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A Human-Computer Interaction Perspective on Clinical Decision Support Systems: A Systematic Review of Usability, Barriers, and Recommendations for Improvement

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***Abstract*—Clinical decision support systems have been increasingly utilized in the healthcare industry to improve patient outcomes and enhance clinical decision-making, taking advantage of the growing digital medical data. Despite their potential, there are still obstacles in an extensive adoption of these systems, such as low usability and human factors. In this systematic review, several articles describing clinical decision support systems with clinical validation are used to address some of the gaps, as well as to map the current academic landscape for the given context. The selected articles are observed through a Human-Computer Interaction perspective, aiming to identify the state-of-the-art, as well as barriers to the application of these principles. From an initial database search resulting in 121 articles, 16 articles were selected that fulfilled the chosen criteria: (1) article must be available and written in English, (2) article must report experimental work, (3) the reported system must be clinically validated. The research strategy followed the PRISMA framework. We highlight the need for clinical validation, a standardized clinical decision support taxonomy and the evaluation of these tools across multiple variables. Based on the found results, a list of recommendations can be formed to aid the development of future CDSS, or the improvement of current ones.**

***Index Terms*—clinical decision support system, human-computer interaction, taxonomy, evaluation, data visualization**

I. Introduction

The clinical setting is a complex and delicate field of work, where a very high volume of data is generated at a growing rate, with an estimated volume of 2314 exabytes in 2020 [1], [2]. Clinical data sources include hospital records, laboratory results, outputs from medical devices, and patient-generated data. There is an increasing search to leverage medical data with digital tools, to improve different aspects related to healthcare, such as efficiency, costs, and patient satisfaction [3].

Clinical Decision Support Systems (CDSS) are designed to improve healthcare delivery by enhancing medical decisions with targeted clinical knowledge, patient information, and other health information [4]. CDSS have the potential to use medical information to improve the efficiency of care delivery by providing timely and relevant clinical recommendations. These systems come in a variety of categories [5] and employ several different technologies, including artificial intelligence (AI) [6], [7], natural language processing (NLP) [8] ontological knowledge [9], [10], and Electronic Health Record (EMR) embedding [11], [12].

Despite the possible benefits of CDSS, the adoption of these systems is still hindered by an assortment of aspects, such as lack of confidence, time constraints, lack of training, ethical risks, high costs, and the multitude of computer systems used [13], [14]. The development of reliable CDSS faces technical challenges, namely associated with the nature of the data used (unstructured data entry, missing values, data conversion and metadata attributes) [15], interoperability [16], transparency, which is necessary to foster trust and conform with legislation [17], and usability. The latter is an often overlooked aspect of CDSS, with great significance in the adoption of the system. Many CDSS systems suffer from usability problems that hinder efficient workflow, and contribute to clinical burnout [18].

Data visualization is the process of creating graphical representations of data to facilitate understanding and decision-

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making. In the context of CDSS, data visualization can be used to present complex clinical data and evidence in a clear and concise manner, enabling healthcare providers to more easily identify patterns, trends, and relationships that may be relevant to patient care. Some common techniques for visualizing data include scatter plots, bar charts, and heat maps.

Human-Computer Interaction (HCI) is a field that focuses on the design, evaluation, and implementation of interactive computing systems for human use. It encompasses the study of how people interact with technology, and how technology can be designed to better meet the needs of users. The application of HCI principles to the development of healthcare information systems and CDSS shows positive receptions of these tools from a clinical perspective [19]. However, the extent to which these principles are used in tested and commercial CDSSs is still unknown.

There are a number of studies that analyze several aspects of CDSSs. Hak, F. et al. provided a general overview of the current features used by CDSSs, with a broad scope for CDSSs applications [20]. On the other hand, Kwan, J. et al., Sunjaya, A. et al., Mebrahtu, T. et al., and Muhiyaddin, R. et al. studied the impact of the implementation of CDSSs, evaluating a diverse number of metrics [21]–[24]. The objective of this systematic review is to analyse the panorama of CDSS with clinical validation, with a focus the adherence to HCI and evaluation methods, over more traditional systems, thus complementing the previously described works. By using general taxonomies and classifications both for CDSS and evaluation metrics, we aim to progress the standardization of categorization terms when applied to this context. Through a careful investigation of the current state of CDSS, we hope to find challenges to overcome, and strategies already employed to do so.

II. Methods

A. Search Strategy

The systematic review followed the guidelines outlined in the PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions. The literature selection and review process were conducted to address the following PICO question: "In clinically validated Clinical Decision Support Systems, how does the implementation and design of the CDSS with a focus on usability and human factors compare with traditional decision-making methods or other CDSS with less emphasis on usability and human factors in improving user experience, clinician performance, and patient outcomes?".

A literature search was carried by searching articles published in the IEEE Xplore, Cochrane, PMC, PubMed and ScienceDirect electronic databases, without a date of publication limitation. Bypassing restrictions associated with date of publication allows the temporal mapping of CDSSs with clinical validation.

The search used the following Boolean expression: ("data visualization" OR "data visualisation") AND "clinical decision support". This Boolean expression was designed to find articles with a special focus on medical data visualization, in conformity with the aspect of CDSS most impacted by the study of HCI.

B. Inclusion Criteria

Screening inclusion criteria was: (1) articles must be available and written in English, (2) articles must report experimental work, (3) the reported CDSS must be clinically validated. The third criteria, related to clinical validation, was considered complied if the CDSS had been deployed in a clinical setting. That is, the developed tool can be implemented in a clinical facility, either academic or not, or use randomized trials with patients.

C. Study selection

Following the PICO strategy and the chosen criteria, the selected articles were reviewed by a single author. The focus of analysis were the title and abstract, resorting to the body of the article in case the criteria fulfillment were inconclusive.

D. Research question

To reach a deeper understanding of the current state of CDSS with clinical practice, the initial PICO question can be further divided in subquestions. These subquestions are designed to establish a guided framework for the remaining of the systematic review.

- How has the number of studied CDSS with clinical validation change over time?
- How can the selected CDSS be categorized?
- How is the clinical validation performed?
- What data representation methods do the selected CDSS use?
- Does the design process of CDSS follow HCI principles?
- What metrics are evaluated for the selected CDSS?
- How are these metrics evaluated?

E. Data extraction

The articles were reviewed in detail by one author, to find relevant information. The derived information aimed at answering the previously mentioned subquestions.

1) Study characteristics: The aggregation of publication details, such as date and venue, permits the observation of the evolution of clinically validated CDSS over time. Another way to get insight into the subjects of the selected articles is through its keywords.

2) Data visualization: The taxonomy of CDSS is a subject of discussion in the academic field, with articles using broader and more general parameters [25], while others center on specific aspects, such as setting and benefits [26]. The lack of a consensual taxonomy difficulties the discussion on the topic, which can lead to miscommunications.

In this report, we used the taxonomy described by *Wright et al.* [5], categorizing the CDSS in six categories: *Medication dose support*; *order facilitators*; *point-of-care alerts*; *relevant information display*; *expert systems*; and *workflow support*. The categorization of the selected article will focus on the main aims of the CDSS, thus limiting the overlap of taxonomies. For a better understanding of the used taxonomies and respective subcategories, refer to *Wright et al.* [5],

Beside the CDSS taxonomy, the selected systems are also studied according to what kind of data visualization representations were used. There is an immense number of usable representations, with some applicable to a generalization of cases, such as line graphs, histograms and scatter plots, and others that are specific to certain fields, like cartograms for geographical regions. As previously mentioned, the way that data is represented can ease the cognitive load of the users, making the analysis of the most used representations an interesting effort.

Another crucial aspect taken into account is if the design process adheres to HCI design principles, when relating to the user interface. In the context of CDSS, this implies that the systems are user-friendly, intuitive, and that support the clinical workflow rather than disrupting it. The selected articles were considered as adherent if the design process was based on co-design with practitioners or if the usability was tested.

3) Evaluation: An adequate evaluation of CDSS is a diverse topic, and crucial in increasing the adoption of these systems in clinical settings. Regarding data visualization, the validation of the tools can be based on distinct metrics, such as communication improvements, performance, user satisfaction, and knowledge discovery [27]. In this review, we describe six different categories for the evaluation of the selected CDSS. **Features** refers to the practical aspects of the CDSS. In articles marked with this evaluation category, the authors present how the tool works, and what it is capable of doing. **Performance** indicates an analysis of the effectiveness and utility of the CDSS. In short, it means that the authors tested if the tool improved the clinical outcomes, either through an accurate automatic diagnosis, decreases in clinical errors, more efficient workflow, and so on. **Usability** tests are used to assess the user satisfaction with the tool. This can be performed through informal feedback, surveys, or technical usability tests. A number of CDSS promote **Knowledge** discovery through its visualization interfaces and algorithms. Since evaluation of knowledge discovery and reasoning is not straightforward, in the present review, this category is used to describe articles that present hypothesis or insights made evident by the respective CDSS. **Communication** is an important aspect both in the patient-clinician relationship, but also in the efficiency of the clinical workflow. Articles that present Communication results focus on either of these aspects. Finally, **Acceptance** relates not only to implementability related results, but also to the degree to which the clinical practitioners use the tool.

III. Results

A. Study selection

The initial probing of the previously mentioned electronic databases resulted in a total of 121 articles, reduced to 109 after duplicate removal. Through an analysis of the title and abstract to verify the first two criteria, related to availability and experimental work, the number of articles was reduced

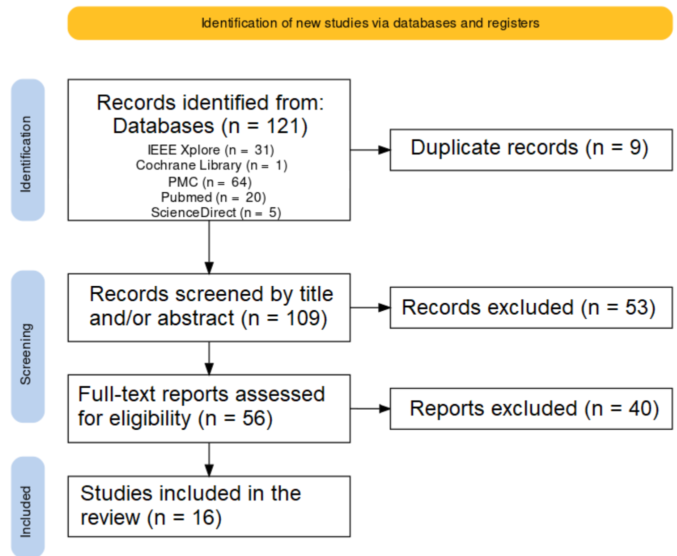

Fig. 1. PRISMA flow diagram describing the study selection process

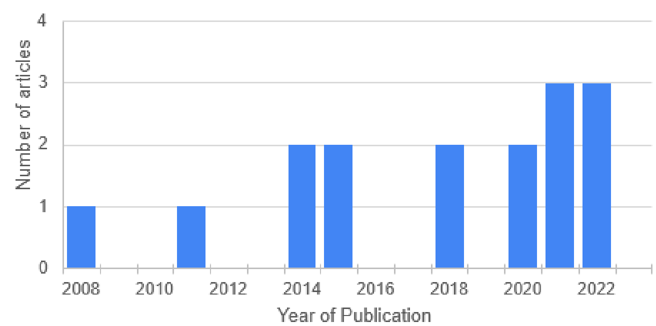

Fig. 2. Histogram detailing the number of published selected articles in each year.

to 56. Finally, through a deeper understanding of the articles, the number of selected articles with clinical validation was reduced to 16. The selection process is described in detail in the diagram of Figure 1.

B. Study characteristics

Out of the 16 selected studies, 81% (13/16) were published in a journal, with the remaining 19% (3/16) published in a conference. Regarding the publication date, the number of articles describing CDSS with clinical validation has been slightly increasing over the years, as shown in Figure 2. The key words of the selected articles were quantified, with ”data”, ”decision”, ”clinical”, ”support” and ”visualization” as the most common terms, followed by ”analytics”, ”learning”, ”electronic”, ”mining” and ”web-based”.

Regarding the clinical validation criteria, it becomes evident that most projects are validated in academic-associated health centers, such as university hospitals. The remaining articles take a variety of approaches, from trials where sensors are installed at patient’s home, to extensive use cases using anonymized clinical data.

C. Data visualization

The respective taxonomies of the selected articles are present in Table I. The most prevalent type of CDSS is the *Expert system*, with 9 CDSS attributed. Regarding the remaining taxonomies, *Relevant information display* has 5 attributed articles; *Point-of-care alerts* has 3 associated systems; both *Workflow support* and *Medication dosing support* have 1 corresponding system each; and finally none of the systems were categorized as *Order Facilitators*.

The proper use of data representations is dependent not only on the nature of the data itself, but also on its visualization purpose. The studied CDSSs employ a variety of data representations, namely system alerts, line graphs with thresholds, tabled values, colour coding, among others. The data visualization methods are noted in Table I.

Of the selected articles, four ([35], [36], [38], [39]) adhered to Human-centered design principles. This correspond to 25% of the selected articles.

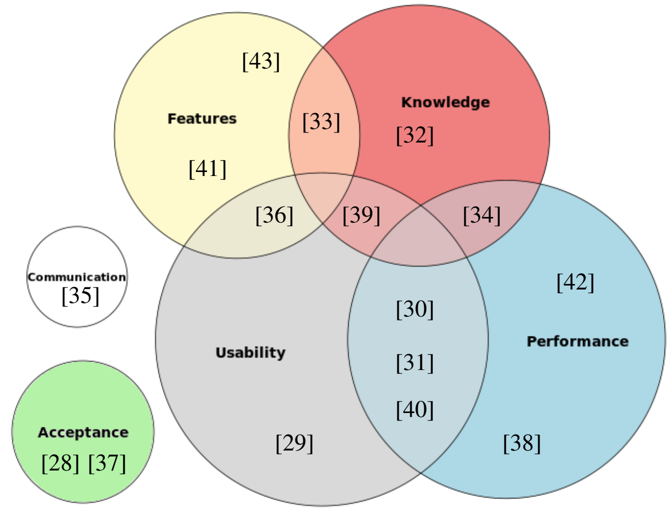

Fig. 3. Euler diagram mapping the selected articles according to the system metrics evaluated.

D. Evaluation

The aspects evaluated in each of the articles are organized in Figure 3, in an Euler diagram. The most evaluated metrics related to *Performance* and *Usability* (6/16), followed by *Knowledge* and *Features* (4/16). The least evaluated metrics are *Acceptance* (2/16) and *Communication* (1/16). The metrics chosen for performance evaluation varied according to the context, with some articles doing test trials with and without the tool, and judging performance based on outcome difference. In terms of usability, most articles reported direct feedback from the end users, namely clinicians. Other methods used for usability testing include individual interviews and questionnaires. The discovery of insights with the support of a CDSS is an intrinsically subjective evaluation, with some of the articles using correlations between the acquired variables and a certain diagnostic, while others opt for providing the clinician with the tools to study trends and patterns. As for the acceptance evaluation, while one of the article highlights implementability factors, the other takes into account the percentage of alarms overridden by the doctors. Finally, the article that evaluates the communication aspect does so by analyzing the interaction between the physician and the patient on several aspects, from topic initiation to visit efficiency.

IV. Discussion

The histogram representing the number of selected articles per year shows a slight evolution of CDSS with clinical validation along the years. This trend is an overall positive: the practical use and testing of the CDSS increases the necessary trust to improve the dissemination and adoption of these systems on a wider scale. The clinical demonstration is an important filter for medical technologies, since some issues related to their use is evidenced by this step. Regarding the key terms used in the selected articles, the most prevalent terms are as expected: ”data”, ”decision”, ”clinical”, ”support” and ”visualization”. Some of the other relevant terms are ”analytics”, ”learning”, ”electronic”, ”mining” and ”web-based”, which gives insights into the kind of technologies and techniques that these CDSS employ.

The most prevalent type of CDSS in the selected articles is *Expert systems*. These systems are the most complex type of CDSS, given their function can be associated with tasks such as diagnosis support, risk assessment and triage tools [5]. The higher prevalence of *Expert systems* was not observed in [5], with *Medication dosing* and *order facilitators* as the most common systems. However, our study has an academic viewpoint, looking into scientific articles, instead of commercial options. *Expert systems* might be harder to be adopted in the clinical practice, justifying the results found in [5], but have a broader potential than other types of CDSS, which explain the academic interest. However, a deep understanding of the other types of systems would also be an important step in recognizing their current shortcomings, which would allow for recognition of better informed strategies to follow. A significant correlation between the article's publication date the the type of CDSS was not found.

The CDSSs analyzed in the chosen articles use a wide variety of data representation methods, notably [43]. Despite the most common representations being quite simple, namely alerts and line graphs, these were often used in tandem with other illustrative techniques, such as threshold marking and colour coding. Graphical tools are often found to be underutilized in clinical settings [44], making a wide variety of data visualization methods useful as a way to represent the data in the most intuitive and straightforward way.

The results of the systematic review indicate that only a quarter of the Clinical Decision Support Systems studied in this review employed human-centered design principles in their development. The usability of a CDSS is seen as a central success factor for the system, and human-centered design is a viable approach to guarantee this characteristic [45]. An ineffectually designed tool can cause fatigue or even

TABLE I
TAXONOMY AND VISUALIZATION METHODS OF THE SELECTED ARTICLES' CDSS

Ref	Pub. date	Taxonomy	Components	Clinical Validation Environment	Evaluation Method
[28]	Oct-2020	Medication dosing support / Point of care alerts	Alerts	Hospital implementation	Override rate (Acceptance)
[29]	Jun-2008	Relevant information display	Facet Browsing; Treemap; Colour code	Clinical partners	Direct clinician feedback (Usability)
[30]	Nov-2015	Expert system	Histogram; Line graph; Link and node graph	Intensive Care Unit implementation	Accuracy, recall and precision (Performance); Questionnaire (Usability)
[31]	Jun-2018	Expert system / Relevant information display	Tables; Line graphs; Hierarchical tree; Colour code; Images; Icons	Hospital implementation	Accuracy comparison of clinical outcome without and with CDSS features support for clinicians, and automatic prediction (Performance); Direct clinician feedback (Usability)
[32]	Sep-2014	Relevant information display	Line graphs	Hospital implementation	Correlation between complex measures and pathological states (Knowledge)
[33]	Oct-2018	Workflow support	Tables; Line graphs; Colour code; Pie chart; Bar columns; Cloud map	Hospital implementation	Trends over time of effects of CDSS, differences between departments and studies (Knowledge)
[34]	Dec-2021	Expert system	N/A	Data from medical center	Determination of patient-specific factors across syndroms and antimicrobial resistence pattern identification (Knowledge); Comparison between CDSS-suggested therapy and physician's decision (Performance)
[35]	Jul-2022	Relevant information display	Line Graph; Tables; Thresholds; Annotations	Primary Care Implementation	Length of discussion, ease of use, and patient involvement (Communication)
[36]	Dec-2020	Expert system	Line graphs; Bar graphs; Colour code; Tables; Trends	Hospital Implementation	Direct written, drawn and verbal clinician feedback, and individual semistructured interviews (Usability)
[37]	Oct-2015	Expert system	N/A	Neo-Natal Intensive Care Unit Implementation	Computing requirements for implementation (Acceptance)
[38]	Nov-2021	Point-of-care alerts	Alerts	Academic Health System Implementation	Comparison of potentially erroneous prescriptions before and after tool implementation (Performance)
[39]	Dec-2011	Point-of-care alerts	Alerts	Living facility implementation	Relevant sensors and patterns for early detection (Knowledge); Iterative review cycles (Usability)
[40]	Aug-2021	Expert system	Table; Colour code	Tertiary Care Center Implementation	Comparison between CDSS responses and past cultures (Performance); Direct clinician feedback (Usability)
[41]	Jun-2022	Expert systems / Relevant information display	Line graphs; video; tables	Neurocritical Care Unit	—
[42]	Apr-2014	Expert system	Alerts; Tables	Hospital Implementation	Sensitivity, specificity and predictive values of tool (Performance)
[43]	Jun-2022	Expert system	Tables; violin plots; bar charts; coordinate visualization; line graphs; scatter plots	Oncology Center Implementation	—

indirectly decrease patient outcome [46], [47]. As such, one of the fundamental design principals of new CDSS, or even improvements to existing ones, should be the usability aspect, through human-centered design frameworks.

A detailed analysis of the evaluation metrics used in the selected articles allows to conclude that there is an unequal attention for these metrics. The most notable example is related to *Communication*, with only one representative example. The relationship between doctor and patient is an often overlooked aspect of the clinical environment, and should be analysed as such. In respect to multidisciplinary validation, out of the selected articles 44% (7/16) evaluate more than one metric. This multidisciplinary validation permits a broader look at how the CDSS impacts the clinical workflow, and should be preferred over a single evaluation metric. There was no observable significant association between the evaluated metrics of each article and its publication date.

A. Limitations

A detailed analysis with a focus on CDSS is still a difficult problem to approach, due to the lack of generalized taxonomies and methods accepted by the scientific community. In this work, some previously described taxonomies were used, such as the one used for the type of CDSS. However, a broader categorization of several aspects of CDSS must be further studied. This would improve scientific communication between CDSS designers, users and researchers.

Some other limitations can be associated to the search process and the selected articles. More specific types of CDSS could be studied to better understand how each field of study deals with their particular challenges. By taking a broader approach, this more particular challenges are not taken into account. Similarly, by only considering CDSS with clinical validation, the number of selected articles was decreased significantly, thus increasing the likelihood of induced bias.

Despite being developed as tools to inform clinicians, a number of the articles that describe these CDSSs do not provide sufficient description of how these informations are presented, namely [34] and [37]. On the other hand, the majority of articles ([29], [30], [31], [32], [33], [34], [36], [40], [41], [42], [43]) show images of parts or the totality of the interface of the developed CDSSs. This not only eases the comprehension of the tool, but is also helpful for comparison studies such as the present systematic review.

B. Recommendations

As a culmination of the previous analysis, a number of insights can be summarized as a list of recommendations for the design of future CDSS, or the improvement of existing ones.

- If possible, validate the CDSS in a clinical setting. This not only increases the trust and success of said system, but can also be an important step in finding flaws or possible improvements.
- Design the interface as to reduce cognitive load. There is a good number of data visualization methods that can be adapted to every context and data type.
- Classify the designed CDSS with taxonomies accepted by the target community. This not only helps to better define the aim of the CDSS, but can also help inform external entities of what it is able to do. However, the potential of the CDSS should not be limited to the taxonomy.
- Visual representations of the user interface can help comprehension of how the tool works and how to utilize it to its fullest potential.
- Preferably, use human-centered design principles during the development phase. Usability is still one of the main gaps between the development and implementation of CDSS.
- Evaluate the CDSS in a variety of metrics. The success of CDSS is not dependent on one singular evaluation source. Instead, the implementation and use depend on the performance in a holistic approach.

V. Conclusions

Even though there are certain challenges particular to each CDSS application, there exist a number of procedures and methods that can be used in general, for the development of more user-friendly CDSS.

Clinical validation is still a limiting factor for a great number of CDSS, and a major obstacle that must be overcome so that these systems are widely accepted in clinical settings. As a method of testing effectiveness, clinical validation also proves itself essential for ensuring the safety of CDSS of the patient while keeping or improving the medical workflow. However, it is often overlooked during the development phase, undermining the credibility and trust in CDSSs.

This review also highlights the lack of defined CDSS taxonomies, which makes it difficult to compare and evaluate CDSS. Furthermore, it also presents challenges for health-care professionals, who may have difficulty navigating and selecting the most appropriate CDSS for their needs. The development of a clear and widely-accepted taxonomy for CDSS is essential for the effective implementation of CDSS in the clinical setting.

Finally, the evaluation of the CDSS was also referenced in this systematic review. By considering multiple dimensions of CDSS evaluation, a more comprehensive understanding of their strengths and limitations can be obtained. This can inform the development of more effective and beneficial systems. The developed CDSS should be evaluated based on different metrics, such as performance, usability, support in insight formation, communication improvements, and implementability.

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