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Review article

Barriers and facilitators influencing medication-related CDSS acceptance according to clinicians: A systematic review

Leonie Westerbeek a,⁎, Kimberley J. Ploegmakers b, Gert-Jan de Bruijn a, Annemiek J. Linn a, Julia C.M. van Weert b, Joost G. Daams c, Nathalie van der Velde b, Henk C. van Weert d, Ameen Abu-Hanna e, Stephanie Medlock f

a Amsterdam School of Communication Research, University of Amsterdam, Amsterdam, the Netherlands
b Department of Internal Medicine, Section of Geriatric Medicine, Amsterdam Public Health Research Institute, AmsterdamUMC, University of Amsterdam, Amsterdam, the Netherlands
c Medical Library, Amsterdam Public Health Research Institute, Amsterdam UMC, University of Amsterdam, Amsterdam, the Netherlands
d Department of General Practice, Amsterdam Public Health Research Institute, Amsterdam UMC, University of Amsterdam, Amsterdam, the Netherlands
e Department of Medical Informatics, Amsterdam Public Health Research Institute, Amsterdam UMC, University of Amsterdam, Amsterdam, the Netherlands

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ABSTRACT

Background: A medication-related Clinical Decision Support System (CDSS) is an application that analyzes patient data to provide assistance in medication-related care processes. Despite its potential to improve the clinical decision-making process, evidence shows that clinicians do not always use CDSSs in such a way that their potential can be fully realized. This systematic literature review provides an overview of frequently-reported barriers and facilitators for acceptance of medication-related CDSS.

Materials and methods: Search terms and MeSH headings were developed in collaboration with a librarian, and database searches were conducted in Medline, Scopus, Embase and Web of Science Conference Proceedings. After screening 5404 records and 140 full papers, 63 articles were included in this review. Quality assessment was performed for all 63 included articles. The identified barriers and facilitators are categorized within the Human, Organization, Technology fit (HOT-fit) model.

Results: A total of 327 barriers and 291 facilitators were identified. Results show that factors most often reported were related to (a lack of) usefulness and relevance of information, and ease of use and efficiency of the system.

Discussion: This review provides a valuable insight into a broad range of barriers and facilitators for using a medication-related CDSS as perceived by clinicians. The results can be used as a stepping stone in future studies developing medication-related CDSSs.

1. Introduction

Medication-related problems are responsible for approximately 3–5% of all hospital admissions and approximately 20% of all readmissions [1,2]. Various aspects, such as relevant patient characteristics and drug-drug interactions, need to be considered by the clinician during medication-related processes (e.g., prescribing, medication review etc.) [3,4]. Errors made during these processes can cause preventable injuries, negatively affecting patient safety and leading to unnecessary health care costs [3]. Therefore, it is of great importance to diminish the number of adverse drug events.

Clinical decision support systems (CDSSs) are systems that link patient health data with health knowledge (e.g., computer-interpretable guidelines) to guide the clinical decision making process [5]. CDSSs can support many aspects of care, such as preventative care, diagnosis, or therapy, including medication [6,7]. A medication-related CDSS is a system that supports medication-related decisions and processes, such as prescribing, administration, and monitoring for effectiveness and adverse effects.

Research shows that medication-related CDSSs offering advice to clinicians can prevent medication errors and thereby improve patient safety and healthcare quality [8–10]. However, clinicians override...
decisions on the first 200 titles screened by any two reviewers were compared and discussed before completing the rest of the screening. All full texts were screened by two reviewers (LW, KP, KV, SG). In both phases, any disagreement was resolved through discussion between the two reviewers, if any uncertainty remained, a third reviewer was consulted (SM).

2.3. Data extraction

Data were extracted from all studies by one author (LW) using a data extraction sheet tested independently by four authors (LW, GB, JW, SM). Title, authors, year of publication, and journal were extracted from each article. Furthermore, for each study we extracted the setting, year of data collection, type of study, type of questions asked, country, aim of the study, number, age and work experience of participants, and type of clinicians participating. Relevant information regarding the CDSS and its target users, and the barriers and facilitators for CDSS acceptance as mentioned by clinicians were extracted. We classified an item as a barrier or facilitator according to the classification used in the source study; no attempt was made to reclassify related items (e.g. “takes time” as a barrier and “saves time” as a facilitator).

2.4. Quality assessment measure

To assess the methodological quality of each of the included studies, the validated QualSyst tool [17] was used, as it allows scoring of both qualitative and quantitative studies. Quality assessment was done concurrently with data extraction by one author (LW). A summary score for each study was calculated by dividing the total score by the total possible score, resulting in a score between 0.0 and 1.0. Studies with a score of 0.5 or higher were considered of sufficient or good quality.

2.5. Data analysis

The extracted barriers and facilitators were categorized using the Human, Organization and Technology-fit (HOT-fit) model, intended for evaluation of health information systems, such as CDSSs [18] (Fig. 1). HOT-fit extends the IS success model’s [19] constructs of Use, User Satisfaction, and Information, System, and Service Quality with the organizational factors and concept of “fit” from the IT-organization fit model [20]. Barriers and facilitators to acceptance among clinicians (Human), technical problems with the software (Technology) and the extent to which the system can be integrated in the organizational environment (Organization) all affect CDSS usage [10]. For each of these dimensions, Yusof and colleagues provide “evaluation measures” [18] which constitute sub-categories of the eight components (e.g. System Quality, Information Quality, Structure etc.), and were used to categorize the extracted barriers and facilitators.

Barriers and facilitators that did not fall into this classification were placed in an “other” category, and then grouped into emergent themes. There seemed to be partial overlap between the component User Satisfaction and other components (which sometimes included indirect

![Fig. 1. The HOT-fit framework [18].](image-url)
indications of satisfaction). Therefore, we defined User Satisfaction as remarks specifically about satisfaction, and not remarks from other categories that imply satisfaction. Categorization was carried out by one author (LW). Any ambiguities were thoroughly discussed by a team of four of the authors (LW, GB, JW, SM). The total number of barriers and facilitators related to each HOT-fit component and underlying evaluation measure was counted, resulting in an overview of the most-frequently-mentioned barriers and facilitators.

3. Results

3.1. Search results

Our search strategy resulted in 6816 records. After removing duplicates (n = 1412), 5404 records remained for title and abstract screening, during which, 5264 records were excluded. Subsequently, the remaining 140 full-text papers were screened. Agreement on independent full-text screening was 86%, all disagreements were resolved after discussion. In total 63 articles were included. Fig. 2 summarizes the complete screening process in a PRISMA flow diagram.

The review includes a mixture of qualitative (n = 42), survey (n = 16) and mixed methods (n = 5) studies. The studies were performed at various sites, with hospitals (n = 31) and general practices (n = 11) being represented most frequently. The studies include data collected in 23 different countries, with the most common being the USA (n = 20) and Australia (n = 12). Information on each included paper can also be found in Table 1. Quality assessment of the included papers yielded an average score of 0.71 (range 0.42–0.89), with two studies having a score below 0.5. We checked to see if these two studies influenced our results. However, the themes presented in our results section below still predominated when excluding these two studies. We therefore retained them in our analysis.

3.2. Barriers and facilitators

In the 63 included studies [21–83], 327 barriers and 291 facilitators were identified. Barriers or facilitators named in more than one study were consolidated, resulting in 195 unique barriers and 174 unique facilitators. Barriers and facilitators were categorized into HOT-fit’s evaluation measures, which are sub-categories of the dimensions Information Quality, Service Quality etc. An overview of the most-frequently-encountered evaluation measures with example barriers and facilitators can be found in Table 2. In this table, the total amount of barriers and facilitators is reported for each evaluation measure. In the text below, we report the unique number of barriers and facilitators for the most frequently encountered evaluation measures. The complete list of barriers and facilitators can be found in Appendix B.

3.2.1. Technology

Barriers and facilitators from all three categories in the Technology component of HOT-fit were encountered. Information Quality was represented in more barriers than facilitators (n total barriers = 97, n total facilitators = 67), while System Quality (n total barriers = 97, n total facilitators = 104) and Service Quality (n total barriers = 2, n total facilitators = 4) were recognized in more facilitators. The most-often-encountered evaluation measures related to Information Quality were usefulness (n unique barriers = 12, n unique facilitators = 16), relevance (n unique barriers = 14, n unique facilitators = 2), format (n unique barriers = 4, n unique facilitators = 17), conciseness (n unique barriers = 5, n unique facilitators = 6), reliability (n unique barriers = 4, n unique facilitators = 6), and

![Fig. 2. Flow chart of the article selection process.](image-url)
Table 1
Characteristics of included studies.

| Authors, year published, country | Study type | Setting | Participant info | Clinician type | CDSS | Questions about |
|----------------------------------|------------|---------|------------------|----------------|------|-----------------|
| Abarca et al., 2006, USA [21]    | Survey     | Pharmacies from 18 metropolitan statistical areas | N = 736 | Pharmacy managers (n = 736) | Existing system. Pharmacy computer system with built in drug-drug interaction (DDI) alerts. | Previous real life experience with system. |
| Agostini et al., 2008, USA [22]  | Qualitative | Large academic medical center | N = 36 | Interns first postgraduate year (n = 29), interns postgraduate year 2 or higher (n = 7) | Developed for this project, has been in place for 1 year. Point-of-care computer based reminder that provided brief educational review of potential adverse effects of medication and offered recommendations. Reminder incorporated in existing system. | Real life experience during the past year. |
| Ahearn et al., 2003, Australia [23] | Qualitative | GPs from 1 rural and 2 urban divisions | N = 22, n female = 7 | GPs (n = 22) | Existing systems. Different systems used by different GPs with prompts, warnings, or links to additional information to assist in the decision-making process and streamline work practices. | Previous real life experience with their own system. |
| Ballard et al., 2017, USA [24]   | Survey     | Academic tertiary healthcare center | N = 105, n female = 53, M work experience = 13.6 years | Nurse practitioner (n = 15), physician assistant (n = 4), physician (n = 39), physician in training (n = 47) | System was developed by the center. Links to the decision aids are located in the Electronic Medical Record (EMR). System helps clinicians and patients discuss pro’s and con’s of statin use and uses electronic issue cards to display the impact of different medications. | Previous real life experience with the system. |
| Bastholm Rahmer et al., 2004, Sweden [25] | Qualitative | General hospital | N = 21, n female = 11, M age = 37, M work experience = 5 years | Physicians | Existing system. Integrated with current medical record systems and gives access to decision-support functions such as recommended drugs, alerts for interactions/pregnancy/breast feeding, search tool for adverse drug effects etc. | Questions about hypothetically implementing this system. |
| Baysari, et al., 2013, Australia [26] | Qualitative | Teaching hospital | N = 7 | Prescribers | System classifies antimicrobials according to a traffic light system (red/orange/green). | Real life experience with system. |
| Baysari, Westbrook et al., 2013, Australia [27] | Survey | Teaching hospital | N = 21 | Registrar (n = 10), resident (n = 6), intern (n = 5) | Existing system. Decision support alerts regarding allergy, intolerance, pregnancy, therapeutic duplication and prescribing advice. Alerts appear immediately after selecting a drug. | Previous real life experience with the system. |
| Baysari et al., 2014, Australia [28] | Qualitative | Teaching hospital | N = 16 | Prescribers | Existing system. Electronic medication management system that links prescribing, pharmacy review and drug administration. Alerts delivered to prescriber right after drug selection. | Previous real life experience with system. |
| Baysari et al., 2017, Australia [29] | Qualitative | Teaching hospital | N = 11 | Senior doctor (n = 11), junior doctors (n = 10) | Decision support was added to an existing CPOE system for this study. Approved indications were incorporated into pre-written orders, so prescribers didn’t have to read a whole alert text but could select from a pre-approved list. | Real life situations right after they occurred. |
| Baysari et al., 2020, Australia [30] | Survey | Teaching hospital | N = 96 | Clinicians (n = 36), nurses (n = 60) | Decision support added to an existing EMR. E.g. allergy and intolerance alerts, therapeutic duplication alerts, pregnancy alerts, and drug-drug interaction alerts. | Real life experience with current alerts and wishes for changes. |
| Böttiger et al., 2018, Sweden & Finland [31] | Survey | Two periotic wards & three primary healthcare centers | N = 40 | Physicians (n = 40) | System developed in this study. Buttons signaling in color if there is safety information to be retrieved for the individual patient, drug-drug interactions, dosing recommendations, and | Real life experience during pilot study. |

(continued on next page)
| Authors, year published, country | Study type | Setting | Participant info | Clinician type | CDSS | Questions about |
|---------------------------------|------------|---------|------------------|---------------|------|----------------|
| Bright et al., 2013, USA [32]   | Qualitative | Two hospitals | N = 12, n female 7 | Resident/fellow physicians (n = 6), nurse practitioners (n = 3), clinical pharmacists (n = 3) | System is in development. Commercial CPOE system providing basic antibiotic decision support. | Functional requirements for the system. |
| Bury et al., 2004, UK [33]      | Qualitative | Hospital | N = 36 | Clinicians | Existing system. Web based service which gives protocol based advice. | Simulated cases |
| Chow et al., 2015, Singapore [34] | Mixed methods (focus groups + survey) | Tertiary care hospital | N focus group = 11, N survey = 265 | Focus group: senior physicians (n = 6), junior physicians (n = 5). Survey: senior physicians (n = 115), junior physicians (n = 150), junior physicians (n = 29), senior physicians (n = 10) | Existing system. Patient-specific antibiotic recommendations at point of prescribing, integrated with CPOE. | Previous real life experience with system. |
| Chua et al., 2018, Singapore [35] | Qualitative | Tertiary care teaching hospital | N = 39, n female 22 | Existing system. Provides patient-specific antibiotic recommendations at point of prescribing. | Previous real life experience with system. |
| Cornu et al., 2014, Belgium [36] | Qualitative | Hospitals | N = 41 | Consultants (n = 13), pharmacists (n = 28) | System does not yet exist. Aim is to create a starting point for developing an oncology CDSS. | Attributes and knowledge of physicians and pharmacists to a CDSS in oncology in general. Previous real life experience with the system. |
| Collins et al., 2012, Singapore [37] | Qualitative | University hospital | N = 164, n female 75 | Prescribers | Existing systems. Several types of basic CDSSs for drug prescribing. Functions such as drug-drug interaction check, dosage information support, presented as passive information/non-interruptive alerts. | Previous real life experience with the system. |
| Day et al., 2011, Australia [38] | Qualitative | Teaching hospital | N = 19 | Medical, nursing and pharmacy staff | Existing system. Electronic medication management system with decision support in the form of alerts. | Previous real life experience with the system. |
| De Vries et al., 2013, The Netherlands [39] | Qualitative | Heart failure clinics | N = 162, n female 110, M age = 48, M work experience = 14 years | Cardiologists (n = 36), heart failure nurses (n = 126) | Existing systems. No specific system, different CDSSs used in the heart failure domain. | Previous real life experience with their own system. |
| Dodson et al., 2019, USA [40] | Qualitative | Local health care systems | N = 10 | Nurse practitioners (n = 10) | Several existing systems. Clinical decision support tools and mobile applications for prescriptive purposes | Previous real life experience with system. |
| Feldstein et al., 2004, USA [41] | Qualitative | Health maintenance organization | N = 20, n female 10, M work experience = 9 years | Physicians (n = 17), physician assistants (n = 2), nurse (n = 1) | Existing system. System provides drug specific alerts and reminders. Alerts and reminders regarding overdue health maintenance procedures. Access to evidence-based guidelines. | Previous real life experience with system. |
| Feldstein et al., 2005, USA [42] | Qualitative | Health maintenance organization | N = 20 | Primary care prescribers | Existing system. System provides drug specific alerts and reminders. Hypothetical cases. | |
| Gansman et al., 2002, USA [43] | Qualitative | Large VA health care system | N = 168, n female 61, M age = 48.5 | Physicians, nurse practitioners, physician assistants | Existing system. A comprehensive electronic medical record including provider order entry. Provides automated drug alerts. | Previous real life experience with system. |
| Goodspeed et al., 2019, USA [44] | Qualitative | Mental Health Center | N = 16 | Physicians and nurse practitioners | System developed in this study. Mental health CDSS integrated in HER. Development based on these focus groups. | Wishes and preferences for the new system. |
| Hellden et al., 2015, Sweden [45] | Qualitative | Two primary healthcare centers | N = 7 | General practitioners | System was developed for this study. Web-based system. GP | Previous real life experience with the system. | (continued on next page)
| Authors, year published, country | Study type | Setting | Participant info | Clinician type | CDSS | Questions about |
|---|---|---|---|---|---|---|
| Henshall et al., 2017, UK [47] | Qualitative | The Oxford Health NHS Foundation Trust & general practice | N = 23, n female = 14 | Consultant psychiatrists (n = 12), primary care general practitioners (n = 6), nurses (n = 5) | must press a button to receive alerts, drug lists etc. System is in development. Allows clinicians and patients to enter simple demographic and clinical variables (i.e. age, gender, severity) and discuss the relevance of the different side effects. Existing, rule based system. Sends several prompts, for instance reminder to ask for medication history and to insert a cholesterol level. Advice is then given on appropriate management of the patient, based on a protocol. | Their wishes for such a tool. |
| Hobbs et al., 1996, UK [48] | Survey | Fourteen primary care practices | Not mentioned | General practitioners | | Previous real life experience with the system. |
| Hor et al., 2010, Ireland [49] | Survey | Multiple general practitioners | N = 98 | General practitioners | | Previous real life experience with their own system. |
| Hum et al., 2014, USA [50] | Survey | Four academically affiliated NICUs | N = 46 | NICU attending physicians (n = 12), neonatology fellows (n = 5), residents (n = 18), house physicians (n = 2), nurse practitioners (n = 9) | System developed for this study. Algorithm based. Provided antimicrobial prescribing recommendations. | General real life experience. |
| Jindal et al., 2018, India [51] | Qualitative | Five community health centers | N = 10 | Nurses (n = 5), physicians (n = 5) | Developed in this study. CDSS for management of hypertension, diabetes and comorbid conditions. | Real life experience with system during 4 month pilot. |
| Johansson-Pajala et al., 2019, Sweden [52] | Qualitative | Two nursing homes | N = 8, n female = 7, median age = 45, median work experience = 11 years | Registered nurses (n = 8) | Web-based decision support system designed for use by healthcare professionals for drug prescribing and reviews. Quality reports provide information about inappropriate drugs, potential drug-drug interactions, contraindications, and possible adverse drug reactions, all in relation to each individual patient. | Real life experience with the system. |
| Johnson et al., 2015, UK [53] | Qualitative | Two hospital trusts in provincial city | N = 8 | Cardiologists (n = 4), specialist cariology nurses (n = 3), cardiac psychologist (n = 1) | Developed in this study. Web-based computerized CDSS to support investigation and medication decisions for patients with new onset stable chest pain. | Real life experience with the system for 4 months. |
| Jung et al., 2013, Netherlands, Argentine, Denmark, France, Ireland, Switzerland, Bulgaria, Austria, Greece [54] | Survey | Multiple hospitals | N = 1018 | Physicians | Existing systems. All hospitals used different systems with varying levels of decision support. | Previous real life experience with their own system. |
| Kappen et al., 2016, Netherlands [55] | Mixed methods (interview and survey) | University medical center | N survey = 53, N interviews = 8 | Anesthesiologists, physicians | Developed for this study. A prediction model has been made for predicting PONV (postoperative nausea and vomiting). This model presented the PONV risk to the clinician. | Previous real life experience with this system. |
| Kazemi et al., 2009, Iran [56] | Qualitative | Teaching general hospital | N = 19 | Specialists/sub-specialists (n = 12), residents (n = 3), interns (n = 4) | Prototype of the CDSS function in existing CPOE. CDSS would concern dose and interval decision support. | Prototype was shown and opinions about it immediately asked. |
| Lapane et al., 2008, USA [57] | Mixed methods (focus groups and survey) | 64 different primary care practices | N survey = 157, N focus groups = 276 | Physicians or residents (n = 128), physician assistants (n = 13), nurse practitioners (n = 19) | Six different existing e-prescribing systems with drug alerts. | Previous real life experience with the different systems. |
| Litvin et al., 2012, USA [58] | Qualitative | Nine different primary care practices | N = 39 | Physicians (n = 27), nurse practitioners (n = 6), physician’s assistants (n = 6) | Developed for this study. CDSS tool reflects guidelines. Recommendations based on patients’ predominant presenting symptoms and the patients’ age. Once diagnosis | Real life experience with the system for the past 15 months. |

(continued on next page)
| Authors, year published, country | Study type | Setting | Participant info | Clinician type | CDSS | Questions about |
|----------------------------------|------------|---------|------------------|---------------|------|----------------|
| Martens et al., 2008, Netherlands | Qualitative | 53 GPs | N = 6 | General practitioners | has been made prompts regarding appropriate antibiotic use are given. | Real life experience with the system for 12 months. |
| Meulenski et al., 2013, Netherlands | Survey | Numerous GPs | N = 184 | General practitioners | | |
| Mulder-Wildemors et al., 2020, Netherlands | Qualitative | Pharmacies | N = 10 | Pharmacists | Web-based CDSS. Gives pop-up alerts for patients older than 70 years taking certain medications. | Real life experience with the system for 1 year. |
| Murphy et al., 2020, Ireland | Qualitative | 14 GPs | N = 14 | General practitioners | Developed in this study. CDSS delivered tailored recommendations to the GP. | Real life experience during the pilot. |
| Omar et al., 2017, Sweden | Qualitative | Hospital | Not mentioned | Pediatricians, resident physicians, pediatric surgeons, neonatologists | Existing system. Offers information of drugs and enables pediatricians to use prefilled drug orders and prescribe in a standardized manner. | Previous real life experience with the system. |
| Peiris et al., 2009, Australia | Mixed methods (survey and interviews) | Eight teaching general practices and three Aboriginal Medical Services | N = 21, n female = 9 | General practitioners | Developed for this study. System uses an algorithm to predict a 5- year risk of a first cardiovascular disease event. | Real life situations. |
| Pimejda et al., 2011, Netherlands | Qualitative | Tertiary academic hospital | N = 12 | Nurses (n = 4), physicians (n = 6), project leaders (n = 2) | Two existing systems. System 1: CPOE which can generate drug alerts. System 2: Designed specifically to provide decision support and plan chemotherapy doses based on patient’s biometric indexes. | Previous real life experience with the systems. |
| Ramanathan et al., 2016, Singapore | Qualitative | Urban academic medical center | N = 16 | Nurses (n = 8), general surgery residents (n = 6), nurse practitioners (n = 2) | Existing system. CDSS through EMR including alerts and order-sets. | Previous real life experience with the system. |
| Reynolds et al., 2019, USA | Qualitative | Two health systems | N = 20 | Nurses | Handheld decision support device in pediatric intensive care settings. Helps calculate dosage, detects unsafe doses etc. | Real life experience with system during pilot. |
| Riekkert et al., 2018, Germany | Qualitative | Multiple GPs | N = 21, n female = 14, M age = 53, M work experience = 16 years | General practitioners | Developed for this study. GP enters data and presses medication review button. System then provides a comprehensive medication review based on current best evidence. | Previous real life experience with the system for 1 year. |
| Robertson et al., 2011, Australia | Qualitative | Numerous GPs | N = 27, n female = 15 | Experienced general practitioners (n = 18), trainees (n = 9) | Existing systems. Different systems used by different GPs. | |
| Russ et al., 2009, USA | Qualitative | Five outpatient primary care clinics | N = 20 | Physicians, nurse practitioners, pharmacists | Existing system. Alerts appear in the Computerized Patient Record System as a pop-up window and require prescriber action to be resolved. | Interviews right after real life observations. |
| Santucci et al., 2016, Australia | Qualitative | Teaching hospital | N = 20 | Senior doctors (n = 7), junior doctors (n = 13) | Existing system. Computerized alerts at point of prescribing, pre-written orders and a reference material search tool. | Interviews right after real life observations. |
| Sedlmayr et al., 2013, Germany | Survey | Tertiary care acute hospital | N = 9 | Senior physicians (n = 2), specialist in internal medicine (n = 1), junior physicians (n = 6) | Developed for this study. CDSS integrated within hospital’s HER. Medication safety checks and embedded drug information system. | Previous real life experience with the system. |
| Seidling et al., 2016, England, France, Portugal | Qualitative | 13 hospitals in 12 countries | N = 20 | Research pharmacists and clinical pharmacists | Existing systems. Different systems in each hospital. Each | Previous real life experience with their own system. |

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facilitators = 1) and completeness (n unique barriers = 8, n unique facilitators = 1). Examples included redundant alerts, irrelevant alerts and information presentation. Related to System Quality, efficiency (n unique barriers = 5, n unique facilitators = 8), ease of use (n unique barriers = 12, n unique facilitators = 6), usefulness of system features and functions (n unique barriers = 5, n unique facilitators = 20) and flexibility (n unique barriers = 9, n unique facilitators = 14) were the most-often-reported evaluation measures and concerned, for example, saving time and the amount of clicks.

3.2.2. Human
Both factors regarding the Human component of HOT-fit were present in the included articles. System Use was mostly encountered in barriers (n total barriers = 72, n total facilitators = 12), while User Satisfaction was mostly visible in reported facilitators (n total barriers = 5, n total facilitators = 11). The most-often-reported evaluation measures related to system use are expectation/belief (n unique barriers = 16, n unique facilitators = 3), training (n unique barriers = 4, n unique facilitators = 2) and reluctance/resistance (n unique barriers = 8, n unique facilitators = 0). Examples included dependence on the system and not receiving adequate training.

3.2.3. Organization
Reported barriers and facilitators were related to both categories in the Organization component of HOT-fit: both Structure (n total barriers = 24, n total facilitators = 5), and Environment (n total barriers = 6, n total facilitators = 2) were most often encountered in barriers. Related to Structure, the evaluation measure clinical process (n unique barriers = 7, n unique facilitators = 3) was most often represented, concerning, for example, the workflow of the clinician.
### Table 2

| HOT-fit dimension | Evaluation measure | Examples from included studies |
|-------------------|---------------------|--------------------------------|
| **Information quality** | **Barrier:** System shows redundant alerts (e.g., an interaction so well known that it provides little added value) [22,38,71,80] | |
|        | **Facilitator:** Patient-safety alerts were considered useful [22,42,43] | |
|        | **Barrier:** Too many irrelevant alerts (e.g., worries about alert fatigue because of the large amount of irrelevant alerts such as a lactation alert for a 60-year-old patient) [23,24,28,36,42,44,45,69,70,71,76,77] | |
|        | **Facilitator:** Not all information is shown at once, user can ask for elaboration [42,43,54,75] | |
|        | **Barrier:** Alerts are presented outside of the visual focus region [35,43,81] | |
|        | **Facilitator:** Prioritizing information with highlights and colors [23,30,73] | |
|        | **Barrier:** System fires too many alerts [25,27,28,30,66,71,80] | |
|        | **Barrier:** Alerts are too long (i.e., too much text) [25,51,75] | |
|        | **Facilitator:** Recommendations based on out-of-date or false information [64,79,80] | |
|        | **Barrier:** System provides evidence on which alert is based [35,36,77] | |
|        | **Barrier:** Missing contextualization of the alerts [54] | |
| **Reliability (n = 23, F = 8) [21,24,25,27,28,30,36,42,43,45,46,51,66,70,71,76,77] | **Barrier:** System use is time-consuming [23,25,31,35,36,38,40,42,45,54,56,62,64,66,67,68,69,70,71,77,80,81,83] | |
|        | **Facilitator:** System saves the clinician time [25,47,50,52,63,65,76,83] | |
| **Conciseness (n = 11, B = 8, F = 3) [23,25,37,38,40,70,77,79] | **Facilitator:** System is easy to use and simple [31,33,36,38,41,45,46,63,65,67,74,77,78] | |
|        | **Barrier:** Too many clicks needed [39,77] | |
| **Completeness (n = 10, B = 9, F = 1) [23,42,44,54,69,70,77] | **Barrier:** System shows patient history [32,40,47,63,80] | |
|        | **Facilitator:** System shows patient history tailored to personal preferences [38,58,78] | |
| **Usefulness of system features and functions (n = 30, B = 5, F = 25) [31,32,40,45,46,47,50,52,62,63,65,67,70,72,74,75,76,77,80] | **Barrier:** Possibility to make minor adaptions to the system tailored to personal preferences [38,58,78] | |
|        | **Facilitator:** Providers can set their own level of sensitivity for alerts [23,57] | |

### Table (continued)

| HOT-fit dimension | Evaluation measure | Examples from included studies |
|-------------------|---------------------|--------------------------------|
| **System quality** | **Barrier:** System use is time-consuming [23,25,31,35,36,38,40,42,45,54,56,62,64,66,67,68,69,70,71,77,80,81,83] | |
|        | **Facilitator:** System saves the clinician time [25,47,50,52,63,65,76,83] | |
| **Ease of use (n = 41, B = 18, F = 23) [23,24,30,31,35,36,38,39,41,45,46,47,51,52,56,63,65,67,70,72,74,75,76,77,80,82,83] | **Barrier:** Too many clicks needed [39,77] | |
| **Usefulness of system features and functions (n = 30, B = 5, F = 25) [31,32,40,45,46,47,50,52,62,63,65,67,70,72,74,75,76,77,80] | **Barrier:** System shows patient history [32,40,47,63,80] | |
|        | **Facilitator:** System shows patient history tailored to personal preferences [38,58,78] | |
| **Flexibility (n = 32, B = 14, F = 18) [23,36,38,44,45,51,57,58,64,65,76,78] | **Barrier:** Facilitator can set their own level of sensitivity for alerts [23,57] | |
| **Evaluation measures encountered less than 10 times:** Availability (n = 9, B = 9, F = 0), Data accuracy (n = 7, B = 4, F = 3), Database contents (n = 6, B = 5, F = 1), Ease of learning (n = 4, B = 2, F = 2), Reliability (n = 4, B = 1, F = 3), Response time (n = 8, B = 6, F = 2), Technical support (n = 3, B = 3, F = 0) | **Barrier:** System shows patient history tailored to personal preferences [38,58,78] | |
| | **Facilitator:** Providers can set their own level of sensitivity for alerts [23,57] | |

In this table, n represents the total amount of barriers and facilitators encountered, B represents the total amount of barriers, and F represents the total amount of facilitators.

### 3.2.4. Net benefits

The last HOT-fit component, Net Benefits, was also recognized repeatedly within the included papers, mainly in reported facilitators (n total barriers = 7, n total facilitators = 66). The most-often-encountered evaluation measures related to Net Benefits were **clinical outcomes** (n unique barriers = 2, n unique facilitators = 10), **error reduction** (n unique barriers = 1, n unique facilitators = 4), **communication** (n unique barriers...
of the barriers and facilitators. Clinicians often mentioned time con

4.2. Interpretations, implications and impact

4.1. Main findings

This systematic review aimed to identify barriers and facilitators for medication-related CDSS acceptance as indicated by clinicians. Our re

view revealed that the included studies mostly focused on barriers and facilitators related to the Technology component from HOT-fit, and more specifically to Information Quality and System Quality. Barriers and facilitators about efficiency and ease of use of the system, and usefulness and relevance of the information were most often reported. Sys
tems being time consuming was the most often encountered barrier, and ease of use was the most often encountered facilitator. The other HOT-fit components, Human, Organization and Net Benefits, were encountered less often. Context was identified as an important new factor.

4.2. Interpretations, implications and impact

The evaluation measure efficiency was most often encountered in all of the barriers and facilitators. Clinicians often mentioned time con
straints as an impeding factor and the system saving them time as a fa
cilitator. While designing a CDSS, developers should keep in mind that system usage should not be time-consuming or ideally even time-saving. Ease of use was also a frequently occurring theme and should be closely monitored while developing new CDSSs. Clinicians often indicated that a simple, easy-to-use system facilitates usage. Complex systems with hard-to-find information inhibited usage according to clinicians.

Furthermore, usefulness and relevance of the information presented were also often mentioned. If clinicians perceived the advice as useful, this facilitated usage. On the other hand, redundant alerts, e.g. if the presented information is already well known, were indicated as a bar
rier. Similarly, irrelevant alerts were seen as a major barrier, for instance if an alert regarding pregnancy was shown for a male patient. In prac
tice, this means that the content of the alerts should be critically eval
uated. Only truly useful and relevant information should be presented to the clinician.

A common theme in the factors discussed above is that clinicians agree that certain factors inhibit or facilitate usage, but have different views on how to achieve this. Clinicians for instance agreed that useful information facilitates usage, but had different visions on which infor
mation is useful. Therefore, during development, clinicians from the system’s target group should be involved. User-centered design could be a suitable method for this, as research has shown its ability to make CDSSs more effective and easy to use [94]. This will allow system de
velopers to make sure that the CDSS’s features overcome barriers and facilitate acceptance of the system before implementation.

Some aspects of the HOT-fit model were found less frequently in our results; specifically, User Satisfaction, Service Quality, and Environ
ment. We defined User Satisfaction as remarks specifically about sati
faction, and not remarks from other categories implying satisfaction,
4.4. Strengths and limitations

There are several methodological strengths of this systematic review. Firstly, the search strategy was made in collaboration with an expert in systematic literature searches and performed in multiple databases. Reference lists were cross-checked to ensure no papers were missed. Furthermore, every record was screened by at least two coders in title/abstract and full text inclusion. This reduces the chance of missing eligible papers. Lastly, the data extraction sheet was created and tested in an iterative process with multiple authors (LW, GB, JW, SM), ensuring reliability of the data extraction process.

The HOT-fit model was considered a useful model for categorization of the barriers and facilitators, and this systematic categorization is a strength of our review. However, the authors of the HOT-fit model provide explanations regarding its main components (e.g. Information Quality, System Use etc.), but the underlying evaluation measures are merely named and not defined. Other systematic reviews using HOT-fit have also reported this issue [87,12]. Additional clarification about how to use and interpret the evaluation measures would make categorization more reliable. Furthermore, even though the categorization was thoroughly discussed by a team of four authors (LW, GB, JW, SM), the entire list was not independently coded by a second person. Applying this approach in the future might also enhance reliability of the categorization.

Furthermore, the results of this review showed some gaps in the literature, as some of the HOT-fit dimensions were barely present in the extracted data. However, our results only show which dimensions are missing, but not why they are missing. The question remains whether these dimensions are understudied, or whether they are simply not as relevant in a CDSS context. Whether a barrier or facilitator emerges in the results of a study depends on what questions were asked, particularly in closed-question survey studies. A limitation of closed-question survey studies is that they direct respondents to select or report items. Surveys with open questions and qualitative studies allow more freedom in responses. Thus a barrier or facilitator might not be mentioned frequently because it is not important to the participants, or because they were focused on other themes. It is important to keep this limitation in mind when interpreting the results of this study. Although a list of common barriers and facilitators is valuable for the design and implementation of future systems, it is not a substitute for the involvement of users in the development process.

4.5. Future research

This study focused on medication-related CDSSs; future research could compare overlap in barriers and facilitators between this and other domains, and assess the reasons behind these differences. It can also be assessed whether some barriers or facilitators are universal for all CDSSs or if there are domain-dependent patterns. Furthermore, it could be interesting to look at how barriers and facilitators might vary per user group and per context. Splitting up the results for different groups in this way can create valuable additional insights. This could eventually lead to guidelines for developing specific kinds of CDSSs.

Overall, the findings of the current review are especially relevant for medication-related CDSS developers. More specifically, in the near future the findings will be used in the development of a medication-related CDSS for general practitioners to reduce older patients’ medication-related fall risk. During the development of this system, and also of other future CDSSs, the barriers and facilitators found in this review can suggest specific features and functions that will help overcome barriers and facilitate usage.

4.6. Conclusion

In short, this review provides valuable insight into a broad range of barriers and facilitators for accepting a medication-related CDSS as perceived by clinicians. The Technological HOT-fit component predominated, and clinicians named many barriers and facilitators related to System Quality and Information Quality, for instance regarding efficiency, usefulness and ease of use. We also found context to be an important additional factor. To our knowledge, the current review is the first large systematic review of barriers and facilitators for medication-related CDSSs. The barriers and facilitators identified by this study can be used as a starting point for designing high-quality CDSSs, although they should not be considered a substitute for involvement of end-users during the development. Furthermore, future research should explore similar overviews of barriers and facilitators for usage in different CDSS domains. Eventually this will contribute to the development of more effective CDSSs and ultimately improve patient care.

Authors’ contributions

LW, KP, GB, AL, JW, NV, SM contributed to the conception and design of the study. JD conducted the search strategy. LW, KP, LS, SG and KV independently screened titles and abstracts for eligibility. LW, KP, SG and KV screened full text for inclusion. SM was consulted in case of disagreement between coders. LW prepared the original draft, KP, GB, AL, JW, JD, NV, HW, AA and SM reviewed the final manuscript.

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Summary table

**What was already known on the topic**

- Medication-related Clinical Decision Support Systems (CDSS) offering advice to clinicians can prevent medication errors and thereby improve patient safety and healthcare quality.
- Even though evidence of its effectiveness exists, a high percentage of CDSS systems are not used, and alerts are overridden or ignored by clinicians.
- Individual studies have investigated clinicians’ reasons for accepting or not accepting medication-related CDSSs, but no attempt has been made to systematically summarize the evidence base of reported barriers and facilitators of medication-related CDSS acceptance.

**What this study added to our knowledge**

- This review provides a valuable, systematic insight into a broad range of barriers and facilitators for medication-related CDSS acceptance as perceived by clinicians.
- Data categorization provides a clear overview of frequently found themes and gaps in the literature.
- The common barriers and facilitators identified by this study can be used as a starting point for the design of high-quality CDSSs, although they should not be considered a substitute for involvement of end-users, preferably from the start of the design process.

Declaration of Competing Interest

The authors report no declarations of interest.

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