, Burack et al. 1994, Flanagan et al. 1999, McPhee et al. 1989, Ornstein et al. 1991) for not adhering to the recommendation. Comparators included usual care or no CDSS, direct comparison against the same CDSS with additional features, or comparison of the same CDSS for different conditions. Limitations included sparse data measuring patient or economic outcomes; few assessments of long-term outcomes of interventions; and the Hawthorne effect, which probably stimulated more comprehensive preventive care across groups. In meta-analysis of these 25 heterogeneous studies (McDonald et al. 1992, Tierney et al. 2003, Gilutz et al. 2009, McDonald et al. 1992, Sequist et al. 2009, Apkon et al. 2005, Bertoni et al. 2009, Burack et al. 1998, Burack et al. 2003, Cannon & Allen 2000, Demakis et al. 2000, Dexter et al. 2001, Dexter et al. 2004, Eccles et al. 2002, Frank et al. 2004, Fretheim et al. 2006a, Fretheim et al. 2006b, Litzelman et al. 1993, McDowell et al. 1986, McDowell et al. 1989b, Overhage et al. 1996, Price 2005, Taylor et al. 1999, Unrod et al. 2007, Dykes et al. 2010, Chambers et al. 1989), the effect of CDSSs on preventive care services was significant (OR, 1.42 [CI, 1.27 to 1.58]) (high evidence). Approximately one half of the studies were good quality, one third were evaluated in multicenter trials, and one fourth addressed multiple clinical conditions. However, most CDSSs were locally developed, not integrated into a CPOE or an EHR, and evaluated in academic medical centers, all of which can affect the generalizability of these findings.

Table Summary of evidence on CDSS impacts in healthcare practice (adapted from Bright et al. 2012)

Clinical outcomes
Morbitiy
Moderate evidence
Mortality
Low evidence
Adverse effects
Low evidence

Health care process measures
Recommended preventive care service ordered or completed
High evidence
Recommended treatment ordered or completed
High evidence
User workload and efficiency outcomes
Insufficient evidence

Economic outcomes
Cost
Modest evidence
Cost-effectiveness
Conflicting evidence

Use and implementation outcomes
Provider acceptance and use
Low evidence
Provider satisfaction and dissatisfaction
Moderate evidence

Health Care Process Measures - Treatment Ordered or Prescribed

Sixty-seven studies evaluated the effect of CDSSs on ordering and prescribing therapy (McCowan et al. 2001, Zanetti et al. 2003, Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Heidenreich et al. 2007, Tierney et al. 2005, Tierney et al. 2003, Gilutz et al. 2009, Brier et al. 2010, Murray et al. 2004, Subramanian et al. 2004, Kuperman et al. 1999, McGregor et al. 2006, Fihn et al. 1994, Apkon et al. 2005, Bertoni et al. 2009, Fretheim et al. 2006a, Fretheim et al. 2006b, Gill et al. 2009, Sequist et al. 2005, van Wyk et al. 2008, Bell et al. 2010, Flottorp et al. 2002, McDonald 1976, Player et al. 2010, Bourgeois et al. 2010, Christakis et al. 2001, Co et al. 2010, Cobos et al. 2005, Davis et al. 2007, Feldstein et al. 2006, Field et al. 2009, Filippi et al. 2003, Fitzmaurice et al. 2000, Fortuna et al. 2009, Goud et al. 2009, Hicks et al. 2008, Krall et al. 2004, Linder et al. 2009, Locatelli et al. 2009, Manotti et al. 2001, Marco et al. 2003, Martens et al. 2006, Martens et al. 2007, Montgomery et al. 2000, Overhage et al. 1997, Peterson et al. 2007, Phillips et al. 2005, Ziemer et al. 2006, Raebel et al. 2007, Rood et al. 2005, Rossi & Every 1997, Rothschild et al. 2007, Samore et al. 2005, Shojania et al. 1998, Simon et al. 2006, Smith et al. 2008, Strom et al. 2010a, Strom et al. 2010b, Tamblyn et al. 2003, Tamblyn et al. 2008, Tamblyn et al. 2010, Terrell et al. 2009, Terrell et al. 2010, Vadher et al. 1997a, Vadher et al. 1997b, Vissers et al. 1996, Vissers et al. 1995, Weir et al. 2003, White et al. 1984). Many studies were conducted in the academic setting, and most were evaluated in the ambulatory environment. Topics addressed included diagnosis (Paul et al. 2006, Apkon et al. 2005, van Wyk et al. 2008, Player et al. 2010, Co et al. 2010, Linder et al. 2009, Montgomery et al. 2000, Samore et al. 2005, Vissers et al. 1996, Vissers et al. 1995), pharmacotherapy (Zanetti et al. 2003, Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Heidenreich et al. 2007, Gilutz et al. 2009, Brier et al. 2010, McGregor et al. 2006, Fretheim et al. 2006a, Fretheim et al. 2006b, Gill et al. 2009, Sequist et al. 2005, McDonald 1976, Player et al. 2010, Bourgeois et al. 2010, Christakis et al. 2001, Davis et al. 2007, Field et al. 2009, Filippi et al. 2003, Fortuna et al. 2009, Krall et al. 2004, Linder et al. 2009, Manotti et al. 2001, Marco et al. 2003, Martens et al. 2006, Martens et al. 2007, Montgomery et al. 2000, Overhage et al. 1997, Peterson et al. 2007, Phillips et al. 2005, Ziemer et al. 2006, Raebel et al. 2007, Rossi & Every 1997, Samore et al. 2005, Shojania et al. 1998, Simon et al. 2006, Smith et al. 2008, Strom et al. 2010a, Strom et al. 2010b, Tamblyn et al. 2003, Tamblyn et al. 2008, Tamblyn et al. 2010, Terrell et al. 2009, Terrell et al. 2010, Vadher et al. 1997a, Vadher et al. 1997b, Weir et al. 2003, White et al. 1984), laboratory test ordering (Gill et al. 2009, Sequist et al. 2005, McDonald 1976, Bourgeois et al. 2010, Overhage et al. 1997), chronic disease management (McCowan et al. 2001, Roumie et al. 2006, Ansari et al. 2003, Tierney et al. 2005, Tierney et al. 2003, Gilutz et al. 2009, Murray et al. 2004, Subramanian et al. 2004, Apkon et al. 2005, Bertoni et al. 2009, Gill et al. 2009, Bell et al. 2010, Bourgeois et al. 2010, Co et al. 2010, Cobos et al. 2005, Feldstein et al. 2006, Fitzmaurice et al. 2000, Goud et al. 2009, Hicks et al. 2008, Linder et al. 2009, Locatelli et al. 2009, Manotti et al. 2001, Phillips et al. 2005, Ziemer et al. 2006, Rood et al. 2005, Smith et al. 2008), preventive care (Gilutz et al. 2009, Apkon et al. 2005, Fretheim et al. 2006a, Fretheim et al. 2006b, Gill et al. 2009, Sequist et al. 2005, van Wyk et al. 2008, Goud et al. 2009, Terrell et al. 2010), and additional clinical tasks (Kuperman et al. 1999, Fihn et al. 1994, van Wyk et al. 2008, Flottorp et al. 2002, Bourgeois et al. 2010, Rothschild et al. 2007, Vissers et al. 1996, Vissers et al. 1995). Typical interventions were locally developed, were integrated into a CPOE or an EHR system, and automatically delivered system-

initiated recommendations in real time to enable decision making during the provider– patient encounter. Eighteen CDSSs required a mandatory response (Zanetti et al. 2003, Kuperman et al. 1999, Fortuna et al. 2009, Krall et al. 2004, Raebel et al. 2007, Shojania et al. 1998, Simon et al. 2006, Smith et al. 2008, Strom et al. 2010a, Strom et al. 2010b, Terrell et al. 2009, Terrell et al. 2010, Vissers et al. 1996, Vissers et al. 1995) or justification (Co et al. 2010, Cobos et al. 2005, Rossi & Every 1997, Rothschild et al. 2007, Tamblyn et al. 2008) for not adhering to the recommendation. Limitations included inadequate follow-up periods to observe sustained results, sparse data demonstrating how changes in clinician ordering and prescribing led to improvements in clinical or economic outcomes, and study designs that did not capture the extent to which nonadherence with recommended therapy resulted in adverse events. Meta-analysis of 46 heterogeneous studies (McCowan et al. 2001, Zanetti et al. 2003, Roumie et al. 2006, Paul et al. 2006, Ansari et al. 2003, Heidenreich et al. 2007, Tierney et al. 2005, Tierney et al. 2003, Gilutz et al. 2009, Brier et al. 2010, Murray et al. 2004, Subramanian et al. 2004, McGregor et al. 2006, Apkon et al. 2005, Bertoni et al. 2009, Fretheim et al. 2006a, Fretheim et al. 2006b, Gill et al. 2009, van Wyk et al. 2008, Bell et al. 2010, McDonald 1976, Player et al. 2010, Bourgeois et al. 2010, Co et al. 2010, Cobos et al. 2005, Davis et al. 2007, Feldstein et al. 2006, Field et al. 2009, Filippi et al. 2003, Hicks et al. 2008, Krall et al. 2004, Linder et al. 2009, Locatelli et al. 2009, Montgomery et al. 2000, Overhage et al. 1997, Raebel et al. 2007, Rood et al. 2005, Rossi & Every 1997, Smith et al. 2008, Strom et al. 2010a, Strom et al. 2010b, Tamblyn et al. 2003, Tamblyn et al. 2010, Terrell et al. 2010, Vissers et al. 1996, Vissers et al. 1995, Weir et al. 2003) showed that intervention providers with decision support were more likely to order the appropriate treatment or therapy (OR, 1.57 [CI, 1.35 to 1.82]) (high evidence). Most studies were good quality, and most were evaluated in multisite trials. However, generalizability may be limited because most studies were implemented in the ambulatory environment, were evaluated in settings where clinicians were experienced EHR users or provided care in an established health IT infrastructure, and incorporated knowledge that was targeted toward specific conditions.

Health Care Process Measures - User Workload and Efficiency
Evidence on the effect of CDSSs on clinician knowledge or improved confidence in managing patient care was insufficient (Hobbs et al. 1996, Holbrook et al. 2009, Emery et al. 2007, Alper et al. 2005, Del Fiol et al. 2008). Seven studies examined the effect of CDSSs on efficiency (Graumlich et al. 2009a, Graumlich et al. 2009b, McGregor et al. 2006, Tierney et al. 1987, Smith et al. 2008, Alper et al. 2005, Del Fiol et al. 2008, Etchells et al. 2010). Limitations included contamination of clinicians in the control group that improved because of knowledge of the intervention, evaluation periods that were too brief to demonstrate an effect on efficiency, and small clinician sample sizes (low evidence). Most interventions contained locally developed knowledge, such as protocols or algorithms derived on the basis of local performance, quality, and outcome data not representative of other sites, and were evaluated in academic settings.

Economic Outcomes - Cost

Twenty-two studies reported costs (Paul et al. 2006, Tierney et al. 2005, Tierney et al. 2003, Khan et al. 2010, Maclean et al. 2009, Murray et al. 2004, McGregor et al. 2006, Apkon et al. 2005, Fretheim et al. 2006a, Fretheim et al. 2006b, Hobbs et al. 1996, Bates et al. 1999b, Harpole et al. 1997, Tierney et al. 1987, Wilson et al. 2006, Cobos et al. 2005, Fitzmaurice et al. 2000, Overhage et al. 1997, Smith et al. 2008, Bird et al. 1990, Frame et al. 1994, Tierney et al. 1988, Cleveringa et al. 2008, Cleveringa et al. 2010, Smith et al. 2009). Objectives of the CDSSs included diagnosis (Paul et al. 2006, Apkon et al. 2005, Hobbs et al. 1996, Harpole et al. 1997, Tierney et al. 1988), pharmacotherapy (Paul et al. 2006, McGregor et al. 2006, Fretheim et al. 2006a, Fretheim et al. 2006b, Overhage et al. 1997, Smith et al. 2008), chronic disease management (Tierney et al. 2005, Tierney et al. 2003, Khan et al. 2010, Maclean et al. 2009, Murray et al. 2004, Apkon et al. 2005, Cobos et al. 2005, Fitzmaurice et al. 2000, Smith et al. 2008, Cleveringa et al. 2008, Cleveringa et al. 2010), laboratory test ordering (Hobbs et al. 1996, Bates et al. 1999b, Tierney et al. 1987, Overhage et al. 1997, Tierney et al. 1988, Smith et al. 2009), preventive care (Apkon et al. 2005, Fretheim et al. 2006a, Fretheim et al. 2006b, Hobbs et al. 1996, Bird et al. 1990, Frame et al. 1994), initiating discussions with patients (Wilson et al. 2006, Frame et al. 1994), and additional clinical tasks (Harpole et al. 1997, Wilson et al. 2006). One study reported reduced hospitalization expenses with CDSS use (Khan et al. 2010, Maclean et al. 2009), and 12 studies reported that use had a positive effect on costs compared with control groups and other non-CDSS groups (Paul et al. 2006, Tierney et al. 2003, McGregor et al. 2006, Fretheim et al. 2006a, Fretheim et al. 2006b, Bates et al. 1999b, Harpole et al. 1997, Tierney et al. 1987, Cobos et al. 2005, Overhage et al. 1997, Smith et al. 2008, Frame et al. 1994, Tierney et al. 1988). Modest evidence from academic and community inpatient and ambulatory settings showed that locally and commercially developed CDSSs had lower treatment costs, total costs, and reduced costs compared with control groups and other non-CDSS intervention groups. Most studies were conducted in the academic ambulatory setting and evaluated locally developed, integrated CDSSs in CPOE or EHR systems that automatically delivered system-initiated recommendations synchronously at the point of care and did not require a mandatory clinician response.

Economic Outcomes - Cost-Effectiveness

Six studies (Fretheim et al. 2006a, Fretheim et al. 2006b, McDowell et al. 1986, McDowell et al. 1989a, Rosser et al. 1992, McDowell et al. 1989b, Palen et al. 2006, Cleveringa et al. 2008, Cleveringa et al. 2010) examined the cost-effectiveness of CDSSs or their effect on cost-effectiveness of care. These demonstrated conflicting findings, with 3 studies suggesting that CDSSs were cost effective (Fretheim et al. 2006a, Fretheim et al. 2006b, Rosser et al. 1992, McDowell et al. 1989a) and 3 reporting that CDSSs were not cost-effective (McDowell et al. 1986, McDowell et al. 1989b, Cleveringa et al. 2008, Cleveringa et al. 2010). Objectives included diagnosis (McDowell et al. 1989a), pharmacotherapy (Fretheim et al. 2006a, Fretheim et al. 2006b), chronic disease management (Cleveringa et al. 2008, Cleveringa et al. 2010), preventive care (Fretheim et al. 2006a, Fretheim et al. 2006b, McDowell et al. 1986, McDowell et al. 1989b), and immunizations (McDowell et al. 1986, Rosser et al. 1992).

Use and Implementation Outcomes - Provider acceptance and use

Twenty-four studies assessed the effect of provider acceptance of CDSSs (McDonald et al. 1984, Fihn et al. 1994, Litzelman et al. 1993, Dykes et al. 2010, Ornstein et al. 1991, Harpole et al. 1997, Sundaram et al. 2009, Cobos et al. 2005, Fortuna et al. 2009, Goud et al. 2009, Rossi & Every 1997, Rothschild et al. 2007, Tamblyn et al. 2008, Tamblyn et al. 2010, Terrell et al. 2009, Vadher et al. 1997a, Bird et al. 1990, Frame et al. 1994, Judge et al. 2006, Maviglia et al. 2006, Rollman et al. 2001, McLaughlin et al. 2010, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000). Topics addressed included diagnosis (Dykes et al. 2010, Harpole et al. 1997, Rollman et al. 2001), pharmacotherapy (McDonald et al. 1984, Fortuna et al. 2009, Rossi & Every 1997, Tamblyn et al. 2008, Tamblyn et al. 2010, Terrell et al. 2009, Vadher et al. 1997a, Judge et al. 2006, Maviglia et al. 2006), chronic disease management (McDonald et al. 1984, Cobos et al. 2005, Goud et al. 2009, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000), laboratory test ordering (McDonald et al. 1984, Litzelman et al. 1993, Ornstein et al. 1991, Sundaram et al. 2009), preventive care (McDonald et al. 1984, Litzelman et al. 1993, Dykes et al. 2010, Ornstein et al. 1991, Goud et al. 2009, Terrell et al. 2009, Bird et al. 1990, Frame et al. 1994, McLaughlin et al. 2010), immunizations (McDonald et al. 1984), initiating discussions with patients (Frame et al. 1994), and additional clinical tasks (Fihn et al. 1994, Harpole et al. 1997, Rothschild et al. 2007). Comparators included usual care or no CDSS and direct comparison with the same CDSS with additional features. One half of the studies required a mandatory response (Litzelman et al. 1993, Harpole et al. 1997, Fortuna et al. 2009, Terrell et al. 2009, Rollman et al. 2001) or justification (Ornstein et al. 1991, Sundaram et al. 2009, Cobos et al. 2005, Goud et al. 2009, Rossi & Every 1997, Rothschild et al. 2007, Tamblyn et al. 2008) for not adhering to the recommendation; however, there was no significant effect on provider acceptance. Limitations included an inconsistent definition of provider acceptance; small sample sizes; and scarce data on clinical outcomes, such as morbidity, length of stay, or adverse events (low evidence). Most of these studies were fair quality and were evaluated in academic medical settings with established health IT infrastructures and experienced EHR users, which may limit the generalizability of the findings. Seventeen studies examined provider use of CDSSs by using such metrics as the number of times the CDSS was accessed by the clinician or provided a recommendation to the clinician (Eccles et al. 2002, Hobbs et al. 1996, Sequist et al. 2005, Emery et al. 2007, van Wijk et al. 2001, Bourgeois et al. 2010, Filippi et al. 2003, Fortuna et al. 2009, Linder et al. 2009, Samore et al. 2005, Strom et al. 2010a, Tamblyn et al. 2008, Del Fiol et al. 2008, Maviglia et al. 2006, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000, Bosworth et al. 2009, Bosworth et al. 2005). Objectives included diagnosis (Hobbs et al. 1996, Linder et al. 2009, Samore et al. 2005), pharmacotherapy (Sequist et al. 2005, Bourgeois et al. 2010, Filippi et al. 2003, Fortuna et al. 2009, Linder et al. 2009, Samore et al. 2005, Strom et al. 2010a, Tamblyn et al. 2008, Maviglia et al. 2006), chronic disease management (Eccles et al. 2002, Bourgeois et al. 2010, Linder et al. 2009, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000, Bosworth et al. 2009, Bosworth et al. 2005), laboratory test ordering (Hobbs et al. 1996, Sequist et al. 2005, van Wijk et al. 2001, Bourgeois et al. 2010), preventive care (Hobbs et al. 1996, Sequist et al. 2005), and additional clinical tasks (Emery et al. 2007, Bourgeois et al. 2010, Del Fiol et al. 2008). Comparators included usual care or no CDSS, direct comparison with the same CDSS with additional features, or comparison of the same CDSS for different conditions. Limitations included sparse data demonstrating how provider

use translated into more appropriate patient care and small sample sizes of clinicians (low evidence). Among the 12 studies (Sequist et al. 2005, van Wijk et al. 2001, Filippi et al. 2003, Fortuna et al. 2009, Linder et al. 2009, Samore et al. 2005, Tamblyn et al. 2008, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000, Bosworth et al. 2009, Bosworth et al. 2005) that provided statistical data about provider use, 8 (Sequist et al. 2005, Bourgeois et al. 2010, Fortuna et al. 2009, Linder et al. 2009, Tamblyn et al. 2008, Maviglia et al. 2006, Hetlevik et al. 1999, Hetlevik et al. 1998, Hetlevik et al. 2000) documented low use (50% of the clinician's time or of patient visits) or that less than 50% of clinicians used the CDSS or received alerts to guide therapeutic action. Most of these studies were fair quality and evaluated locally developed interventions in multiple community and ambulatory settings.

Use and Implementation Outcomes - Provider satisfaction and dissatisfaction
Provider satisfaction with CDSSs was examined in 19 studies (McCowan et al. 2001, Graumlich et al. 2009a, Graumlich et al. 2009b, Heidenreich et al. 2007, Sequist et al. 2009, Apkon et al. 2005, Sequist et al. 2005, Emery et al. 2007, Sundaram et al. 2009, Wilson et al. 2006, Co et al. 2010, Fortuna et al. 2009, Martens et al. 2006, Martens et al. 2007, Smith et al. 2008, Vissers et al. 1996, Vissers et al. 1995, Weir et al. 2003, Alper et al. 2005, Del Fiol et al. 2008, Bird et al. 1990, Maviglia et al. 2006). Topics addressed included diagnosis (Apkon et al. 2005, Co et al. 2010, Vissers et al. 1996, Vissers et al. 1995), pharmacotherapy (Heidenreich et al. 2007, Sequist et al. 2005, Fortuna et al. 2009, Martens et al. 2006, Martens et al. 2007, Smith et al. 2008, Weir et al. 2003, Maviglia et al. 2006), chronic disease management (McCowan et al. 2001, Apkon et al. 2005, Co et al. 2010, Smith et al. 2008), laboratory test ordering (Sequist et al. 2009, Sequist et al. 2005, Sundaram et al. 2009), preventive care (Sequist et al. 2009, Apkon et al. 2005, Sequist et al. 2005), and initiating discussions with patients (Wilson et al. 2006). Comparators included usual care or no CDSS and direct comparison with the same CDSS with additional features. Seven CDSSs required a mandatory response (Sequist et al. 2009, Fortuna et al. 2009, Smith et al. 2008, Vissers et al. 1996, Vissers et al. 1995, Alper et al. 2005) or justification (Sundaram et al. 2009, Co et al. 2010) for not adhering to the recommendation. Limitations included the narrow assessment of the role of provider satisfaction with CDSSs on patient-specific outcomes and small sample sizes of clinicians. Twelve studies demonstrated provider satisfaction with CDSSs (Heidenreich et al. 2007, Sequist et al. 2009, Sequist et al. 2005, Wilson et al. 2006, Co et al. 2010, Fortuna et al. 2009, Martens et al. 2006, Martens et al. 2007, Smith et al. 2008, Alper et al. 2005, Del Fiol et al. 2008, Bird et al. 1990, Maviglia et al. 2006); 4 showed a significant effect of satisfaction among intervention providers compared with control providers (Wilson et al. 2006, Co et al. 2010, Alper et al. 2005, Maviglia et al. 2006). Provider dissatisfaction with CDSSs was also reported in 6 studies (McCowan et al. 2001, Apkon et al. 2005, Emery et al. 2007, Sundaram et al. 2009, Vissers et al. 1996, Vissers et al. 1995, Weir et al. 2003) (moderate evidence). Most studies were good quality and evaluated CDSSs integrated into CPOE or EHR systems in multiple interventions outside of environments with an established and robust health IT. However, most CDSSs were locally developed and implemented in the ambulatory setting.

Features of successful CDSSs

Clinical decision support features

The success rates of clinical decision support systems with and without potentially important features have been summarized in a study comprising 71 CDSSs (Table) (Kawamoto et al. 2005). For five of 15 CDSS features, the success rate of interventions possessing the feature was significantly greater than that of interventions lacking the feature. Most notably, 75% of interventions succeeded when the decision support was provided to clinicians automatically, whereas none succeeded when clinicians were required to seek out the advice of the decision support system (rate difference 75% (37% to 84%)). Similarly, systems that were provided as an integrated component of charting or order entry systems were significantly more likely to succeed than stand-alone systems (rate difference 37% (6% to 61%)); systems that used a computer to generate the decision support were significantly more effective than systems that relied on manual processes (rate difference 26% (2% to 49%)); systems that prompted clinicians to record a reason when not following the advised course of action were significantly more likely to succeed than systems that allowed the system advice to be bypassed without recording a reason (rate difference 41% (19% to 54%)); and systems that provided a recommendation (such as "Patient is at high risk of coronary artery disease; recommend initiation of blocker therapy") were significantly more likely to succeed than systems that provided only an assessment of the patient (such as "Patient is at high risk of coronary artery disease") (rate difference 35% (8% to 58%)). Finally, systems that provided decision support at the time and location of decision making were substantially more likely to succeed than systems that did not provide advice at the point of care, but the difference in success rates fell just short of being significant at the 0.05 level (rate difference 48% (− 0.46% to 70.01%)).

Table Success features (defined as statistically and clinically significant improvement in clinical practice) of clinical decision support systems (CDSS). Results of 71 control-CDSS comparisons (adapted from Kawamoto et al. 2005)

Experimentally verified features†	**"Best practice" features**‡
<u>General system features</u>	<u>General system features</u>
Integration with charting or order entry system†	Local user involvement in development process
Computer based generation of decision support†	<u>Clinician-system interaction features</u>
<u>Clinician-system interaction features</u>	Provision at time and location of decision making‡
Automatic provision of decision support as part of clinician workflow†	No need for additional clinician data entry
Provision at time and location of decision making‡	
Request documentation of reason for not following system recommendations†	
<u>Communication content features</u>	
Provision of a recommendation, not just an assessment†	

Recommendations executed by noting agreement
Communication content features
Promotion of action rather than inaction
Justification via provision of research evidence
Justification via provision of reasoning
Auxiliary features
Provision of decision support results to both clinicians and to patients
CDSS accompanied by periodic performance feedback
CDSS accompanied by conventional education
†Difference between success rates statistically significant.
‡Feature found contributing to success in literature review

Of the CDSS features shown to be important, four were identified as independent predictors of system effectiveness in a meta-regression analysis (Table). Most notably, this analysis confirmed the critical importance of automatically providing decision support as part of clinician workflow ($P < 0.00001$). The other three features were providing decision support at the time and location of decision making ($P = 0.0263$), providing a recommendation rather than just an assessment ($P = 0.0187$), and using a computer to generate the decision support ($P = 0.0294$). Among the 32 clinical decision support systems incorporating all four features (Rossi & Every 1997, Overhage et al. 1997, Frame et al. 1994, Barnett et al. 1983, McPhee et al. 1991, McDonald 1976, Dexter et al. 1998, Chambers et al. 1991, Lobach & Hammond 1997, Tierney et al. 1993, Tierney et al. 1986, Kuperman et al. 1999, McDonald et al. 1980, McPhee et al. 1989, Becker et al. 1989, Fordham et al. 1990, Demaskis et al. 2000, McDonald et al. 1984, Burack et al. 1994, Gimotty et al. 2002, Burack & Gimotty 1997, Lobach & Hammond 1994, Burack et al. 1996, Nilasena & Lincoln 1995, Rosser et al. 1991, Rosser et al. 1992, Rosser & McDowell 1992, McDowell et al. 1989a, McDowell et al. 1989b, McDowell et al. 1986, McDonald et al. 1992, White et al. 1984, Williams et al. 1998, Burack et al. 1998, van Wijk et al. 2001, Bates et al. 1999b, Bates et al. 1995, Zanetti et al. 2003), 30 (94% (80% to 99%)) significantly improved clinical practice. In contrast, clinical decision support systems lacking any of the four features improved clinical practice in only 18 out of 39 cases (46% (30% to 62%)). The subset analyses for computer based clinical decision support systems and for non-electronic clinical decision support systems yielded results consistent with the findings of the primary regression analysis (table 6).

Table . Features of CDSSs associated with improved clinical practice. Results of meta-regression analyses of 71 control-CDSS comparisons (adapted from Kawamoto et al. 2005)

Primary analysis (all CDSS, n=71)
Automatic provision of decision support as part of clinician workflow
Provision of decision support at time and location of decision making
Provision of recommendation rather than just an assessment
Computer based generation of decision support
Secondary analysis (computer based CDSS, n=49)
Automatic provision of decision support as part of clinician workflow
Secondary analysis (non-electronic CDSS, n=22)
Provision of recommendation rather than just an assessment

Direct experimental evidence
Randomised controlled trials in which a clinical decision support system was evaluated directly against the same clinical decision support system with additional features were studied in detail. In support of the regression results, one study found that system effectiveness was significantly enhanced when the decision support was provided at the time and location of decision making (Tierney et al. 1986). Similarly, effectiveness was enhanced when clinicians were required to document the reason for not following system recommendations (Litzelman et al. 1993) and when clinicians were provided with periodic feedback about their compliance with system recommendations (Lobach 1996). Furthermore, two of four studies found a significant beneficial effect when decision support results were provided to both clinicians and patients (McPhee et al. 1989, Becker et al. 1989, Fordham et al. 1990, Burack et al. 1996, Gans et al. 1994). In contrast, clinical decision support system effectiveness remained largely unchanged when critiques were worded more strongly and the evidence supporting the critiques was expanded to include institution-specific data (Harpole et al. 1997), when recommendations were made more specific (Meyer et al. 1991), when local clinicians were recruited into the system development process (Sommers et al. 1984), and when bibliographic citations were provided to support the recommendations made by the system (McDonald et al. 1980).

CDSS challenges
In parallel to the obvious potential, there are also potential risks associated with the introduction of CDSS in sickness introduction practice. Just as approaching CDAM, evaluations of effectiveness and usability of CDSSs are key to avoiding patient harm and waste in health care systems (Magrabi et al. 2011). The so called "e-iatrogenesis" (Weiner et al. 2007) arising from information systems has more potential pitfalls when the basis for decisions include also non-medical factors, e.g. relating to the legal framework for sickness certification or patient preferences with regard to rehabilitation options. Rigorous evaluations are needed to test CDSSs before and after their deployment to guarantee patient safety (Denham et al. 2013, Kilbridge et al. 2006). However, there is a general lack of rigorous evaluations of CDSS effectiveness and usability in a variety of settings (Black et al. 2011, Bright et al. 2012). Actual improved clinical performance rather than just behaviour change in general is in the scientific CDSS literature supported by only weak evidence. While studies have been able to demonstrate behavioural changes among clinicians, these changes have not always translated into the provision of higher quality care in terms of patient outcomes. While some subgroups seem to fare better than others, the evidence is still only modest at best. The most notable of findings are hallmarked by relative consistency across findings and thusly provide moderate evidence. These included improved provision of preventive care measures, effective monitoring of side effects, and decreased use of unnecessary or redundant care – the latter two mainly associated with pharmacotherapy. Efforts at influencing practitioners to change practice patterns to adhere to a certain model of care were however less successful. No evidence was indicated for an impact on patient outcomes outside prescribing; while surrogate outcomes were modestly improved in some cases. Patient safety needs to be assured by rigorous evaluation, not only of the underlying

software/technologies but also of their real-world interaction with users (Coiera 2003). Only a few approaches to evaluating human-computer interaction (c.f. Horsky et al. 2012, Phansalkar et al. 2010). We place CDSS challenges pertinent for their introduction in sickness certification practice into three chief categories:

- Improve CDSS effectiveness
- Create new CDSS applications
- Disseminate existing CDSS knowledge

Within each of these broad categories, we have identified several particular issues, which are briefly described below.

Improve CDSS effectiveness

1. Manage patients with comorbidities

Current CDSSs, for the most part, are not sufficiently adjusted to the fact that many patients have multiple co-morbidities and medications that must be addressed simultaneously when planning treatment and rehabilitation (Boyd et al. 2005, Fraccaro et al. 2015). A challenge when developing CDSSs for sickness certification practice is thus to create mechanisms to identify recommendations for patients presenting with comorbid conditions and multiple rehabilitation needs. One of several reasons why CDSSs are underutilized in practice is because they do not adequately address these co-morbidity issues (McDonald et al. 1996). Addressing this challenge may require new combinatorial and logical approaches to combining and cross-checking recommendations from two or more guidelines. Very few CDSS studies have referred to multimorbidity using a patient-centered approach, which is the ideal (Le Reste et al. 2013). Riano et al. (2012) adopted a comprehensive approach to integrated care; however, user intervention is necessary to personalize treatments when multimorbidity is present. Another important challenge of multimorbidity in CDSS is the combination of rehabilitation guidelines in a nonharmful way (Sittig et al. 2008). One solution has been introduced by Jafarpour & Abidi (2013), who created an ontology with merging criteria provided by experts. Although rigorous evidence is lacking, to exploit physicians' "clinical mind-lines," such as "tacit guidelines that are internalized and collectively reinforced from the experience and discussion with colleagues and patients to embody the complex and flexible knowledge needed in practice" (Gabbay & le May 2010), has been proposed as a solution. However, this is a challenging task, due to that the current reality is that multimorbid patients often face more than two simultaneous pathologies (Boyd et al. 2005).

2. Integrate patient and provider values in decision support

Closely linked with the management of comorbidity is the need of integrating an evidence-based utility model into the CDSS, thus highlighting patient preferences and life style, cost to the individual (and/or organization), and the location in the clinician's workflow. Moreover, self-management is key in multimorbidity management (Bayliss et al. 2007). No CDSS adapted for multimorbid patient self-management were found. The main challenge here is to appropriately account for competing influences and values impacting clinical decision making, and thus clinical decision support. A related challenge is to rank in priority order, and reduce the number of computer-generated recommendations that a clinician or patient has to deal with to a manageable number based upon an explicit value

model, thus reducing the ‘‘alert fatigue’’ that is a frequent cause of user dissatisfaction. This challenge results from both the clinician’s limited time and attention, as well as the patient’s limited ability to accurately administer a large number of medications or make multiple, difficult, life-style changes at one time.
3. Improve the human–computer interface
A human-computer interface (HCI) paradigm is needed that facilitates the process by which CDSS is made available to clinicians to help them prevent both errors of omission and commission. Ideally, a CDSS for sickness certification practice should be user-friendly, intuitive, and easy to handle. It should unobtrusively, but effectively, remind clinicians of things they have truly overlooked in their sickness certification practice and support corrections, or better yet, put key pieces of data and knowledge seamlessly into the context of the workflow or clinical decision-making process, so the right decisions are made in the first place (Berner & Moss 2005, Miller et al. 2005). This also implies that the details of statistical and other model engines can be assumed to be perceived as being of less importance from the clinical user’s perspective than that the HCI design is of a state-of-the-art quality. For a clinician user with multiple analyses to assess for the same patient, ‘‘wrapping’’ them all in a common shell would further enhance the user’s ability to evaluate them. Unsolicited CDSS alerts and reminders are often overridden (Weingart et al. 2003) for a multitude of reasons, one of which is the poor human/computer interfaces that are currently in use Improved HCI design may include increased sensitivity to the needs of the current clinical scenario; provide clearer information displays, with intrusiveness proportional to the importance of the information; and make it easier for the clinician to take action on the information provided.

Create new CDSS applications
1. Management of Big Data
From a methodological point of view, knowledge-based systems constituted most commonly reported CDSS applications. Data-driven methods, such as machine-learning techniques, have been more rarely used (although promising studies have been reported (Suojanen et al. 2001)). New such CDSS applications for sickness certification practice can be developed and put into service, based on knowledge that has not yet been fully synthesized. New algorithms and techniques can be tested to allow mining of large clinical and health data repositories to expand the global knowledge with relevance for sickness certification, which in turn can be used to underpin CDSS applications. In addition to the technical challenges associated with the creation, testing, and execution of these algorithms, the social and political challenges facing researchers as they gain access to large databases must be addressed. For example, as these data resources begin to cross institutional and organizational boundaries, efforts will be required to insure that patient-identifiable information will remain private and secure (Safran et al. 2007). In other words, we should be able to program our computers to ‘‘learn’’ from large aggregate databases (Warner Jr 1989).
2. Prioritize CDSS content development and implementation
Development and implementation of the CDSS content required to help clinicians and organizations deliver the highest quality sickness certification practice will still take several years. Deciding which content to develop or implement first (in the sickness certification context – prognosis estimates, choice of rehabilitation, etc.), must be based on a multitude of factors including value to patients, cost to

the health care and sickness insurance systems, availability of reliable data, difficulty of implementation, and acceptability to clinicians and patients, among others. While prioritization by national interest and overall healthcare value may lead to longer and more difficult discussions prior to some future CDSS deployment, in the long run this prioritization should greatly facilitate the widespread use of the most valuable CDSS and lead to a greater overall impact. Over time, ad hoc approaches to local implementations must be supplanted by a concerted and systematically prioritized and executed approach.

Disseminate existing CDSS knowledge

1. An architecture for sharing CDSS modules

A set of standards-based CDSS services supporting sickness certification that any EHR system could ‘‘subscribe to’’ can be developed, thus allowing healthcare organizations implement CDSS applications for sickness certification with little extra effort on their part (Osheroff et al. 2007, Kawamoto & Lobach 2007). These knowledge modules might be designed so that they can be loaded into a clinical information system (Hripcsak et al. 1993), or they might be designed to execute as a remote service, with the local clinical system invoking them over a network according to a standardized interface (Wright 2007). A key component of this challenge would be to identify and standardize the definitions of and interfaces to the data required by the various CDSS modules. In addition this architecture should not require a specific knowledge representation scheme, but rather encapsulate the clinical knowledge in such a way that many different inference mechanisms could be used. Similarly, the architecture should describe the general intervention device used (e.g., alert, order set, intelligent form) and its key parameters, while still allowing for experimentation and commercial competition on the human/ computer interface within these broad guidelines.

2. Disseminate best practices in CDSS design

Some healthcare organizations have had successful and enduring experience with CDSSs (Chaudhry et al. 2006). When these organizations are studied, common success factors emerge, from design to communication to clinical practice style to management; yet, this knowledge is frequently not readily available to other organizations seeking to develop CDS programs (HIMSS 2007, Ash et al. 2007). Experiences from early efforts (Osheroff et al. 2005, Dexter et al. 2004) should be deployed in developing more robust methods to identify, describe, evaluate, collect, catalog, synthesize and disseminate best practices for CDSS design, development, implementation, maintenance, and evaluation. Specifically, measurement tools are needed to help us identify the most usable, economical and effective methods of implementing these CDSS-related initiatives. Additionally, best-practice information also applies at the level of the individual CDSS applications (Dexter et al. 2004). Identification of CDSS best practices implies the dire need for reliable measurements and feedback mechanisms to assess CDSS performance (Leonard & Sittig 2007, Thompson et al. 2007), and comparisons across different implementations of the same CDS tools and services, see for example (Bates et al. 2003). To accomplish this, there is a need to achieve consensus on a standard taxonomy of CDSS applications and outcomes that would allow to accurately describe the best practices as well as compare outcomes between implementations of different systems and across organizations.

Summary and recommendations

This study set out to perform a meta-narrative analysis in order to identify factors that are of relevance when clinical decision support systems are introduced for improving clinical sickness certification practice. The purpose was to condensate knowledge, experience and "best practice" from decision support tools and systems for exploitiation in the Swedish SRS project. The report thus summarizes relevant experiences (opportunities and threats) from investigations, requirements gathering, development, pilot operation, deployment, operation and management of a clinical decision support tools and systems and their implemention in healthcare practice.

We found no reports of CDSS use in the sickness certification context. Therefore, no corresponding narrative resulted from the analyses. Instead, two main narratives emerged, retelling experiences from the use of CDAM in the clinical sickness certification setting and accouting for experiences from CDSS use in healthcare, respectively. While numerous uses of decision analytic methods were included in the former narrative, no particular applications of decision support systems for sickness certification were included in the narrative accounting for actual CDSS use. In the CDAM narrative, we recount that these methods today generally are regarded as valuable when applied in healthcare practice, not the least in light of that patients are able to access medical evidence through the internet and therefore are bot willing and capable to share decisions about their healthcare. Nevertheless, we also acknowledge that several issues need to be considered when planning to implement CDAM in Swedish sickness certification practice. As emphasized in the TRIPOD statement (Collins et al. 2015), caution is required when interpreting results of CDAM analyses and applying them in clinical practice. Data collected in other contexts than where they are to be used for predictions usually display poor performance. When applying CDAM in Swedish sickness certification practice, it is therefore likely that it will be necessary to use data recently collected within the Swedish sickness certification setting. To ensure high-quality predictions voer time, each step in the modelling process should also be accompaigned by a regularly repeated external validations. A usual compensation for deficiencies in validation has been that the models are made ‘‘transparent’’. Unfortunately, rather than increasing the credibility of models, this may lead to inappropriate simplification, and, paradoxically, to even poorer performances. Moreover, the patients’ values should be reflected in decision-making regarding rehabilitation plans in the sickness certification setting. CDAM combines available evidences, but EBM brings to the fore that the manner in which this evidence is interpreted and reflected in the rehabilitation process decision should depend on the experiences of the entire clinical team and the preferences of the patient. Since the patient’s opinion should be reflected in the decision-making, decision aids for patients should be developed in parallel to CDAM development for sickness certification practice. Decision aids are instruments that help patients make value-based decisions in accordance with their individual preferences and are different from educational material for patients. Given that research has consistently shown that these instruments are helpful for patients, more decision aids in the rehabilitation area should be developed.

Once CDAM models for sickness certification practice have been designed, their implementation requires building an information infrastructure for management of input, carrying out calculations, and presenting results. In parallel to the obvious potential, there are also potential risks associated with the introduction of CDSS in sickness introduction practice. We placed CDSS challenges pertinent for their introduction in sickness introduction practice into three chief categories: Improvement of CDSS effectiveness, creation of new CDSS applications, and dissemination of existing CDSS knowledge. Just as approaching CDAM, evaluations of effectiveness and usability of CDSSs are thus key to avoiding patient harm and waste in health care systems. However, there is a general lack of rigorous CDSS evaluations. Actual improved clinical performance, rather than just behaviour change in general, is in the scientific CDSS literature supported by only weak evidence. While studies have been able to demonstrate behavioural changes among clinicians, these changes have not always translated into the provision of higher quality care in terms of patient outcomes. While some subgroups seem to fare better than others, the evidence is still only modest. The most notable findings are improved provision of preventive care measures, effective monitoring of side effects, and decreased use of unnecessary or redundant care – the latter two mainly associated with pharmacotherapy. Efforts at influencing practitioners to change practice patterns to adhere to a certain model of care have however been less successful. Little evidence has been indicated for an impact on patient outcomes outside prescribing; while surrogate outcomes have been modestly improved in some cases. Patient safety needs to be assured by rigorous evaluation, not only of the underlying software/technologies but also of their real-world interaction with users. Until today, only a few approaches to evaluating human-computer interaction effects on CDSS performance have been reported.

Mapping factors and providing recommendations for the effective implementation of eHealth projects is a challenging task. There is no universally acknowledged methodology either for evaluation or for the development and implementation of eHealth projects, while efforts to ensure at least a step forward in this field are limited. Although reasonably susceptible to subjectivity and arbitrary interpretations, the meta-narrative analysis provides an insight into the development of relevant components of eHealth and the general progress of clinical decision support systems for sickness certification practice. The main limitations of the analyses concern the choice and outline of the main narratives. Moreover, several commercial systems (for example, Reed Group's Disability Guidelines (MDGuidelines™)) were excluded because their development level only could be accouted for on the basis of secondary source information without empirical testing and the practical validation of integrated systems in healthcare environments. These issues should be properly resolved in further analyses aimed at establishing an evidence-base for development of clinical decision support systems for sickness certification practice in national and international contexts.

We thus contend that the challenges involved with the development of CDSSs for sickness certification practice extend to a wide range of areas, from technical and economic issues to public trust and stakeholder engagement. In a recent comparative examination of the eHealth development in Slovenia, Austria, and

Denmark (Stanimirowich & Vintar 2014]), factors were identified that are crucial for the success of large-scale eHealth projects. Some of these factors can be deemed relevant also for the effective enactment of the SRS project. Despite various methodological dilemmas, the analysis revealed issues which directly influence eHealth projects and offer an impression of the critical factors. Taking the above limitations into regard, the experiences from previous large-scale eHealth projects, and the results from the present meta-narrative review, factors with apparent influence on the realization of the SRS project can be outlined, divided into four spaces: the political, regulatory, institutional and technological (Table).

Table . Factors decisive for effective implementation of the SRS project (adapted from Stanimirowich & Vintar 2014]).

Political factors
Political commitment to CDSS introduction
Inclusion of stakeholders and effective collaboration
Realistic agenda and adequate budget
Strong project management team
Commitment to evidence-based evaluation framework and continuous validation
Promotional campaign, media presentations and mobilization of public support
Regional cooperation and international integration

Institutional factors
Openness to restructuring of sickness insurance and healthcare systems
Business process reengineering to include employers in rehabilitation
Shared process and service standardization
Intra- and interinstitutional agreements, cooperation and joint public procurement
Promoting CDSS use, education, and training
Partner relationship and user helpdesk
Responsiveness to user comments and feedback
Prompt resolution of problems

Regulatory factors
Promoting enabling legal environments
Adaptation of existing legislation and sectoral laws
Adoption and implementation of regulations for CDSS validation and code of practice
Harmonization of national regulation with international conventions and agreements

Technological factors
Specialized CDSS development team and adequate funding
Early collaboration and testing of CDSS solutions with stakeholders
Adequate technological infrastructure and enterprise architecture
Transfer of good practice, international experience, and consultancy
Monitoring and technology watch
Continuous technical adjustments and optimization
Maintenance, continuity and development

Despite the fact that these factors belong in different project phases, their presence or absence are likely to impact the effective implementation of the SRS project. On the combined basis of the above factors, eleven summary recommendations for the of the project are presented below:

1. Ensure political support from the highest level, ensure the necessary funds, human and other resources, and prepare credible and viable strategy documents.
2. Promote legislative amendments and adopt necessary regulations concerning the implementation (personal data protection, liability and risk issues, data storage and security, professional ethics, electronic signature, and record keeping).
3. Examine current and projected healthcare issues, determine national healthcare priorities, identify sickness insurance targets and beneficiary groups, define nature and coverage of services and projected results, and provide an action plan clearly specifying how a CDSS for sickness certification practice will contribute to the addressing of national healthcare priorities.
4. Mobilize stakeholder commitment, material and moral support, encourage their active participation and constructive criticism, promote collaboration between policymakers, healthcare professionals, healthcare management, and ICT professionals and users.
5. Select a top manager and a quality project team with experience in large ICT projects, form a steering committee including seasoned experts, assess risk and define change management issues, clearly structure the project plan, and determine the objectives and timeline of the project by reaching mutual consensus with all stakeholders.
6. Establish a robust CDAM validation framework based on the TRIPOD consensus document. This framework should include the motivations and objectives of the validation, stakeholder groups, benchmark and evaluation metrics. Define and specify strategic and operative measures.
7. Reflect the patients' values in the decision-making regarding rehabilitation plans in the sickness certification setting. Decision aids in the rehabilitation area need to be developed.
8. Improve or build a comprehensive ICT infrastructure and provide a blueprint for the future enterprise architecture (business, application and technology layers).
9. Implement gradually CDSS solutions in healthcare practice and repeatedly test the applicability of system components in pilot projects. Emphasize evaluatations of the human-computer interaction design.
10. Organize education and training of medical staff, and facilitate internal and external communication and collaboration. Ensure openness for user opinions, ideas and criticism, provide a reasonable transition period, and arrange for early problem detection and solving.
11. Inform and sensitize the public, promote project achievements so far, organize a marketing campaign to popularize the eHealth project and

increase user acceptance of eHealth services, facilitate helpdesks in healthcare institutions (online), gain support from the media, experts and citizens; eHealth is a socio-technical project.

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