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The Role of Data Science in Electronic Health Records: How Medical Decision Making can be improved based on a Comprehensive Electronic Medical Record?

Ph.D. Thesis
Ph.D. program in Computer Engineering
Department of Computer Science and Automation

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Francisco José García-Peñalvo, Ph.D., Full Professor in the Department of Computer Science and Automation at the University of Salamanca (Spain), as supervisor of the Ph.D. thesis entitled "The Role of Data Science in Electronic Health Records: How Medical Decision Making can be improved based on a Comprehensive Electronic Medical Record?" developed by Ali Azadi.

Hereby declare that

This Ph.D. thesis, developed in the context of the Ph.D. The Programme of Computer Science of the Department of Computer Science and Automation at the University of Salamanca (https://ror.org/02f40zc51) presents enough merits (theoretical and practical) evaluated through the proper assessment, publications, and original proposals to be given and defended publicly.

Salamanca, Spain, December 2025

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Abstract

Despite the integration of modern technologies in medical applications, a significant gap remains in achieving high-level interaction between medical staff, physicians, and the systems they utilize. This gap often results in inefficiencies, user frustration, medical errors, and, in some cases, compromised patient safety, highlighting the critical need for improved system design. To address this issue, this thesis examines the impact of user interaction with these systems in medical settings, with a focus on the crucial role of Human-Computer Interaction (HCI) elements. A comprehensive systematic literature review (SLR) was conducted to identify and categorize HCI elements applicable within Clinical Decision Support System (CDSS) environments, emphasizing the necessity for Electronic Medical Records (EMRs) to be designed with these elements in mind, as they serve as the primary data source for CDSS.

The current thesis extracted and categorized various HCI evaluation methods from existing studies based on their technical characteristics, providing a structured guideline for future investigations. Furthermore, the thesis details the impact of each HCI element on CDSS functionality, distinguishing between positive contributions and negative factors (termed "HCI barriers") that hinder effective interaction. Solutions to these barriers are also discussed in a dedicated chapter.

Fundamentally, this thesis introduces a pivotal bridge between HCI principles and the critical domains of medical data management and quality. This foundational work has already led to the publication of three peer-reviewed scientific papers in prestigious journals, demonstrating its significant contribution to the field. Moreover, the benefits of integrating these HCI elements into other interconnected medical platforms, such as Personal Health Records (PHRs), were articulated.

A novel cyclical EMR model is proposed that restructures patient data into distinct treatment cycles, thereby aligning digital records with the iterative nature of clinical workflows. This model enhances several critical HCI elements (including interface clarity, individuality, explainability, and user satisfaction) while improving data analysis and decision support accuracy. Empirical evaluations based on the proposed model reveal that structured data categorization and cycle-based data entry enhance the transparency and explainability of CDSS outputs, contributing to improved system usability and interpretability.

Ultimately, this thesis presents a scientific framework that bridges the gap between HCI and medical data management, offering both theoretical insights and practical contributions to medical informatics. The significance of these contributions is further demonstrated by the publication of four peer-reviewed papers in prestigious journals, establishing a robust foundation for advancing CDSS development and user-centered system design in future research.

Keywords: Human-Computer Interaction; Clinical Decision Support Systems; Electronic Medical Records; Data Quality; Cyclical Approach; User-Centered Design; Usability Evaluation Methods

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List of Acronyms

AI – Artificial Intelligence
ANOVA – Analysis of Variance
API – Application Programming Interface
CDSS – Clinical Decision Support System
EC – Exclusion Criteria
EHR – Electronic Health Record
EMR – Electronic Medical Record
FHIR – Fast Healthcare Interoperability Resources
GDD – Goal-Directed Design
GOMS – Goals, Operators, Methods, and Selection Rules
GUI – Graphical User Interface
HCI – Human–Computer Interaction
HCPs – Healthcare Providers
HL7 – Health Level Seven
HTN – Hypertension
IC – Inclusion Criteria
IoT – Internet of Things
iPaaS – Integration Platforms as a Service
IU – Intention to Use
IUFD – Intrauterine Fetal Demise
MDSS – Medical Decision Support System
MIMIC – Medical Information Mart for Intensive Care
MQs – Mapping Questions
NLP – Natural Language Processing
PHR – Personal Health Record
PhD – Doctor of Philosophy
RQs – Research Questions
RSME – Rating Scale Mental Effort
SDOH – Social Determinants of Health
SLR – Systematic Literature Review
SNOMED-CT – Systematized Nomenclature of Medicine Clinical Terms
SUS – System Usability Scale
TAP – Think-Aloud Protocol
UTAUT – Unified Theory of Acceptance and Use of Technology

Chapter 1

Introduction

1.1 Introduction

Electronic Medical Records (EMRs) are structured digital repositories of patient health information that serve as the foundational data source for Clinical Decision Support Systems (CDSS). EMRs capture longitudinal clinical data (such as diagnoses, medications, lab results, and treatment plans), which CDSS algorithms analyze to generate context-specific, evidence-based recommendations that support clinical decision-making [1]. While EMRs are typically confined to data generated within a single healthcare organization, Electronic Health Records (EHRs) extend this scope by integrating patient information across multiple institutions and care settings. Despite this distinction, both EMRs and EHRs are frequently used interchangeably in the medical context, and each serves as a critical data source for CDSS functionality, contributing structured clinical inputs that inform system logic and decision pathways [2].

CDSS rely firmly on the quality and structure of data prepared within EMR and eHealth systems. The relationship between CDSS and data preparation in these systems is critical: well-organized and accurately entered data enhances the CDSS's ability to provide precise and reliable recommendations, thereby improving patient outcomes [3]. Proper data organization and structures facilitate efficient data retrieval and analysis, which are essential for adequate decision support [4]. In this regard, Human-Computer Interaction (HCI) elements play a pivotal role in medical information systems, significantly affecting how healthcare professionals interact with these systems, enabling easy and minimal learning needs and efforts [5]. The importance of human interaction with medical systems cannot be overridden, as poorly designed interfaces can lead to data entry errors, incomplete records, and user frustration. Conversely, user-friendly interfaces and interactive features can enhance user experience, streamline data entry processes, and ensure the generation of structured data that is ready for analysis and decision-making [6]. In this way, many of the probable problems that may arise in the next steps of the decision-making process can be avoided.

From another perspective, since EMR and the design of data forms and fields serve as the gateway for medical data preparation, it is crucial to pay sufficient attention to HCI elements. Encouraging healthcare professionals to interact with the system effectively ensures the collection of well-structured data, making this focus on HCI elements a serious necessity.

Identifying the HCI elements applicable in CDSS environments is crucial. These elements include user interface design, data control, and interactive features, all of which contribute to the effectiveness with which healthcare professionals can input and access data. Well-designed HCI elements can reduce the cognitive load on users, minimize errors, enhance the overall efficiency of medical data management, and ultimately reduce treatment costs in terms of both time and finances [7],[8].

To evaluate medical information systems and CDSSs effectively, it is essential to be familiar with the available methods for assessing HCI aspects tailored for CDSS environments. This includes understanding their categorizations and aims, as well as determining the most suitable assessment method for each specific situation and research context [9]. Through this clear methodological instruction, we will be able to evaluate the medical information systems and CDSS results more precisely and assess these systems after the change and implementation of each HCI element [10]. In this way, the magnitude of the effectiveness relevant to each HCI element can be measured.

For a medical information system to be comprehensive, it must possess a suitable infrastructure to receive medical data competently, control data entry, prepare structured data for decision processing, and ultimately generate precise outputs [11]. In other words, achieving such a comprehensive system is impossible without considering the HCI elements explicitly defined for the CDSS environment. By employing these HCI elements, the functionality of CDSS can be significantly improved. Enhanced interfaces and better system design enable healthcare providers to interpret data more accurately and make informed decisions swiftly [12],[13].

As medical data has become more complex and its volume has increased, the integration of HCI principles into CDSS principles has come to the fore [14]. In the context of digital healthcare transformation, intuitive and efficient interfaces are becoming increasingly important [15]. Advanced HCI elements enhance usability and enable healthcare providers to fully leverage the potential of CDSS without feeling overwhelmed by its complexity [16]. Additionally, CDSS remains relevant and efficient in dynamic clinical environments through iterative evaluation and improvement, based on user feedback and HCI principles [17].

Additionally, understanding the specific challenges and requirements of different medical contexts is essential for tailoring HCI elements to meet diverse needs. For instance, emergency care settings may require rapid data entry and retrieval, whereas chronic care management might prioritize comprehensive and longitudinal data analysis [18],[19]. By customizing HCI elements to these unique needs, CDSS can offer more precise and contextually appropriate support, ultimately leading to better patient care [20],[21].

Advances in machine learning and artificial intelligence further reinforce the importance of HCI in CDSS. As these technologies become an integral part of decision support, the interfaces through which healthcare providers interact with AI-driven insights must be designed to enable seamless integration into clinical workflows [22]. Ensuring that these interactions are intuitive and transparent can increase confidence in the system's recommendations and encourage wider adoption among clinicians.

This PhD thesis will first introduce the evaluation methods for HCI elements within CDSS environments, categorizing these methodologies based on their suitability for different contexts. Following this, we will identify the specific HCI elements that can be extracted through these evaluation methods. Finally, we will examine the role of the identified HCI elements in enhancing the functionality and performance of CDSS. By comprehensively analyzing these components, this research aims to create a clear and structured framework for improving CDSS through targeted HCI enhancements. This approach ensures that each part of the research work builds on the previous one, creating a cohesive understanding of how HCI elements can be systematically identified, evaluated, and integrated to optimize CDSS outcomes.

1.2 Problem description and the research contributions

Exploiting HCI elements within CDSS is crucial for their successful implementation and utilization [23]. However, to effectively detect and incorporate these HCI elements, we first need to understand how CDSS systems can be evaluated and which methodologies can be applied to reach this purpose. There is a significant gap in accomplished studies regarding the categorization and holistic comprehension of these evaluation methods.

Existing studies have explored HCI elements in various medical applications, but they often lack a specific focus on CDSS environments. This omission is critical because the concerns and nuances in CDSS can differ markedly from those in other medical applications [24]. For instance, the complexity and critical nature of decision-making in CDSS require tailored HCI approaches to achieve precision, reliability, and user satisfaction [25].

The necessity of distinguishing HCI elements specifically for CDSS, as opposed to general decision support systems, lies in the unique demands of the healthcare environment. CDSS must seamlessly integrate complex medical knowledge, ensure adherence to stringent clinical guidelines, and accurately handle sensitive patient data, all while minimizing the cognitive load on healthcare professionals [26]. These systems serve as a cornerstone for supporting clinical decisions that directly impact patient outcomes, making usability and user experience paramount. Unlike generic Decision Support Systems, CDSS must navigate the intricate and high-stakes nature of medical decision-making, necessitating a tailored approach to HCI elements that can address these specialized requirements effectively [27].

On the other hand, it remains unexplored how these HCI elements specifically facilitate CDSS functionality. For example, well-structured data entry mechanisms and intuitive interfaces reduce cognitive overload, allowing physicians to focus on clinical reasoning rather than navigating the system [28]. Effective alert design minimizes user fatigue by prioritizing critical notifications without overwhelming users [29]. Furthermore, features such as explainability and data visibility enhance transparency and interpretability, fostering trust and enabling shared decision-making between clinicians and patients [30]. These examples suggest that HCI elements are not merely supportive features, but relatively central to enhancing the efficacy (accuracy, reliability, and clinical relevance of outputs) and efficiency (time savings, error reduction, and workflow integration) of CDSS. Hence, it is crucial to discover the link between the HCI elements and different aspects of CDSS functionality (efficacy, efficiency, and user satisfaction) to investigate HCI elements applicable to the CDSS context.

In this respect, we conducted current research to identify the HCI elements that apply to improve CDSS functionality. Moreover, a noticeable gap exists in categorizing HCI elements specific to CDSS environments. While some researchers have identified and discussed HCI elements broadly, few have delved into classifying them in a way that highlights their impact and applicability within CDSS contexts.

Research contributions

This PhD Thesis aims to address these gaps by making the following contributions:

1. **Categorization of evaluation methods**: We will identify and categorize the methodologies used for evaluating HCI aspects in CDSS environments. This will provide a structured approach to determining the optimal methods for various situations and research contexts.
2. **Identifying HCI elements**: We will conduct a detailed investigation to determine the HCI elements that specifically affect CDSS functionality and outputs. This includes examining how these elements influence user experience, system performance, and the overall effectiveness of CDSS.
3. **Impact analysis**: We will investigate the impact of identified HCI elements on the outcomes of CDSS. This involves understanding how different HCI components affect the accuracy and reliability of clinical decisions supported by CDSS and determining in which aspects these elements can improve CDSS outputs.
4. **Development of methodological guidelines**: We will propose a set of methodological guidelines for evaluating and enhancing HCI in CDSS based on our findings. These guidelines will be designed to be applicable in various healthcare settings and adaptable to future technological advancements.

By addressing these research gaps, this study will contribute to the development of more user-friendly and effective CDSS, ultimately enhancing the adoption and impact of these systems in medical practice.

1.3 Research objectives and questions

Despite the rapid growth in innovative and modern technologies, particularly in medical settings, a significant gap exists in paying adequate attention to the HCI principles in this realm [31]. CDSSs are impacted by this gap in adoption and utilization by physicians. CDSS is designed to assist healthcare providers in making informed clinical decisions by analyzing large volumes of medical data and providing evidence-based recommendations [32]. However, without proper attention to HCI axioms, these systems become a burden to use, leading to user dissatisfaction, reduced adoption rates, and potential errors in clinical decision-making [33].

The significance of this research lies in its ability to improve the usability and effectiveness of CDSS by focusing on the interaction between healthcare professionals and medical information systems. A better user experience can be ensured with improved HCI elements, making CDSS not only technologically sound but also effective and user-friendly. This encourages the physicians to interact with the designed system, consequently enhancing the benefits that can be derived. A lack of research on the evaluation methods and the elements of HCI, specifically those tailored to CDSSs, also emphasizes the current need to explore these topics. Addressing this gap is crucial for developing systems that meet the practical needs of healthcare providers and ultimately improve patient outcomes.

In this context, we examine the existing studies to identify the methods used to assess the HCI axioms relevant to CDSS environments. After the assessment, we aim to identify the HCI elements tailored to the CDSS ambiance and evaluate their impact on the CDSS results. The primary objective of the main investigation is to integrate HCI principles into CDSS to enhance usability, functionality, and clinical outcomes. In this regard, we aim to address several key objectives and research questions:

Research objectives

1. Identify and Categorize Evaluation Methods: Conduct a comprehensive investigation to identify and categorize the evaluation methods used in various CDSS applications and situations. This will help us understand the most effective methods for assessing HCI elements within CDSS environments.
2. Examine HCI Elements in CDSS: Explore the specific HCI elements that influence the functionality and outputs of CDSS. This involves analyzing how different HCI components contribute to system performance and user satisfaction.
3. Assess Impact on CDSS Outcomes: Investigate the consequences of implementing different HCI elements on the effectiveness and efficiency of CDSS. Determine how these elements affect clinical decision-making processes and patient outcomes.

Research questions

1. Which methodologies are used to evaluate HCI elements in CDSS environments?
   - ➢ How are these methods categorized?
   - ➢ In each situation, which of these methods is more suitable?
2. What are the HCI elements that can affect CDSS functionality and outputs?
   - ➢ Which HCI factors have the potential to influence CDSS performance?
   - ➢ What best practices can be derived for integrating these HCI elements into CDSS design?
3. What is the impact of HCI elements on the outcomes of CDSS?
   - ➢ How do the identified HCI components affect the accuracy and reliability of clinical decisions supported by CDSS?
   - ➢ In which aspects can CDSS output be improved by incorporating these HCI elements?

By addressing these objectives and answering these research questions, this study aims to bridge the gap in HCI integration within CDSS, thereby enhancing the usability, efficiency, and overall impact of these systems in medical practice.

1.4 Research methodology

Researchers select the most suitable method based on the study's purpose, current context, and available resources [34]. A study's methods must be aligned with its objectives and context to ensure accurate and reliable results [35]. In this study, we have employed a combination of Systematic Literature Review (SLR) and qualitative methods to explore HCI elements within CDSS environments comprehensively.

To provide a clear overview of the methodological structure and its alignment with the thesis objectives, Figure 1.1 summarizes the integrated research design adopted in this study. The figure presents how the selected research methods collectively support the investigation of HCI elements within CDSS environments. By visually linking the SLR, qualitative analysis, and quantitative empirical evaluation, the figure clarifies how these methods interact to build a coherent and evidence-driven research pathway**.** This integrated design ensures that the study progresses from identifying existing knowledge gaps to interpreting HCI elements in context and finally to validating proposed frameworks through empirical assessment. The figure, therefore, serves as an orienting map, illustrating how the methodological choices contribute to the development and justification of the thesis outcomes.

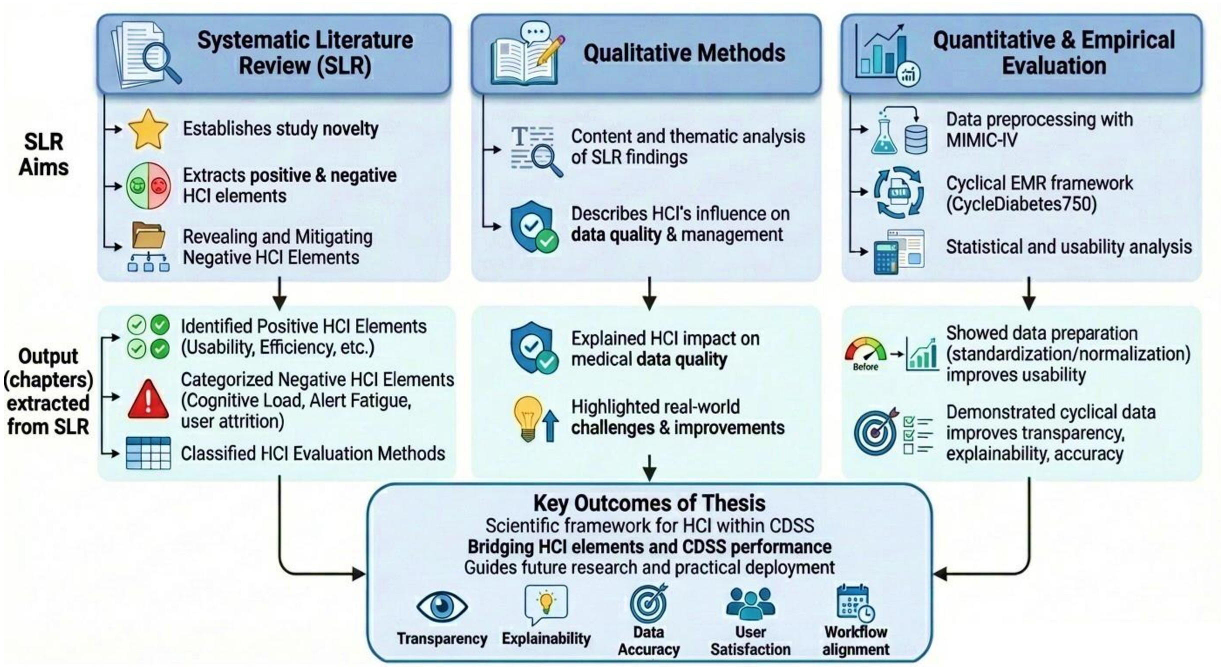


Figure 1.1: Overview and rationale of the research methodology and resulting outcomes

As depicted in Figure 1.1, the research design is organized into three methodological components, each of which is examined in detail in the following subsections**.** These components collectively structure the progression of the study: the SLR establishes the foundational evidence base, the qualitative analysis deepens the conceptual understanding of HCI elements, and the empirical evaluations assess the practical impact of the proposed frameworks. The following sections expand on each methodological component, outlining their procedures, analytical focus, and specific contributions to achieving the thesis objectives.

1.4.1 Systematic literature review

To ensure the novelty and comprehensiveness of our study, we began with an SLR [36],[37]. Launching the SLR method is firmly valuable for several reasons:

Establishing novelty: By systematically reviewing the existing literature, we can confirm that this is the first comprehensive investigation that discusses all HCI elements related to the CDSS environment. This step is crucial to establishing the uniqueness and contribution of our research.

Extraction of HCI factors: The SLR allows us to identify and extract various HCI factors relevant to CDSS. This involves a detailed analysis of existing studies to pinpoint specific elements that influence CDSS functionality and user interaction.

Evaluation methods categorization: SLR also allows us to categorize and extract methodologies used in CDSS environments for evaluating HCI elements. This categorization provides a structured framework for understanding the most effective assessment methods for various situations and research contexts.

The systematic approach of SLR ensures that our study is grounded in a thorough understanding of the existing body of knowledge, highlighting gaps that our research aims to fill and providing a robust foundation for further analysis.

1.4.2 Qualitative methods

In addition to the SLR, we employed qualitative analysis [38],[39],[40] to gain deeper insights into specific aspects of HCI in CDSS:

Content analysis of existing studies: We performed a detailed content analysis of the studies included in our SLR to extract qualitative data related to HCI elements. This method allows us to identify common themes, patterns, and insights from diverse research articles.

Thematic synthesis: We systematically identified and analyzed themes within the qualitatively analyzed literature employing thematic synthesis. The method allows us to contextualize our findings within a real-life context and to understand their broader implications.

Contextual understanding: The qualitative analysis enables us to explain the significance of data entry topics and highlight both positive and negative HCI elements in this realm. It enriches our study by providing a detailed and context-specific understanding of how HCI elements affect CDSS functionality.

1.4.3 Quantitative empirical evaluation

In addition to the methods outlined, this thesis incorporates a series of empirical evaluations to assess the effectiveness of the proposed approaches. These evaluations rely on both real-world datasets and a synthetic dataset developed for this study.

First, MIMIC-IV (Medical Information Mart for Intensive Care IV) was employed in Chapter 6 to analyze the role of data transformation (standardization and normalization) in enhancing CDSS functionality. This real, de-identified dataset, publicly available through PhysioNet, contains detailed information on ICU patients and is widely used in healthcare research. In this thesis, selected laboratory results and demographic variables were extracted to evaluate how structured preprocessing can improve CDSS outputs.

Second, MIMIC-III served as the foundation for generating a synthetic dataset used in Chapter 7. To investigate the proposed cyclical EMR framework, we constructed a dataset named MIMIC-Cycle750, which extends MIMIC-III with additional fields capturing treatment cycles, outcomes, and temporal dynamics. Unlike MIMIC-IV, which was used directly, MIMIC-Cycle750 is a synthetic dataset specifically designed to test the cyclical approach.

By combining real-world data (MIMIC-IV, MIMIC-III) with this enriched synthetic dataset (MIMIC-Cycle750), the thesis provides a comprehensive evaluation: (i) assessing the impact of data preprocessing on CDSS performance, and (ii) demonstrating how cyclical structuring of EMRs can improve data transparency, usability, treatment analysis, and alignment with HCI principles. For clarity, an overview of the datasets used within the empirical sections of this thesis is summarized in Table 1.1.

Table 1.1: Overview of datasets used in this thesis

Dataset Name	Source	Type	License	Preprocessing Summery
MIMIC-IV	PhysioNet	Real-world	PhysioNet Credentialed Health Data License 1.5.0	Used in Chapter 6 for lab event analysis and normalization; accessed under credentialed agreement
MIMIC-III	PhysioNet	Real-world	PhysioNet Credentialed Health Data License 1.5.0	Used as structural inspiration for a synthetic dataset; no direct patient data reused
CycleDiabetes750	Synthesized from MIMIC-III	Synthetic	Open-access via Zenodo Repository	Custom fields added to simulate treatment cycles; glucose-based tagging; validated against MIMIC-III distributions

All datasets (listed in the table above) and associated Python scripts used in the analyses are available via Zenodo repositories, as referenced in the relevant chapters.

The empirical findings provide robust evidence that the proposed framework enhances diagnostic precision and aligns more closely with real-world clinical workflows. In other words, the integration of HCI considerations highlights the importance of interface design and user experience in enhancing treatment decision support.

We have combined this approach to ensure that our study is comprehensive and nuanced, addressing research questions from multiple angles and offering robust conclusions for future research and practical applications.

In summary, the selected research methodology is designed to provide a thorough and credible investigation of HCI elements in CDSS environments. The SLR lays the groundwork by systematically synthesizing existing knowledge, while qualitative analysis enriches this foundation with detailed, context-specific insights. The integration of quantitative empirical evaluation further validates the proposed cycle-based framework, effectively bridging technical performance with key HCI considerations to contribute valuable advancements to the field.

1.5 PhD thesis structure

This PhD thesis will deconstruct the organizational framework employed throughout its eight constituent chapters. Each chapter will be demonstrably cohesive, adhering to a singular, well-defined purpose that contributes to the thesis's overarching objective.

Chapter 1 sets the stage for research by introducing the field of study and the specific area that has piqued interest in this topic. This chapter examines the core problem that this research seeks to address, highlighting the existing knowledge gap and its significance for further investigation. It outlines the research objectives that render this dissertation, along with the specific methodology chosen to tackle the problem. Furthermore, the chapter details the research questions that will drive the investigation and the anticipated contributions this research will make to the field.

Chapter 2 presents a systematic literature review to establish the novelty of this research and identify relevant existing work. This SLR aims to pinpoint knowledge gaps in the current body of literature and confirm whether this study represents the first comprehensive examination of HCI elements within CDSS environments. The chapter meticulously details the defined SLR protocol, the specific databases employed, and the formulated SLR queries. By analyzing the final selection of papers and extracting relevant data, Chapter 2 lays the groundwork for the subsequent chapters.

Chapter 3 focuses on harnessing established evaluation methods employed in HCI assessments, particularly those used in the final stages of research studies. It examines which HCI evaluation methods are most effective and adaptable within the context of CDSS environments. The chapter will provide a nuanced framework for selecting the most appropriate method based on the research question and specific circumstances. Additionally, it will explore strategies for assessing the accuracy of the CDSS itself, ensuring a comprehensive evaluation approach.

Chapter 4 describes the negative (dark side) HCI elements that can adversely affect CDSS environments. By introducing these elements, we aim to prevent their occurrence and, consequently, user fatigue, which is a serious barrier to enhancing overall system performance. This chapter highlights the potential risks associated with poorly designed HCI elements and their impact on user interaction with the system and decision-making accuracy.

Chapter 5 illustrates the bridge between the identified HCI elements and data quality concepts. The relationship between some HCI elements (such as alerts, HCI facilitators, data visibility, and ease of use) and data science dimensions will be addressed in detail. In this chapter, we articulate why HCI elements must be considered to improve data quality, thereby elevating the accuracy level of medical decisions made by CDSSs.

Chapter 6 underscores the critical importance of data management and data entry control. It examines the extent to which medical data can be managed and controlled to provide suitable information for informed decision-making. This chapter highlights the value of data integration and unifying isolated subsystems to make more accurate medical decisions. We indicate why data entry is considered the gateway for data supply within CDSS and how it can impact the CDSS performance.

Chapter 7 explores system design approaches within CDSS environments, focusing on ongoing debates and differing priorities among HCI experts. It critically assesses the limitations of current systems in addressing physicians' practical needs during medical treatments. This chapter presents a cyclical medical framework that aims to enhance alignment between CDSS design and real-world clinical workflows. Through an empirical examination, this approach is evaluated to determine how it enables physicians to track treatment plans, compare evolving medical outcomes, and refine interventions based on data-driven insights, ultimately enhancing usability, efficiency, and decision accuracy.

Chapter 8 concludes the study by summarizing the key findings and highlighting the contributions to the field. It provides recommendations for implementing HCI improvements in CDSS environments and reflects on the overall significance of the research. This chapter also states the potential impact of these findings on other research projects within this realm and suggests directions for future work.

Chapter 2

Literature review

2.1 Introduction

Clinical Decision Support Systems are designed to enhance patient care by equipping physicians with intelligently structured clinical knowledge and patient-specific data. However, their effectiveness is often compromised by poorly designed user interfaces (UIs), which can lead to cumbersome data entry and a decline in data integrity [41],[42]. Consequently, the performance of medical information systems integrated with CDSSs can be impacted [43]. Given that CDSSs rely on electronic medical records as their primary source of patient data, inaccuracies in data entry (such as typos, inconsistent formatting, and missing values) pose significant challenges for further analysis [44]. These data inconsistencies lead to flawed CDSS recommendations, which healthcare professionals frequently attribute to insufficient user interaction and system usability issues [45]. Human-computer interaction (HCI), rooted in ergonomics, cognitive science, and psychology, plays a pivotal role in addressing these challenges by designing technology that prioritizes usability and efficiency [46]. A well-integrated HCI approach fosters a more profound understanding among healthcare providers (HCPs) of their workflows, ensuring that data within EMRs is structured for optimal clinical utility to prevent mental fatigue [47].

While HCI research traditionally focuses on interface design and human-computer engagement [48], its application in healthcare extends beyond aesthetics (it aims to improve physician-system interaction), making technology more intuitive and accessible [49].

Studies reveal that poorly designed graphical user interfaces (GUIs) can frustrate physicians, thereby reducing the adoption and effectiveness of CDSSs [50]. Conversely, integrating HCI principles into CDSS design significantly improves user satisfaction and enhances system functionality [51].

Despite various studies on HCI elements, a clear gap remains in identifying which factors most influence CDSS performance. To bridge this gap, this study conducted a systematic literature review (SLR) focusing on key HCI elements that shape the usability and effectiveness of CDSS. The review systematically evaluated design components (including text formatting, font choices, layout strategies, and usability metrics) that impact user interaction and information processing [52]. By assessing usability principles, we ensure that CDSS development aligns with both technical precision and user experience requirements, resulting in systems that are more functional and accessible.

The findings from this SLR serve as a foundation for subsequent chapters. By analyzing HCI evaluation methods and their impact on CDSS performance, this chapter lays the groundwork for refining system design and enhancing physician-system interaction. Ultimately, this study establishes a structured approach for optimizing CDSS usability, data integrity, and clinical decision support, making it a valuable contribution to advancing HCI research in healthcare.

2.2 Review process

In this section, we describe the systematic literature review (SLR) process we followed to ensure a thorough and unbiased summary of the existing research. Using the methodology outlined by Kitchenham and Charters [53],[54], we set out to capture the complete landscape of related studies clearly and systematically. To add further context and depth to our findings, we also employed a systematic literature mapping approach, as outlined in the work of Kitchenham, Budgen, and Brereton [55].

We structured our review process into three main stages (planning, execution, and reporting), ensuring that each step was carefully documented so that others can reproduce our work. By adhering to the strict protocols recommended in [56], we maintained transparency throughout the review. This rigorous yet accessible approach has enabled us to present our findings in a manner that not only withstands academic scrutiny but also invites readers to fully understand and appreciate our methodology.

2.3 Review planning

Effective SLRs require meticulous planning to ensure rigor, transparency, and reproducibility [57]. In this thesis, the planning phase began with the formulation of research questions (RQs) designed to focus on specific aspects (such as evaluating the impact of HCI elements in CDSS environments) alongside mapping questions (MQs) to survey the literature landscape comprehensively. The PICOC framework was then employed to define explicit inclusion and exclusion criteria based on population, intervention, comparison, outcome, and context, ensuring that only the most pertinent studies were considered. By integrating both RQs and MQs, a balanced approach was achieved that provided both depth and breadth to the review process. Quality assessment measures were subsequently applied to examine the methodological rigor and reliability of the selected studies, thereby enhancing the credibility and validity of the findings. This structured approach established a clear roadmap (from initial planning to the synthesis of results) for delivering a robust and comprehensive analysis of HCI elements in CDSS environments.

2.3.1 Research questions

The scope of our study was defined through the careful formulation of research questions (RQs) that precisely reveal the focus of our investigation [58]. By systematically addressing both research and mapping questions, this study seeks to reveal and consolidate essential insights into HCI elements within CDSS environments, thereby contributing to advancements in the field.

Based on these identified areas of concern, the following review questions were raised:

- **RQ1**: Which evaluation methods have been applied to assess the CDSS environment?

- **RQ2**: What are the HCI elements in medical information systems that can affect CDSS functionality?
- **RQ3**: What is the effect of considering the identified elements on improving CDSS performance?

To broaden our understanding of the context and scope of our systematic literature review, a set of mapping questions (MQs) was developed to steer our analysis. These MQs offer valuable insight into the overall landscape and distribution of pertinent studies:

- **MQ1**: Year-wise distribution of studies – What has the distribution of studies been by identified HCI elements over the years?
- **MQ2**: Publication venues – What is the distribution of studies between journal papers and conference papers?
- **MQ3**: Geographical distribution of studies – Where have the studies related to HCI elements in CDSS been conducted worldwide?
- **MQ4**: Focus distribution – What percentage of the identified studies discuss each HCI element (e.g., alerts, workload adversity, system design defects, mental efforts)?

2.3.2 PICOC framework

To address the questions raised, the PICOC approach advanced by Petticrew and Roberts [59] has been utilized to delineate the scope of the review. PICOC refers to Population, Intervention, Comparison, Outcome, and Context and has been utilized to systematize and clarify the focus of the research review.

Population (P): The review will consider all the studies dealing with software solutions, subjects of all implementations, and design. Although the review focuses on properties and attributes related to EMRs, the targeted studies are those examining HCI factors within CDSSs.

Intervention (I): The interventions examined in this study focus on approaches that introduce or adapt specific factors aimed at addressing HCI considerations within EMRs and eHealth systems.

Comparison (C): No comparison intervention has been planned.

Outcome measure (O): The main outcome of this review is to identify and establish key HCI elements that play a critical role in enhancing the functionality and effectiveness of CDSS, ensuring improved user interaction and system performance.

Context (C): The review delves into all the studies relevant to the EMR and eHealth systems. It will include all the papers describing the successful experience in implementing and designing EMR in the medical environment, such as hospitals or medical centers, throughout the world.

2.3.3 Inclusion and exclusion criteria

A set of inclusion criteria (IC) and exclusion criteria (EC) was established to systematically filter articles, ensuring that only those capable of addressing the research questions (RQs) were selected while dismissing studies that fell outside the scope of the review. The initial search was conducted in July 2024 and subsequently updated on October 15, 2025, to incorporate the most recent developments. Since 2000, significant interactions have been observed between HCI elements and CDSS applications [56]. Although the concept of HCI began to receive formal academic development in the early 1980s, CDSS emerged even earlier, in the 1970s [60]. The previous cutoff of July 2024 corresponded to the preparation of the peer-reviewed article included in this thesis; however, the review has now been extended to ensure that the thesis reflects the most current literature available at the present time of thesis preparation (October 15, 2025).

IC1: The papers propose a pragmatic and implementable solution (methods, techniques, model, tool, framework) AND

IC2: The proposed solution is applied on software OR application OR platform OR service OR infrastructure OR system AND

IC3: The papers that were written about (Electronic medical records OR EMR OR eHealth OR HER

OR Electronic Health Records) AND

IC4: The proposed solution supports or addresses tailoring attributes and criteria to improve or enhance medical decision support capabilities AND

IC5: The papers are written in the English language AND

IC6: The paper has been published after 2000 and before October 15, 2025 AND

IC7: The full paper should be available AND

IC8: The tailoring capabilities are related to the Human-computer Computer Interaction OR usability OR user interface OR user experience OR user-centered AND

IC9: The articles are published in peer-reviewed Journals, Books, or Conferences (only including conferences that are peer-reviewed and ranked B or above in the CORE Conference Ranking or are considered the top two quartiles (Q1 or Q2) in the SJR)

The exclusion criteria are derived from the inclusion criteria as their opposite:

EC1: The papers do not propose a pragmatic and implementable solution (methods, techniques, model, tool, framework) OR

EC2: The proposed solution is not applied to software OR application OR platform OR service OR infrastructure OR system OR

EC3: The papers that were not written about (Electronic medical records OR EMR OR eHealth OR EHR OR Electronic Health Records) OR

EC4: The proposed solution does not support or address tailoring attributes and criteria to improve or enhance medical decision support capabilities) OR

EC5: IC5: The papers are not written in the English language OR

EC6: The paper has been published before 2000 or after October 15, 2025 OR

EC7: The documents for which the full paper is not available OR

EC8: The tailoring capabilities are not related to the Human-computer interaction OR usability OR user interface OR user experience, or user-centered OR

EC9: The articles are not published in peer-reviewed Journals, Books, or Conferences (only conferences that are peer-reviewed and ranked B or above in the CORE Conference Ranking or are considered the top two quartiles (Q1 or Q2) in the SJR).

2.3.4 Search strategy

The three most appropriate databases (Scopus, Web of Science, and PubMed) were chosen as the primary sources based on the following criteria:

- It is a reference database in the research field.
- It is a relevant database in the research context.
- It allows for the use of search strings along with Boolean operators to refine and enhance the retrieval process, ensuring comprehensive and relevant results.

According to the research objectives, we investigated exclusively the studies focused on HCI elements that have a direct or indirect impact on medical decision-making within CDSS environments.

2.3.5 Quality assessment

While inclusion and exclusion criteria help identify the relevant work to study, they do not account for the quality of the retrieved papers in terms of their ability to address the posed research questions. To guarantee the strength and validity of our results, a new quality assessment criterion was determined prior to inclusion in the final literature review.

Assessment of quality is a major part of the SLR process because it ensures that only the most adequate studies in terms of relevance and rigor are used in the final analysis [61]. It not only strengthens our findings, both conceptually and practically, but also enables the identification of potential limitations or biases in existing literature.

In this research, a scoring system was adopted where each co-author independently responded to every question using Kitchenham and Brereton's guidelines [62]. This method minimizes individual bias and boosts the reliability of our assessment. In our system, a "Yes" scored 1 point, "Partially" 0.5 points, and "No" 0 points (with a study able to earn a maximum of 7 points).

To ensure clarity and consistency, the quality questionnaire and its associated phases are outlined below:

1. **Design clarity and relevance:** Are the research aims and objectives clearly stated and aligned with the study's focus on HCI elements in CDSS?
2. **Data collection and relevance:** Does the paper provide comprehensive and relevant data pertinent to HCI elements within CDSS, including metrics for evaluation?
3. **Empirical measurement and methodology:** Are the HCI elements empirically measured with well-defined metrics, and is the methodology for evaluating these elements clearly described?
4. **Analysis and documentation:** Are the research results documented granularly, including the participants' information, observational units, and analysis methods?
5. **Conclusion validity and research questions:** Do the study's conclusions adequately answer the research questions, and are the implications for HCI and CDSS clearly articulated?
6. **HCI evaluation method:** Is the HCI evaluation method used in the study justified and described in sufficient detail?
7. **Relation between HCI elements and CDSS Outcomes:** Does the study adequately illuminate the relationship between the applied HCI elements, the CDSS outputs or results, and their consequences?

The studies must score at least 5 out of 7 to reach the next phase of the review. This threshold ensures that only studies of the highest rigor and relevance are included, filtering out lower-quality studies that might skew the results or introduce bias.

The minimum score for the studies to progress to the next stage of the review should be 5 out of 7. This threshold ensures the inclusion of only rigorously conducted and relevant studies, excluding those of low quality that could potentially distort the results or introduce bias. To further confirm the quality assessment process as well as to establish inter-rater reliability, we calculated Krippendorff's alpha [63], an inter-rater reliability measure. Krippendorff's alpha was 75.33%, which implies the data were interpreted acceptably and in a similar manner among the co-authors. This measure of consistency is important to establish that the quality assessment process was utilized uniformly and objectively for all the studies. When disagreements arose, we exchanged views to reach a consensus. These discussions were imperative to clarify differences in interpretation to enable the overall decision to represent a mutual understanding among the co-authors.

2.3.6 Query strings

Each of the considered sources was searched using relevant terms developed from the PICOC method's results [64], joined by Boolean AND / OR operators. The standard search formula creates a template with a standard design to maintain consistency between databases. This standard search formula is then customized for the syntax of each database [65]. The applied exclusive commands are as below:

1) SCOPUS:

(TITLE-ABS-KEY (“human-computer interaction" OR "HCI" OR "usability" OR "user experience" OR "user interface" OR "User-Centered") AND TITLE-ABS-KEY (“Electronic Medical Records" OR "EMR" OR "Electronic Health Records" OR "EHR") AND TITLE-ABS-KEY ("Clinical Decision Support Systems" OR "CDSS" OR "*decision support system*" OR "DSS" OR "artificial intelligence" OR "AI"))

2) WoS:

(TS= ("human-computer interaction" OR "HCI" OR "usability" OR "user experience" OR "user interface” OR “User-Centered”) AND TS= ("Electronic Medical Records" OR "EMR" OR "Electronic Health Records" OR "EHR") AND TS= ("Clinical Decision Support Systems" OR "CDSS" OR "decision support system*" OR "DSS" OR "artificial intelligence" OR "AI"))

3) PubMed:

(("human-computer interaction" OR "HCI" OR "usability" OR "user experience" OR "user interface" OR "User-Centered") AND ("Electronic Medical Records" OR "EMR" OR "Electronic Health Records" OR "EHR") AND ("Clinical Decision Support Systems" OR "CDSS" OR "decision support system*" OR "DSS" OR "artificial intelligence" OR "AI"))

2.4 Data extraction process

The process of gathering data to perform the current SLR has been divided into different phases, where numerous inspections are carried out. PRISMA flow diagram [66] has been used to illustrate the carried-out actions in a detailed manner to obtain the necessary data (Figure 2.1).

After the search was carried out, the paper selection process was done, consisting of the following phases:

A) The raw data, consisting of records obtained from executing the queries in three databases, are available in the associated dataset [67], accessible via the Zenodo repository: Raw Data SLR.

This dataset is organized into separate sheets for each database: 551 papers from Scopus, 224 from WoS, and 267 from PubMed.

B) After arranging the records, duplicate papers were eliminated. This means 334 works were removed; 708 works (67.9%) were left for the next steps.

C) At the first step of the screening, reading the titles, abstracts, and keywords and applying inclusion and exclusion criteria, 514 studies were eliminated as they did not meet the criteria, so 194 papers (18.6%) were selected for the next phase.

D) Since 6 papers were not accessible to read the full text, the 188 papers that had arrived at this stage were read in detail and further scrutinized. After exhaustive text examination, 120 papers (11.5%) were removed for the following reasons:

- 58 papers contained the HCI elements even in medical environments, but these detected elements were unrelated to CDSS subjects.
- 42 papers did not explicitly express the HCI or usability elements, although they discussed the CDSS functionality.
- 20 papers did not describe lucidly the relationship between pointed HCI factors and CDSS functionality.

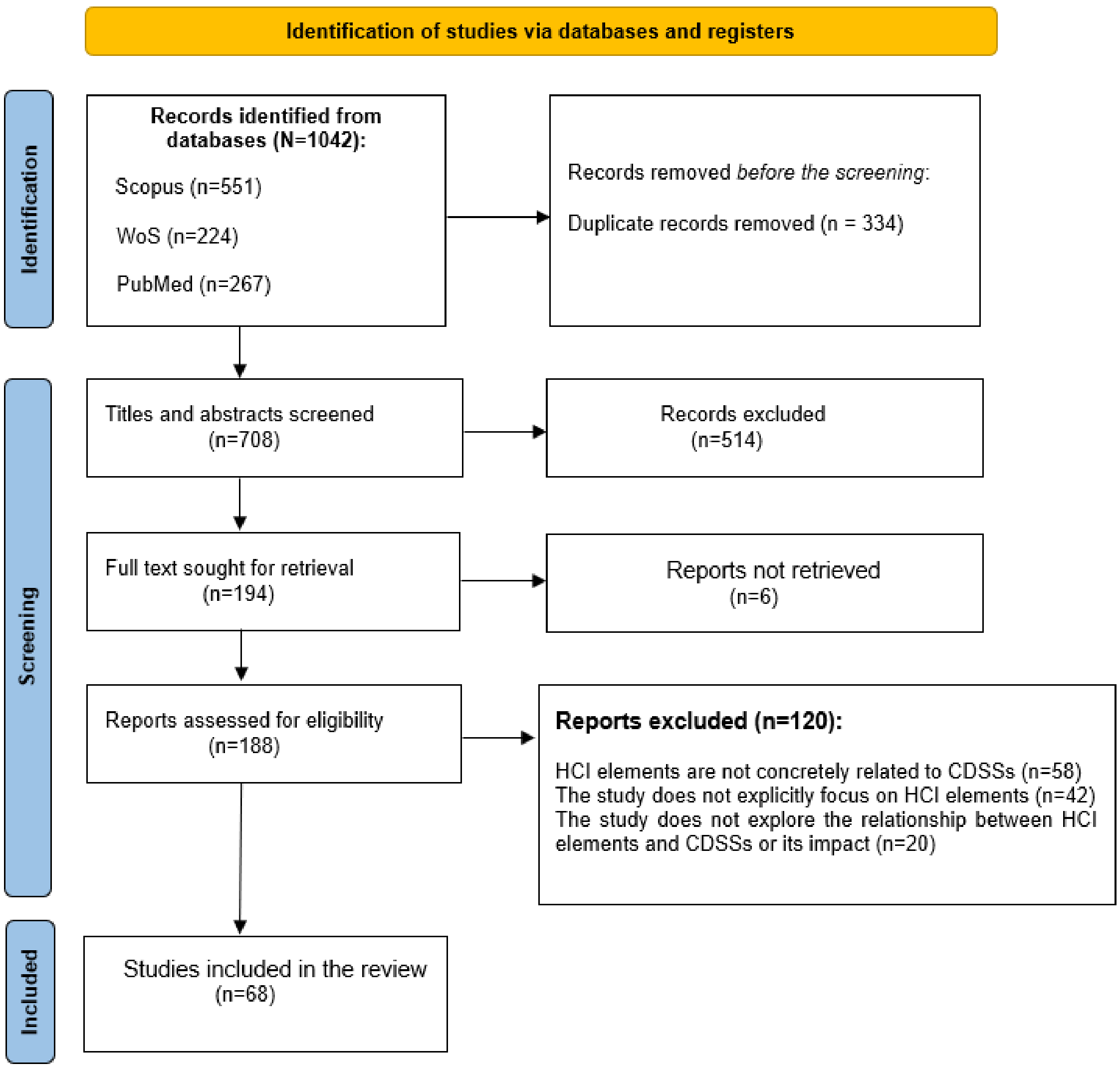


FIGURE 2.1: PRISMA 2020 flow diagram for the phases and outcomes of the systematic reviews (updated review process carried out on October 15, 2025)

After excluding irrelevant papers based on the outlined criteria, 68 papers were selected for the final analysis and review. This represents 6.52% of all unique retrieved papers and 36.17% of the full-text assessed papers. The complete list of selected studies is available in the associated dataset [68], accessible via Zenodo: Final Stage Papers.

2.5 Results of systematic literature mapping

This section presents the results of the systematic literature mapping conducted to explore the broader landscape of research on HCI factors influencing CDSS. Guided by a set of mapping questions (MQs), the analysis focuses on identifying publication trends, geographical and temporal distributions, and the venues in which relevant studies have appeared. The mapping also highlights the extent to which specific HCI elements have been addressed across the literature. These findings offer valuable contextual insights into the evolution and concentration of research efforts, thereby helping to frame the scope and relevance of subsequent review activities.

2.5.1 What is the year-wise distribution of studies by identified HCI elements? (MQ1)

After the review process, 12 key HCI elements were identified. Each final-stage paper primarily focuses on one dominant element, as illustrated in Figure 2.2. While some studies explored multiple aspects, the figure highlights the main HCI element addressed in each case. The chart also illustrates the evolution of attention to various HCI elements in relation to CDSS over the years. Although CDSS technology began to take shape in the 1990s [26], interest in HCI (especially in areas such as usability, user experience, and interface design) started gaining traction in healthcare around the same time [69]. This study highlights the convergence of HCI and CDSS functionality, a trend that has been evident since 2003 and has accelerated notably since 2015, as shown in Figure 2.2.

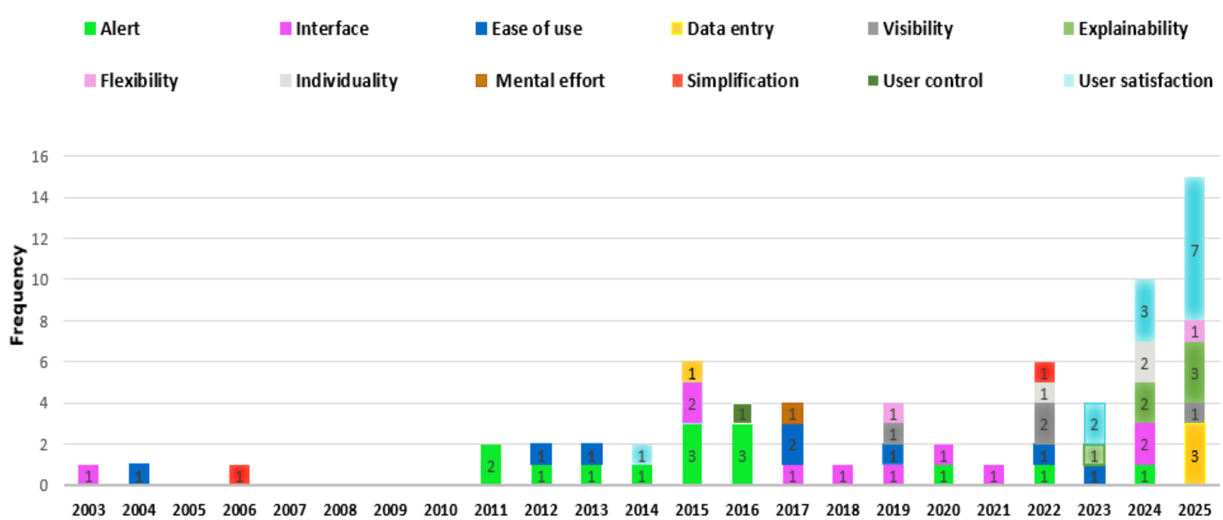


Figure 2.2: Temporal distribution of HCI elements in CDSS over the years

Additionally, the chart above illustrates a significant surge in recent years, particularly in the user satisfaction element. This trend highlights the growing recognition of user-centered design as a crucial component in healthcare technology. By prioritizing usability and efficiency, it seeks to enhance the effectiveness of CDSS in facilitating informed and accurate clinical decision-making [70].

2.5.2 Publication venues and study type distribution (MQ2)

An analysis of the final-stage papers reveals that most of them were published in academic journals.

Table 2.1: Distribution of HCI element research across top journals

Journal Name	Number of published articles	Representative Studies	Target HCI elements
Journal of Biomedical Informatics	5	[71], [72], [73], [74], [75]	Alerts, Ease of use, Interface
International Journal of Medical Informatics	6	[76], [77], [78], [79], [80], [81]	Alerts, Ease of use, Interface, Simplifying, Explainability
JMIR Human Factors	5	[82], [83], [84], [9], [85]	Alerts, Ease of use, Visibility, user satisfaction
Applied Clinical Informatics	5	[86], [87], [88], [89], [90]	Alerts, Mental efforts, Ease of use, user satisfaction, Data entry
Applied Sciences-Basel	1	[91]	Data entry
Computers in biology and medicine	1	[92]	User satisfaction
Data journal	1	[93]	Data entry
Studies in health technology and informatics	1	[94]	flexibility
Journal of Medical Internet Research	4	[95], [96], [97], [98]	user satisfaction, Individuality, explainability
Medical Informatics and Decision Making	1	[99]	user satisfaction
Journal of Personalized Medicine	1	[100]	user satisfaction
Health Policy and Technology	1	[101]	explainability
Journal of Multidisciplinary Healthcare	1	[102]	Visibility
Health Informatics	1	[103]	user satisfaction
JAMIA Open	1	[104]	Alerts
American Medical Informatics Association	1	[105]	explainability
hepatology communications	1	[106]	Interface
JMIR Research Protocols	1	[107]	Interface

The journals with the highest proportion of published articles in this field are listed in Table 2.1. This table also reveals which HCI elements have been investigated by each journal.

This indicates a strong preference for publishing research findings related to the HCI aspects of CDSS through peer-reviewed journal articles, which are highly respected in the academic world. Additionally, we identified one paper as a book chapter, which offered in-depth summaries and discussions of subjects, making valuable contributions to the field as well.

According to the response to MQ2, such a distribution indicates the quality and rigor of the studies included, ensuring that the conclusions and results presented in this review are grounded in well-explored and well-analyzed data.

2.5.3 What is the geographical distribution of the studies that were conducted? (MQ3)

Our research to answer MQ3 reveals that a single study was conducted collaboratively in Spain, the United Kingdom, and Sweden. We have a total of 68 studies across 17 countries. As shown in Figure 2.3, the geographical distribution reveals an intense concentration of studies in the United States and Europe. This reflects a global interest in advancing CDSS through improvements in HCI-related factors. The United States leads with the highest contribution, accounting for 41% of the included studies (30 articles).

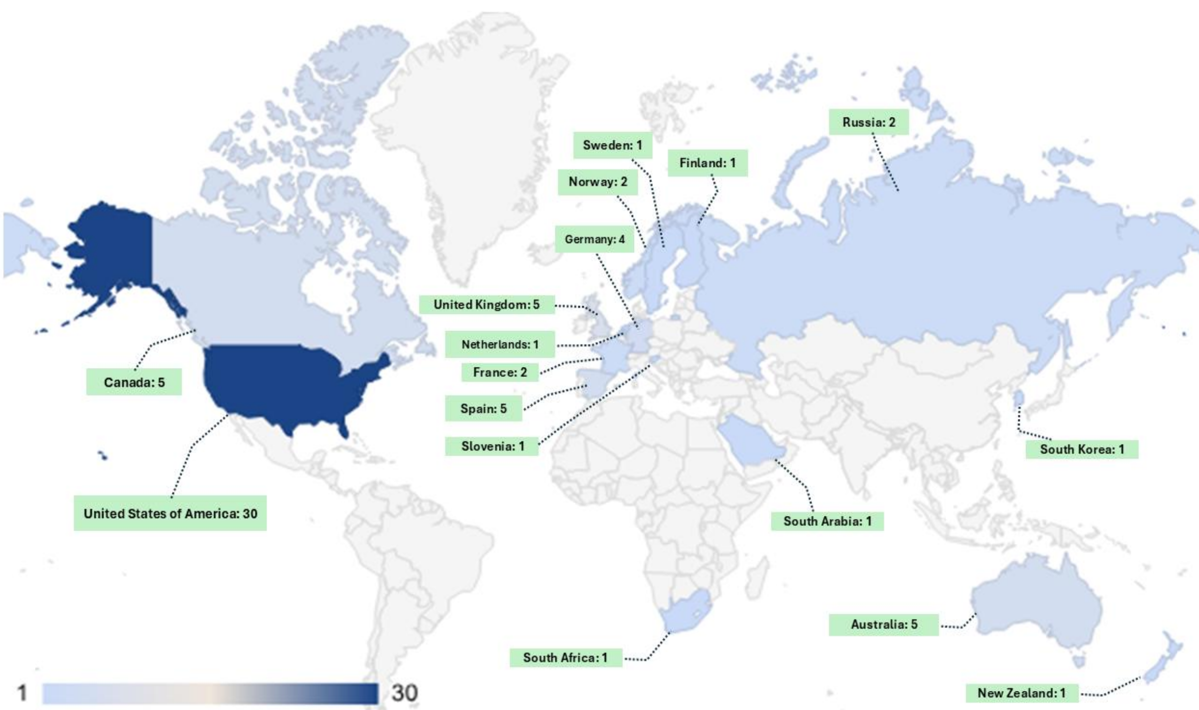


Figure 2.3: Geographical distribution of performed studies throughout the world

Next is the United Kingdom with 8.8% (6 articles), followed by Canada and Australia, each contributing 7.35% (5 articles). Spain and Germany both account for 5.8% of the studies. In this respect, France, Russia, and Norway contribute at lower levels, each representing approximately 3% of the reviewed literature.

Table 2.2 presents the countries where these studies were conducted, along with their distribution and key focus areas.

Table 2.2: Geographical distribution of HCI research focused on CDSS

Country	Number of Studies	Representative Studies	Target HCI Elements
USA	30	[108], [86], [82], [9], [72], [75], [76], [77], [78], [79], [83], [87], [88], [109], [110], [111], [112], [113], [114], [115], [116], [117], [96], [89], [99], [90], [97], [104], [106], [105]	Alerts, Ease of use, Explainability, User satisfaction, Interface, Mental efforts, User control, Visibility, Individuality
United Kingdom	6	[74], [84], [118], [119], [92], [98]	Ease of use, Interface, User satisfaction, Explainability
Canada	5	[73], [80], [120], [101], [107]	Ease of use, interface simplifying, Explainability
Russia	2	[121], [122]	Alerts, Data entry
France	2	[71], [123]	Alerts, Simplifying
Australia	5	[124], [125], [95], [81], [95]	Alerts, Ease of use
Spain	4	[126], [91], [93], [85]	Ease of use, Data entry, User satisfaction
Finland	1	[127]	Alerts
Germany	4	[128], [129], [94], [102]	Individuality, User satisfaction, flexibility, Visibility
Netherlands	1	[130]	Interface
New Zealand	1	[131]	Flexibility
Norway	2	[132], [133]	User satisfaction, Individuality
South Africa	1	[134]	Visibility
Sweden+Spain+UK	1	[135]	Visibility
Slovenia	1	[136]	User satisfaction
Saudi Arabia	1	[133]	User satisfaction
South Korea	1	[103]	user satisfaction

Although Asia has seen rapid technological growth and rising healthcare demands, our analysis identified only two studies addressing HCI aspects in the CDSS domain across the region. In contrast, no relevant studies were found in South America, indicating a complete lack of investigation in this field. These findings highlight a significant research gap in the global development and evaluation of HCI-integrated CDSS.

Our analysis reveals that the focus on different HCI aspects varies from one country to another, depending on specific needs and established policies and priorities. In the USA, studies of the HCI factors in CDSS alerts (10/30 papers), interaction with the user interface (4/30 papers), and user satisfaction (4/30 papers) have been researched more extensively than other HCI aspects. While the above main HCI aspects are essential, specific HCI needs can be prioritized based on different cultural aspects and localized requirements [137].

2.5.4 Focus distribution of HCI elements influencing CDSS functionality (MQ4)

As discussed in earlier sections, our in-depth analysis of 68 full-text studies identified 12 distinct HCI elements that have the potential to influence the functionality of CDSS. These elements were classified based on their intrinsic characteristics, application context, and relevance to the user experience, particularly from the perspective of medical professionals.

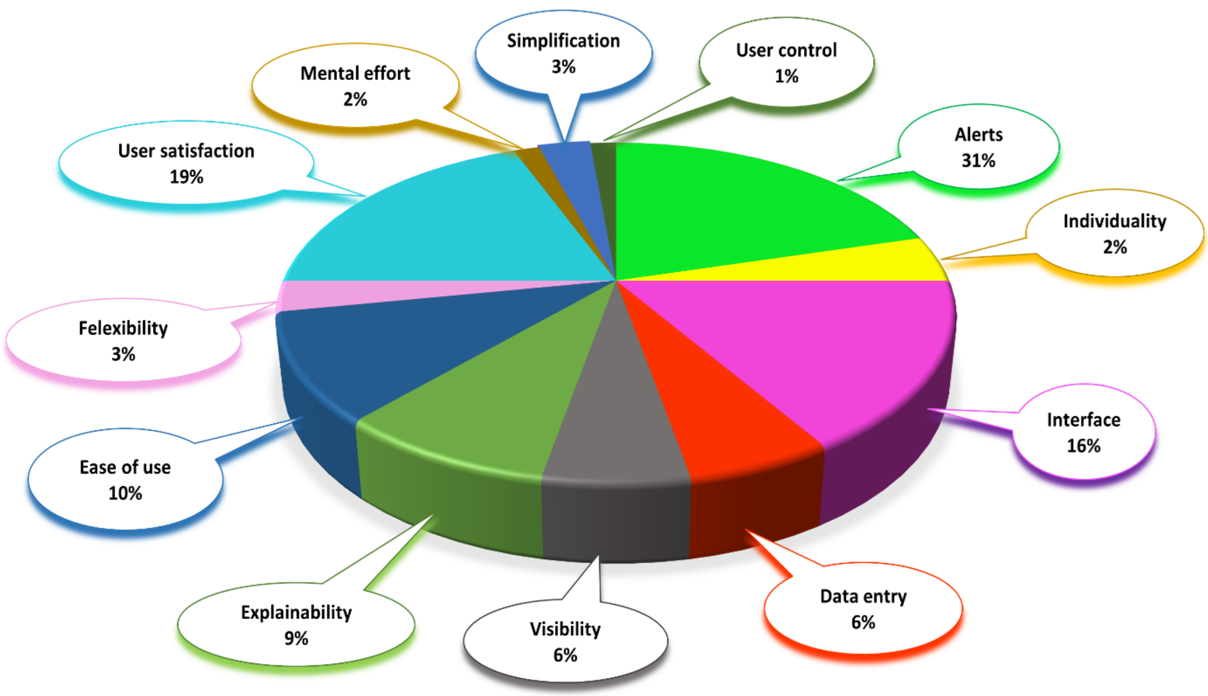


Figure 2.4: Frequency distribution of identified HCI elements

As illustrated in Figure 2.4, the emphasis on each element varies across the reviewed literature. Based on this classification, each HCI element plays a unique role in shaping the usability and effectiveness of the CDSS. The following subsections provide a closer look at these elements, highlighting their significance, practical implications, and varying degrees of emphasis within existing research.

2.6 Results of the SLR (RQ2, RQ3)

This section presents the results of the systematic literature review, which aimed to identify and analyze key HCI elements relevant to the design and performance of CDSS. A total of 68 studies were selected for in-depth analysis and the extraction of these HCI elements.

The evaluation methods employed in the reviewed studies are comprehensively discussed and analyzed in Chapter 3. This chapter addresses *RQ1* by comprehensively introducing and categorizing the techniques used in CDSS environments. The primary focus of the current section is to identify the specific HCI elements addressed in the literature and to analyze how these elements influence the functionality and performance of CDSS.

Before presenting the identified HCI elements, it is important to clarify their functional roles within CDSS environments. Based on the literature, these elements can be conceptually grouped into two categories: those that act as barriers to system performance and must be mitigated, and those that serve as facilitators and should be enhanced to improve usability and decision support. This classification reflects the dual nature of HCI in clinical contexts (some elements introduce friction or cognitive burden, while others streamline workflows and improve user experience). Figure 2.5 presents this categorization, offering a visual summary of the twelve HCI elements identified from the SLR.

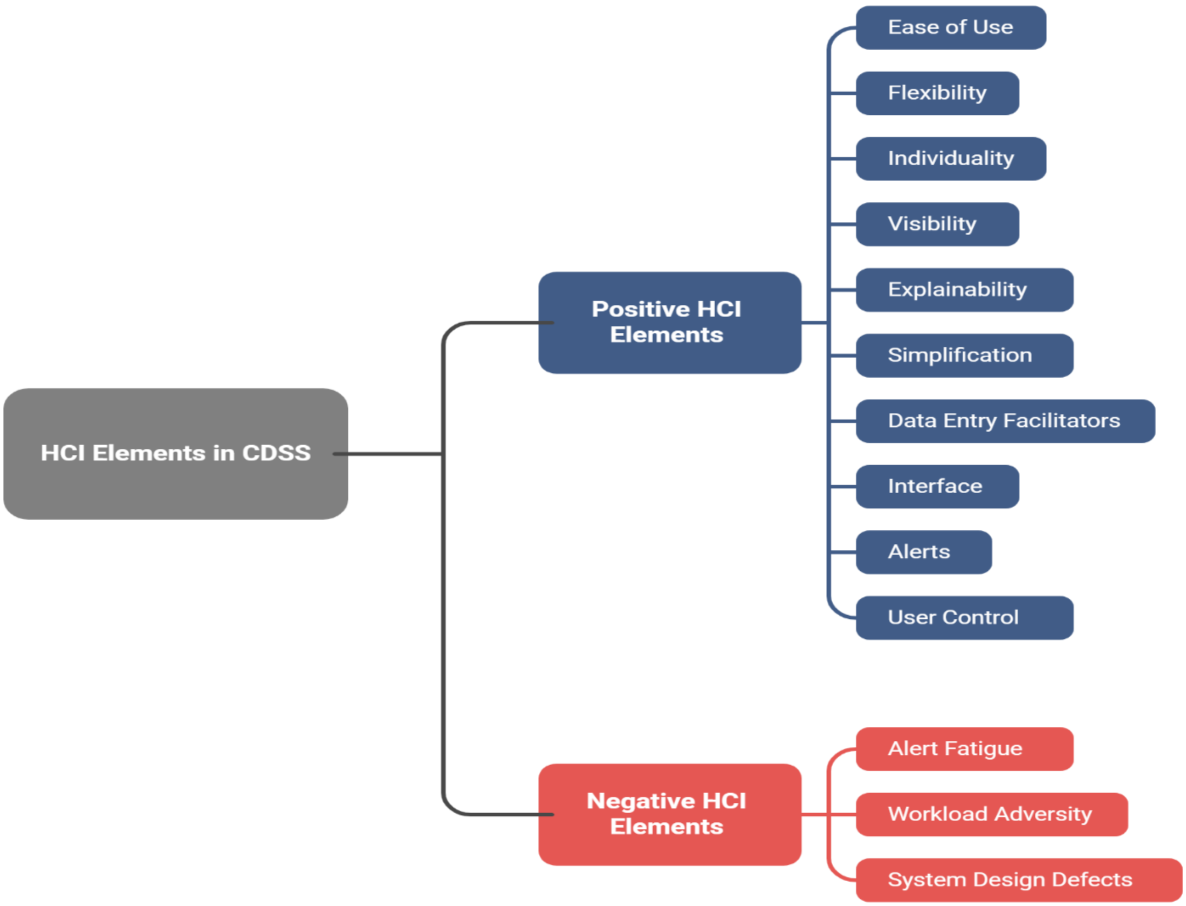


Figure 2.5: Categorization of positive and negative HCI elements

One of the identified HCI elements (alerts) appears in both groups. This reflects its dual role: well-designed alerts can guide clinicians effectively and improve decision quality, whereas poorly configured or excessive alerts contribute to alert fatigue and interrupt clinical workflows.

The harmful HCI elements and the solutions proposed in the literature to mitigate them will be discussed in detail in Chapter 4. In the following subsections, RQ2 and RQ 3 will be answered by describing each of the HCI elements observed across the reviewed studies and their specific roles in CDSS functionality.

2.6.1 Alerts have been introduced in this research as the most prominent HCI element within CDSSs. These alerts help improve patient safety and clinical efficiency by delivering timely information that healthcare professionals can act upon. Clinical Decision Support System alerts serve as critical tools, notifying healthcare professionals about potential drug interactions, pinpointing severe allergies, and highlighting abnormal laboratory findings that require urgent attention from physicians. Alert systems contribute to improved patient care by reducing medical errors while ensuring rapid clinical responses and guideline adherence, which together enhance patient outcomes and workflow efficiency [76],[138].

Practical exploration of alert-related issues requires differentiating between alerts and alarms, as merging them results in a flawed system design. HCI contexts require alerts and reminders to be treated as separate entities because they perform different functions [139]. Alerts deliver urgent, real-time notifications that reduce cognitive load, enabling users to make informed, immediate decisions. Reminders provide continuous cues to ensure critical tasks are completed while supporting long-term adherence to guidelines [140]. Too many reminders or those that are irrelevant result in cognitive overload and frustration. Alerts become barriers when they fail to serve their purpose, but transform into facilitators when they help physicians perform their tasks effectively [141]. The usability and functionality of CDSS require optimization through a balanced HCI design that makes this distinction.

According to Figure 2.4, precisely 31% of the final review papers focus on topics related to alerts. Most of the research shown in Figure 2.2 was conducted between 2011 and 2016, with additional focus in 2020 and 2022. Three primary thematic areas of alert studies are described in Table 2.3.

Table 2.3: Three principal alert categories impact CDSS functionality

Alert fatigue (Override) phenomena	[86]	[82]	[111]	[47]	[104]	
Usability flaws	[71]	[108]				
Alert (design) recommendation	[76]	[109]	[72]	[77]	[124]	[110]

A current challenge with CDSS tools is alert fatigue, when users begin to ignore or override alerts due to their excessive frequency [142]. This issue can reduce the effectiveness of the system and compromise patient safety. Gong and Kang [111] proposed five strategies to combat alert fatigue: (1) Increase alert specificity to reduce irrelevant interruptions; (2) Prioritize alerts based on severity; (3) Apply key human-centered design principles, such as clear formatting, appropriate content, legibility, and effective use of color; (4) Tailor alerts to individual patient characteristics; (5) Customize alerts to suit the needs and preferences of medical professionals.

Another critical factor is timing. Alerts should appear at moments that support thoughtful clinical decision-making. They must be noticeable enough to prompt attention, but not so disruptive that they interfere with the care process [86]. Striking this balance is essential to prevent what's known as habitual override (a common symptom of alert fatigue).

Usability flaws related to CDSS that prevent reductions in performance with alerts are described in the following [71]**:**

- The differentiating visualizations do not effectively display the confusion and variety of severity and risks associated with the alerts.
- The information provided before the alerts has a lot of material (too much) and is not brief.
- A low signal-to-noise ratio means the number of correct alerts is small compared to the errors caused by outdated or inaccurate data.
- There are problems with alert contents due to missing relevant material to alert objectives, identifying data to assess, or meaningful guidance on what to do.
- Insufficiency of information as to what causes the alerts.
- Clinicians are not directed to rectify the situation that the alert addressed.
- Alert calamitousness initiated by the system may not meet the needs of the different user types.
- Workload impacts caused by the alerts generate numerous tasks to recover from the errors or retrieve the necessary information.

Two alert deficiencies are common in medical information systems, including both general and specific ones. General alert flaws occur because alerts are nonspecific or do not clearly communicate their severity [108]. Specific alert flaws occur because alerts do not adequately contextualize the individual patient's or healthcare provider's own needs. There are too many alert notifications, or notifications that are not important or meaningful [143].

The alert recommendations for improving alert functionality were examined from multiple angles to boost overall alert performance. Here's an overview of the key aspects:

- **The visual interface:** It enhances alert clarity by employing varied colors, bullet points, and clear guidelines, along with well-crafted text [76]**.**
- **Appropriateness in workflow:** It ensures alerts are triggered at the right moment within clinical workflows, making them timely and relevant [72].

- **Avoiding False Alarms:** Base alert logic on accurate, up-to-date information, and avoid rigid calibration that could lead to false alarms [109].
- **Alert Placement:** Position alerts based on their urgency (critical alerts might interrupt the workflow to capture immediate attention) [72].
- **Habituation:** Reduce repetitive, low-impact alerts to prevent user desensitization and alert overrides, thereby minimizing fatigue [109].
- **Consistent Terminology:** Use standardized language to enhance clarity and consistency across different scenarios and regions [144].
- **The mental model:** Consider that users develop personal interpretations (such as the color red signifying "stop"), which can shape their responses to alerts. [109].
- **Concise content** briefly describes the reason for the triggered alert or medical repercussions [145], although further details are accessible through the related data links [146].
- **Font and size:** Leverage typography (through appropriate fonts and sizes) to highlight the alert's significance [77],[147].
- **Alert visibility** is a prominent HCI factor that should be considered in alert design within the CDSS environment [124]. It optimizes the display of alerts by carefully balancing size, brightness, contrast, and typography, ensuring they catch attention quickly [148], [149].
- **Severity:** The intensity of an alert should match the seriousness of the medical issue. For minor problems, a gentle nudge is enough [77]. For critical situations, such as a potentially deadly drug error, the alert should be bold and may even pause the doctor's work to ensure they address the problem immediately [124].
- **Proximity of the decision-making components:** It means incorporating decision-making aids, such as hyperlinks to relevant medical resources, directly within the alert for immediate action [110].

Enhancing how alerts function in CDSS not only streamlines clinical workflows but also ensures timely access to crucial information, reduces alert fatigue, builds user trust, and ultimately supports more informed and adequate decision-making in healthcare [130].

2.6.2 Ease of use is one of the most critical user concerns, with a rate of concern of 10% in 68 complete review papers (Figure 2.4). This is to be expected, and it is a standard expectation for the user, especially physicians. In this context, the system should be designed to enable users to use it with ease; this is referred to as Perceived Ease of Use (PEU). A higher level of PEU leads to an increase in Intention to Use (IU) [126].

The user should easily navigate the system's sections, and the system should be free of potential negative feelings, such as disappointment or anxiety, regarding their choices [84].

An easy-to-use system will positively increase learnability because it allows users to understand the steps more clearly and remember them more easily [150].

In CDSS applications, the ease of use can significantly enhance system utility and functionality, providing healthcare professionals with quick and uncomplicated access to clinical guides and aids for decision-making [125].

2.6.3 Interface, another important HCI element**,** has been paid attention to as much as ease-of-use elements (16%), especially between 2015 and 2024. One key area of HCI is user interface design. This involves designing the visual and interactive aspects of a computer or technology product, such as buttons, menus, and icons. The goal is to create interfaces that are easy to use, efficient, and satisfying for the user [3]. Although interface design often encompasses multiple HCI elements, the six papers we analyzed offer distinct insights that extend beyond the scope of the other factors discussed. These studies provide targeted recommendations for enhancing interface design, which can significantly improve user interaction by optimizing system usability and promoting intuitive use.

Despite recent advances in computerized technologies, the defective design of GUIs in medical environments may lead to frustration among physicians [151]. In the context of CDSS, the UI refers to the graphical or visual representation through which users interact with the system to access, input, and interpret information [115]. An effective UI should be intuitive, user-friendly, and tailored to the needs and workflows of healthcare professionals [79]. By integrating with EHR, well-designed interfaces can present a list of possible diagnoses in the CDSS environment associated with medical symptoms, as well as the compatibility percentage between the patient’s current medical factors and the factors in the diagnosed illness [152], [118]. Leonardo et al. [74] proposed the five key UI factors influencing CDSS functionality: documentation time efficiency, availability, expressivity, structure, and quality. In the UI context, the design documentation time efficiency implies timely access to patient data, while availability ensures continuous access to the system. Expressivity and structure contribute to the clarity and organization of interface elements, facilitating user interaction.

A responsive and interactive UI enables clinicians to swiftly navigate through complex medical data, facilitating quick access to critical information during decision-making processes [153], meaning that the required medical data will be adequately fed to the decision-makers even in multiple presentation layers if necessary, so that the physicians can make the best possible decision [154], [155].

2.6.4 Visibility has been tackled in 6% of the reviewed papers, highlighting that rapid access to information requires making data easily accessible within a brief period and ensuring that medical data is available where users anticipate finding it [134]. In CDSS treatment cycles, visibility pertains to the clarity and transparency of workflow stages and progress. This ensures that healthcare providers can effortlessly monitor and comprehend the status of the treatment process, including diagnostic tests, medication administration, and patient outcomes [9].

The visibility criteria facilitate efficient patient care tracking by providing a clear and transparent overview of the treatment cycle. This enables informed decision-making based on real-time treatment progression, ultimately optimizing patient outcomes [156]. Furthermore, visibility in CDSS can also help reduce errors and improve communication between healthcare teams. By providing a shared understanding of the patient's treatment progress, visibility fosters better collaboration and coordination, ensuring that all team members are aligned and can contribute to the best possible patient care. This shared visibility fosters coordination among team members, thereby minimizing the chances of miscommunication and ensuring that treatment protocols are followed accurately [26].

2.6.5 Simplification elements were addressed in 3% of the final reviewed papers. The concept of optimizing these elements involves removing unnecessary complexities and creating a workflow that aligns closely with real-world practices [157]. Pantazi et al. [80] introduced a theory that highlights a paradox within medical systems: simplifying a system can enhance usability, but often at the expense of addressing only straightforward problems. Conversely, tackling more complex issues typically requires a level of complexity that may reduce overall usability. This paradox suggests that while simplified systems are user-friendly, they may handle intricate medical challenges. Despite this trade-off, it is crucial to find a balance between complexity and usability [158]. Achieving this balance enables the avoidance of unnecessary complications in medical processes, contributes to time efficiency, and supports the ability to make swift decisions in emergencies [159],[160]. By carefully managing the complexity of medical systems, it is possible to enhance both the effectiveness and the practicality of clinical decision support systems, ultimately leading to better patient outcomes.

2.6.6 User satisfaction was emphasized in 19% of the final full-text review and is recognized as a critical factor in determining the success and overall effectiveness of CDSS. As illustrated in Figure 2.2, this element has gained noticeably more attention in recent years, reflecting a growing awareness of its importance in system design and adoption. This concept is closely linked to key aspects, including system acceptability, learnability, memorability, and accessibility [132]. Learnability, for instance, refers to the ease with which users can quickly grasp how to use the system, thereby enhancing their initial engagement and reducing the learning curve [161]. On the other hand, memorability ensures that once users have learned how to operate the system, they can easily recall the program's functions without having to undergo frequent retraining, which plays a crucial role in long-term efficiency and retention [162]. Accessibility is another essential component, as it ensures that the necessary medical information and patient history are readily available within the system, enabling timely decision-making in clinical settings [119].

When these factors (learnability, memorability, and accessibility) are optimized, they collectively enhance user satisfaction, thereby fostering user acceptance and encouraging the widespread adoption of CDSS in healthcare environments.

2.6.7 Explainability emerged as a focal point in 9% of the papers analyzed during the final review phase. This concept is increasingly recognized as a critical issue within the CDSS realm and medical AI [163]. In the context of CDSS, explainability is pivotal because it directly influences user trust in the system. High-level transparency, which is essential for fostering user confidence, is primarily driven by the extent to which a system's processes and decisions can be explained and understood by its users [164].

Explainability enables healthcare professionals to comprehend the underlying reasoning and mechanisms that drive the system's recommendations and solutions [165]. When a CDSS clearly articulates the rationale behind its advice, physicians are more likely to trust and rely on the system. Through this understanding, the CDSS becomes more credible to its audiences, and its professional development will be enhanced. As they engage with the system's explanations, clinicians can refine their clinical decision-making skills, gradually improving their ability to make optimized, evidence-based decisions in patient care over time [112].

Therefore, explainability is a critical intermediary between technological innovation and clinical application, fostering trust and efficacy in AI-powered systems that support healthcare professionals' complex decision-making tasks.

2.6.8 Flexibility, although underrepresented in the literature and discussed in only 3% of the reviewed papers, holds significant potential for enhancing the functionality of Clinical Decision Support Systems (CDSS). Flexible medical systems tend to achieve higher adoption rates, particularly when they anticipate and accommodate the adaptability needs of physicians [166]. In this context, three key dimensions of flexibility have been identified as critical to improving CDSS effectiveness [167]:

- The ability for users to revisit and revise previous stages within the system.
- The option to enter data in various sequences accommodates different workflows.
- The capability to present data in customizable formats tailored to individual user preferences.

When designing digital pathways, these flexibility features must be aligned with the realities of clinical workloads. This alignment ensures that treatment processes are responsive to the actual needs of physicians and conducive to patient care [168]. Integrating flexibility into CDSS design can enhance decision support accuracy, boost user satisfaction, and ultimately improve patient outcomes [169].

2.6.9 User control is recognized as a key HCI element in one of the 68 reviewed papers, highlighting the importance of designing instructions that are congruent with real-world workflows. Such alignment not only supports users in recovering from errors but also helps prevent their recurrence, thereby enhancing the system's overall usability and efficiency [117]. This focus on user control is directly linked to the improvement of the Unified Theory of Acceptance and Use of Technology (UTAUT) [170]. This model predicts and explains the acceptance and adoption of new technologies. UTAUT encompasses factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, all of which are crucial in fostering a positive user experience and ensuring the effective integration of technology in clinical settings [171].

2.6.10 Data entry has been explored in 6% of the final-stage review papers, focusing on developing systems designed to minimize potential user errors [122]. Data entry management is crucial in CDSS, ensuring that data is organized, standardized, and systematic. Effective data entry management is closely tied to the overall data management process, which is vital for maintaining the integrity, accuracy, and reliability of the information within the CDSS [172].

The integration of emerging technologies, such as voice recognition and natural language processing (NLP), has significantly improved the data entry process in eHealth systems. These technologies streamline the input of clinical data, reduce the likelihood of errors and inconsistencies, and enhance the accuracy of the information captured [173]. This, in turn, directly impacts the reliability and effectiveness of CDSS in supporting clinical decision-making. These advancements help ensure that healthcare providers have access to accurate information, improving the data entry process and providing timely data, which is essential for making informed decisions and improving patient outcomes [174].

Furthermore, structured data entry management is crucial for efficient data capture, subsequent data retrieval, and analysis. In one study [175], we demonstrated that CDSS designers implemented structured data entry to generate highly reliable medical data for subsequent analysis and decision-making. The project findings revealed a substantial reduction in the rate of false recommendations by applying one technology for text generation based on structured data entry. A properly managed data entry process enables the CDSS to function optimally, allowing data storage, retrieval, and interpretation to occur efficiently and effectively. This structured approach is crucial in complex healthcare environments, where accurate data is essential for supporting clinical workflows, diagnosing conditions, and tailoring treatment plans to individual patients [176].

2.6.11 Individuality is addressed in one of the 68 reviewed papers, where Klumpp et al. [128] explore HCI implications through a theory that highlights four crucial aspects shaping individuals' interactions with computerized systems. The first aspect of this theory is the identification of technology, which encompasses all technological features integrated into the system [177]. This identification is crucial for understanding how users interact with and perceive the system.

The second aspect involves the assignment, which refers to the specific task or mission for which the technology is employed. The nature of the task influences the choice of technology, as different tasks require different technological capabilities to meet user satisfaction and achieve desired outcomes [178]

The third key issue is context, which can vary significantly depending on geographic, corporate, or community settings. This implies that recommendations and system functionalities should be tailored to accommodate local conditions, including geographic location and other contextual factors [179]. Customizing the system according to these variables ensures it remains relevant and effective across diverse environments.

The fourth aspect focuses on human dimensions, which include population characteristics, cognitive abilities, and individual attitudes. This dimension emphasizes the need for customizability based on the target population's specific needs, attributes, and preferences [180]. The system becomes more intuitive and user-friendly by aligning with the users' unique approaches and desires.

Emphasizing system individualization and customization is critical for enhancing the accuracy and effectiveness of decisions in CDSSs. By addressing these four aspects (technology identification, task assignment, contextual adaptation, and human dimensions), CDSS can be better tailored to the needs of its users, ultimately leading to improved decision-making accuracy and overall system performance [128].

2.6.12 Mental effort has been identified as an HCI element in one of the papers reviewed in the final stage. The concept is often evaluated using the Rating Scale Mental Effort (RSME), a tool first introduced by Zijlstra [166], which accurately gauges the perceived mental effort exerted during task performance. RSME measures the mental demand of a task from a user's perspective, essentially measuring the subjective sense of cognitive load required to complete a task [87].

In the context of CDSS, RSME serves as an essential metric for evaluating how well these systems support healthcare professionals without unnecessarily complicating their decision-making processes. A low RSME score indicates that the CDSS is effectively integrated into clinical workflows, enhancing functionality without imposing a substantial cognitive burden on the user [181]. In other words, the system is user-friendly and intuitive, allowing medical practitioners to focus on patient care rather than struggling with its complexities.

By minimizing mental effort, CDSS can significantly improve the efficiency and effectiveness of clinical decisions, ultimately leading to better patient outcomes. Hence, it is essential to carefully design and monitor mental efforts in CDSS to ensure they do not become another source of stress or error for healthcare providers.

2.7 Conclusions

The systematic literature review in this chapter confirmed a striking research gap: despite numerous usability studies in healthcare, no prior work has systematically identified and categorized the full spectrum of HCI elements that truly shape CDSS performance. By rigorously analyzing 68 final-stage papers, we identified twelve pivotal HCI factors (ranging from interface design and alert configuration to data entry workflows and explainability). We revealed the variety of evaluation methods these studies deployed, including expert-based, user-based, and hybrid approaches (will be discussed in Chapter 3). Equally important, our review surfaced the “dark side” of HCI in CDSS (alert fatigue, excessive cognitive load, and design flaws), which we will examine in detail in Chapter 4.

Our findings also clarified the extent to which leveraging HCI elements within CDSS can be significant. In busy, high-pressure environments, quick data entry and subtle alerts are key to streamlining the medical process, whereas in specialized or infrequently used tools, deep explainability and guided navigation take precedence. Separating closely related concepts such as ease of use and system simplification allowed us to highlight their distinct contributions (one shapes the immediate user experience, the other streamlines underlying workflows).

By employing these insights, we proposed a cyclical design model (Chapter 7) that aligns data entry with actual treatment cycles. This approach not only enhances explainability (clinicians instantly recognize how each data field fits within a patient’s care pathway) but also boosts user satisfaction by mirroring real-world workflows. Empirical evaluation using the MIMIC-III dataset demonstrated that this design yields more reliable recommendations and measurable improvements in decision accuracy.

In summary, this chapter drives a coherent framework for HCI-informed CDSS design by:

1. **Mapping HCI elements** (both positive and negative) in CDSS contexts.
2. **Categorizing evaluation methods** tailored to clinical scenarios.
3. **Demonstrating contextual variability** in element importance.
4. **Emergence of an idea for a treatment-aligned, cyclical model** that improves explainability, data quality, and clinical outcomes.

For further details and complementary insights, **Annex *A*** provides access to the full text of the published paper in a prestigious journal.

Chapter 3

Evaluation procedure of clinical decision support systems: Methodological approaches and categories

3.1 Introduction

Human-Computer interaction plays a fundamental role in the design and functionality of CDSS, directly impacting how effectively healthcare professionals engage with these systems [182]. Assessing HCI elements within CDSS is undoubtedly essential, as it allows us to measure and understand how well these systems facilitate clinical workflows, optimize decision-making, and improve patient care outcomes [183]. Accurate, timely, and efficient decision-making is critical in the healthcare system, so ensuring that CDSS integrates well with human users through robust HCI principles is indispensable. Hence, evaluating these systems has necessitated assessing their effectiveness, user experience, and adaptability within clinical settings [184].

Since system design with poor HCI components may lead to errors, inefficiencies, and decreased user satisfaction, the importance of evaluating HCI aspects in CDSS cannot be ignored [185],[186]. In this respect, considering the complexities inherent in clinical environments, selecting the appropriate evaluation method is often a concern for experts. The evaluation method will be chosen, taking into account the circumstances, such as the time the user can dedicate, the investigation purpose, the specific context of the system's deployment, and the aspects of HCI being examined [187].

Within the scope of this thesis, the objective is to investigate how paying attention to HCI elements can affect the overall performance and utility of CDSS. To do so, we must first identify and select the most suitable HCI evaluation methods, which require a thorough understanding of the available approaches and their applicability in the context of CDSS. This chapter aims to categorize and explore prevalent HCI evaluation methods, providing insights into their strengths, limitations, and relevance to assessing CDSS.

While various studies have explored HCI factors and their impact on CDSS functionality, none have systematically introduced and categorized the available evaluation methods based on the specific circumstances encountered in these systems. In previous studies, the applied evaluation method was mainly briefly described. This chapter addresses this gap by offering a comprehensive taxonomy of HCI evaluation methods applicable within CDSS environments, considering factors such as the system's context, constraints, and the specific HCI elements under investigation.

Based on the SLR conducted (Chapter 2), we will examine the HCI evaluation methods employed in the final-stage papers, specifically those focused on the CDSS environment. In this way, **we aim to answer the question raised (RQ1)** in this SLR and establish a framework for selecting evaluation techniques that most effectively address the HCI elements identified in the SLR.

Another consideration in this chapter is determining whether a relationship exists between specific HCI factors and the evaluation methods used. By classifying and analyzing methods related to the particular HCI element, we aim to understand how to select the most effective method for investigating the aspect. In this chapter, we strive to establish a new standard for assessing and enhancing CDSS performance by employing a more comprehensive evaluation method.

3.2 Usability evaluation methods

Usability refers to the desired user experience with the system, including user satisfaction and ease of use when the user interacts with the designed system [188]. In the context of CDSS, evaluating usability depends on the study objectives, the amount of time that can be dedicated, and who will examine the system (end-users or HCI experts). The most appropriate method will be chosen [189]. In this research, we classify evaluation methods based on practical components.

3.2.1 Expert-based evaluation methods

Once we select the usability evaluation method, several key criteria need to be considered, including the availability of real users, time constraints, budget, and the level of expertise required to provide meaningful feedback. Generally, in situations where real end-users face challenges, HCI examiners often turn to HCI experts for usability assessments. Getting help from the expert's experience and knowledge will expedite the assessment process, requiring less time [190]. We describe some standard expert-based methods:

- **Heuristic evaluation:** This is one of the most popular methods introduced by Nielsen and Molich [191]. In this method, a small group of usability experts evaluates the system (user interface) against guidelines and usability principles. These experts identify where the system falls short of meeting these standards.
- **Cognitive walkthrough**: A cognitive walkthrough is a structured approach to evaluating the usability of a system. It is considered a task-based method that involves a cross-functional team of reviewers walking through each step of a task flow and answering a set of prescribed questions to identify those aspects of the interface that could be challenging to new users [192]. The expert team will record the outcomes of these questions, in their opinion, and use these observations to improve the system further [193].
- **GOMS:** The acronym GOMS stands for Goals, Operators, Methods, and Selection Rules. Indeed, this method includes a series of steps consisting of Operators that the user or the experts perform. This method may require the sub-goals to be complied with, so the methods have a hierarchical structure [194].

3.2.2 User-based evaluation methods

User-based methods involve real users interacting with the system to recognize usability issues in the user experience. Some HCI specialists believe that, despite the time-consuming nature of this manner, the extracted feedback will be more reliable to interpret [195]. In the medical environment, considering its unique complexities, workload conditions, pressures, and emergent circumstances, the real users and their satisfaction are the most effective measurement tools for evaluating HCI factors [196]. In this study, we identify and stratify the common user-based methods in this regard:

- **Think-aloud protocol**: The think-aloud protocol (TAP) consists of two components: one part is the think-aloud interview, a technique for collecting verbal data, and the other is protocol analysis, a method for predicting and analyzing verbal data [197]. Users are asked to think aloud while completing routine tasks. They should express their thoughts and feelings when performing their functions through the designed system [198].
- **User testing**: This method focuses on observing how users interact with the system to assess its performance and ensure that tasks are completed satisfactorily [199]. Despite the think-aloud method, in which users are asked to verbalize their thoughts continuously, the tester observes how users interact with the interface, the actions they take, and where they encounter difficulties [200]. Despite some existing similarities between this method and think-aloud, in terms of data collection, think-aloud collects qualitative data based on verbal reports. In contrast, the user testing method yields both qualitative and quantitative data. The current process is often exploited to evaluate usability once a working prototype or near-final product is available [201].
- **Near-live:** Also known as "simulated" or "quasi-experimental" methods, near-live testing involves users interacting with the system in a controlled but realistic environment [202]. Although it is less commonly referenced in leading HCI textbooks, it is employed in clinical and intricate environments, such as medical system evaluations.
- **A quick and dirty usability scale:** John Brooke [203] introduced a theory that explains usability cannot be assessed in an absolute manner, meaning it can be defined exclusively in the context in which it is being used. He described that, generally, it is impossible to characterize a system's usability without first identifying its intended users, the expected tasks, the special circumstances, and the environmental conditions. Moreover, he claims that the SUS (System Usability Scale) is entirely suitable for usability evaluation purposes at a lower cost. It is usually assumed that a Likert scale [204] is simply a type of forced-choice question, where the respondent is presented with a statement and then asked to rate their level of agreement or disagreement with it on a scale of 5 (or 7).

3.2.3 Hybrid methods (expert-based and user-based)

Although the introduced methods are inherently classified as expert-based and user-based, some can be adapted for mixed-manner usage. For instance, we can mention the Cognitive

Walkthrough and Think-Aloud methods, which can be employed in the hybrid procedure depending on how the evaluation is conducted. We attempt to articulate customized methods.

- **Cognitive walkthrough**: While initially designed as an expert method, it can be adapted for use with actual users. In a user-based walkthrough, users are observed as they try to accomplish tasks, and their problem-solving processes are analyzed. This is more common in complex systems, such as CDSS [205].
- **Think-aloud**: Although primarily user-based, experts can also use a think-aloud method to articulate their thought processes while evaluating a system. This approach is used in expert reviews to capture insights into usability problems from the evaluator's perspective [206].

We summarized the methods mentioned in Table 3.1 to clarify whether they can be exploited in a user-based, expert-based, or hybrid manner.

Table 3.1: Categorization summary of HCI evaluation methods

Method	Expert-Based	User-Based	Key References
Heuristic evaluation	Yes	No	[9], [195], [191]
Cognitive walkthrough	Yes	Can be	[193], [192], [205]
Think-aloud	Can be	Yes	[198], [206], [129]
User testing	No	Yes	[199], [200], [201], [99]
GOMS	Yes	No	[194], [207]
Pluralistic walkthrough	Can be	Can be	[208], [209]
Near-live testing	No	Yes	[202], [210], [104]

The pluralistic usability walkthrough and cognitive walkthrough are expert-based methods used in usability evaluations, but they differ significantly in focus, process, and participants. This means that a cognitive walkthrough method focuses on evaluating the usability of a system, particularly from the perspective of how easily new users can learn to interact with it [205]. In this method, the primary concern is to assess whether users can achieve their goals using the interface, especially first-time or infrequent users [192]. Conversely, a pluralistic usability walkthrough aims to combine the perspectives of multiple stakeholders (such as end users, designers, and usability experts) to evaluate the system's usability. It focuses on first-time use and simultaneously on collaborative input from different viewpoints to identify usability issues and provide richer feedback [209].

3.3 Applied HCI methods during the studies and in different circumstances

According to the diverse range of HCI evaluation methods introduced, which encompass both user-based and expert-based approaches, it is now crucial to examine the contexts in which these methods have been applied in the literature. This section aims to identify the specific evaluation methods employed in these studies, thereby elucidating their practical relevance. Furthermore, we will investigate the appropriateness of these evaluation methods for each of the HCI elements discussed in the previous chapter within the context of CDSS.

3.3.1 HCI evaluation methods during the performed studies

As extensively described in Chapter 2, we contacted 68 papers in the final stage of the carried-out review. To investigate the evaluation methods exploited in the mentioned studies, we extracted the method name and the status of user-based or expert-based methods. Throughout this comprehensive literature review, apart from SLR and targeted review, we found that seven different HCI evaluation methods have been utilized. These methods are illustrated in Figure 3.1.

As illustrated in the figure below, HCI assessment within CDSS environments emerged in 2012. Although the remaining studies in the final-stage review were initiated in 2003, before 2012, HCI evaluation methods in CDSS research were predominantly theoretical or literature-based, relying on secondary analysis and reviews rather than hands-on, practical experimentation. These studies synthesized findings from previous research, providing foundational insights but lacking direct, experimental testing in real-world or simulated environments.

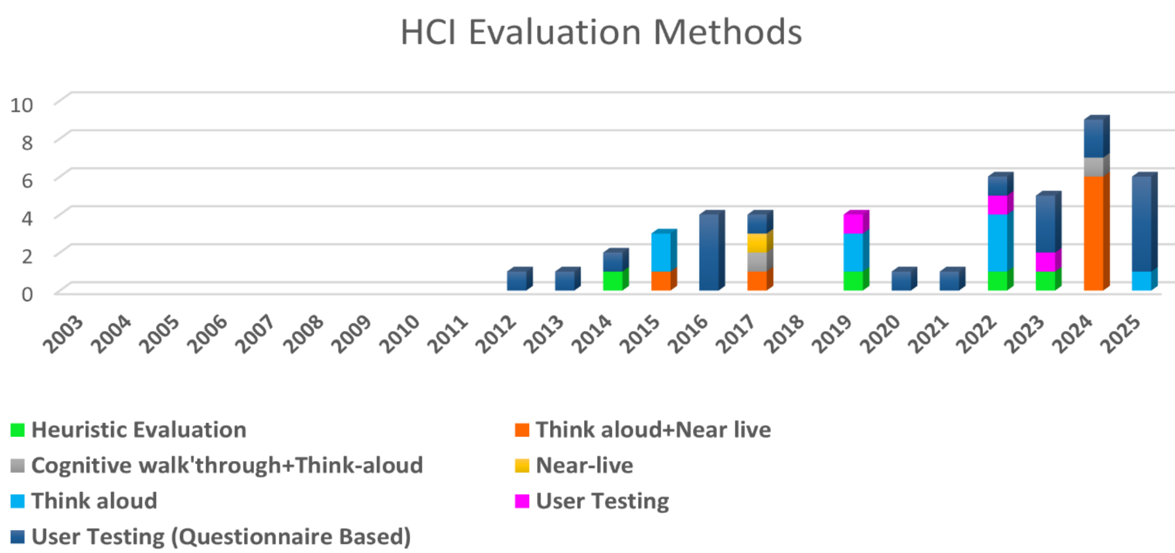


Figure 3.1: Exploited HCI evaluation methods within CDSS environments

In this work, we distinguish between two user testing approaches to clarify their respective roles. Standard user testing involves directly observing users as they interact with the system. In contrast, questionnaire-based user testing gathers subjective feedback through structured questions. This method offers insights into user satisfaction, perceived usability, and other qualitative aspects that may not be evident through observation alone [211]. Regarding the significance of purposeful assessment, HCI inspectors prefer to use questionnaires and predefined questions instead of observational sessions for the user testing method.

Figure 3.1 illustrates that, while heuristic evaluation, as an expert-based approach within HCI evaluation methods, has been employed in recent years, user-based methods are more prevalent. This indicates a growing emphasis on user-centered design (reflected in the increasing use of questionnaire-based user testing methods) among developers and evaluators of CDSS systems.

As evidenced in the diagram above, while the near-live method offers a time-efficient approach, particularly within the constraints of medical environments where practitioners may not prioritize HCI evaluation, its adoption has been less prevalent compared to other user-centered methodologies. This disparity stems from the preference of HCI experts for a more comprehensive evaluation method over a simulation-based method, which may lead to the probable omission of some critical aspects of HCI when time is limited.

Delving into the applied HCI evaluation methods reveals that in the HCI realm, users are at the center of attention, and their satisfaction is defined as the primary goal of HCI experts.

3.3.2 Discovering the relevance between the evaluation method and the intended HCI element

In Chapter 2, we identified fifteen distinct HCI elements relevant to CDSS functionality. A pivotal concern for HCI experts is determining the most appropriate evaluation method to investigate and assess each HCI element. This study aims to establish a correlation between specific HCI elements and suitable evaluation methods, aligning with the identified elements.

To further elucidate the relationship between HCI elements and the employed evaluation methods, we constructed a mapping diagram (Figure 3.2). This visual model connects specific HCI elements to the evaluation methods utilized in our studies through directional lines. As depicted in the figure, some HCI elements were assessed using a single process, while others were investigated through multiple methods, depending on the specific research circumstances.

While Figure 3.1 highlights the prevalence of user testing, Figure 3.2 offers a more detailed view of how these methods were applied to specific HCI elements. As illustrated, user testing questionnaire-based methods were employed to evaluate a diverse range of HCI elements.

HCI elements, such as user satisfaction, which heavily rely on user feedback and contentment, are best assessed through user testing. However, a combination of methods may be necessary for specific elements, such as alerts. For instance, medical alerts have been examined using user testing, near-live evaluation, cognitive walkthrough, and heuristic evaluation. Additionally, some studies have explored alerts through SLRs and targeted reviews, drawing on academic and theoretical resources.

As articulated in studies like [75], the researchers often extract HCI tags to inform future investigations. In such cases, expert-based methods, such as Heuristic Evaluation, are particularly suitable. Experienced experts can assess medical systems against predefined criteria, providing valuable insights. Figure 3.2 shows the heuristic evaluation method in green to highlight the discrepancy (expert-based) between this method and other evaluation methods.

Figure 3.2 illustrates that the near-live method is ideal for assessing mental effort, as it simulates realistic user interactions, thereby revealing cognitive load under conditions similar to actual use. Through this method, the experts can consider some control variables that might lead to diverting the investigation from the right path. Moreover, dynamic adjustments enable researchers to adjust the scenario or system in real-time, allowing them to explore different design variations and their impact on user mental effort [202].

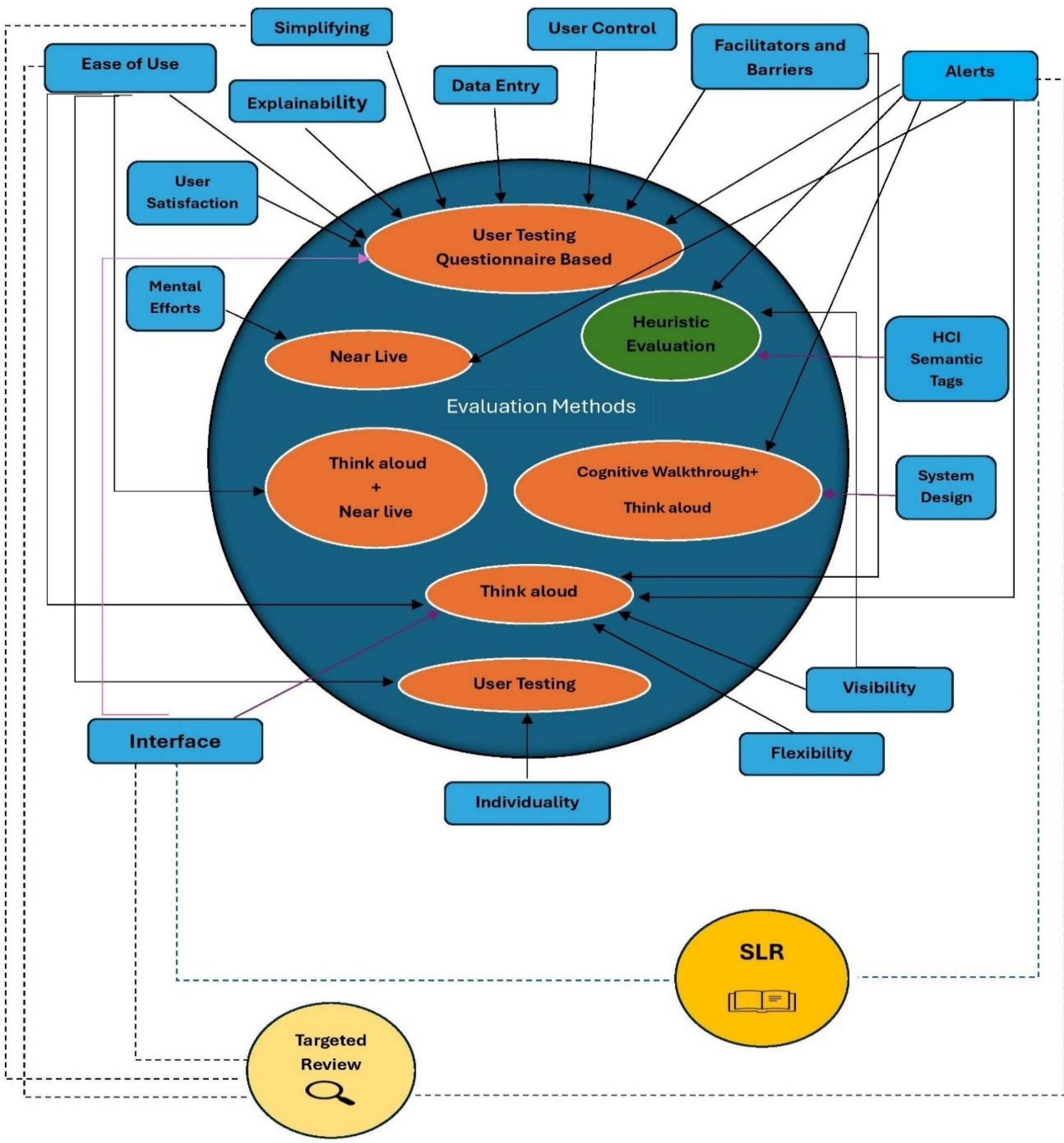


Figure 3.2: Diagram mapping HCI elements to appropriate evaluation methods

It is generally acknowledged that to investigate HCI elements, such as facilitators and barriers, within CDSS environments, which are often revealed during daily task performance, the most appropriate techniques are primary user-centered methods, including user testing and think-aloud protocols.

Due to its complexity as an HCI element, system design often requires a mixed-methods approach for thorough evaluation. As shown in Figure 3.2, the combined use of cognitive walkthrough and think-aloud methods allows evaluators to capture task-based challenges (through cognitive walkthrough) and real-time user insights and thought processes (via think-aloud). It leads to providing a comprehensive understanding of usability issues in complex systems.

To assess the ease of use within the CDSS environment, a mixed-methods approach combining think-aloud protocols and near-live evaluation has been employed. During think-aloud sessions, users verbalized their thoughts as they performed routine tasks. In this way, some insights into their cognitive processes can be acquired. Simultaneously, near-live evaluation enabled researchers to manipulate specific system components under controlled conditions, allowing for the observation of user behavior and the identification of potential usability issues. This integrated approach provided a comprehensive understanding of the extent to which the system usage and its learning are easy, particularly for new users.

As depicted in the figure, certain HCI elements within CDSS, such as data entry, user control, explainability, and simplification, were primarily assessed through Questionnaire-Based User Testing, a core user-centered method. This approach observes user interactions with the system and collects data through predetermined questionnaire items. Combining qualitative observations with quantitative data from questionnaires enables a comprehensive analysis of HCI elements.

While one study may not focus on a specific HCI element as its primary goal, it is crucial to consider the most significant HCI elements based on expert perspectives. A comprehensive investigation of these elements can be achieved by employing appropriate evaluation methods, such as user testing, think-aloud protocols, or expert reviews. Furthermore, conducting systematic literature reviews or targeted reviews can provide valuable insights from existing research, aiding in the analysis of specific HCI elements within the context of the study.

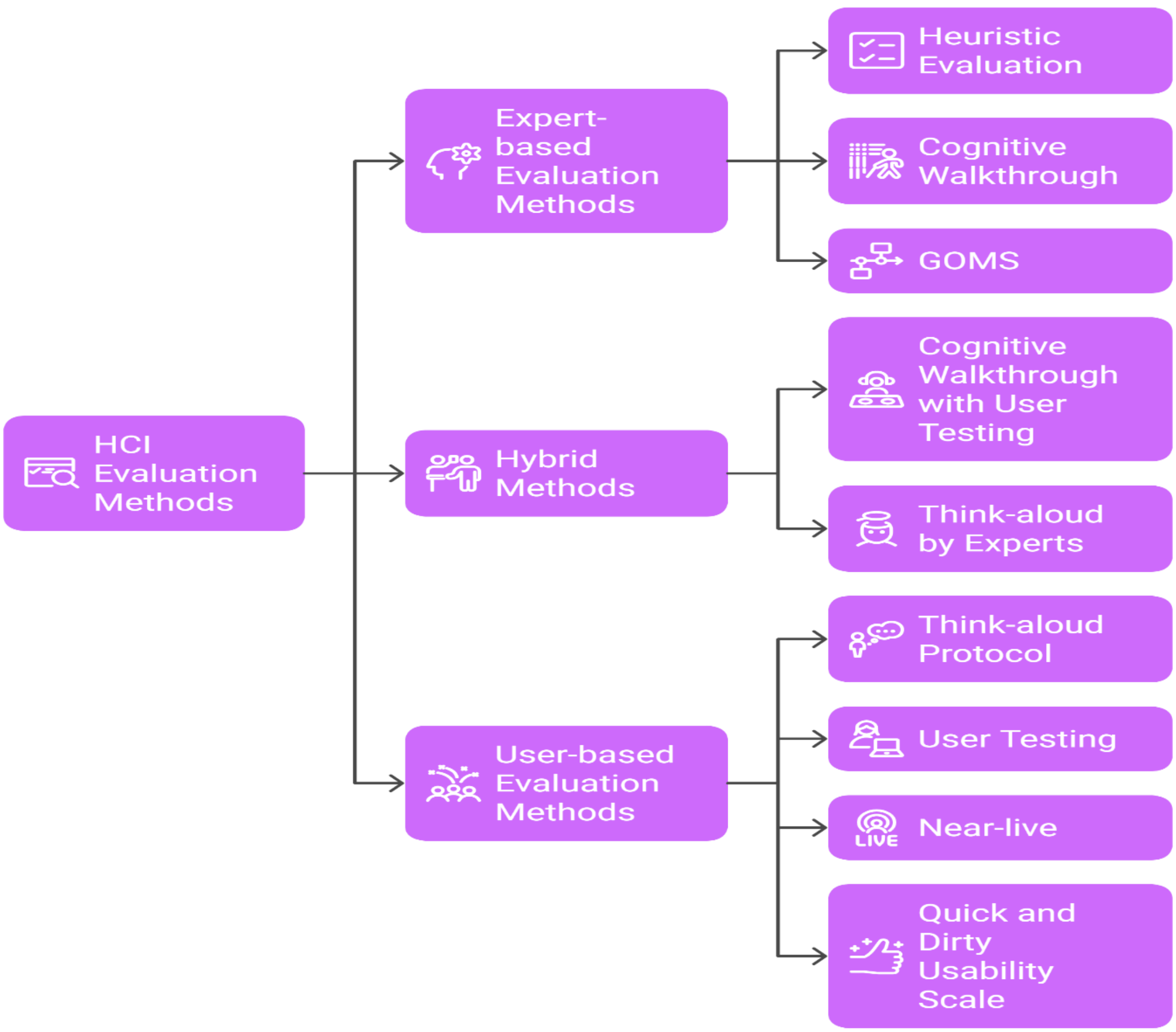
3.4 Discussion

Although some studies have introduced HCI evaluation styles, a gap remains in categorizing the existing methods. The most suitable method can vary, considering the influence of components such as time dedication, the target group within medical environments, and highlighted daily tasks. In addition to the effective items mentioned, determining which HCI element is being investigated will impact the choice of evaluation method.

We conducted this chapter to address the recognized research gap and provide a scientific framework to streamline the HCI evaluation method selection process. We first aggregated the available methods utilized throughout the studies to achieve this objective. Then, we identified two primary tiers, based on who provided feedback about the system status: users or experts.

To support this classification visually, Figure 3.3 has been included below. This figure categorizes HCI evaluation methods into three main approaches: expert-based, user-based, and hybrid approaches. It illustrates how techniques such as heuristic evaluation, cognitive walkthrough, and user testing are positioned within this framework, depending on who performs the assessment and how feedback is obtained. This visual structure helps clarify the methodological landscape and highlights the flexibility of specific techniques that can be adapted across categories. For example, cognitive walkthrough is typically expert-based but may involve users, while both users and experts can apply think-aloud protocols. Moreover, the diagram emphasizes the necessity of tagging evaluation methods not only by evaluator type but also by contextual suitability (such as clinical realism, time constraints, and the specific HCI element under investigation). This supports the broader goal of aligning evaluation strategy with practical healthcare settings.

Figure 3.3: Categorization of HCI evaluation methods in medical environments



Both user-based and expert-based methodologies are exploited to acquire user feedback. While user-based methods often involve real users, expert-based methods, such as heuristic evaluation, employ experts to simulate user behavior. In contrast, techniques such as the near-live method analyze real users' reactions in controlled or simulated medical environments. It can be stated that HCI specialists implementing the HCI evaluation properly will effectively prevent the target users or environmental components as needed.

Although evaluation methods can be preferred and chosen according to specific conditions, there is no absolute and explicit instruction for selecting the most suitable evaluation method. For instance, when examining a medical subsystem alongside technical guidelines or sequential duties, expert-based methods are a more logical choice. In contrast, the use of other methods or mixed methods can be justified.

Typically, HCI evaluations are conducted to assess multiple HCI elements rather than a single one. To select the most suitable evaluation method, it is essential to consider various factors, such as the specific HCI elements being evaluated, the desired level of detail, the available resources, and the target user group. In this respect, some evaluation methods are flexible enough, meaning that although they may be user-based (such as the think-aloud method), HCI experts can employ them. Conversely, cognitive walkthrough is an expert-based method that, if necessary, can be executed by real users.

3.5 Conclusions

Given the pivotal role of physician interaction with CDSS, there is a crucial need for rigorous tools to measure and evaluate these systems accurately. Even a CDSS developed with advanced technology may fail to improve medical decision-making accuracy if healthcare professionals do not adopt it. In other words, the success of a CDSS depends on its acceptance and effective use by medical staff.

This chapter aims to aggregate the existing HCI evaluation methods used in current studies and highlight the unique applications of each technique. The identified methods have been stratified based on who performs the assessment, the environmental circumstances identified, and the reasons for conducting this evaluation. Regarding the identified HCI elements (in Chapter 2) as the investigation objectives within CDSS, the evaluation methods were classified.

This study provides a methodological framework for upcoming HCI studies within CDSS environments. Moreover, throughout the subsequent chapters, when we discuss the impact of HCI improvement on the quality of prepared data for clinical decision-making, the defined metrics for HCI assessment are fully outlined.

For further details and complementary insights, Annex *B* provides access to the full text of the corresponding published conference paper.

Chapter 4

Tackling user attrition: Identifying dark side HCI elements to optimize CDSS performance

4.1 Introduction

The rapid increase in various biomedical data enables extensive research studies, which require customized computational solutions [212]. This promotes smooth and user-friendly interaction with the developed system [213]. Although the physicians' adoption of EHR is increasing and recognized as a major prerequisite, permanent user resistance cannot be denied [214],[215],[216]. This resistance arises from existing usability difficulties and insufficient attention to user needs and attitudes [217],[218]. The design of the CDSS has primarily focused on effectiveness, error prevention, and medical recommendations rather than addressing user attraction tricks within the system [219],[220]. CDSS sometimes encompasses complexities that obligate users to engage with poorly structured, uncertain, and potentially conflicting information from various sources [74]. Poorly designed GUIs in these systems can lead to frustration among medical practitioners who are involved with computerized technologies [50]. To enhance CDSS usability, it is essential to identify the prevalent barriers and find a solution that assists CDSS designers in addressing the identified difficulties [221]. Given the current paucity of studies addressing HCI barriers within CDSS environments, this chapter aims to address this gap by extracting and categorizing these barriers. We highlight the HCI difficulties relevant to the CDSS context in which user orientation to the system may decrease.

Throughout our investigation, we examine various dimensions of the obstacles highlighted in the existing literature, extracting key insights from the conducted SLR in Chapter 2. Since these elements are recognized as the dark side of HCI elements, we avoid reaching these elements. We will discuss the common alert fatigue issues in the second section. The third section will address the probable workload difficulties that may occur in the CDSS environment. The defects detected during the system design will be articulated in the fourth section as the other probable CDSS bottleneck. The fifth section will argue extensively about the required mental efforts while the user interacts with the system. Afterward, the malicious side of the HCI elements and likely challenges in this realm will be discussed. Finally, we conclude with the crucial clues and required modifications to approach an improved CDSS, and consequently, more accurate medical decisions as the valuable output.

4.2 Alert fatigue

Medical alerts are significant tools that notify doctors of crucial information that may influence their medical decisions [222]. Based on their importance, these alerts can interrupt a doctor's work process [223]. The alarms are triggered by predetermined rules that consider a range of scenarios and different philosophies [224], [225]. The frequent triggering of alarms can be perceived as burdensome and disruptive by physicians, often leading to the emergence of a phenomenon known as alert fatigue [226]. Alert fatigue poses a serious threat, as it can lead to the neglect of crucial alerts that may signal potential harm to patients, especially when overwhelmed by irrelevant or less important alarms [227]. Launching unnecessary alerts frequently causes another serious problem known as the override [228]. If the system fails to meet the actual needs of physicians, the number of ignored alarms will constantly increase [229]. Consequently, this may cause various unintended and adverse consequences for patient outcomes [185], [230]. Hence, the override rate is considered a key metric in assessing the CDSS functionality [228].

Table 4.1: Alert fatigue categorization and attributes

Category	Description	Key discrepancy
Cognitive overload [231]	It occurs when too many alerts saturate a physician's cognitive capacity, leading to decreased attention to each alert.	Focuses on the overall mental burden from multiple alerts
Desensitization [232]	It develops over time as clinicians become accustomed to frequent alerts, potentially causing important alerts to be overlooked.	Involves a reduction in responsiveness due to familiarity
Habituation [233]	A form of desensitization where the response to repeated alerts diminishes, leading physicians to ignore even critical alerts.	Specific to the diminishing response to repeated exposure
Interruptive alerts [234]	Alerts can significantly disrupt workflow, potentially leading to frustration and a lack of attention to alerts if they are perceived as obstructive.	Emphasizes the disruptive nature of alerts on daily tasks

The user attrition derived from the improperly designed alert can be categorized into four different types. As illustrated in Table 4.1, these categories vary based on the reason that triggers the alert.

Cognitive overload situations occur when clinicians are overwhelmed by the volume and frequency of triggered alerts, leading to divided attention and diminished importance of the alerts [235]. Irrelevant or poorly timed alerts can foster a sense of apathy toward arisen alerts, undermining their intended purpose [236]. To mitigate this desensitization phenomenon, it is essential to carefully analyze the rationale and design of alerts during the system development phase, ensuring their relevance and alignment with clinical workflows [237]. Due to some inadequate alert designs, physicians often become accustomed to ignoring pop-up alerts as a daily habit, which can lead to missing critical alerts [238]. The alerts can disrupt the medical workflow depending on their severity. When they appear in unnecessary circumstances and interrupt ongoing tasks, the perceived importance of critical alerts will be diminished, even when they require immediate attention [239].

During the studies carried out on this matter, several **solutions** have been recommended to mitigate the mentioned difficulties [240]:

- **Enhancing the specificity of the alerts**: Designing alerts with higher specificity minimizes false positives and guarantees that only medically relevant alerts are displayed. This reduces unnecessary interruptions and helps maintain clinician trust in the system.
- **Categorizing alerts by severity:** Alerts can be stratified into levels of urgency, such as high, medium, and low severity. By emphasizing high-priority alerts, clinicians can better focus on critical tasks, while less urgent notifications can be addressed at more suitable times. Alerts can be displayed in various positions, colors, and with distinct sounds, depending on their designated severity level.
- **Incorporating human factors into alert design:** Applying human factors principles helps us design alerts that align with cognitive capabilities and workflow patterns. This includes simplifying the interface, reducing cognitive load, and prioritizing the presentation of high-severity alerts to prevent user overload.
- **Alert compatibility with the patients' characteristics:** Tailoring alerts based on individual patient characteristics (such as medical history, current medications, and risk factors) enhances their relevance and medical importance. This will decrease the likelihood of dismissing or ignoring alerts triggered.
- **Personalizing alerts for individual physicians:** Customizing alerts based on individual preferences, specific vulnerabilities, and estimated workloads for particular scenarios. It causes the raised alerts to be both actionable and non-intrusive.

Efforts to reduce alert fatigue enable physicians to dedicate sufficient attention to triggered alarms and capitalize on the benefits of various alert types, including interruptive, informative, and predictive alerts, throughout different stages of medical treatment [241].

4.3 Workload adversity

In the context of CDSS, the user's perceived workload often hinders satisfaction with the designed system. This workload typically stems from two primary sources [235], [242]:

- **Excessive Workload:** The system may impose a heavy burden on the user, requiring them to process large volumes of data, perform complex tasks, or frequently interact with the system.
- **Process Incompatibility:** The defined work processes may not align with the real world, leading to additional workflows, increased error rates, and user frustration.

Several factors can affect the workload imposed on medical professionals who utilize CDSS, including the volume of data entry required, the frequency of system-generated alarms, the accessibility of the medical user guide, and the level of system simplification. These factors can be measured and varied within different medical domains [242], [243], [244].

Several potential solutions were proposed throughout the relevant studies. They were selected based on their consistent mention in the literature and their potential to alleviate key workload challenges identified in various CDSSs [245]:

- **Subsystem integration:** By implementing advanced integration techniques, subsystems can seamlessly share and synchronize data, significantly reducing users' manual workload and even some duplicate data entries [246].
- **Optimized data entry forms:** Designing data forms that prevent redundant or duplicated patient data entry can streamline workflows. Some forecasted features, such as the medical text report generator, facilitate data entry [244], [247].
- **Medical data auto-populated techniques:** Employing advanced methods to fetch medical data automatically minimizes the need for manual data entry. The recent technologies to transfer medical signs (e.g., body temperature, blood pressure) from installed sensors to EMRs can be a practical example in this field [113].
- **Customizable alerts:** Personalized alert systems can be configured to suit individual user preferences and relevance. Minimizing unnecessary notifications tailored to the physicians' expectations reduces cognitive overload, allowing users to prioritize critical tasks effectively and enhancing overall system acceptance [124].
- **User-centered design in CDSS**: System design and development that utilizes the user-centered approach makes the system compatible with healthcare professionals' actual needs and workflows. In other words, when users are involved in system design and implementation, the system acceptance rate will be firmly elevated [248].

Excessive workload can hinder healthcare efficiency. In such circumstances, the probability of user error can increase during system interactions. Additionally, physicians may become less focused on essential elements of the treatment plan. Therefore, it is crucial to consider the physicians' workload capacity to improve user interaction with the system within CDSS environments.

4.4 System design defects

Inadequate system design within a CDSS environment can impact its effectiveness and usability. Deficiencies in interface, navigation, functionality, and overall user experience can hinder user adoption, satisfaction, and the system's ability to support clinical decision-making [249]. These flaws within CDSSs can hinder user interaction, resulting in confusion, frustration, and errors in decision-making. These deficiencies ultimately compromise the data quality and the system output [88]. The mentioned flaws lead to user attrition and deter physicians from engaging with the system. In such conditions, physicians may prefer to bypass the system, relying on their judgment rather than the recommendations provided by the system.

CDSS experts have proposed methodologies to address and mitigate identified system design deficiencies. One prominent approach is Goal-Directed Design (GDD). This user-centered method actively involves end users in the development process to create systems aligned with their specific goals and requirements [250]. GDD leverages persona-driven and scenario-based design techniques to ensure that the system is tailored to meet the real-world needs of its users [251],[252]. A persona is a fictional representation of a typical user, containing characteristics and behaviors of the target user group. These symbolic personas assist the system designers, ensuring they reflect the expectations of the actual users. Scenario-based design complements this approach by focusing on the tasks and information needs of these users, emphasizing practical workflows and usability over system-centric features or technological complexity [250]. By employing GDD, the system design better aligns with user needs and expectations. It effectively reduces user attrition and enhances engagement. This alignment fosters improved user satisfaction and facilitates the adoption and sustained use of the system [253].

System designers seek to simplify the system design to elevate the system's usability level, while the system's ability to solve intricate problems requires complicating the system's structure. Regarding the pointed concern, Stefan et al. [80] articulated a theory that posits an opposition between the system's usability and its perceived usefulness. This suggests that while a highly usable system can effectively address simple issues, more complex problems may require a system with a more sophisticated structure. This paradox is illustrated in Figure 4.1.

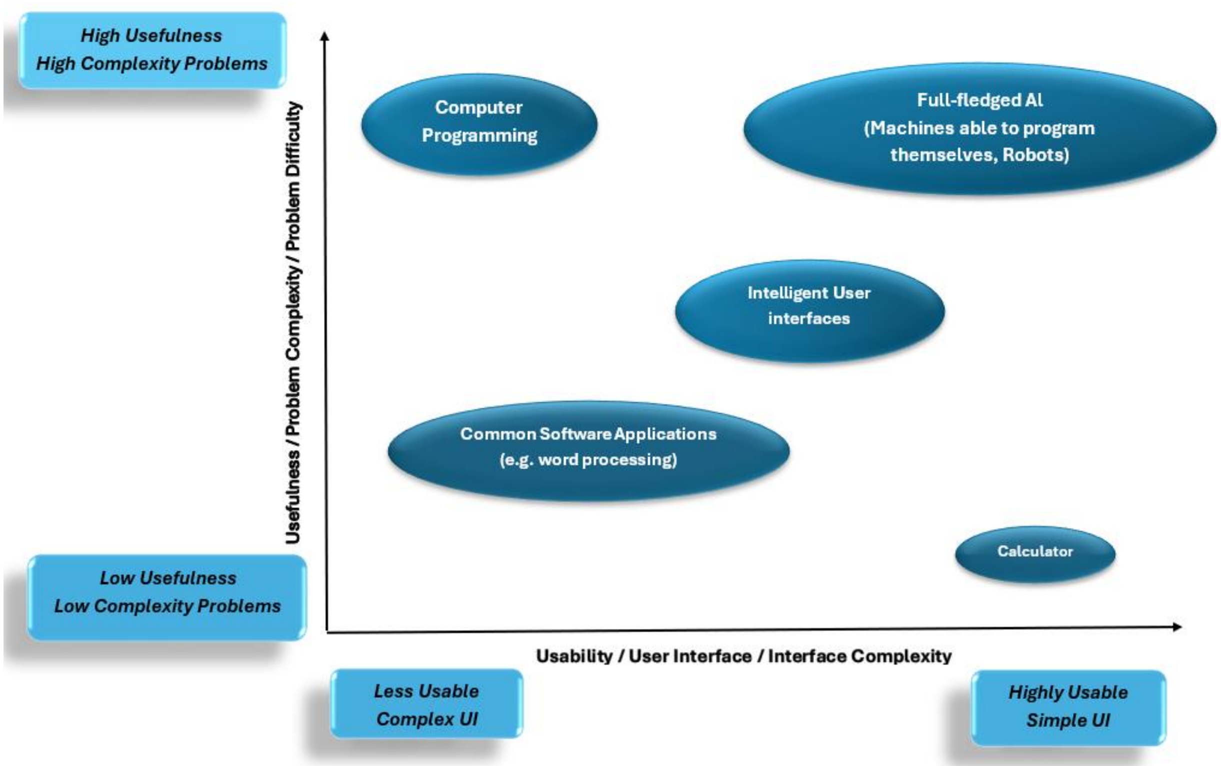


Figure 4.1: Relationship between system complexity and system usability [80]

As shown in the figure above, although previous versions of the software programs had sufficient potential to handle complex cases, they faced numerous usability issues. Conversely, some medical calculators embedded in medical information systems are highly usable among medical staff, but they are less valuable when faced with intricate problems. Recently, by leveraging full-fledged artificial intelligence technology in the medical realm, CDSS designers have developed systems that are both useful and usable for medical practitioners.

Despite the paradox, providing the necessary prerequisites to decrease user attention and enhance user satisfaction is crucial. In this respect, system designers should be informed of user feedback and recommendations. Nowadays, medical practitioners, as end-users, are actively involved in the system development process, particularly through methodologies such as Agile. It assists CDSS designers in collecting user feedback and comments continuously, thereby enhancing the system's usability [254].

4.5 Mental efforts

The term *"mental effort"* is scientifically used to describe the extent of cognitive difficulty a person experiences when performing specific tasks or activities [87]. In the HCI realm, this concept refers to the imposed workload or users' mental struggles when interacting with the system. This implication encompasses several factors, including the user's attention, memory utilization, decision-making, problem-solving, and learning [255]. This HCI concept seeks to streamline tasks within the CDSS environment, making user interaction more intuitive and easier. This objective is followed by minimizing the cognitive load required to operate the system and providing an intuitive and easy-to-learn interface [256].

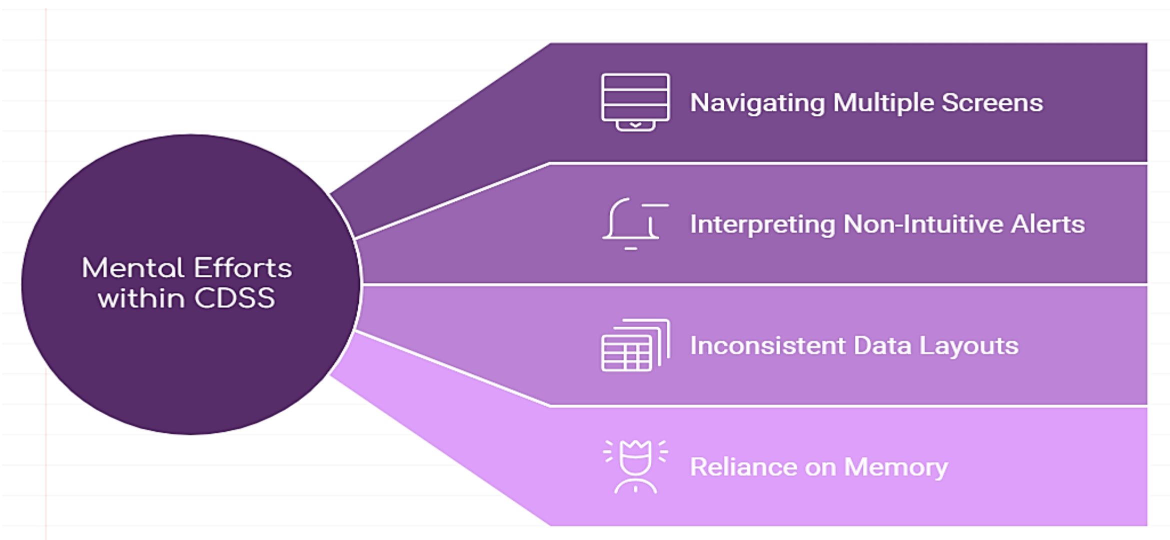


Figure 4.2: Mental efforts dimensions within CDSS

In the CDSS context, high mental efforts stem from poorly designed interfaces, excessive information density, or unclear workflows. As illustrated in Figure 4.2, navigating through multiple screens to retrieve patient data or interpreting non-intuitive alerts can increase cognitive load, leading to decision fatigue among healthcare providers [257]. Moreover, some difficulties, such as inconsistent data layout or non-integrated subsystems, can exacerbate these challenges and force expert users to rely on memory and personal potential, which can lead to user fatigue [258].

From a technical perspective, reducing mental effort involves employing methods such as:

- **Cognitive load measurement tools:** Techniques such as eye-tracking or task completion time analysis can identify areas of high cognitive demand within the system, enabling targeted design improvements [259].
- **Streamlined user interfaces:** Implementing minimalist designs and grouping related information into intuitive clusters can significantly reduce unnecessary mental efforts within the CDSS ambiance. Excessive information exposure causes confusion among physicians [166].
- **Adaptive systems**: Leveraging machine learning to customize the display of information based on user behavior and context can further minimize mental workload [260].
- **Task automation**: Automating repetitive or time-consuming tasks, such as auto-filling data fields or summarizing patient information, can alleviate user burden [261].

Users' mental efforts during interaction with the system depend strongly on their mental models [262]. Mental efforts in the CDSS context are shaped by how well a user's mental model aligns with the system's actual design and functionality. When users encounter a system that does not conform to their mental model, cognitive load increases, often leading to frustration, errors, and disengagement. Thus, mitigating mental effort in system interaction depends on the extent to which the system designers' mental model and the user's mental model are compatible [262],[263]. The concept of mental models was initially investigated by Donald Norma [264] to clarify how users can understand, interpret, and learn a system based on their personal experience, knowledge, and comprehension, which forms the mental model.

In CDSS design, the mental model can be employed in two different positions [265], [266]:

- **Designer's mental model**: This reflects how designers conceptualize the system's functionality, workflows, and interactions during development. System designers often build the system based on their professional definitions and implications.
- **User's mental model**: This represents how end-users understand the system after interacting with it, shaped by interface cues, documentation, and prior experience.

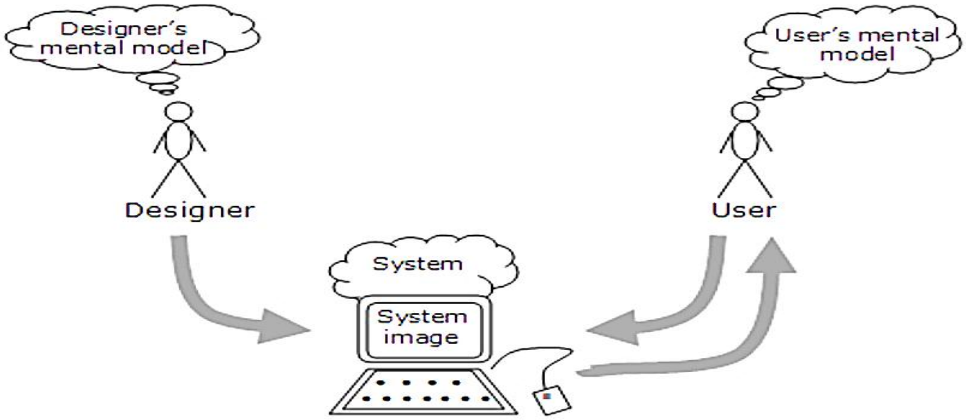


Figure 4.3: Aligning the user's mental model with the designer's model [267]

The critical challenge in CDSS design is bridging these two mental models to minimize discrepancies. A mismatch between the designer's and the user's mental models may cause a higher cognitive load for users, as they must exert additional mental effort or discover the system's behavior [265]. As depicted in Figure 4.3, the proximity of both mentioned mental models can help the user understand the system during interaction with it. In this respect, CDSS designers evaluate the system using methods such as cognitive walkthrough, in which designers attempt to simulate the real user's perspective, aiming to minimize the user's mental effort [192],[205].

Mental efforts impact users' engagement with the system [87]. A high level of cognitive effort signifies imposing more fatigue on the user, leading to diminished interaction with the system. This highlights the importance of developing CDSS that reduce mental effort to enhance CDSS performance [245].

4.6 Discussion

Nowadays, medical system designers can implement CDSS environments by leveraging recent technological advancements to provide attractive applications for physicians as end-users. They must be familiar with harmful HCI elements that can impact CDSS performance in relation to this objective. Despite incorporating cutting-edge technologies such as speech recognition and advanced sensors for vital sign monitoring into medical information systems, medical staff still do not intend to interact with the system, and they often prefer to use paper-based methods to manage medical treatment. We can encourage them to utilize the CDSS system when annoying HCI elements are identified and addressed. These in-depth HCI studies dedicated to specialized environments, such as CDSS, are seriously needed.

Anne et al. [82] discussed one of the prevalent HCI difficulties users face: the alert fatigue phenomenon, which forces them to ignore the raised medical alerts. Other studies have articulated that the workload of physicians is derived from frequent manual processes, double data entry, and mismatches between the designed system and the real world. This work overload causes user attrition within the CDSS [235], [242]. Moreover, HCI experts are concerned about the medical profession's mental exhaustion. They recognize an inverse relationship between users' mental efforts and interaction levels. Hence, mental efforts as a negative HCI element must be reduced so that users can learn and operate the system efficiently [87]. Despite considering usability as an essential component within CDSS, HCI specialists also consider the existing paradox between usability level and system usefulness [80]. This contradiction has been highlighted in several studies in the realm of HCI.

Although scattered articles address the HCI elements, the current study attempted to fill the research gap by gathering the harmful HCI elements applicable within CDSS. This chapter highlights the dark side of HCI elements within CDSS, which can hinder user attrition by neglecting the negative aspects relevant to these elements.

4.7 Conclusions

This chapter consolidates key harmful HCI elements (alert fatigue, workload adversity, mental effort, and system design flaws) that hinder effective interaction between healthcare professionals and CDSS. By identifying and addressing these challenges, this work highlights the need to refine these systems to foster more meaningful engagement with users. Mitigating such harmful elements not only encourages physicians to adopt CDSS in their workflows but also promotes a seamless and intuitive interaction, reducing frustration and mental strain. Although exploiting the latest technologies assists medical practitioners in sustaining mutual interaction with the systems, simultaneously, it is essential to keep users away from negative HCI factors. Once physicians become more attuned to using CDSS effectively, the quality of data entered and the accuracy of medical decisions can significantly improve.

The content of this chapter was presented as part of the 2023-2024 academic activity ***PROGRAMA JORNADA DE SEGUIMIENTO DE LA ACTIVIDAD INVESTIGADORA****. The prepared file for this event is available in* ***Annex C*****.**

Chapter 5

HCI elements' influence on data quality and data management within CDSS

5.1 Introduction

Human-computer interaction principles are essential in evolving interfaces that optimize user experience, simplify user data processing, and enhance system usability [118]. In the data science field, where data structure, data accuracy, and data analysis are prominent, HCI elements significantly influence how the data structure is shaped, how it is interpreted, and finally, how it is analyzed [268], [269]. By considering HCI elements applicable within CDSS environments, we can develop systems that minimize user errors, increase productivity, and enable users to engage with complex data effectively. In the data science context, particularly in dynamic environments such as medical decision-making, these interactions form the foundation for high-performance decision support [117].

CDSSs are designed to assist physicians by leveraging data science to interpret vast amounts of data and provide actionable insights. However, the success of CDSS in supporting healthcare decisions relies heavily on the quality of data originating from the data entry framework, data integrity, and user interaction with the system [270]. Medical decision-maker systems designed by observing practical HCI elements will improve the user experience and, consequently, data accuracy, leading to an enhancement in the quality of patient care [126].

This chapter aims to illustrate how specific HCI elements, when optimized, can positively impact key aspects of data science, including data quality, data exploration, and model interpretability. Building on this objective, we bridge the HCI elements applicable in the CDSS environments with the relevant data science aspects. In other words, considering each HCI element will boost some data quality dimensions. First, this chapter will discuss the relationships between the HCI elements and the data science dimensions. Then, some of the HCI features relevant to the medical data field, such as medical alerts, HCI facilitators, visibility attributes, and ease-of-use factors, will be discussed extensively. Finally, we argue how HCI factors impact the prominent facets of data science and conclude why HCI elements must be considered to improve the accuracy of the medical decisions made by CDSSs.

5.2 The yield of employing HCI elements on data accuracy and data quality

The interactive and user-engaging system, in which the user has a mutual relationship with the system, provides ready-to-analyze data. This means that complex preprocessing steps (such as data classification, cleaning, or integration) are not required, since the data was captured in a standardized format from the outset [271],[272]. In this respect, we describe the role of each

HCI factor in enhancing the data quality prepared by medical information systems, resulting in a higher accuracy level for the medical decisions as the output of CDSSs.

5.2.1 Alerts and data quality enhancement

Since the alerts are designed to notify healthcare providers about critical information or necessary actions, they are pivotal in improving clinical data quality and enhancing decision-making processes when implemented thoughtfully. From a data science perspective, the design of alerts impacts the quality of data collection, noise reduction, and even model interpretability [273].

Alerts serve as a bridge between raw data and clinical action, transforming passive records into actionable triggers that facilitate informed decision-making. Their effectiveness depends not only on technical implementation but also on alignment with clinical workflows, user expectations, and cognitive ergonomics [274]. When appropriately integrated, alerts can elevate the reliability of EMR systems and contribute to a more structured, validated, and context-aware data environment.

- **Noise reduction through intelligent alerting**

Once the alerts are designed in conjunction with user behavior, the mental cognitive load is less likely to override the alerts, thereby mitigating alert fatigue issues [82]. The system can deliver relevant and timely alerts by utilizing context-aware algorithms and user-centered design, thereby minimizing the number of irrelevant notifications. It will reduce noise in the data and enhance signal clarity, which is critical for training machine-learning models [275].

In clinical settings, excessive or poorly timed alerts can lead to desensitization, where users begin to ignore or dismiss notifications. Intelligent alerting systems mitigate this risk by incorporating contextual filters (such as patient severity, recent actions, and clinician role) to ensure that only pertinent alerts are surfaced [276]. This selective triggering not only improves user responsiveness but also reduces the volume of redundant or low-value data entries, thereby streamlining the dataset for downstream analytics.

- **Data annotation and validation improvement**

Well-designed alerts prompt users to verify or input additional data points crucial for data analysis. The system might request additional data inputs through a pop-up alert to determine a flag [277]. This feedback loop helps annotate the dataset with validated inputs, which enhances the label quality for supervised learning models. A predictive model for disease detection might trigger an alert when specific biomarkers reach critical levels. If the clinician validates this alert by confirming the diagnosis, the alert system provides high-quality, annotated data for improving the model's training set [278].

This mechanism transforms alerts into active data curation tools. By prompting clinicians to confirm, reject, or refine system-generated suggestions, alerts create a semi-supervised annotation layer that enriches the dataset with expert-validated labels. This is particularly valuable in domains such as disease progression modeling, where accurate temporal tagging and outcome confirmation are crucial for training robust predictive algorithms.

- **Real-time data collection and stream processing**

Alerts allow real-time data collection, especially when integrated with streaming data architectures [279]. The system can capture critical decision points in real-time by triggering alerts based on incoming patient data, which then feeds this information back into the data pipeline. This continuous feedback improves the timeliness and relevance of the data used for predictive analytics [280].

Real-time alerting systems act as dynamic sensors within the EMR infrastructure. They monitor incoming data streams (such as lab results, vital signs, or medication orders) and respond instantly when predefined thresholds are crossed. This immediacy enables the system to log decision-critical moments with precise timestamps, facilitating time-series analysis and enhancing the granularity of clinical datasets. Moreover, it supports adaptive learning models that evolve based on live feedback [281].

- **Integration with natural language processing**

In some cases, where alerts are triggered based on free-text inputs (e.g., clinical notes), natural language processing (NLP) techniques can be employed to interpret the text and identify relevant keywords or phrases [282]. This feature boosts the alert precision. Moreover, it enhances the system's ability to update and rectify the data inputs based on the context provided by the clinician's notes. In other words, when physicians write medical notes, the NLP technique triggers more precise medical alerts originating from the mentioned text, leading to improved data quality [282], [283].

NLP-enhanced alert systems extend the reach of structured data by mining insights from unstructured clinical narratives. For example, if a physician writes "patient shows signs of ketoacidosis," the system can detect this phrase and trigger a glucose-related alert (even if no lab value has yet been entered). This capability not only improves alert relevance but also retroactively enriches the dataset by linking textual observations to structured outcomes [284]. It bridges the semantic gap between free-text documentation and algorithmic decision support.

5.2.2 The HCI facilitators to elevate data quality

In the HCI context, the facilitators are the features that the system designers provide to make it easier for users to interact with the system effectively. In other words, the identified difficulties (barriers) can be mitigated to encourage users to interact with the system [127]. Once user engagement is facilitated, especially for data entry topics, the prepared data will be ready for analysis and machine learning tasks [113]. In this section, we explore the potential facilities where data can achieve a higher quality, enabling more accurate medical decisions.

- **Manual data entry reduction through system interoperability**

One of the prevalent difficulties during user engagement with medical information systems is the substantial amount of manual data entry required for medical information. This phenomenon increases the likelihood of unintended mistakes [285]. These barriers are mitigated by enabling the CDSS to integrate seamlessly with other healthcare systems, such as EHRs, Laboratory Information Systems (LIS), and Pharmacy Information Systems (PIS). By automatically fetching patient data from these systems, the need for manual data input is reduced, decreasing the risk of human error and ensuring more accurate and complete data entries [286], [287].

- **Enhancing data completeness with automated data fetching**

Facilitators, such as real-time data synchronization and automated retrieval of historical patient data, can ensure that all relevant information is readily available for clinical decision-making, without relying solely on user input. This improves the completeness of data, a critical aspect of data quality in healthcare analytics [113]. When a physician opens a patient's record in the CDSS, the system can automatically retrieve the latest medication history from the pharmacy system, recent diagnostic results from the laboratory system, and previous visit notes from the EHR. This comprehensive data view reduces the need for manual updates and enhances the accuracy of clinical recommendations [288].

- **Facilitating data accuracy with standardized data exchange protocols**

System designers may encounter barriers related to inconsistent data entry, which can be resolved by utilizing standardized data exchange protocols, such as FHIR (Fast Healthcare Interoperability Resources) and HL7 (Health Level Seven). These standards simplify the automated retrieval and data exchange process between disparate systems, ensuring uniformity and reducing discrepancies [289], [290]. A CDSS utilizing FHIR can request patient data directly from an EHR using standard API (Application Programming Interface) features. As Figure 5.1 depicts, the data exchange between different healthcare systems involves several key stages to achieve data consistency. Data from inconsistent entry points is processed through standardized protocols, normalized to remove discrepancies, and retrieved automatically for feature extraction. The mentioned pipeline leads to consistent data presentation and facilitates interoperability and reliable data usage across various systems. This eliminates potential data entry errors and ensures that the data is supplied in a consistent format, facilitating data normalization and feature extraction for streamlined data science tasks [291].

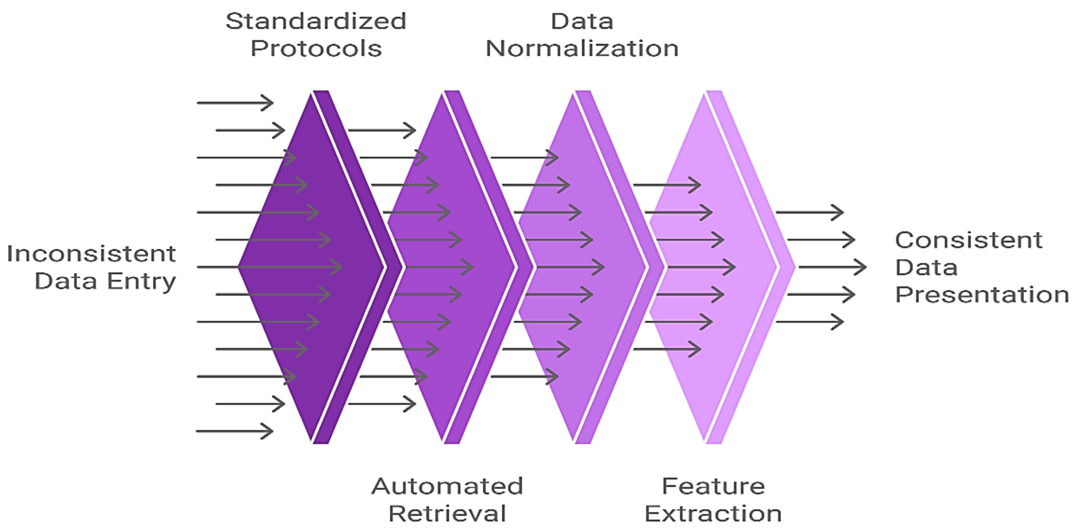


Figure 5.1: Streamlining healthcare data exchange

- **Reducing cognitive load with intelligent data prefill (default values):**

Automated data prefill mechanisms are another facilitator form that can ease the user's cognitive load by filling the form fields with existing data fetched from integrated systems. This reduces the time and effort required for data entry, allowing users to focus on analyzing the information rather than inputting it. Moreover, in many cases, the user can realize the proper data format used in this specific data field as a real instance [292].

In an EMR platform, when a clinician starts entering a patient's symptoms, the CDSS can use integrated data sources to prefill related fields (such as patient age, known allergies, and recent lab results). This will expedite data entry, reduce the risk of missing critical information, enhance the user experience, and improve data quality [293].

5.2.3 Effect of visibility on the quality of prepared data

As the visibility element represents rapid access to the required information and ensures that medical data is available where users anticipate finding it, it is evident that the remaining data entry will be fulfilled based on transparent and real-time information. This characteristic will augment the reliability of the subsequent processes within the CDSS [134]. From a data science perspective, the visibility attributes can impact the data quality utilized by CDSSs in various facets.

- **Amending data accuracy and completeness**

Visibility properties guarantee on-time access to the required medical information. When the patient's data is easily visible and accessible within a CDSS, missing or overlooked data is less likely to occur [135]. In many cases, displaying a clear summary that includes the patient's medical history, lab results, and current medications helps prevent data gaps that could lead to incomplete or inaccurate decision-making [294]. This aspect of visibility directly contributes to data completeness as a crucial component of data quality in medical information systems [134].

- **Preserving data consistency through clear presentation**

A CDSS designed with adequate visibility presents data in a consistent format, reducing the risk of misinterpretation. Consistency in the visibility element causes physicians to insert, find, and retrieve medical data directly and without any probable confusion. This consistency can be achieved through a uniform layout and clear visualization, utilizing standardized icons, tables, and charts [77]. In this manner, the data is properly checked, analyzed, and interpreted. The considerations mentioned boost the system's trustworthiness and support data reliability as the key attributes for high-quality data [295].

- **Streamlining communication and data sharing**

In a communication context, the visibility attribute can be signified by presenting an explicit and shared view of the patient's data. When all the medical staff have access to the same transparent data fields, it mitigates the potential for misunderstandings or discrepancies during the treatment plan [296]. This shared visibility is particularly beneficial in multidisciplinary teams, where different specialists need to quickly understand the patient's status based on the same unified data presentation. Considering this aspect of the visibility element leads to more accurate medical data being analyzed and generated by the different professions [75].

- **Supporting data preparedness through clear workflow stages**

As the other yield when visibility is considered in the system design, we can point out the clarity and transparency of the workflow stages in the treatment process. When each diagnosis and treatment process is visible to the physician and the patient, the CDSS can steer clinicians through a structured and logical progression of tasks [9].

This structured visibility facilitates the preparation of data for the next stage of the medical process in a timely and adequate manner. In other words, each completed task feeds validated and prepared data into the subsequent phase. Once a diagnostic test is completed, the result is explicitly flagged and integrated into the dataset, ready for analysis in decision-making support algorithms [297], [298].

5.2.4 Ease of use element and data quality amelioration

Ease of use, as a critical HCI element within the CDSS environment, plays a significant role in shaping data quality. Employing ease-of-use fundamentals during the system design, such as easy navigation, jargon avoidance, and promoting an intention to use, the CDSS can improve the quality of input data and the subsequent analysis carried out by data science algorithms [299],[300]. A user-friendly CDSS design can significantly improve data quality across multiple dimensions.

- **The impact of the easy navigation attribute on data quality**

One of the core aspects of ease of use is the ability to navigate the system easily, which allows healthcare providers to interact with it seamlessly. In the designed CDSS, considering intuitive navigation, users can quickly input patient data, find required information, and update records without confusion or delays. This approach ensures accurate data entry and easy retrieval, thereby enhancing data quality and facilitating more precise medical decisions [301],[84].

- **Jargon avoidance and improved data consistency**

The use of technical jargon and complex medical terminology can hinder the usability of CDSS, particularly for users unfamiliar with certain specialized terms. Although the standard jargon is utilized among the healthcare sectors, the unnecessary use of short abbreviations that are not standard for medical or dental use acts as a barrier for both doctor-patient communication and between professional groups due to the overuse of jargon [302], [303]. The user interaction with the CDSS can be easier to understand by avoiding jargon and employing clear and plain language. This simplicity contributes to data consistency, reducing the likelihood of user misunderstanding and probable mislabeling of data due to unfamiliar terminology and novel [84],[304].

Consistency in data labels and values is pivotal for accurate analysis and processing in data science. Inconsistent data entries (e.g., using different abbreviations or terms for the same condition) can generate noise and reduce the effectiveness of data mining and machine learning models [305]. By promoting jargon avoidance, CDSS systems ensure that the input data remains uniform and standardized, a serious prerequisite for achieving reliable and repeatable results in data analysis [306].

- **The impact of the intention to use factor on data completeness**

The intention to use is a key yield of perceived ease of use within CDSSs. When users find a system that is easy to operate, their intention to use it consistently and frequently increases [126]. In the CDSS context, a high IU causes more regular and comprehensive data entry by healthcare providers. This consistent usage leads to higher data completeness, as users are more encouraged to engage with the system continuously and update records in real-time. This comprehensive and up-to-date data provides a strong foundation for data-driven clinical decision-making [307].

➢ **Enhanced learnability leading to improved data entry practices**

An easy-to-use system is often more learnable, meaning that users can quickly understand how to interact with it and remember the procedures for future use. Enhanced learnability reduces the time required for training and helps ensure that healthcare providers are proficient in using the system, leading to more consistent and accurate data-entry practices [132].

In the data science context, consistent data entry practices contribute to the creation of structured datasets, which are easier to clean, preprocess, and analyze. Structured and uniform data is essential for applying machine learning algorithms and statistical analyses effectively, enabling the CDSS to provide better data-driven insights [308].

5.3 Discussion

In this chapter, we presented an in-depth analysis of how specific HCI elements within the CDSS environment can enhance various aspects of data science, including data quality, data exploration, and model interpretability. We aimed to illustrate a clear and practical relationship between improved user interaction and optimized data-driven outcomes in medical decision-making processes. In this respect, we mapped HCI elements to relevant data science dimensions.

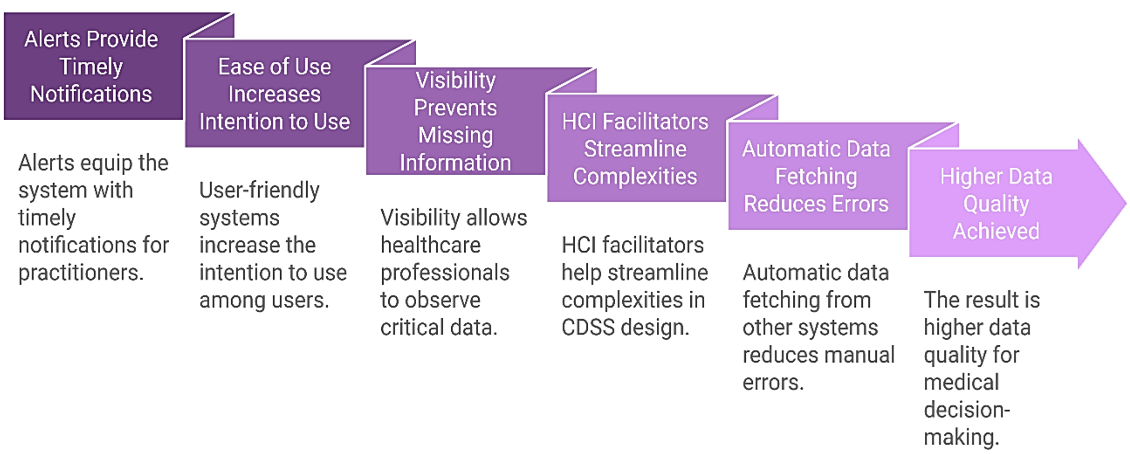


Figure 5.2: Enhancing data quality in medical decision-making

As Figure 5.2 presents, each mentioned HCI element plays a pivotal role in the route of data quality upgrade provided for medical decision-making purposes. Our findings demonstrated that alerts equip the system with timely and adequate notifications for medical practitioners, minimizing data entry errors and reducing the likelihood of missing critical information [76]. Ease of use attributes lead to an increasing Intention to Use (IU) among users [126]. The systems are intuitive and easy to navigate, minimizing user errors and ensuring that data is entered correctly and completely. This leads to better-prepared datasets for analysis [84], [301]. Since visibility enables healthcare professionals to monitor the status of patient data and treatment processes, critical information is readily accessible and visible in standard and expected locations. Considering this consistent visibility prevents physicians from missing practical information for medical decisions [9], [135]. CDSS designers strive to streamline potential complexities by leveraging specific HCI facilitators. By incorporating mechanisms such as automatically fetching data from other systems, these facilities reduce manual errors, leading to improved data quality [113].

Despite the recognized importance of user-centered design in healthcare systems, the explicit relationship between HCI elements and their impact on data quality and data science aspects within CDSS environments has remained underexplored. Although previous studies have often discussed data analysis techniques and data preparation processes, the role of user interaction with the system has not been sufficiently addressed. By introducing the rational bridge between HCI elements and data quality, we established a new perspective that emphasizes the employment of HCI elements within CDSS to enhance data analysis capabilities in medical settings.

5.4 Conclusions

The medical decisions made by CDSSs will be more accurate and reliable when the provided data meets the data science criteria. In this chapter, we emphasize the significance of the user's interaction level with the system in determining the quality of high-quality data, and how leveraging the introduced HCI elements can enhance data quality in the CDSS environment. In other words, considering these HCI elements, the generated data, which is the fruit of user interaction with the system, will be comprehensive, well-structured, appropriately tagged, and ultimately ready for data analysis and processing. This leads to boosting data quality and, consequently, more precise decisions as the main output of the CDSS.

Chapter 6

A synergistic Bridge between Human-Computer Interaction and Data Management within CDSS

6.1 Introduction

Clinical decision support systems are playing an increasingly vital role in assisting clinicians throughout the care process [309]. As healthcare systems evolve and generate vast, complex datasets, effective data management becomes crucial to ensure reliable and efficient decision-making [310]. This involves multiple stages (data generation, retrieval, tagging, and processing), all of which must be handled with precision [311], [312].

The integration of heterogeneous, low-quality data from multiple subsystems further underscores the need for robust data management practices [313]. Data entry and generation play a crucial role in this process, serving as foundational elements of human-computer interaction that shape user-system interactions in healthcare [314]. The quality of medical data, whether entered by users or pulled from other systems, directly influences CDSS performance [315],[316]. Reliable, timely data entry ensures clinicians have access to consistent, actionable information during critical decisions [317], while poor systems can increase cognitive load, frustration, and even medical errors [318], [319].

Although many studies have examined data management and integration in CDSS, the role of HCI in these processes is often overlooked. Addressing this gap is key to improving system usability and clinician adoption. This chapter highlights why data entry management should be treated as a core HCI concern and explores how data integration can enhance HCI-related aspects of CDSS.

Ultimately, the chapter proposes a scientific framework linking HCI principles with data management strategies, offering a roadmap for developing more intuitive, user-centered CDSS environments.

This chapter is organized into sections that collectively address the critical role of data management and integration within CDSS environments, highlighting their impact on HCI elements. In the upcoming sections, we begin by examining data entry management and control, focusing on existing features for their implementation. In the next section, we will articulate the significance of data standardization and normalization within CDSS and their concurrent role in enhancing HCI. The subsequent section will address data integration within CDSS, exploring its diverse forms. Then, we will discuss the described sections to illustrate the controversial topics outlined above and demonstrate the practical benefits of data management. Ultimately, we conclude that their collective effect enhances data quality and improves the accuracy of CDSS.

6.2 Data entry management and control

After surgery, clinicians often document rare cases using varied terminology. For example, one surgeon might write "unicornuate uterus with a rudimentary horn," while another might refer to the same condition as a "rudimentary horn anomaly." This inconsistency in medical language makes it difficult for researchers to locate and analyze specific cases. When studying rare conditions, such variability can hinder data retrieval, affect the accuracy of research findings, and emphasize the critical role of standardized data entry.

In Electronic Health Record (EHR) systems, data entry continues to be a significant bottleneck that frequently reduces their efficacy [320]. Clinicians may become frustrated and abandon the system due to its complexity or poorly designed input methods, which prevent them from utilizing it to its full potential [321],[322],[323],[324]. Designers of clinical systems are particularly concerned about ensuring accurate and complete data entry, as it directly impacts the quality of clinical recommendations [325]. Even minor errors in data entry can alter treatment outcomes or mislead physicians [326].

Incorporating HCI elements is essential to address these challenges [122]. Healthcare professionals frequently cite poor user-system interaction as a significant source of error in clinical environments [45]. High-quality, accurate data input not only enhances the precision of CDSS but also contributes to improved patient outcomes [327]. In this section, two methods to control medical data entry will be introduced.

6.2.1 Data range control

In medical information systems, specific data fields require predefined acceptable ranges to prevent inaccurate entries. This limitation is employed to increase the reliability of the data used by the CDSS [328]. These ranges are flexible (clinicians can adjust them based on clinical context). To support this, visual features such as color changes are often used; for example, as shown in Figure 6.1, a field may turn red if a value is entered outside the normal range. In this way, it indicates a possible error or abnormality [329].

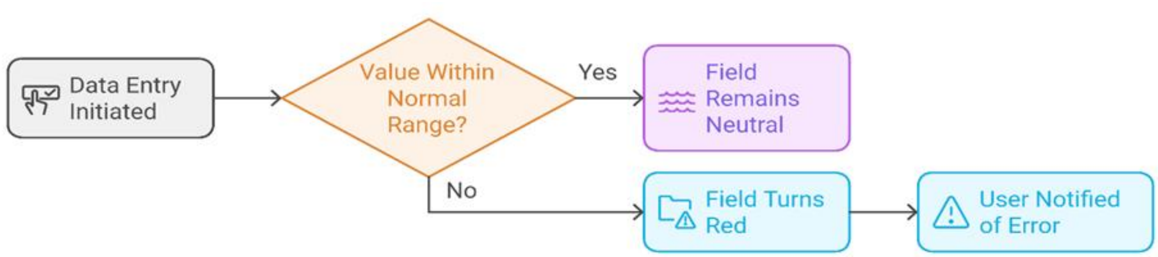


Figure 6.1: Visual feedback for out-of-range data entry [93]

Out-of-range data entries can lead to discrepancies between research findings and clinical decisions. Studies show that such anomalies can distort statistical analyses and reduce the accuracy of predictions and treatment outcomes [295]. Hence, there is a serious need to detect and control out-of-range data entries to maintain data quality and facilitate data analysis.

The most common causes of data entry errors include transcription errors, inaccurate lab measurements, and misinterpreted reference ranges. To identify and improve data entries that fall outside the usual range, studies emphasize the importance of data quality control procedures and validation evaluation [330]. In healthcare systems, these constraints encourage the use of more trustworthy data.

6.2.2 Data entry obligations controlling

The mandatory medical data fields are essential for ensuring the accuracy and completeness of the data.
Missing data fields and incomplete health records will be significantly reduced because of this necessity, which stops data-missing phenomena [331], [332].

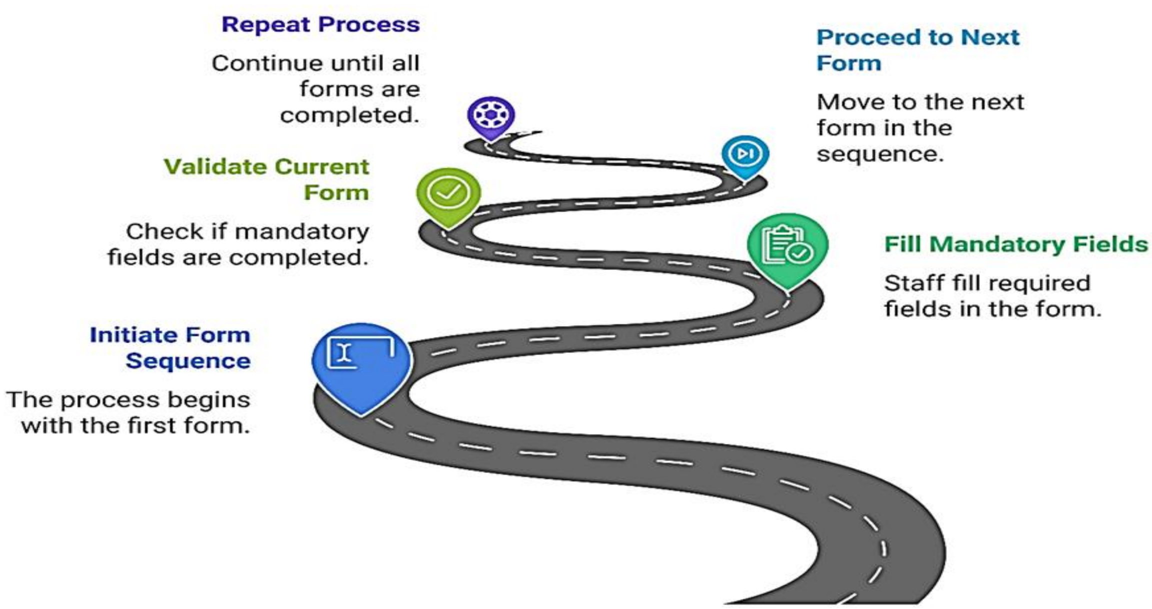


Figure 6.2: Sequential and mandatory data entry in medical forms [93]

As shown in Figure 6.2, some medical systems enforce strict data entry requirements by organizing forms sequentially, preventing users from progressing to the next section until all mandatory fields in the current form are completed.

This approach offers several key benefits. First, it guarantees data completeness, providing physicians with the essential information needed for effective decision-making. Second, by requiring specific fields to be filled, as defined by clinicians, it reduces the risk of errors and inconsistencies. Ultimately, this method supports a more streamlined workflow, enabling users to have timely access to accurate data, which in turn leads to better patient outcomes [333].

6.2.3 Leveraging automated text generation for accurate data entry management

Based on the data entry concerns mentioned in the previous sections, we conducted an empirical study to introduce a new technology designed to address data management issues [175]. This innovative platform is designed to meet the needs of professionals, including sonographers, radiologists, and surgeons, enabling them to generate medical reports in text format easily. First, the medical personnel fill in the data fields of the medical forms, considering the system's policy during data entry. Once completed, the medical text (report) originating from the data fields will appear automatically. By employing this technology, the data entry process can be managed and controlled step by step, preventing missed or out-of-range data. This diminishes the need for manual report writing (reducing errors, inconsistencies, and variability between practitioners) and ensures more complete and reliable documentation.

One of the advantages of the proposed system is the *data range control mechanism*. Each data field must observe predefined acceptable values. If a user enters a value outside the allowed range, the system provides immediate feedback, prompting the user to correct their input. The platform also enforces mandatory completion of fields. It prevents users from saving or submitting records unless all required information is entered, ensuring the collection of high-quality, comprehensive data. Another helpful feature of this technology is its focus on *user-centric design*. The interface is user-friendly and seamlessly integrates into clinicians' daily routines, minimizing disruptions. It enables effortless data entry, reducing mental effort. In this way, the medical staff can concentrate on the treatment plan instead of typing.

This study compared errors in traditional text-based systems and automated text-generating systems, with a focus on missed or out-of-range data. The introduced technology reduced data errors and boosted accuracy and reliability. It also revealed a key research gap: the need to understand better how HCI elements influence data management, accuracy, and medical decision-making.

6.3 Data standardization and normalization

Data standardization and normalization are pivotal for managing complex medical data in CDSS. They maintain data consistency across diverse sources, including lab results, radiology reports, medical histories, and wearable devices [334]. They assist the system in accurately interpreting and analyzing medical data. Observing these attributes enables accurate data interpretation and analysis, even within different systems and platforms [335].

By standardizing and normalizing data, CDSS enhances the user experience in several HCI dimensions:

- **Improved user interface:** Uniform data formats and terminology simplify navigation and learning [336].
- **Reduced cognitive load:** Normalized data structures simplify data entry and retrieval processes, reducing physicians' cognitive burden [337], [338].
- **Enhanced decision-making:** Consistent data representation across different platforms and systems allows for more accurate and reliable clinical decision-making [295].
- **Increased system interoperability:** Standardized data formats facilitate seamless integration with other healthcare systems, improving data sharing and collaboration [334].

Ultimately, prioritizing data standardization and normalization leads to a more efficient, reliable, and user-friendly CDSS, resulting in enhanced clinical workflows and improved patient care.

6.3.1 Data transformation pipeline

Standardizing medical data is crucial for ensuring its compatibility with CDSS functionality. This achievement can be acquired through a data transformation pipeline that facilitates the normalization and integration of heterogeneous, incomplete, and inconsistently formatted data [339],[340]. This process resolves inconsistencies and data gaps, which may mitigate decision accuracy.

From an HCI perspective**,** data transformation has a direct impact on usability and user experience within CDSS. The system's usability level depends on its ability to present clean, standardized, and interpretable data to end-users [341],[342]. By resolving inconsistencies and structuring data properly, physicians receive reliable and actionable information, thereby eliminating the need to adjust or interpret flawed inputs manually. This reduces cognitive load (one of the most critical HCI elements), allowing users to focus on clinical decision-making rather than troubleshooting data issues [343].

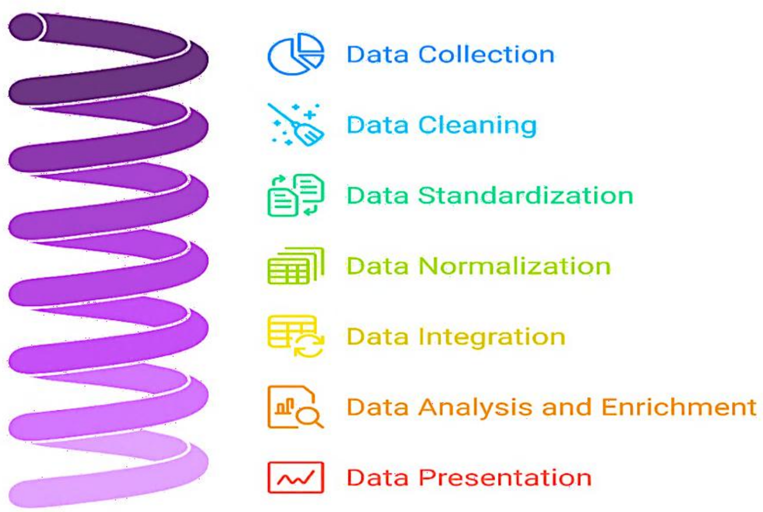


Figure 6.3: Healthcare data transformation pipeline [93]

As illustrated in Figure 6.3, to achieve the mentioned objectives, a practical implication called "data transformation pipeline" is implemented, ensuring that medical data is collected, cleaned, standardized, integrated, and presented in a structured format [344], [345], [346].

Ultimately, this pipeline is not merely a technical necessity but a foundational component of an effective HCI strategy. By ensuring the data presented to users is accurate and coherent, it fosters trust, reduces user fatigue, and improves system acceptance (all essential for successful decision support in complex healthcare environments).

Once data has undergone this transformation process, it becomes ready for decision-making, with potential gaps identified across several key areas:

- **Incomplete data**: Missing entries in critical fields, such as medication history or lab results, can significantly impact clinical decisions. Studies indicate that data incompleteness remains a common challenge in healthcare, often affecting patient outcomes [347].
- **Inconsistent data**: Variations in terminology, such as "hypertension" vs. "HTN," can create discrepancies that complicate analysis. Specific predictive models are designed to manage these inconsistencies effectively [348].
- **Fragmented data**: When information is scattered across disconnected systems without proper integration, it can lead to fragmented medical data, and consequently, poor outcomes and increased costs [349].
- **Outdated data**: Since decisions based on obsolete information can compromise accuracy and relevance, updating medical data is essential for adequate clinical support [350].

Since this pipeline plays a crucial role in addressing various data gaps, it helps reduce specific issues associated with CDSS:

- **Clinical risk:** Missing or data gaps can compromise the CDSS functionality, affecting the quality of disease identification and therapeutic strategies [280]. For instance, Insufficient lab results, incomplete medical images, or gaps in a patient's medication history may hinder physicians from determining the proper course of medical treatment. Likewise, inaccurate records might obscure allergies, contraindications, or coexisting conditions, leading to flawed treatment choices. This highlights the need for a robust, integrated data pipeline to ensure that CDSS delivers a complete and accurate patient profile, empowering clinicians to make informed decisions [295].
- **User dissatisfaction:** When physicians encounter recommendations generated by the CDSS based on incomplete data, they will be unable to trust the system [351]. They rely on data that is timely, accurate, and complete to make medical decisions. If data gaps or inconsistencies appear in the system's output, healthcare providers may be disinclined to spend extra time manually verifying information or tracking down missing details. This not only increases cognitive load but also disrupts workflows, reduces efficiency, and leads to frustration. Over time, these issues erode confidence in the CDSS, ultimately limiting its adoption and effectiveness in clinical settings [300].
- **Algorithm bias:** Machine learning algorithms in CDSS rely on comprehensive, representative datasets to generate precise predictions. When datasets are exposed to

data gap problems (due to incomplete records, underrepresented populations, or inconsistent data integration), bias may seep into the model. This bias can result in predictions that favor one demographic group over another, ultimately undermining fairness and equity in patient care [352]. Furthermore, missing data compromises model stability and reduces predictive accuracy, leading to recommendations that may hinder clinical decision-making. Overcoming these challenges requires robust data integration and effective management of incomplete records, ensuring that CDSS tools deliver fair and consistent outcomes [353], [354].

To ensure CDSS works smoothly, the data feeding into them must be consistent and coherent, even if it comes from different sources [295]. To achieve this, a robust data transformation process is required. The introduced transformation pipeline will empower the data integration procedures within the CDSS. In this way, the system's reliability and overall usability will be significantly improved [351].

6.3.2 Empirical analysis of data standardization and normalization in CDSS

To substantiate the role of data transformation in enhancing the effectiveness of Clinical Decision Support Systems, we conducted an empirical analysis using the MIMIC-IV (Medical Information Mart for Intensive Care) dataset [355]. This dataset is widely used in healthcare research and provides de-identified data on patients in the ICU (Intensive Care Unit). It is publicly available through PhysioNet and has been used extensively to study medical data management, making it a robust choice for this analysis.

The MIMIC-IV dataset contains various types of medical data, including lab test results, patient demographics, medication history, and clinical notes. For this section, we focused on lab test results (such as glucose, sodium, and hemoglobin levels) from the “lab events” table and patient demographics from the “patients” table. The data are essential for CDSS, as they contribute directly to clinicians' decision-making. This empirical section aims to apply standardization and normalization procedures to demonstrate how data transformation can improve the usability and decision-making potential of CDSS.

Although real-world clinical data, such as MIMIC-IV, inherently reflect the complexity of medical environments, these complexities do not compromise the identity or applicability of EMR datasets. The preprocessing pipeline (including unit harmonization, terminology standardization, and normalization) was designed to preserve the clinical integrity of the data while enhancing its analytical usability. Specifically, we followed established data transformation protocols, including LOINC-based (Logical Observation Identifiers Names and Codes) terminology mapping, SNOMED-CT (Systematized Nomenclature of Medicine—Clinical Terms) alignment, and unit conversion standards recommended by HL7 (Health Level Seven International) and clinical laboratory guidelines [356], [357]. These protocols ensure semantic consistency, interoperability, and comparability across diverse hospital systems.

By adhering to these standards, the resulting dataset remains representative of broader ICU settings, supporting generalizability to other hospital systems and clinical decision support contexts. Nonetheless, studies using real-world EMR data must remain vigilant to potential sources of bias. These include selection bias (e.g., ICU-specific patient profiles), measurement bias (e.g., inconsistent lab equipment or documentation practices), and temporal bias (e.g., evolving clinical protocols over time) [358], [359]. In this chapter, such risks were mitigated through robust data cleaning, rule-based anomaly detection, and normalization techniques that preserved distributional characteristics while reducing the influence of outliers. These safeguards enhance both internal validity and external applicability of the findings.

6.3.2.1 Methodology

We followed a comprehensive data transformation pipeline, which included key steps such as data cleaning, standardization, normalization, and data analysis. These steps were carefully designed to address common issues in medical data, such as missing values, inconsistent units, and diverse terminologies. First, the medical data passes through the pipeline's steps and will be refined for presentation in the final stage. We describe these steps by explaining the technical details within the dataset.

6.3.2.2 Data preprocessing and cleaning

Before diving into technical analysis, we first performed essential *data cleaning* steps to handle missing values, erroneous entries, and discrepancies across datasets:

- **Missing data imputation**:

In the "labevents" table, which contains records of laboratory tests, some entries were incomplete; specifically, the results for specific lab tests (lab_value) were missing. To address this issue, we employed a technique known as mean imputation [360]. This method involves calculating the average result for each specific type of test based on all the available data and then filling in the missing values with that average. For example, if a blood glucose test had missing results in some records, the average blood glucose value from the remaining data was used as a substitute for the missing entries. This approach works particularly well for standard lab tests, where the overall data variability is small, ensuring that the imputed values are reasonably representative of the actual data.

By applying this method, the dataset becomes complete and more usable for further analysis, which is crucial for improving decision-making in clinical systems.

- **Erroneous data management**:

During data preprocessing, we identified and removed anomalies in the dataset, such as glucose values exceeding 1000 mg/dL, which are considered implausible based on established medical standards (e.g., references to specific guidelines or textbooks). To achieve this, we employed a rule-based approach [361], establishing upper and lower bounds for critical lab values in accordance with accepted medical guidelines. This method ensures that only data within physiologically plausible ranges is retained for further analysis.

6.3.2.3 Data standardization

This step involved standardizing the data, ensuring that test results recorded in different formats and units across multiple systems could be effectively compared and integrated. In the following subsections, we will explore the specific approaches taken for unit conversion and terminology standardization. These processes are essential for creating a cohesive and reliable data environment that supports evidence-based decision-making in healthcare settings.

- **Unit Conversion:** Different lab systems recorded results in various units, such as glucose levels in mg/dL or mmol/L. To standardize the data, we converted all glucose measurements to mmol/L using the conversion factor (1 mg/dL = 0.05551 mmol/L) [362]. This conversion was performed programmatically using Python's Pandas library, where a unit conversion function was applied across relevant columns. Standardizing units ensures that all measurements are on the same scale, facilitating more reliable and consistent analyses [363].
- **Terminology Standardization:** Lab test names, such as "glucose," "sodium," and "hemoglobin," were mapped to a unified terminology using established medical coding systems, such as LOINC (Logical Observation Identifiers Names and Codes) [364] and SNOMED-CT (Systematized Nomenclature of Medicine Clinical Terms) [365]. We leveraged existing mappings in the MIMIC-IV documentation to ensure consistency in lab test identification. Standardizing terminology is vital for integrating data from diverse sources and improving the interoperability of healthcare information systems.

6.3.2.4 Data normalization

After cleaning and standardizing the data, we applied normalization to make lab results comparable across patients, regardless of the test type or scale. This step was crucial for ensuring consistency in clinical decision-making, particularly for lab tests like glucose and sodium, where raw values can vary significantly between patients and tests.

We chose Min-Max Normalization, a technique that scales data to a fixed range between 0 and 1, preserving the shape of the original distribution and reducing the impact of outliers compared to other normalization methods [366]. The formula used for Min-Max Normalization is:

$$\text{Normalized Value} = \frac{\text{Raw Value} - \text{Min Value}}{\text{Max Value} - \text{Min Value}}$$

To clarify the implications of the above formula, they have been described as follows:

- **Raw Value**: Refers to the original, unprocessed data as collected from medical systems. For example, glucose levels in this dataset are reported in their natural measurement unit, mg/dL (milligrams per deciliter), before any transformation or scaling.
- **Min Value**: Represents the smallest observed value in a dataset. During normalization, it is used as a reference point to scale the raw values to a uniform range (commonly between 0 and 1).

- **Normalized Value**: The transformed value that has been scaled to fit within a predefined range (0 to 1 in this case). This is achieved using a Min-Max Normalization formula:

For example, if a glucose test has a minimum value of 70 mg/dL and a maximum of 300 mg/dL, a patient with a raw value of 150 mg/dL would have a normalized value of:

$$\frac{150-70}{300-70}=0.333$$

This normalization process ensures that no single test dominates the analysis due to its scale, particularly in machine learning models where feature scaling can significantly affect model performance. We selected Min-Max Normalization over other techniques, such as Z-score normalization [367], because our data did not follow a Gaussian distribution [368]. Additionally, we addressed potential limitations, such as sensitivity to outliers, by implementing robust data-cleaning steps before normalization. This step was crucial for lab tests, such as glucose and sodium, where the raw values varied significantly between patients and tests. Normalizing the data enabled a more uniform comparison, which helped improve the consistency of clinical decision-making.

6.3.2.5 Result of data processing

To better understand the effects of the data transformation pipeline, we visualized the data at different stages of this process. The distribution of glucose levels before and after normalization was compared using histograms. Before normalization, the glucose data exhibited a skewed distribution, characterized by significant variations in values. After normalization, the data distribution became more uniform, demonstrating how the normalization process helped scale the data for more accurate and comparable results. Exploiting the normalized dataset, we prepared two charts to depict the impact of data normalization on usability. The dataset and the Python script containing the code used in this study are available at the following repository: Zenodo Repository.

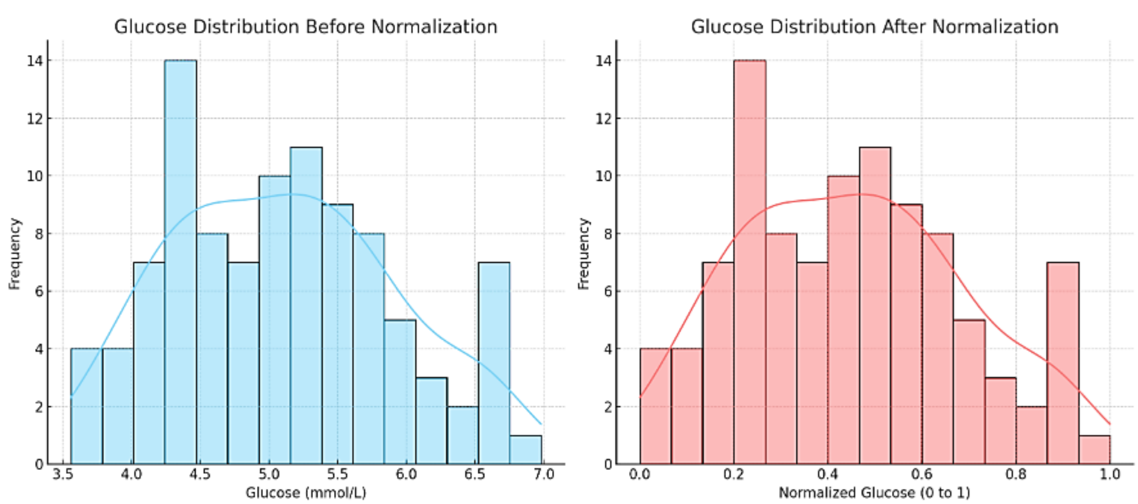


Figure 6.4: The effect of normalization on glucose distribution

The figure above visualizes the consequences of the recent normalization—the distribution of glucose levels before and after normalization was compared. Before normalization, the glucose data exhibited a skewed distribution, characterized by significant variations in values. After normalization, the data distribution became more uniform, demonstrating how the normalization process helped scale the data for more accurate and comparable results. In other words, this difference can be interpreted as follows:

- *On the left*, we can see the glucose levels in mmol/L before normalization. The distribution is skewed and has varying ranges.
- *On the right*, after applying min-max normalization to the glucose values, the data has been scaled to fit a range between 0 and 1. This uniform distribution facilitates easier comparisons and is more consistent within Clinical Decision Support Systems.

Examining the glucose distribution before and after normalization revealed improvements in different facets:

- **Variability**: In the raw data (left), glucose levels have a wide range and varying units, which may hinder compatibility across systems. After normalization (right), the data is standardized, allowing seamless integration into decision-support systems.
- **Consistency**: Normalized data removes the impact of extreme values (outliers) and ensures all data points are proportionally adjusted. This reduces errors in interpretation and enhances interoperability between CDSS modules.
- **Usability**: From an HCI perspective, normalized data reduces cognitive load for clinicians, as they no longer need to interpret raw values manually. Instead, the CDSS provides clean, actionable insights based on pre-processed data.

By applying normalization, the pipeline transforms heterogeneous and inconsistent medical data into a standardized format suitable for analysis and decision-making. This process exemplifies how standardization and normalization contribute to improving data accuracy, usability, and the overall reliability of CDSS in clinical practice.

6.3.2.6 Statistical evaluation of glucose normalization

To evaluate the impact of Min-Max normalization on glucose data, a series of statistical tests was conducted comparing the raw and normalized distributions. These tests were selected to assess distributional characteristics, variance stability, and the magnitude of transformation effects, ensuring that the preprocessing step meaningfully improved the dataset's analytical quality for CDSS applications.

- **Normality Assessment:** The Shapiro–Wilk test [369] was applied to both raw and normalized glucose values to assess whether the data followed a normal distribution. The test returned a W statistic of 0.9779 and a p-value of 0.0904 for both variables, indicating no statistically significant departure from normality at the 0.05 threshold. This supports the use of parametric methods in subsequent analyses and confirms that the normalization process preserved the underlying distributional shape.
- **Variance Homogeneity:** To determine whether normalization affected the spread of glucose values, Levene's test [370] was used to compare variances between the raw and normalized datasets. The test yielded a statistic of 212.82 with a p-value of 3.25×10^{-33},

indicating a highly significant difference ($p < 0.001$). This result confirms that normalization substantially reduced variability, which is critical for improving consistency across patient records and enhancing the reliability of CDSS input data.

- **Mean Comparison via ANOVA:** A one-way ANOVA [371] was conducted to evaluate whether normalization introduced a statistically significant shift in the central tendency of glucose values. The analysis yielded an F statistic of 3902.05 and a p-value of 2.93×10^{-132}, indicating a statistically significant difference in means between the raw and normalized datasets. This result validates the transformation's impact on data structure and supports its role in standardizing clinical metrics.
- **Effect Size Estimation:** To quantify the magnitude of the observed change, Cohen's d [372] was calculated using the pooled standard deviation of both distributions. The resulting value was 8.83, indicating a substantial effect size. This suggests that normalization not only achieved statistical significance but also introduced a significant and practically meaningful shift in the data's scale and interpretability.
- **Confidence Interval for Mean Difference** The mean difference between raw and normalized glucose values was 91.48, with a 95% confidence interval ranging from 88.62 to 94.34. The narrow interval and extremely low p-value ($p < 0.001$) reinforce the precision and reliability of the transformation, confirming that the normalization process consistently scaled glucose values across the dataset.

Together, these statistical findings demonstrate that Min-Max normalization is a robust and effective preprocessing step for clinical data. It preserves distributional integrity while reducing variance and standardizing scale, thereby enhancing the usability of glucose values within CDSS workflows. The Python script used to generate the statistical analysis mentioned is available for public access in the related Zenodo repository, which is linked within the supplementary materials, allowing for replication or extension of this analysis.

6.4 Data integration within clinical decision support systems

Data integration refers to the process of combining information from multiple sources into a unified, cohesive format. In the context of CDSS, this integration is crucial for delivering timely, accurate, and relevant information that enables healthcare providers to make informed decisions [373]. Medical data is often scattered across different systems, including Electronic Health Records, laboratory information systems, radiology reports, and real-time monitoring devices. By consolidating these diverse sources, practitioners obtain a comprehensive view of the patient, ensuring that no critical details are overlooked [374].

Data inconsistency, data scattering, or missed data are phenomena that may affect the accuracy level among CDSSs. To prevent them, data integration can play a significant role within CDSS. It means that through data integration, a seamless and comprehensive data gathering will be carried out. As a result, more precise data analysis and recommendations will be achieved [375].

6.4.1. Bridging data integration with human-computer interaction

Data integration can firmly improve the user experience and system usability by delivering essential information to physicians in a clear and unified format [376]. The integration process can be implemented in two different dimensions: data integration and interface integration. While these concepts are closely related, as Figure 6.5 illustrates, each plays a distinct role in enhancing the system's usability and user experience [376],[377]. Since physicians can access integrated data from multiple sources, it elevates their trust in the system's accuracy and completeness. At the same time, a smooth, unified interface (rather than various platforms) makes information easier to access and interpret, leading to more efficiency and user satisfaction.

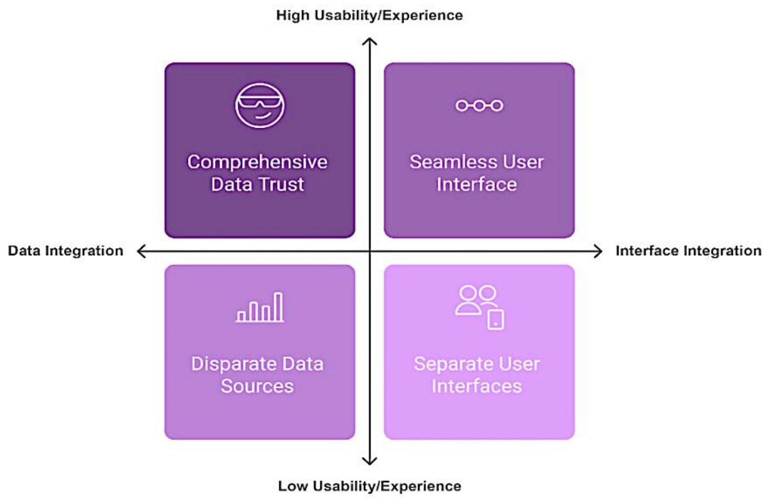


Figure 6.5: Enhancing usability and user experience through integration [93]

Considering the significance of this perspective on data and interface integration, medical system designers have recently attempted to unify existing systems, leveraging new cloud technologies. Services like iPaaS (Integration Platforms as a Service) present a collection of integration potentials, including data integration, application integration, and API (Application Programming Interface) management [378], [379].

Data integration in CDSS enhances user experience in several important aspects. By standardizing and integrating data, clinicians can find medical information and receive recommendations without the probable confusion stemming from scattered data sources [380]. Moreover, the user's trust in the system will be enhanced by obtaining accurate information, which will encourage them to engage with the system consistently [381]. This trend establishes a positive feedback loop between a higher HCI level and increased accuracy in medical decision-making.

6.4.2. Classifying data integration employed for improving clinical decision support systems' usability and functionality

Within CDSS applications, proper data integration is crucial for streamlining medical processes, making evidence-based decisions, and achieving optimal diagnostic outcomes. Considering the diverse needs of physicians, classifying data integration based on its nature presents a clear framework to demonstrate its impact on system functionality and HCI aspects [382]. The classification mentioned in Table 6.1 illustrates that integration strategies lead to improvements in HCI aspects, such as mitigating mental effort, enhancing data accessibility, and ensuring interface consistency.

Table 6.1: Different data integration types within CDSS [93]

Data Integration Type	Description	References
Electronic Health Record Integration	Incorporating patient data from EHRs into CDSS	[121]
Genomic Data Integration	Incorporating genomic information into CDSS	[383]
Medical Imaging Integration	Incorporating imaging data (e.g., X-rays, MRIs) into CDSS	[384]
Laboratory Data Integration	Incorporating lab results into CDSS	[385]
Pharmacy Data Integration	Incorporating medication data into CDSS	[386]
Wearable Device Data Integration	Incorporating data from patient wearables (e.g., heart rate monitors) into CDSS	[387]
Social Determinants of Health (SDOH) Data Integration	Incorporating socioeconomic and environmental data into CDSS	[388]
Research Data Integration	Incorporating the latest clinical research findings into CDSS	[389]
Patient-Reported Data Integration	Incorporating data directly reported by patients (e.g., symptoms, outcomes) into CDSS	[390]
Administrative Data Integration	Incorporating administrative information (e.g., billing, scheduling) into CDSS	[391]

Different types of data integration can each influence the HCI aspects of a CDSS and shape decision-making outcomes. In this respect, integrating EHRs improves access to comprehensive patient data and reduces manual entry, although careful workflow design is necessary [3]. Proper data arrangements. Genomic data integration streamlines individual therapy options, but modern visualization features are needed to manage its complex nature [383]. Linking medical imaging with textual information enhances diagnostic accuracy but relies on intuitive navigation [384]. Integrating laboratory data is crucial for enabling real-time decision-making and improving the speed and accuracy of diagnostics [385]. Similarly, pharmacy data integration can enhance pharmaceutical safety if implemented with a well-designed interface to avoid alert fatigue [386]. Data from wearable devices supports real-time monitoring by providing subtle alerts that benefit both physicians and patients [387].

Additionally, combining Social Determinants of Health (SDOH) with clinical data improves system explainability and promotes equitable care [388]. Research data integration reinforces evidence-based practices through efficient data filtering [389]. Incorporating patient-reported information ensures a patient-centered approach; however, a user-friendly interface and an easy-to-use navigation system are prerequisites for collecting imperative medical data [390]. While administrative data integration may not directly impact clinical decisions, it reduces administrative burdens, enabling providers to focus on patient care [391].

According to the various advantages of data integration, it enhances HCI elements and leads to an augmentation of CDSS performance.

6.4.3 Case studies on the effect of data integration on decision accuracy and HCI within CDSS

Several studies have empirically investigated the relationship between data integration, data accuracy, and human-computer interaction in medical settings. Liyuan et al. [392] conducted a data integration project that incorporated a best practice database into a CDSS. Their findings showed that providing real-time access to evidence-based clinical guidelines through data integration significantly enhanced diagnostic accuracy and reduced the time needed for diagnoses. This integration enabled physicians to access relevant information without interrupting their workflow, thereby improving decision-making accuracy [392], [393]. They emphasize that systems with poorly integrated interfaces can increase cognitive load, leading to frustration among healthcare professionals.

Another research project [394] highlighted the successful implementation of data integration within a Medical Decision Support System (MDSS) framework, aiming to boost user confidence through the use of Internet of Things (IoT) devices. This research demonstrated that integrating data from various IoT sources significantly improved system performance.

Additionally, we conducted a separate empirical study [246] where an attendance-tracking subsystem was integrated with a hospital's medical information system. This integration allowed for seamless cross-checking of patient attendance with clinical records, reducing manual data entry errors, streamlining workflows, and enhancing the user experience in decision-making. The reception rate, a key metric in medical settings, is used to track the number of admitted patients in hospitals and is calculated as follows:

Reception rate = number of admitted patients ÷ number of useful working hours

By calculating this metric before and after integrating the attendance-tracking subsystem, we identified discrepancies originating from potential manual errors. This integration allowed users to calculate the reception rate based on active working hours, excluding passive hours. It means that the calculation begins when the user logs into the system, using only the active hours for the reception rate. Accurate calculation of this metric was previously not feasible due to the absence of the attendance subsystem.

The increased accuracy resulting from these integration cases improved the system's reliability and user acceptance, leading to greater user interaction with the system. Consequently, the system demonstrated improvements in several aspects of HCI, including user satisfaction [132], ease of use [73], and data entry issues [122]. These empirical studies illustrate how data integration in medical settings can have a positive effect on HCI.

6.5 Discussion

This chapter has explored a critical yet often neglected area of healthcare technology: the relationship between data management and HCI concepts within CDSS. By looking into data entry management, standardization practices, and the integration of various medical subsystems, this research addresses a less-studied aspect of healthcare technology: the connection between data science and HCI.

Although many studies have focused on the technical side of data management and integration, few have examined how these factors influence user interaction with the systems. Discussions around data entry often center on reducing errors, but the cognitive challenges caused by poor data presentation (an essential HCI element) have received little attention [395], [396]. This gap highlights an area needing further research. Although the automated text generation technology discussed in this study significantly minimizes manual errors, it also helps reduce physicians' frustration and mental burden when entering repetitive or complex data. Systems that incorporate these features become more intuitive, enhancing user interaction and mitigating issues related to inconsistent terminology [175],[397].

Despite recent progress in data management technologies, several challenges remain in the design of CDSS. One major issue is the variability in medical terminology, which poses a significant barrier to understanding. Inconsistent terms can complicate both data entry and retrieval, ultimately affecting the accuracy of research and clinical decision-making [398], [399]. While implementing range controls and mandatory data fields has been suggested as a potential solution, these systems must be regularly updated to reflect the latest medical advancements [285]. Additionally, the differences in standards across countries create substantial obstacles for data formatting, which hampers efforts to achieve standardization and normalization through a structured data transformation process [397].

Wearable devices and IoT solutions produce large volumes of real-time data, including vital signs, activity levels, and sleep patterns. Although these technologies can significantly improve continuous patient monitoring and early warning systems, they present some challenges. One major issue is the large volume of data, which can complicate the functionality of CDSS and make it more difficult for physicians to make informed decisions. Additionally, the deficiencies in standardizing IoT data formats and device protocols can hinder seamless integration with existing CDSS [400]. In the context of data integration, it's crucial to review alert sensitivity and the rules that trigger alerts to avoid alert fatigue. Medical alerts that share similar concerns and come from different subsystems before integration can negatively affect the system's usability and lead to alert abandonment [401], [402].

Despite these challenges in bridging data management and HCI concepts, the interconnection between them is undeniable. Effective data management and integration can enhance user interaction by providing consistent data presentation and reliable medical information, thereby improving the overall user experience. This, in turn, enhances system usability and HCI aspects, reducing data entry errors and missed information, and ultimately ensuring that appropriate data is available for informed medical decision-making, thereby strengthening data management practices. This reciprocal relationship creates a positive feedback loop:

improved HCI enhances data management by ensuring high-quality data, while effective data management contributes to a seamless and user-friendly experience.

This chapter presents various scalable solutions, including automated text generation, designed to address data entry challenges and alleviate user workload. Additionally, by combining data management strategies with HCI elements, this research demonstrates how effective data practices can improve user satisfaction and build trust in CDSS. As a result, the system's usability across different aspects of HCI will be enhanced, leading to meaningful improvements in clinical outcomes.

Looking ahead, future research should focus on developing advanced natural language processing (NLP) tools to address inconsistencies in medical terminology and facilitate the real-time harmonization of terms. Creating globally standardized data formats is essential for ensuring seamless interoperability across diverse systems and regions. Furthermore, enhanced training programs will prepare healthcare providers to navigate complex, integrated systems effectively. Progress in these areas will foster innovation and improve both the functionality of CDSS and patient outcomes.

6.6 Conclusions

This chapter could introduce a bridge between key concepts of HCI elements and essential principles of data science, including data management, transformation, and integration, all within the context of CDSS. Through practical examples, we have illustrated how data entry management and data integration influence key HCI aspects, including usability, cognitive load, and user satisfaction, and how these elements interact with one another. Our analysis reveals the interconnectedness of data science and HCI, highlighting how careful system design can improve both data quality and user experience.

Our findings suggest that emphasizing HCI elements leads to improved data accuracy and consistency, which are crucial for making informed medical decisions. High-quality data, achieved through controlled data flow and smooth integration, enhances the reliability and functionality of CDSS, ultimately contributing to better patient outcomes. By presenting this scientific framework, we aim to deepen the understanding of how incorporating HCI into data practices can boost the performance and acceptance of advanced healthcare technologies.

For further details and complementary insights, **Annex *D*** provides access to the full text of the published paper in a prestigious journal.

Chapter 7

Aligning system design with HCI principles: Enhancing medical recommendations and decisions.

7.1 Introduction

In contemporary healthcare, the design of medical systems has a pivotal role in shaping effective human-computer interaction, resulting in optimization of system functionality [85]. A system designed with high-level HCI elements not only encourages the users to interact with the system but also concerns itself with navigating and arranging medical data [403]. This means that during data entry, when generating medical information and interacting with users through the designed system, it is essential to prioritize data quality and analysis. Even if the provided medical data is thorough and complete, if it is not appropriately organized for the next stage (data analysis) and lacks effective data tagging, it will not result in accurate and desired medical decisions [26],[404].

A significant shortcoming in the existing system design is incompatibility with contemporary medical processes [405]. One of the identified issues is the cyclical nature of the treatment plan that stands out as a critical requirement. A treatment cycle typically consists of several specific phases, including diagnosis, treatment planning, and outcome evaluation. However, the current designs of medical information systems fail to accommodate the cyclical nature of these phases [406]. Electronic Medical Records (EMRs), which serve as the primary platform for collecting medical data, are also subject to this issue. As they act as data sources for CDSS, their system design must align with real-world requirements [407]. In the existing system design, medical data is typically located in fragmented sections, making it difficult for physicians to gain a comprehensive understanding of the patient's medical history and critical treatment requirements. In other words, it is unclear which treatment cycle the recorded data pertains to. This uncertainty diminishes the essential transparency for data analysis [408].

Another advantage of optimizing human-computer interaction is the ability to deliver tailored content for patient training based on their specific medical needs and circumstances. This can be achieved by categorizing informative content, allowing each patient to receive more relevant information in their Personal Health Record (PHR) [409],[161]. In this context, the medical data pertinent to the patient’s training entered into the EMR should be categorized through data tagging. This allows medical practitioners to select the most suitable informational package to include in the patient’s PHR [410].

Current system designs frequently focus on the entry and retrieval of medical data within EMRs, without considering how data categorization and labeling influence subsequent data analysis and the accuracy of medical decisions [411],[412].

In this chapter, we demonstrate how considering HCI elements and physicians' real needs in medical system design can influence data quality and analysis, ultimately improving patients' outcomes. In this regard, we highlighted the importance of integrating the cyclical nature of treatment plans into CDSS applications. By exploiting cyclical data tagging within EMR data, the data arrangement will be tailored to meet the needs of physicians and patients, thereby streamlining medical data analysis. On the other hand, adequate data arrangement and tagging will assist physicians in categorizing patients' data properly, allowing it to be applied in various scenarios, such as making accurate decisions or managing PHR portals.

Throughout the current chapter, the cyclical nature of treatment plans is first illustrated, and the importance of leveraging this concept in medical system design is explained. Then, we articulate how the proposed approach can be implemented in the EMRs and what advantages this approach can provide for medical data analysis. In another section, we explain to what extent the patients' data categorization can assist the medical practitioners in presenting the most suitable educational content within PHR, considering each patient's profile exclusively. It is described as one of the prominent benefits of the introduced approach.

7.2 The treatment cycle insight

Medical processes, like other non-medical fields, follow a cyclical pattern. Since administrative, industrial, and financial operations are scrutinized within repetitive loops for improvement, medical plans often follow a similar trend [413],[414]. This section will delve especially into the context of "treatment cycles" within medical settings. A clear definition of this term and its significance in medical practice will be provided. By understanding the cyclical nature of treatment, we can identify opportunities to improve data organization and retrieval within EMR systems.

7.2.1 Defining treatment cycle in clinical context

A treatment cycle is a well-organized process that includes repeated phases of therapy with rest intervals that may involve no treatment or alternative interventions. For instance, a typical cycle might consist of one week of active treatment followed by three weeks of rest. When these cycles are repeated over time, they form a complete treatment regimen, often referred to as a treatment plan [415].

This cyclical structure is essential to treatment plans, which detail the timing, dosage, and sequence of interventions customized to meet each patient's unique needs. Clinical pathways (standardized, evidence-based protocols) help guide these cycles by outlining the diagnostic, therapeutic, and monitoring steps for specific patient populations. This approach ensures consistency while allowing flexibility based on the patient's clinical progress [416].

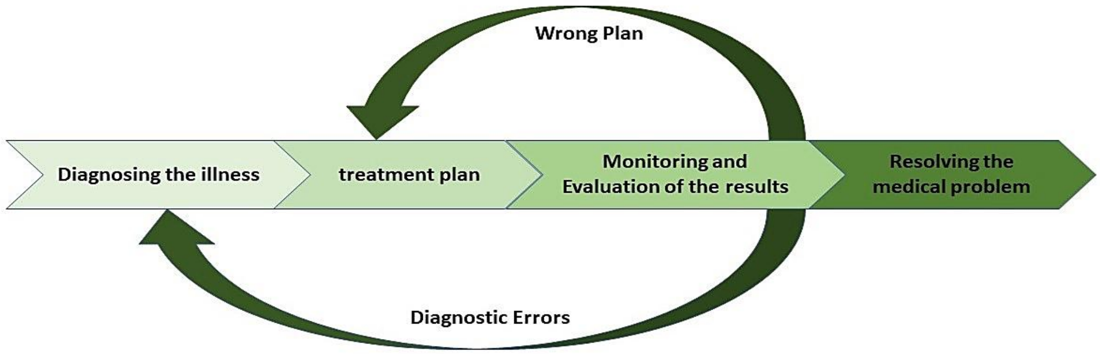


Figure 7.1: Treatment cycle overview [91]

The medical process involves a series of sequential steps that need to be carried out systematically. As shown in Figure 7.1, each stage holds its own priorities and occupies a distinct role within the broader framework. Both the diagnosis and the selected treatment plan will be evaluated considering the fulfilled steps.

7.2.2 The role of the cyclical approach in medical procedures

As shown in Figure 7.1, a series of functions are typically involved in both the diagnosis and treatment planning stages. Medical processes preferably need regular reviews and reassessments [417]. Evaluating and refining throughout the treatment stages are crucial, leading to the development of a cyclical approach in medical settings. Clinical pathways are structured models that outline the essential medical steps needed to treat specific patient populations [415]. They provide a clear depiction of a patient's diagnostic and treatment journey [418]. This highlights the importance of a cyclical approach, which fosters ongoing evaluation and improvement. Such an iterative process not only improves patient outcomes but also optimizes data analysis by enabling the integration of feedback and adjustments at every stage of care [419].

Treatment plans typically consist of distinct phases that are repeated over time. This cyclical approach enables the connection of data points to specific phases within a treatment cycle, thereby improving data organization. It facilitates the tracking of progress, the identification of trends, and the comparison of data across different cycles [420].

7.3 Comparison of the prevalent and cyclical approaches within EMRs

EMR systems have attained a critical point in their adoption and use. As healthcare professionals become increasingly skilled in utilizing these systems, their potential to improve clinical decision-making and enhance patient outcomes continues to be elevated [421]. To achieve these benefits, the EMR systems must be designed with transparency and efficiency. This section explores existing and proposed methods for structuring medical processes within EMRs, assessing their effectiveness, and areas for improvement.

7.3.1 Prevalent approach

Healthcare professionals are increasingly using EMRs to optimize clinical workflows, with innovations like smart forms enhancing their functionality [422]. The primary function of these systems is to support clinical decision-making by providing software solutions adaptable to patient-specific needs [423]. Physicians document patient information in designated forms during clinical encounters, updating data fields as treatment progresses and recording outcomes for later evaluation.

A fundamental requirement in EMR design is that data entry procedures reflect real-world clinical workflows while ensuring transparency in documentation and, ultimately, in the decision-making process. During patient visits, physicians enter pertinent medical information into structured data forms within the EMR system. As the treatment advances, they regularly update these records to capture the evolving clinical context. Upon completion of the treatment, the outcomes are documented to support a thorough and continuous evaluation of care quality and effectiveness.

One of the significant deficiencies of the conventional EMR systems is the lack of a clearly defined treatment cycle structure. It causes scattered data entry, where each data field is recorded separately, regardless of its connection to other relevant data. This issue hinders the tracking and assessment of the cure's progression, and consequently, the identification of therapy patterns. To resolve this issue, we proposed a new EMR model that facilitates the implementation of the mentioned treatment cycles.

7.3.2 Leveraging the treatment cycle approach into EMR

The successful adoption of EMRs heavily depends on meaningful physician engagement, which is often driven by both incentives for usage and consequences for non-compliance [424],[425]. However, for EMRs to deliver actual clinical value and be user-friendly, the data entered throughout the treatment process must represent the realities of medical workflows. To address this need, we propose an innovative cycle-based model that restructures how treatment data is recorded and interpreted within EMRs. This approach organizes the entire treatment plan into clearly defined cycles, offering a more coherent and transparent view of a patient's care journey. It enables us to repeatedly evaluate the results of the therapeutic plan and refine it as needed.

As depicted in Figure 7.2, the proposed model introduces a structured sequence for organizing data forms, where each form (except the initial one) requires the completion of preceding entries before it can be accessed or filled out. This approach prioritizes the logical order of data entry, with forms arranged sequentially according to their predefined importance. Although each form is assigned to a specific medical department and may be used independently by its respective users, the model preserves a sense of interconnection and continuity, binding the forms together in a cohesive, chain-like progression.

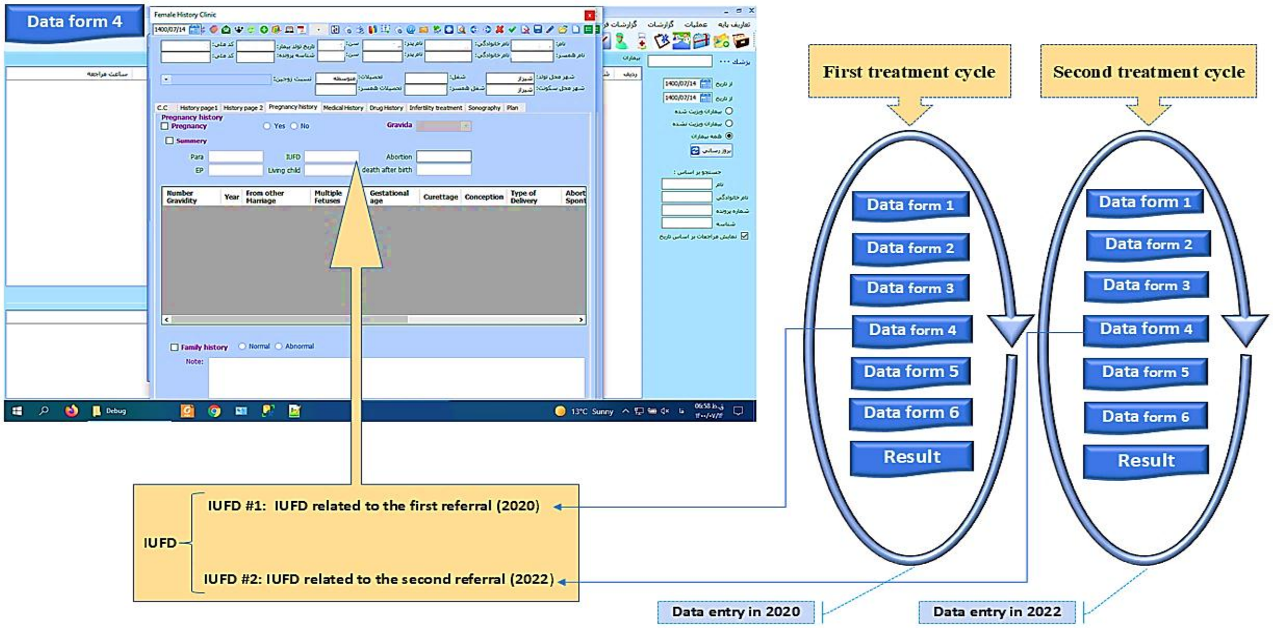


Figure 7.2: Challenges in current EMR systems for linking data entries to treatment cycles [91]

This structured framework addresses the current discrepancy between treatment cycles and associated data forms by establishing a coherent and logical sequence of events. By enforcing this order, the model improves data integrity and promotes a more consistent and accurate representation of the treatment process. To demonstrate its practical implementation, Figure 7.2 showcases a sample data field related to intrauterine fetal demise (IUFD), illustrating how the treatment cycle can be systematically structured.

In the proposed model, each IUFD data field associated with a patient referral is assigned a unique cycle number, clearly delineating individual treatment cycles. For example, IUFD records from 2020 can be distinctly separated from those in 2022 by referencing their respective cycle numbers. This patient experienced two independent treatment cycles, each following a different clinical path and outcome. The inclusion of a cycle number within medical reports enables healthcare professionals to accurately link each data entry to its corresponding treatment phase, supporting more precise evaluation of clinical progress and outcomes. Furthermore, the model allows for flexibility in defining and expanding treatment cycles, accommodating multiple data forms as necessary to suit specific clinical contexts. The structure and parameters of each cycle can be tailored to meet diverse medical needs, enhancing its applicability across various scenarios. To assess the effectiveness of this model, an empirical evaluation was conducted, comparing it to traditional EMR design and highlighting its advantages in organizing and interpreting medical data.

7.4 Empirical analysis of the cycle approach's application in EMRs

To evaluate the benefits of a cyclical approach in EMR data management and analysis, we developed a synthetic dataset (CycleDiabetes750) with 750 records modeled after real clinical data and emphasizing iterative treatment cycles and data tagging. Based on the MIMIC-III database [426], this dataset, which comprehensively covers diabetes-related variables (e.g., demographics, glucose levels, treatment details, diagnoses, and admissions), offers a robust foundation for simulating diabetes treatment scenarios. (available at https://doi.org/10.5281/zenodo.14968775 https://bit.ly/MIMIC-Cycle750).

To capture the inherent cyclicity of treatment plans, we enriched the original dataset with custom fields: 'treatment_cycle', 'cycle_tag', 'cycle_outcome', 'treatment_start_date', 'treatment_end_date', and 'total_cycles'. The 'treatment_cycle' field separates successive treatment phases (Cycle 1, 2, 3), while 'cycle_tag' categorizes patient glucose states (Initial_VeryHigh, Followup_Moderate) to indicate clinical severity and advancement. Meanwhile, 'cycle_outcome' records treatment efficacy per cycle, and the date fields track the duration of interventions. Furthermore, 'total_cycles' captures the overall number of treatment cycles per patient, enabling detailed longitudinal analysis. These enhancements transform a static, single-event dataset into a dynamic, cycle-oriented framework.

To reinforce the validity and generalizability of this chapter's findings, the synthetic dataset was constructed following established protocols for medical data simulation, including statistical fidelity, clinical plausibility, and transparent variable engineering [427], [428]. The CycleDiabetes750 dataset preserves the demographic and clinical distributions observed in MIMIC-III. At the same time, the added cycle-specific fields were derived using rule-based logic grounded in clinical thresholds (e.g., glucose level ranges) rather than arbitrary or subjective labeling. This approach aligns with best practices in synthetic EMR generation, minimizing risks of systematic bias and enhancing internal validity. Additionally, the dataset was reviewed for confounding effects across admission types, age groups, and comorbidity profiles to ensure that cycle assignments did not disproportionately reflect any single subgroup.

To further mitigate bias, we addressed potential sources, including selection bias (e.g., overrepresentation of specific admission types), measurement bias (e.g., uniform success rate values), and observer bias (e.g., subjective cycle tagging). These risks were mitigated through the use of transparent variable definitions, objective thresholding, and validation against real-world distributions, consistent with recommendations for bias-aware EMR simulation [429].

While synthetic datasets inherently lack temporal drift, the structure of CycleDiabetes750 was designed to simulate longitudinal progression, allowing for future integration with real-time EMR streams. The cyclical tagging framework (comprising treatment phases, severity labels, and outcome tracking) is not disease-specific. It can be adapted for use with other chronic conditions, such as hypertension, asthma, or cancer, where treatment unfolds in iterative stages. This generalizability stems from the modular nature of the cycle fields, which can be redefined based on domain-specific biomarkers and intervention protocols. As such, the proposed framework offers a scalable model for enhancing EMR usability across diverse clinical domains, supporting both retrospective analysis and real-time decision support.

The primary objective of this empirical analysis is to demonstrate that a cyclic approach in EMRs yields enhanced analytical precision and insights that are not attainable with conventional designs. By comparing results from studies that incorporate cycle tagging against those that do not, we highlight the added value of this framework in tracking treatment dates, assessing cycle-specific outcomes, and evaluating success rates.

7.4.1 Comparison of conventional and cyclical models

In this section, we conducted a thorough analysis of the treatment plan results by comparing criteria across treatment cycles and overall performance. We applied statistical tests and created visualizations to gain a better understanding of the variations. All analyses were carried out using Python, and you can access the associated code here: Comparison Cycling and non-cycling approaches.

Cyclical analysis: Patients were grouped according to their respective treatment cycles. This allowed us to examine variations within each cycle by calculating summary statistics (such as the mean and standard deviation) and by visualizing the unique data distributions for each phase. This approach helped reveal trends that might have been hidden in a straightforward aggregated analysis.

Table 7.1: Cycle-based metrics [91]

treatment cycle	post_treatment glucose_mean	treatment_success rate_mean	treatment_success rate_std	treatment_success rate_min	treatment_success rate-max
1	8238.71	14.26	11.62	0	25
2	8172.4	13.67	9.94	5	25
3	6672.6	25	0	25	25

Table 7.1 illustrates how we use a cyclical approach to break down data by treatment cycle. For each cycle (e.g., Cycle 1, Cycle 2, etc.), we calculated various metrics (mean, standard deviation, median, minimum, maximum, and count) for post-treatment glucose levels, as well as treatment success rates. Each row represents a treatment cycle, and each column a specific metric. For example, the cell at row 2, column 1 shows the average post-treatment glucose level for Cycle 2, giving a summary of that cycle's outcome and highlighting variations across cycles.

Non-cyclical analysis: For comparison, we also analyzed the entire dataset as one group, without distinguishing between treatment cycles. This aggregated view of treatment outcomes highlights how omitting cycle information can result in a loss of detail.

Table 7.2: Conventional model [91]

treatment cycle	post_treatment glucose_mean	treatment_success rate_mean	treatment_success rate_std	treatment_success rate_min	treatment_success rate-max
Overall	8158.12	14.53	11.15	0	25

Table 7.2 shows the conventional method, where all data is combined into a single group and common metrics (mean, standard deviation, median, etc.) are calculated for the entire dataset. This approach gives an overall view of post-treatment glucose levels and treatment success, but overlooks the variability between treatment cycles.

In contrast, the cycle-based analysis captures these details; for example, cell [2, 1] in the cycle-based table shows the average post-treatment glucose for Cycle 2. While the overall summary provides a unified benchmark, it can obscure significant differences that become visible only when examining each treatment cycle individually.

7.4.2 Statistical analysis

To examine the impact of our cyclical approach on treatment outcomes, we conducted a statistical analysis using *Analysis of Variance (ANOVA)* [430]**.** We chose ANOVA because it allows us to compare means across multiple treatment cycles simultaneously, reducing the risk of Type I errors associated with pairwise tests [431]. Since each treatment cycle is examined independently (owing to its unique circumstances), ANOVA is particularly well-suited for our analysis compared to other methods.

ANOVA specifies whether the means of multiple groups differ significantly by comparing the variance within groups to the variance between groups. The test statistics (F-statistic) are calculated as follows:

$$F = \frac{\text{Variance between groups}}{\text{Variance within groups}}$$

To evaluate the impact of our cyclical approach on treatment outcomes, we conducted a comprehensive statistical analysis using one-way ANOVA [371], supported by assumption checks, effect size estimation, post-hoc comparisons, and confidence intervals. These methods were selected to ensure both statistical rigor and interpretability across treatment cycles.

Assumption Checks

Before applying ANOVA, we verified two key assumptions:

- **Normality** was assessed using the Shapiro–Wilk test [369]. While Cycle 3 showed perfect normality for treatment success rates ($W = 1.0$, $p = 1.0$), other groups exhibited non-normal distributions ($p < 0.001$), particularly for post-treatment glucose levels. Given the robustness of ANOVA to mild deviations from normality and the large sample size, we proceeded with the analysis.

- **Homogeneity of variances** was tested using Levene's test [370], which indicated significant variance differences across cycles for both variables ($p < 0.001$). This suggests that group variances are unequal, and results should be interpreted with caution. However, ANOVA remains valid under these conditions when sample sizes are balanced, as is the case in our study.

ANOVA results

We applied one-way ANOVA to compare post-treatment glucose levels and treatment success rates across three treatment cycles:

- **Post-treatment glucose levels**:

  $F(2, 747) = 64.68$, $p < 0.001$ → Strong evidence of significant differences between cycles.

- **Treatment success rates**:

  $F(2, 747) = 14.48$, $p < 0.001$ → Statistically significant variation across cycles.

These ANOVA results indicate that the differences observed in treatment outcomes across cycles are not due to random variation but are statistically significant. The F-statistic quantifies how much the group means differ relative to the variability within each group. In both cases (post-treatment glucose levels and treatment success rates), the high F-values and p-values below 0.001 suggest that at least one cycle differs meaningfully from the others. This supports the hypothesis that treatment effectiveness evolves over time and that analyzing cycles separately reveals clinically relevant patterns. Consequently, the cyclical structure of the dataset is validated as a more informative framework than conventional aggregation.

Effect Size Estimation

To quantify the magnitude of these differences, we calculated **eta-squared (η^2)** [432]:

- **Post-treatment glucose**:

  η^2 = **0.148** → Indicates that 14.8% of the variance is explained by cycle grouping (a significant effect).

- **Treatment success rate**:

  η^2 = **0.037** → Suggests that 3.7% of the variance is attributable to cycle differences (a small-to-moderate effect).

These values indicate the proportion of outcome variability that can be attributed to the treatment cycle itself. A higher η^2 reflects a more substantial influence of cycle grouping on the results, confirming that the cyclical structure captures meaningful clinical variation beyond random noise.

Post-Hoc Comparisons (Tukey's HSD)

To further explore which specific treatment cycles differed significantly, we applied Tukey's Honest Significant Difference (HSD) test [433] following the ANOVA results. This method enables pairwise comparisons while controlling Type I error.

To identify specific cycle differences:

- **Glucose levels**:
    - Cycle 3 vs Cycle 1: $p < 0.001$
    - Cycle 3 vs Cycle 2: $p < 0.001$
    - Cycle 1 vs Cycle 2: $p = 0.217$ (not significant)
- **Success rates**:
    - Cycle 3 vs Cycle 1: $p < 0.001$
    - Cycle 3 vs Cycle 2: $p < 0.001$
    - Cycle 1 vs Cycle 2: $p = 0.412$ (not significant)

The findings reveal that Cycle 3 consistently yields superior outcomes compared to Cycles 1 and 2, with statistically significant differences in both glucose levels and success rates. In contrast, the similarity between Cycle 1 and Cycle 2 suggests that the most notable improvements occur in later treatment phases, reinforcing the importance of tracking longitudinal changes in EMR-based analyses.

Table 7.3: 95% Confidence intervals for group means

Variable	Cycle	Mean	95% CI Lower	95% CI Upper
post_treatment_glucose	1	8238.71	8188.0	8289.4
	2	8172.40	8028.3	8316.5
	3	6672.56	6515.3	6829.9
treatment_success_rate	1	14.26	13.26	15.27
	2	13.67	12.29	15.04
	3	25.00	-	-

To complement the post-hoc findings, Table 7.3 presents the 95% confidence intervals (CIs) for the group means of post-treatment glucose levels and treatment success rates across cycles. A 95% CI represents the range within which the true population mean is expected to fall with 95% certainty, assuming the data are randomly sampled, and the model assumptions hold [434].

These intervals provide insight into the precision and reliability of the observed means. In other words, narrower intervals indicate more stable estimates, while wider intervals suggest greater variability. In this case, the absence of interval bounds for Cycle 3's success rate reflects its zero variance, and it exhibits distinct and consistently superior outcomes within the third cycle.

Therefore, this enhanced statistical evaluation confirms that treatment outcomes vary significantly across cycles, both statistically and practically. By incorporating effect sizes, confidence intervals, and post-hoc tests, we demonstrate that the cyclical approach captures meaningful clinical trends that are obscured in conventional aggregated models. These findings support the integration of cycle-based tagging in EMRs to improve decision-making and patient care. The complete Python script used to perform these analyses is available in the Zenodo repository.

7.5 Results

The findings of this chapter demonstrate the potential of leveraging the HCI elements in medical systems and the critical role of the proposed approach to organizing medical data by structuring it around treatment cycles. It has been demonstrated how this method enhances data management and supports informed clinical decision-making. Moreover, we revealed how building on this foundation enables the delivery of personalized educational content to patients via PHRs (Personal Health Records), thereby enhancing patient engagement and satisfaction. Together, these results highlight the crucial role of HCI in integrating data organization with practical healthcare outcomes.

7.5.1 Structuring medical data via treatment cycles to enhance clinical decision-making

This section presents the results of evaluating a cyclical approach to organizing medical data, highlighting its advantages in facilitating effective interaction between clinicians and digital systems. By aligning data structures with the iterative nature of treatment processes, this method enhances the usability and analytical power of medical records.

Figure 7.3 (presented on the next page) illustrates the conceptual and functional differences between traditional EMR systems and the proposed cycle-based framework. In traditional EMRs, forms are scattered across encounters without contextual linkage, making it challenging to trace therapeutic progression or analyze outcomes. In contrast, the cycle-based model organizes forms by treatment phase, allowing for the coherent grouping of diagnoses, labs, and treatments within each clinical cycle.

This structured arrangement introduces a new level of data transparency**.** By tagging each form with both its type and cycle number (e.g., 11 = diagnosis in Cycle 1, 23 = labs in Cycle 3), the system can reconstruct complete treatment sequences. This traceability enables clinicians and algorithms to track the progression of care over time, compare interventions across cycles, and identify patterns in patient responses.

The meaningful naming convention (combining form type and cycle number) supports not only traceability but also enhances explainability. CDSS algorithms benefit from this contextual clarity, as they can now associate specific interventions with outcomes within defined cycles. This improves the accuracy of decision support and enables more precise recommendations. Moreover, the increased explainability fosters trust and usability**.** When clinicians can understand how and why a system reaches its conclusions, they are more likely to engage with it. This encourages the adoption and integration of CDSS tools into routine practice.

The cyclical model also mirrors the reality of clinical workflows. Treatment plans typically follow an iterative process of diagnosis, testing, and intervention. By reflecting this natural structure, the proposed framework aligns digital records with real-world medical logic, improving both usability and analytical relevance.

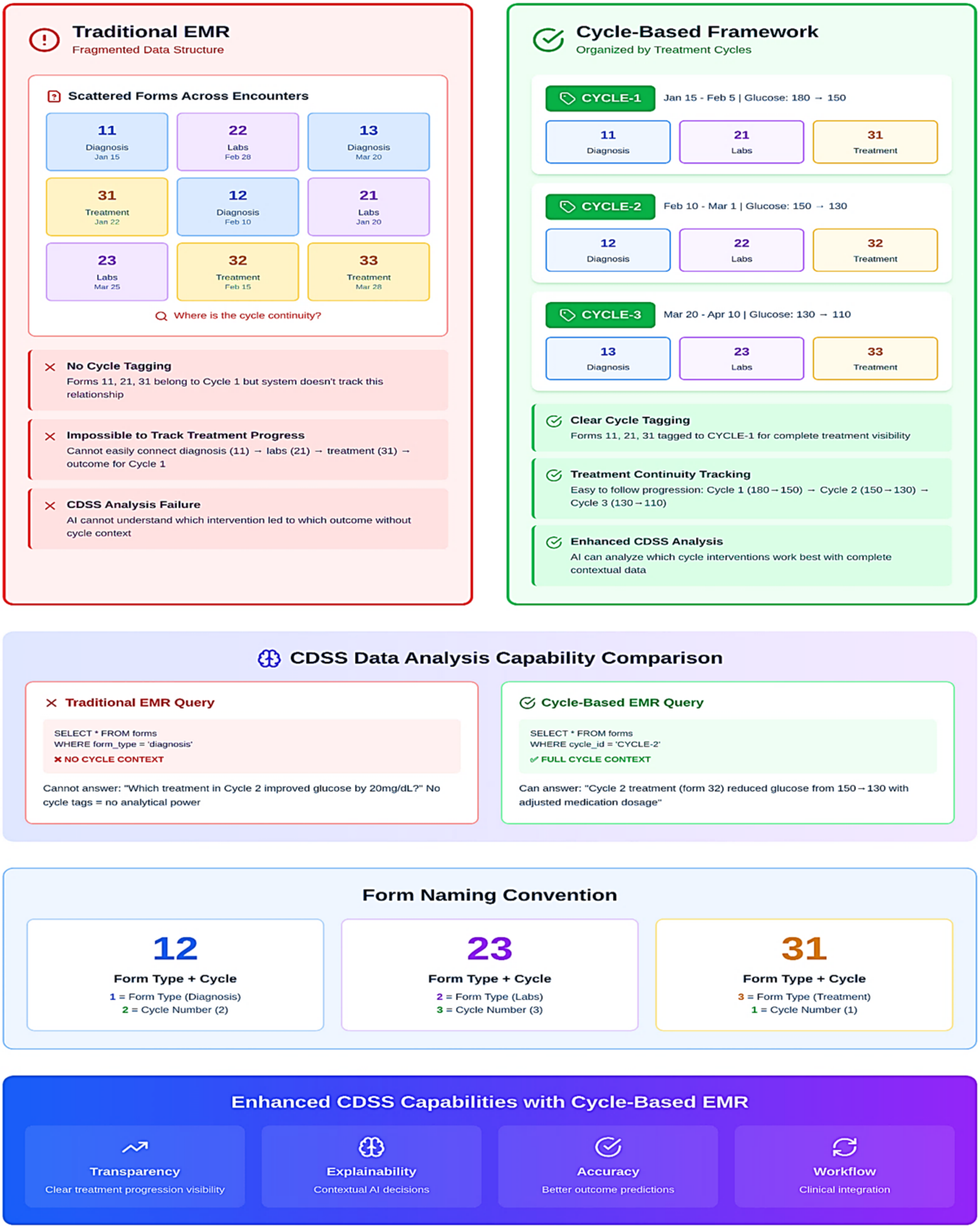


Figure 7.3: Comparison between Traditional EMR and cycle-based framework

On the other hand, the ability to query data by cycle (e.g., SELECT * FROM forms WHERE cycle_id = 'CYCLE-2') empowers CDSS systems to deliver cycle-specific insights. This targeted analysis enhances decision accuracy and supports personalized care strategies.

As shown in Figure 7.3, the cycle-based model enables clear tagging, structured progression tracking, and contextual data analysis (features that are lacking in traditional EMRs)**.** This visual representation supports the empirical claim that cycle-based structuring improves decision accuracy, transparency, and clinical integration.

7.5.1.1 Statistical evidence of treatment variability across cycles

This evaluation utilizes a synthetic dataset designed to mimic real-world clinical scenarios, comprising 750 patient records with detailed treatment cycle information. Statistical analysis revealed significant variations in patient outcomes across different treatment phases:

- **Glucose level variations:** An analysis of variance (ANOVA) test indicated notable differences in post-treatment glucose levels across cycles, with an F-statistic of 64.6814 and a p-value < 0.001. This suggests that treatment effectiveness evolves, necessitating a structure that captures these changes rather than aggregating data into a single, static view.

- **Success rate differences:** A similar ANOVA test on treatment success rates yielded an F-statistic of 14.4841 and a p-value < 0.001, confirming that success rates also vary significantly between cycles. This finding highlights the importance of tracking iterative interventions to assess their cumulative impact.

These statistical outcomes indicate that a cyclical structure allows clinicians to identify critical trends in patient responses (insights that are obscured in traditional, non-cyclical systems). By presenting data in a way that reflects clinical workflows, this approach enhances the interaction between healthcare providers and the system, enabling more precise and informed decision-making.

7.5.1.2 Quantifying information loss in the traditional approach

Further analysis quantified the information lost when treatment cycles are not considered:

- **Glucose level insights:** The cyclical structure accounted for 14.96% of the variance in post-treatment glucose levels. Without this framework, nearly 15% of the variability in patient responses would remain unaccounted for, thereby reducing the accuracy of clinical assessments.

- **Success rate insights:** For treatment success rates, 37.31% of the variance was explained by the cyclical organization. This substantial portion indicates that over a third of the factors influencing treatment outcomes are tied to the progression of cycles, a detail lost in conventional data aggregation.

This evidence underscores the extent to which the cyclical approach, as an HCI enhancement, improves data transparency and usability, directly supporting clinicians in optimizing patient care.

Complementary insights into the proposed cyclical approach are presented in the published paper *"Aligning EMR Structure with Treatment Cycles: Enhancing Data Management and CDSS Functionality"* [91], which appeared in the *Applied Sciences Journal*. The complete text of this article is provided in **Annex *E*** of this thesis.

7.5.2 Personalized patients' learning through PHR: leveraging structured data

According to the significance of the data categorization revealed in the proposed cyclical approach, we conducted another study on integrating e-learning into PHRs [410]. It demonstrates how well-categorized medical data, structured around treatment cycles, enables the delivery of tailored educational content, enhancing patient satisfaction as a key HCI outcome.

7.5.2.1 Delivering tailored educational content

The conducted study showed that PHRs can utilize structured medical data (such as treatment histories, lifestyle factors, and cycle-specific plans) to provide patients with highly personalized educational materials:

- **Customization Based on Data:** For example, an infertile couple could receive content tailored to their specific treatment cycle, incorporating details like the husband's smoking habits and the wife's surgical plan [410]. This customization stems from the granular categorization of data within the medical system, ensuring that only relevant information is presented.
- **Reduced Complexity:** By filtering out irrelevant general advice, the system minimizes patient confusion, making educational content more accessible and actionable. This targeted delivery reflects a core HCI principle: designing interactions that respect individual user needs [128].

This personalization not only improves patient understanding but also strengthens their engagement with their care process, a direct result of effective data structuring upstream.

7.5.2.2 Enhancing engagement and satisfaction

The integration of e-learning within PHRs yielded additional benefits tied to HCI principles [410]:

- **Interactive Monitoring:** Medical personnel could track patient interactions with educational materials, ensuring adherence to learning goals. This level of control, unavailable in standalone e-learning platforms, enhances the system's interactivity and responsiveness to patient behavior.

- **Improved Satisfaction:** Patients reported higher satisfaction when receiving content tailored to their unique circumstances, feeling more supported and involved in their treatment. This aligns with HCI's emphasis on user satisfaction, achieved here through individualized data presentation.

These findings demonstrate how PHRs, a product of advanced data categorization, transform structured medical records into a patient-facing tool, thereby fostering a collaborative healthcare environment.

For further details and complementary insights into leveraging HCI principles and data categorization within PHR, the published paper *"Private Health Record System: Improving the Patient's Medical Knowledge with an e-Learning Approach"* [410], presented at the international TEEM22 conference, is included in **Annex *F*** of this thesis.

7.6 Discussion

This chapter illustrates the substantial impact of integrating HCI elements with data science techniques to enhance medical systems, aligning digital frameworks with the iterative realities of clinical practice. By implementing a cyclical approach to organizing medical data within EMRs, we have shown how structured data arrangement improves clinical decision-making. This method organizes patient data into treatment cycles, creating a transparent and intuitive structure that represents the progression of real-world treatment processes [91]. Such alignment as an HCI foundation reduces clinicians' cognitive load by presenting data in a workflow-compatible manner, thereby enhancing usability and enabling more accurate and timely decisions [93]. The empirical findings from our cycle-based framework reveal that this structure preserves critical variations in patient responses (accounting for 14.96% of variance in post-treatment glucose levels and 37.31% in treatment success rates). These insights would be lost in traditional, non-cyclical EMR designs. This granularity enhances CDSS by providing high-quality, contextualized data inputs, resulting in more precise recommendations and improved medical outcomes.

System design and medical data arrangement together form a pivotal HCI element, serving as the critical interface between complex datasets and human users, whether clinicians or patients. For clinicians, effective system design ensures that data is not only accessible but also meaningfully organized, reducing ambiguity and enhancing decision-making efficiency within CDSS [435]. This is evident in how cycle identifiers tag data to specific treatment phases, allowing medical teams to track progress and evaluate outcomes with precision. Without such a design, data fragmentation hinders analytical transparency, undermining decision accuracy [91]. For patients, this HCI element extends its impact through PHRs, where well-categorized medical data, derived from EMRs, enables personalized learning experiences. By leveraging structured data (such as treatment histories segmented into cycles), PHRs deliver tailored educational content that reflects individual patients' current treatment phases or conditions [161]. Features like interactive modules and user-friendly interfaces, grounded in HCI principles of personalization and interactivity, empower patients to engage actively with their health information, improving health literacy and elevating user satisfaction [119], [128]. Thus, system design and data arrangement, as a unified component of HCI, bridge analytical precision with practical usability, optimizing clinical decisions.

The synergy of HCI and data science creates a robust ecosystem where data-driven insights enhance both clinician and patient experiences. For clinicians, the cyclical approach streamlines data retrieval and analysis, aligning with the performed research that emphasizes the value of structured data in improving predictive analytics for chronic disease management. In this case, although the explainability and transparency of the provided medical recommendations are augmented, the physicians' satisfaction is likely downgraded due to strict data entry rules [285]. For patients, PHRs transform complex medical data into actionable, individualized knowledge, supporting the goal of precision medicine to deliver responsive, tailored healthcare. This chapter highlights the indispensable role of HCI in presenting medical data to patients and physicians in a suitable format, facilitating better data analysis and enhanced user engagement with the designed system.

7.7 Conclusions

Our findings in this chapter indicate the significant potential of combining HCI principles with data science to advance medical systems. By introducing a cyclical approach to EMR data organization, we have highlighted its ability to enhance clinical decision-making by providing clinicians with a structured, workflow-aligned system that improves decision accuracy and efficiency. Additionally, this structured data underpins patient-facing tools, such as PHRs, delivering personalized educational content that enhances patient engagement and satisfaction. In other words, we demonstrated how proper system design and data arrangement play a crucial role in HCI, benefiting integrated subsystems (such as PHR and CDSS) that are linked to EMRs to support precision medicine and responsive care delivery. This interdisciplinary convergence of HCI and data science is vital for future healthcare advancements, striking a balance between analytical rigor and user-centric design. It streamlines to improve diagnostic accuracy and to optimize the treatment plan, leading to enhanced patient care.

Chapter 8

Conclusions

The current thesis explores the application of HCI elements within CDSS environments by investigating how usability-oriented design principles can enhance the **structure**, **interpretability**, and **functionality** of digital clinical environments. In this regard, it hypothesizes that the integration of HCI elements into CDSS can improve specific aspects of their functionality (particularly the explainability of medical decisions and the reliability of system outputs).

To explore this hypothesis, an SLR was first conducted that consolidated existing studies addressing HCI in CDSS environments. This review enabled the identification of **twelve distinct HCI elements** that influence CDSS performance, revealing both the **positive aspects** of HCI (such as explainability, visibility, and ease of use) and the **negative or "dark side" factors**, including alert fatigue, workload burden, and cognitive overload. These elements were not only cataloged but also contextualized within the broader landscape of clinical informatics, revealing both their enabling and inhibiting roles in decision-making processes [85].

One of the novel contributions of this thesis lies in the classification of **HCI evaluation methods**. By analyzing how these methods are applied across studies, a taxonomy was developed that distinguishes between expert-based, user-based, and hybrid approaches. This classification supports future researchers and system designers in selecting evaluation strategies that align with their goals, constraints, and user contexts [187].

Beyond identification and classification, the thesis focused on the practical implications of HCI elements (particularly their **impact on the quality of medical data** and user experience). It has been demonstrated that structured and purposeful data entry, when aligned with clinical workflows, can enhance the clarity, traceability, and interpretability of medical records. Consequently, it enhances the **explainability of CDSS outputs**, making them more transparent and trustworthy for physicians [93].

To operationalize these insights, a **cyclical model** of EMR design was proposed and evaluated. This model **organizes data entry** around treatment cycles, allowing clinicians to associate each data point with a specific phase of care. The model was empirically tested using the MIMIC-III public dataset, and the results demonstrated that cycle-wise structuring of data leads to distinct distribution patterns and improved interpretability, as well as key indicators of **enhanced explainability** [91].

By leveraging the cyclical approach, the system was tailored to reflect the actual needs and practices of healthcare providers, ensuring that its structure resonates with clinical reasoning and **workflow logic**. This alignment not only improves the usability of the interface but also reinforces trust in the system's outputs. The **reliability of clinical recommendations** is strengthened by organizing medical data into clearly defined treatment phases, allowing physicians to interpret suggestions within a familiar and contextually grounded framework. Ultimately, these improvements converge to support more effective interaction with the CDSS, leading to increased **user satisfaction**.

Figure 8.1 provides an integrated overview of the thesis outcomes. It illustrates how the theoretical results (particularly the identification of HCI elements and the development of a scientific framework) supported the formulation of the proposed cyclical EMR approach, which in turn contributes to enhancing CDSS functionality. The figure also highlights how both the theoretical and practical implications of this work create a foundation for future research, including AI-driven conversational interfaces and NLP-based medical systems.

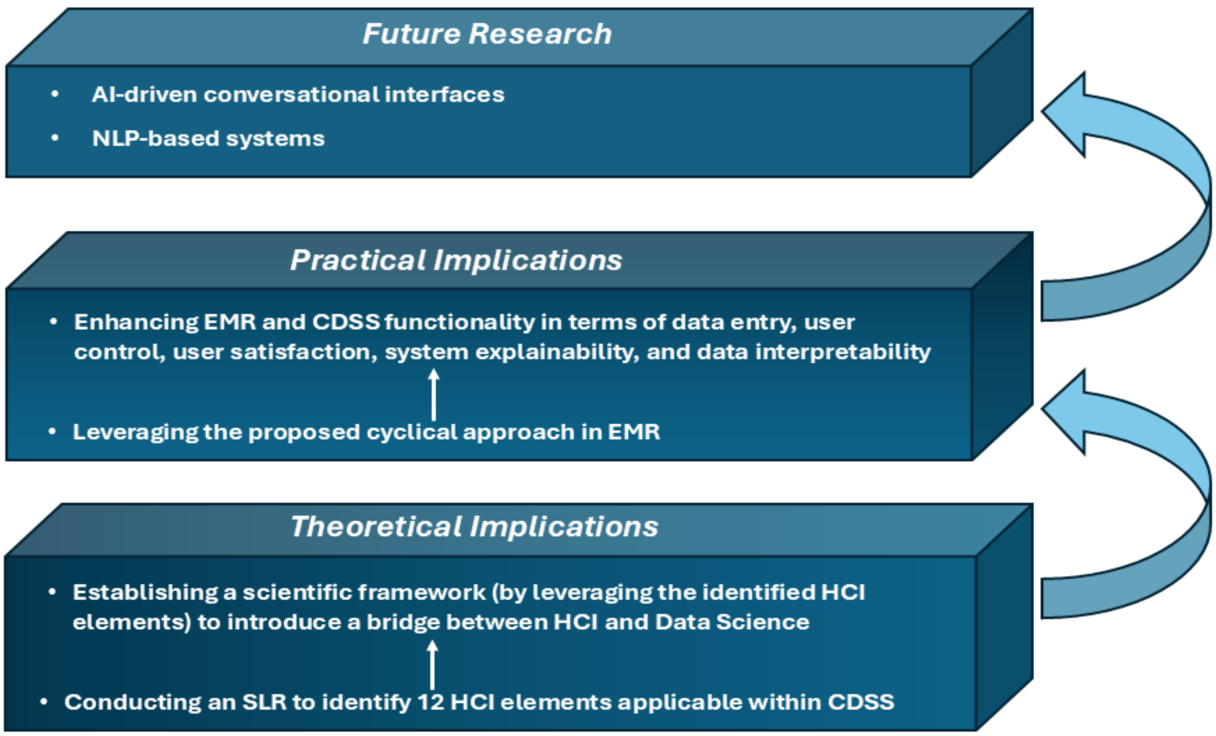


Figure 8.1: Summary of theoretical, practical, and future implications of the thesis

In summary, the combination of SLR findings, empirical analyses, and model validation enables us to affirm that the main objective and its derived sub-objectives have been achieved, and following its outcomes, the hypothesis posed at the beginning of this thesis is valid.

8.1 Limitations and Ethical Considerations

While this thesis presents a scientific framework (including data gathering, integration from multiple sources, and the proposed cyclical approach) for enhancing CDSS through leveraging the HCI elements and cyclical EMR modeling, several ethical, legal, and organizational considerations remain beyond the scope of the technical implementation.

Throughout the proposed approach (particularly in sections involving data integration, transformation, and the cyclical reuse of treatment insights), patient data is employed to train learning models and inform decision-making algorithms. Although anonymization techniques and encryption protocols are routinely applied to safeguard confidentiality, the secondary use of clinical data raises essential concerns regarding data governance, consent, and regulatory compliance. In this regard, adhering to frameworks such as the General Data Protection Regulation (GDPR) is essential when integrating and transforming medical data across institutional or national boundaries.

Moreover, despite the proposed features' aim to improve explainability, transparency, and user trust, physicians remain legally and ethically responsible for the final clinical decisions. CDSS tools may assist in decision-making, but they do not absolve clinicians of legal or ethical responsibility. This distinction must be preserved in any real-world deployment. This requirement underscores the importance of auditability, ensuring that every step in the decision-making process can be traced and reviewed to maintain trust among clinicians, patients, and regulatory bodies.

From an organizational perspective, the adoption of such HCI-centric redesigns is not merely a technical matter but a multi-layered process involving governance structures, licensing procedures, and administrative approval. Before real-world deployment, proposed systems must pass regulatory scrutiny, obtain the necessary certifications, and demonstrate compliance with institutional and governmental policies. These steps are particularly relevant for integrated systems that involve the exchange and transformation of medical data at national or international levels.

Although the bias considerations in this thesis were addressed in detail in Chapter 7 (where the synthetic dataset was constructed following established medical data simulation protocols and multiple safeguards were applied to mitigate selection, measurement, and observer bias), it is important to acknowledge that the use of synthetic data still introduces inherent limitations. Synthetic datasets, even when carefully engineered for statistical fidelity and clinical plausibility, may not fully capture the irregularities, rare events, or heterogeneous treatment trajectories present in real-world EMRs. To mitigate these potential biases, it is essential to complement synthetic datasets with real-world data through hybrid modeling approaches, which can enhance the robustness of analyses and ensure a more comprehensive understanding of clinical scenarios. Additionally, iterative refinement of the synthetic generation rules (guided by domain experts and real-world distributions) can further reduce divergence between simulated and actual clinical patterns.

Likewise, although the cyclical EMR model was designed with flexibility and individuality as fundamental HCI considerations (two HCI elements that support user-centered interaction), its applicability may vary across different medical specialties. Certain domains, particularly those with highly individualized or non-iterative treatment pathways, may require domain-specific adaptations or customized cycle definitions. In these circumstances, before deploying the cyclical model in specialized clinical contexts, its configurability and alignment with local workflows should be carefully evaluated to ensure that the framework remains intuitive, clinically meaningful, and supportive of decision accuracy.

Therefore, while the proposed models presented in this thesis demonstrate clear scientific potential to enhance system reliability, user adoption, and treatment outcomes, their translation into clinical practice necessitates addressing broader ethical, legal, and organizational dimensions. Only by embedding robust governance, respecting patients' rights, and ensuring transparency in both design and deployment can medical system designers fully harness the potential of advanced CDSS to achieve widespread improvements in healthcare decision-making.

8.2 Future work and research directions

This thesis streamlines the way for multiple innovative directions in future research. As healthcare increasingly incorporates AI-driven technologies, particularly chat-based applications, employing HCI elements becomes crucial in creating more interactive and engaging environments. These AI applications can significantly enhance interactions between providers and the users (patients or physicians) by offering a customizable interface, real-time feedback, and accessible information. However, for these systems to be effective, careful attention must be paid to HCI elements, ensuring that they are designed to provide a better user experience and elevate user satisfaction. This focus on HCI can help mitigate potential barriers to adoption, such as user frustration or distrust, ultimately leading to improved clinical outcomes.

The proposed cyclical approach provides a robust framework for integrating HCI elements into new medical AI. By organizing medical data into recurring cycles, this method enables a more detailed understanding of how patients interact with AI systems. This structured approach not only refines data organization and analysis but also facilitates the creation of AI applications that can adapt flexibly to the changing demands of both patients and healthcare staff. In other words, as data is continuously collected and analyzed through the cyclical model, AI systems can learn from user interactions, enhancing their ability to provide relevant and timely support.

Furthermore, as Natural Language Processing (NLP) becomes increasingly integrated into medical systems, future research should explore how HCI elements (such as user control, feedback, explainability, and individualization) can enhance interactions with NLP-driven tools. In clinical settings, where physicians and patients rely on accurate and intuitive communication, optimizing the usability of NLP interfaces is essential. It means trustworthy, and context-aware responses must align with users' expectations to support effective decision-making. Future studies should focus on developing HCI evaluation frameworks tailored to NLP applications in healthcare.

By pursuing these research directions, scholars can further enhance the understanding of the interplay between HCI elements and CDSS effectiveness. The presented scientific framework serves as a foundation for ongoing exploration, ultimately contributing to the development of more effective, user-centered clinical decision support systems that improve patient care and outcomes in an increasingly AI-driven healthcare landscape.

8.3 Ph.D. thesis' outcomes

Throughout the development of this doctoral research, several scientific contributions have been published to validate and disseminate the findings of the proposed approaches. These publications have facilitated valuable feedback from experts in medical informatics and human-computer interaction, contributing to the refinement of the thesis's core ideas. In total, the research has resulted in four peer-reviewed articles published in indexed journals and three papers presented at international conferences, demonstrating the work's relevance and impact across multiple scholarly platforms.

· JCR-SCIE Indexed Journals:

1. A. Azadi, and F. J. García-Peñalvo, "Aligning EMR Structure with Treatment Cycles: Enhancing Data Management and CDSS Functionality: A Cyclical EMR Model," Applied Sciences, vol. 15, no. 10, p. 5273, 2025, doi: 10.3390/app15105273. ISSN: 2076-3417. (JCR SCIE – ENGINEERING, MULTIDISCIPLINARY – Q2; COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS – Q2) – JIF 2.679 (JCR JCI – ENGINEERING, MULTIDISCIPLINARY – Q2; COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS – Q2) – JCI 0.61 (SJR 0.521 – Computer Science Applications – Q2) (CiteScore 5.5 – General Engineering – Q1; Instrumentation – Q1; ENGINEERING, MULTIDISCIPLINARY – Q2; Computer Science Applications – Q2) [91].

2. A. Azadi, and F. J. García-Peñalvo, "A Synergistic Bridge Between Human–Computer Interaction and Data Management Within CDSS," Data, vol. 10, no. 5, p. 60, 2025, doi: 10.3390/data10050060. ISSN: 2306-5729. (JCR SCIE – COMPUTER SCIENCE, INFORMATION SYSTEMS – Q3; INFORMATION SCIENCE & LIBRARY SCIENCE – Q3) – JIF 1.6 (JCR JCI – COMPUTER SCIENCE, INFORMATION SYSTEMS – Q3; INFORMATION SCIENCE & LIBRARY SCIENCE – Q3) – JCI 0.45 (SJR 0.34 – Information Systems – Q3; Computer Science (Misc.) – Q3) (CiteScore 2.8 – Computer Science (Misc.) – Q3; Information Systems – Q3) [93].

3. A. Azadi, and F. J. García-Peñalvo, "Optimizing Clinical Decision Support System Functionality by Leveraging Specific Human-Computer Interaction Elements: Insights from a Systematic Review," JMIR Human Factors, vol. 12, no. 1, e69333, 2025, doi: 10.2196/69333. ISSN: 2292-9495. (JCR SCIE – MEDICAL INFORMATICS – Q2; HEALTH CARE SCIENCES & SERVICES – Q2) – JIF 3.1 (JCR JCI – MEDICAL INFORMATICS – Q2; HEALTH CARE SCIENCES & SERVICES – Q2) – JCI 0.78 (SJR 0.954 – Health Informatics – Q1; Human Factors and Ergonomics – Q1) (CiteScore 3.6 – Health Informatics – Q1; Human Factors and Ergonomics – Q1) [85].

4. A. Azadi, and F. J. García-Peñalvo, “Synergistic Effect of Medical Information Systems Integration: To What Extent Will It Affect the Accuracy Level in the Reports and Decision-Making Systems?” Informatics, vol. 10, no. 1, p. 12, 2023, doi: 10.3390/informatics10010012. ISSN: 2227-9709. (JCR SCIE – COMPUTER SCIENCE, INFORMATION SYSTEMS – Q3; HEALTH CARE SCIENCES & SERVICES – Q4) – JIF 1.5 (JCR JCI – COMPUTER SCIENCE, INFORMATION SYSTEMS – Q3; HEALTH CARE SCIENCES & SERVICES – Q4) – JCI 0.42 (SJR 0.31 – Information Systems – Q3; Health Informatics – Q3) (CiteScore 2.7 – Information Systems – Q3; Health Informatics – Q3) [246].

· **Proceedings of International Conferences:**

1. A. Azadi and F. J. García-Peñalvo, "Optimizing Data Entry Management in Healthcare: Leveraging HCI to Enhance Medical Decision Accuracy," in Proceedings of TEEM 2023. The Eleventh International Conference on Technological Ecosystems for Enhancing Multiculturality (Bragança, Portugal, 25-27 October 2023), J. A. Carvalho Gonçalves, J. L. Sousa de Magalhães Lima, J. P. Coelho, F. J. García-Peñalvo, and A. García-Holgado, Eds. Lecture Notes in Educational Technology, pp. 271–279, Singapore: Springer Nature Singapore, 2024. doi: 10.1007/978-981-97-1814-6_26 [175].
2. A. Azadi and F. J. García-Peñalvo, "Unpacking the Evaluation Proceeding of Clinical Decision Support Systems: A review of methodological approaches and categories," in IVUS 2023 Information Society and University Studies 2023. Proceedings of the 28th International Conference on Information Society and University Studies (IVUS 2023). Kaunas, Lithuania, May 12, 2023, A. Lopata, T. Krilavičius, I. Veitaitė, and A. García-Holgado, Eds. CEUR Workshop Proceedings Series, no. 3575, pp. 356–363, Aachen, Germany: CEUR-WS.org, 2023 [187].

3. A. Azadi and F. J. García-Peñalvo, "Private Health Record System: Improving the Patient’s Medical Knowledge with an e-Learning Approach," in Proceedings TEEM 2022: Tenth International Conference on Technological Ecosystems for Enhancing Multiculturality. Salamanca, Spain, October 19–21, 2022, F. J. García-Peñalvo and A. García-Holgado, Eds. Lecture Notes in Educational Technology, pp. 182–191, Singapore: Springer Nature, 2023. doi: 10.1007/978-981-99-0942-1_18 [410].

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Annexes

Annex *A*.

Optimizing Clinical Decision Support System Functionality by Leveraging Specific Human-Computer Interaction Elements: Insights From a Systematic Review

Review

Optimizing Clinical Decision Support System Functionality by Leveraging Specific Human-Computer Interaction Elements: Insights From a Systematic Review

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Abstract

Background: Clinical decision support systems (CDSSs) play a pivotal role in health care by enhancing clinical decision-making processes. These systems represent a significant advancement in medical information systems. However, optimizing their effectiveness requires accounting for various human-computer interaction (HCI) elements that influence their functionality and user acceptance.

Objective: This study aimed to identify and categorize key HCI elements that impact CDSS performance to enhance system usability, adaptability, and decision-making accuracy.

Methods: We conducted a systematic literature review, identifying 923 studies from the databases PubMed, Scopus, and Web of Science. Papers were screened and selected based on predefined inclusion criteria. A rigorous quality assessment process was applied to ensure the relevance and reliability of the included studies. Ultimately, of the 923 papers identified, 43 (4.7%) that specifically addressed HCI elements applicable to CDSS environments were included in the final analysis. Data extraction and synthesis were performed to answer the research questions regarding HCI elements.

Results: A total of 12 distinct HCI elements were identified, each with the potential to influence CDSS functionality. These elements align with the International Organization for Standardization (ISO) 9241-11 framework, which defines usability in terms of effectiveness, efficiency, and satisfaction. "User satisfaction," "flexibility," and "individuality" enhance satisfaction by improving system adaptability and user acceptance. "Visibility," "explainability," and "user control" strengthen effectiveness by supporting decision-making and error prevention. "Ease of use" improves efficiency by streamlining interactions and reducing cognitive load. Some elements influence effectiveness and efficiency, such as "data entry," which ensures structured inputs for decision accuracy while optimizing workflows. Likewise, "alerts" provide timely information for effective decision-making and, simultaneously, are designed to avoid overwhelming users and maintain system efficiency. "Simplification" and "mental effort" also optimize workflows and reduce complexity. Furthermore, "interface" impacts effectiveness and efficiency by supporting accurate decision-making and streamlining user interaction. This categorization, aligned with ISO 9241-11, underscores the context and task dependency of usability, highlighting that HCI elements must be adapted to different user needs and environments for effective clinical decision-making.

Conclusions: This study addresses a critical gap in CDSS research by offering a comprehensive framework of HCI elements tailored to the CDSS environment. Incorporating these elements into system design can improve user satisfaction, reduce data errors, and enhance the accuracy of medical decisions. The findings lay the groundwork for future research, offering practical guidelines for developing more reliable and efficient CDSS systems in medical informatics fields.

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KEYWORDS
human-computer interaction; clinical decision support system; usability; user-centered design; artificial intelligence

Introduction

Background

Clinical decision support systems (CDSSs) provide clinicians with computer-generated clinical knowledge and patients with relevant health information presented at the right time to support optimal patient care [1]. Poorly designed user interfaces (UIs) may impede structured data entry, potentially compromising data quality and resulting in incomplete datasets [2]. Such shortcomings can negatively impact the effectiveness of integrated medical information systems when used within a CDSS framework [3]. CDSSs, as a prominent method for enhancing clinical decisions effectively, rely on patient-entered data in electronic medical records (EMRs). Data scientists face challenges in analyzing data obtained from EMRs due to the prevalence of errors, including typos and incorrect entries. In other words, incomplete medical advice originates from incomplete and unstructured prepared data for CDSSs [4]. Physicians often express these errors as stemming from an inadequate interaction with the system [5]. Human-computer interaction (HCI), based on the solid principles of ergonomics, cognitive science, and psychology, is pivotal in creating practical and beneficial technology for all users [6]. Indeed, HCI science advocates for physicians through technological solutions and enhances their comprehension of the significance of their daily processes and the subsequent use of data stored in electronic health records (EHRs) [7].

Although the HCI concept typically encompasses how computer systems are designed for ease of use, efficiency, and effectiveness [8], HCI in the medical realm implies the investigation and design of computer systems that expedite productive and intuitive interaction between physicians and technology to boost user experience (UX) and achieve the desired result [9].

Neglecting HCI elements in medical systems can lead to inadequate graphical UIs, potentially hindering physician adoption and efficacy within the digital health care landscape [10]. Conversely, some studies have demonstrated that incorporating HCI elements improves user acceptance and enhances the effective use of CDSS functionalities [11]. Despite several studies addressing HCI elements and their components, the lack of studies on HCI elements that can affect CDSS performance is quite noticeable. In this regard, related concepts, such as usability, UX, or user-centered design (UCD), all of which contribute to physician satisfaction, need to be investigated. HCI assists in identifying system requirements, including text style, fonts, layout, graphics, and color. Meanwhile, usability focuses on efficiency, effectiveness, utility, ease of learning, and ease of assessment. Combining these perspectives ensures a comprehensive approach to designing a CDSS that meets technical and user-centric demands [12].

The necessity of distinguishing HCI elements specifically for CDSSs, in comparison with decision support systems (DSSs), is derived from the unique demands of the health care environment [13]. CDSSs must seamlessly integrate complex medical knowledge, ensure adherence to stringent clinical guidelines, and accurately handle sensitive patient data, all while minimizing the cognitive load on health care professionals [14]. These systems support clinical decisions that directly impact patient outcomes. This is why elements of usability and UX must be considered. Unlike generic DSSs, CDSSs must navigate the intricate nature of medical decision-making. Hence, a tailored approach to HCI elements is needed to address these specialized requirements effectively [15]. In addition, EMRs must be designed using comprehensive HCI elements to serve as a gateway to the data required by the CDSS. Poorly designed HCI in EMRs can lead to improper data entry or retrieval [16]. These errors can have serious consequences, potentially impacting patient safety and even leading to loss of life. Conversely, well-designed HCI can facilitate accurate data handling, improving patient care and significantly enhancing outcomes [17].

Due to the absence of targeted studies that focus on leveraging HCI elements within the CDSS environment, conducting this research is crucial. By systematically identifying and evaluating practical HCI elements specific to CDSSs, this study provides a comprehensive guide to enhance the performance and usability of these systems. This focused investigation offers a unique framework that health care professionals and system developers can use to implement more effective and user-friendly CDSS solutions. The scientific contribution of this study lies in providing a structured methodology to improve CDSS performance, ensuring better integration of HCI elements tailored to the health care context.

Systematic Literature Review

Conducting a systematic literature review (SLR) [18] was the most effective method for this research because it allowed for a rigorous and comprehensive collection of existing studies in the field. An SLR provides a transparent and replicable process for identifying, evaluating, and synthesizing relevant literature. Using the SLR approach, we endeavored to extract and categorize HCI elements that are especially applicable within the CDSS environment, ultimately paving the way for improved CDSS performance.

On the basis of the concerns highlighted in this study, we formulated the following research questions (RQs):

- RQ1: Which HCI elements in medical information systems can affect CDSS functionality?
- RQ2: How does incorporating the identified elements improve CDSS performance?

By seeking a response to the first RQ, we aimed to identify and extract HCI components that have the potential to affect CDSS functionality, as pointed out in the reviewed papers. The second RQ focuses on investigating how the identified HCI elements, when applied within medical environments and information systems, contribute to enhancing CDSS performance.

The remainder of this work is organized as follows. The Methods section describes the methodology and the review steps. The Review Planning subsection details the SLR planning phase, while the Review Process subsection presents the review and data extraction steps. The Results section presents the findings from the analyzed studies to answer the RQs. Finally, the Discussion section presents the principal findings, with some clues and future research lines outlined in the Conclusions subsection.

Methods

Overview

This study followed the SLR methodology outlined by Kitchenham [19] and Kitchenham and Charters [20] to ensure a thorough and unbiased synthesis of existing research. The SLR was complemented by a systematic literature mapping following the method proposed by Kitchenham et al [21]. This segment outlines the protocol used to perform the SLR, providing the necessary information to support the subsequent findings. According to the guidelines provided by Kitchenham [19] and Kitchenham and Charters [20], the SLR process consists of 3 principal phases: planning, conducting, and reporting the study. We adhered strictly to the defined SLR protocols and methodological nuances articulated in the study by Pati and Lorusso [22] to ensure transparency in both the research process and results.

Before planning this SLR, a preliminary search was conducted to ascertain that no recent SLR had been undertaken to identify HCI elements within CDSSs. This preparatory appraisal involved searching various electronic databases, including Scopus, Web of Science, and PubMed, using terms related to the methodology (eg, *SLR* or *systematic literature review*) and the review focus (eg, *HCI*, *usability*, *user experience*, *elements in CDSS*, and equivalent concepts). The results of this preliminary search confirmed the absence of an SLR on the specified theme, thereby justifying the implementation of this review to fill the identified research gap.

Review Planning

The review planning process involves identifying and defining various dimensions to provide the foundation for executing the review, such as formulating the RQs, detailing the protocol followed, and any other relevant information to ensure the traceability of the review process. We outline these dimensions in this subsection.

Mapping Questions

This study's main concerns and RQs are outlined in the Introduction section. To further explore the context and breadth of our SLR, we formulated 4 mapping questions (MQs) to guide our analysis:

- MQ1 (geographic distribution of studies): Where have studies related to HCI elements in CDSSs been conducted worldwide?
- MQ2 (year-wise distribution of studies): What is the distribution of studies by identified HCI element over the years?
- MQ3 (publication venues): What is the distribution of studies between journal papers and conference papers?
- MQ4 (focus distribution): What percentage of the identified studies discuss each HCI element (eg, alerts, interface, system design defects, and mental effort)?

It is important to note that MQ4 (focus distribution) does not have a dedicated subsection. Instead, it has been addressed throughout the identification and discussion of each HCI element. By addressing these MQs, we aim to provide a comprehensive overview of the current research landscape, highlighting key trends and patterns that inform the influence of HCI elements on CDSS performance and user interaction.

Population, Intervention, Comparison, Outcome, and Context Framework

Regarding the questions posed, the population, intervention, comparison, outcome, and context method proposed by Petticrew and Roberts [23] (outlined in the following subsections) and which provides a structured framework for research reviews was used to define the review scope.

Population

We considered all studies that involved software solutions, regardless of their implementation or design. Although the review focuses on the properties and attributes of EMRs, the target studies addressed HCI elements within CDSSs.

Intervention

The interventions of interest included those that suggested or introduced some elements addressing HCI issues in EMRs or eHealth systems, excluding stand-alone solutions such as mobile health apps.

Comparison

No comparison between interventions was planned.

Outcome

The fundamental outcome of this review is to identify key HCI elements that can enhance the functionality of CDSSs.

Context

We considered all studies relevant to EMR and eHealth systems. The review includes all papers describing the successful implementations and designs of EMRs in medical environments, such as hospitals and medical centers worldwide.

Inclusion and Exclusion Criteria

After defining the review's scope, we established inclusion and exclusion criteria (Textbox 1) to choose pertinent literature for addressing the RQs.

Textbox 1. Inclusion and exclusion criteria.

Inclusion criteria

- The paper proposes a pragmatic and implementable solution (eg, method, technique, model, tool, or framework).
- The proposed solution is applied to software, applications, platforms, services, infrastructures, or systems.
- The study focuses on electronic medical records, electronic health records, or eHealth.
- The proposed solution supports or addresses the tailoring of attributes and criteria to improve medical decision support capabilities.
- The paper is written in English.
- The paper was published between 2000 and July 2024 (when the search queries were executed).
- The full paper is available.
- The tailoring capabilities relate to human-computer interaction, usability, user interface, user experience, or user-centered design.
- The article is published in a peer-reviewed journal, book, or conference (including only conferences ranked B or higher in the CORE Conference Ranking list or classified in the top 2 quartiles in the Scimago Journal Rank index).

Exclusion criteria

- The paper does not propose a pragmatic and implementable solution (eg, method, technique, model, tool, or framework).
- The proposed solution is not applied to software, applications, platforms, services, infrastructures, or systems.
- The study is not focused on electronic medical records, electronic health records, or eHealth.
- The proposed solution does not support or address the tailoring of attributes and criteria to improve medical decision support capabilities.
- The paper is not written in English.
- The paper was published before 2000 or after July 2024 (when the search queries were executed).
- The full paper is not available.
- The tailoring capabilities do not relate to human-computer interaction, usability, user interface, user experience, or user-centered design.
- The article is not published in a peer-reviewed journal, book, or conference (including only conferences ranked B or higher in the CORE Conference Ranking list or classified in the top 2 quartiles in the Scimago Journal Rank index).

Search Strategy

It is imperative to identify the most significant databases regarding the search domain in which the queries will be executed to obtain relevant outcomes from the investigation. For this study, 3 electronic databases were selected: Scopus, Web of Science, and PubMed. These databases were chosen based on the following criteria:

- They serve as reference databases in the research domain.
- They are highly relevant to the study context.
- They support the use of search strings and Boolean operators to augment the results of the retrieval process.

On the basis of the research context used to construct the search query, the following terms were included:

- Usability—this concept refers to efficiency, effectiveness, and physician satisfaction [24,25]. It emphasizes maximizing system facilitators to enhance usability [26,27].
- All terms related to HCI—HCI involves interaction and communication between users and computer systems, encompassing the exchange of information, symbols, and actions to facilitate seamless interaction between humans and computers [28]. In this regard, *HCI elements* are defined as the specific elements or attributes that influence user interaction and experience within the determined framework [29]. *HCI elements* and *HCI factors* in medical settings highlight the importance of UCD, ensuring that medical staff are integrally involved in developing and refining medical systems for enhanced performance and satisfaction [30,31]. The terms *HCI factors* and *HCI elements* are sometimes used interchangeably in HCI literature. *HCI factors* often refer to broader influences on usability, while *HCI elements* represent specific design components.
- User-centered design (UCD)—UCD emphasizes the essentiality of considering end users' viewpoints in shaping or evolving a product or software, predominantly based on end-user feedback [32].
- User interface (UI)—in medical information systems, the UI serves as the direct interface between the system and physicians. It can be categorized as static, appearing the same for all users; or dynamic, adapting to varying circumstances based on user interactions with the system [33].
- CDSS—CDSSs encompass a broad range of tools and interventions, both computerized and noncomputerized, to aid clinicians in their complex decision-making processes [34,35]. They are being integrated into EMRs and computerized clinical workflows worldwide, empowering health care providers to access timely and pertinent information, ultimately leading to better patient outcomes through informed decision-making during clinical care [14].
- Artificial intelligence (AI)—in medicine, AI refers to the ability of medical systems to respond to environmental factors and support decision-making, achieving results

comparable to human medical professionals [36]. CDSSs that use AI function as digital dynamic knowledge systems that leverage patient data to create tailored recommendations for clinicians [37]. In other words, CDSSs are meant to assist rather than perform clinical decision-making [38].

In line with the research goals, we only investigated HCI elements that directly or indirectly impact systems designed for medical decision-making. Hence, HCI elements not relevant to this context were excluded from consideration.

Quality Assessment

Overview

Although inclusion and exclusion criteria help identify relevant works for a study, they do not address the quality of the papers retrieved regarding their ability to address the RQs. Therefore, we developed a separate set of quality assessment criteria. We adopted a scoring system in which each coauthor independently evaluated the studies using the quality questionnaire proposed by Kitchenham and Brereton [39]. The scoring was as follows: a "yes" response earned 1 point, a "partially" response earned 0.5 points, and a "no" response earned 0 points. The maximum score a study could receive was 7 points. The quality questionnaire and its corresponding assessment phases are detailed in the following subsections.

Design Clarity and Relevance

Are the research aims and objectives clearly stated and aligned with the study's focus on HCI elements in CDSSs?

Data Collection and Relevance

Does the paper provide comprehensive and relevant data pertinent to HCI elements in CDSSs, including metrics for evaluation?

Empirical Measurement and Methodology

Are the HCI elements empirically measured with well-defined metrics? Is the methodology for evaluating these elements clearly described?

Analysis and Documentation

Are the research results documented with granularity, including participant information, observational units, and analysis methods?

Conclusion Validity and RQs

Do the study's conclusions adequately answer the RQs? Are the implications for HCI and CDSSs clearly articulated?

HCI Evaluation Method

Is the HCI evaluation method used in the study justified and described in sufficient detail?

Relationship Between HCI Elements and CDSS Outcomes

Does the study adequately illuminate the relationship between the applied HCI elements and the CDSS outputs or results and their consequences?

Quality Assessment and Interrater Reliability

The maximum score a study could receive was 7 points. To advance to the next phase of the review, studies were required to score at least 5 out of 7 points. To validate the quality assessment results and demonstrate process consistency, we computed a measure of interrater reliability using Krippendorff α [40]. The Krippendorff α value was 75.33%, indicating that the data were interpreted similarly and acceptably among the coauthors. When discrepancies arose, we engaged in discussion sessions to reach a consensus.

Query Strings

Overview

The search strings for each considered source were generated using relevant search terms derived from the population, intervention, comparison, outcome, and context methodology outcomes [41], connected by Boolean "and" or "or" operators. The canonical search equation provides a standardized template that ensures consistency across different databases. This canonical search equation is then adapted to fit the specific syntax of each database. The canonical search equation is as follows: ("human-computer interaction" OR "HCI" OR "usability" OR "user experience" OR "user interface" OR "user-centered") AND ("electronic medical records" OR "EMR" OR "electronic health records" OR "EHR") AND ("clinical decision support systems" OR "CDSS" OR "decision support system*" OR "DSS" OR "artificial intelligence" OR "AI").

Using the canonical search equation, we formulated the following queries tailored to each of the 3 selected databases to retrieve all relevant studies, including those addressing the implications of physicians' interactions with systems. Each database required distinct syntax, as outlined in Textbox 2.

Textbox 2. Search syntax for each database.

Scopus

(TITLE-ABS-KEY (“human-computer interaction” OR “HCI” OR “usability” OR “user experience” OR “user interface” OR “user-centered”) AND TITLE-ABS-KEY (“electronic medical records” OR “EMR” OR “electronic health records” OR “EHR”) AND TITLE-ABS-KEY (“clinical decision support systems” OR “CDSS” OR “*decision support system*” OR “DSS” OR “artificial intelligence” OR “AI”))

Web of Science

(TS= (“human-computer interaction” OR “HCI” OR “usability” OR “user experience” OR “user interface” OR “user-centered”) AND TS= (“electronic medical records” OR “EMR” OR “electronic health records” OR “EHR”) AND TS= (“clinical decision support systems” OR “CDSS” OR “decision support system*” OR “DSS” OR “artificial intelligence” OR “AI”))

PubMed

((“human-computer interaction” OR “HCI” OR “usability” OR “user experience” OR “user interface” OR “user-centered”) AND (“electronic medical records” OR “EMR” OR “electronic health records” OR “EHR”) AND (“clinical decision support systems” OR “CDSS” OR “decision support system*” OR “DSS” OR “artificial intelligence” OR “AI”))

Limiting Retrieved Results

Each database required distinct syntax, as outlined in the query strings presented above. In subsequent stages of this review, the retrieved results were limited to those that had the potential to address the predefined RQs.

Review Process

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [42] were followed for reporting this SLR. Refer to Multimedia Appendix 1 for the PRISMA checklist.

The data-gathering process was segmented into several stages, during which various inspections were performed.

Once the search was completed on July 25, 2024, the paper selection process was conducted in the following stages:

1. The raw data, consisting of records retrieved from the 3 databases, were compiled into a Zenodo repository (Multimedia Appendix 2). This dataset, which contains data from 923 papers, is organized into separate sheets for each database: Scopus (n=506, 54.8%), Web of Science (n=188, 20.4%), and PubMed (n=229, 24.8%).
2. After arranging the records, duplicate papers were eliminated. Of the 923 papers, 326 (35.3%) were removed, leaving 597 (64.7%) for the next stage.
3. At the first step of the screening, reading the titles, abstracts, and keywords and applying the inclusion and exclusion criteria resulted in 444 (74.4%) of the 597 papers being excluded, leaving 153 (25.6%) for the next phase.
4. Of these 153 papers, the full text of 5 (3.3%) was not accessible; hence, we read in detail and further scrutinized 148 (96.7%) papers. After an exhaustive examination of these 148 papers, we removed 105 (70.9%) for the following reasons: 49 (46.7%) involved HCI elements in medical environments, but these elements were unrelated to CDSSs; 38 (36.2%) did not explicitly focus on HCI or usability elements, although they discussed CDSS functionality; and 18 (17.1%) did not clearly explain the relationship between the identified HCI elements and CDSS functionality.
5. Ultimately, of the initially identified 923 papers, 43 (4.7%) were selected for the final analysis and review (Multimedia Appendix 3 [7,43-84]).

Results

Overview

This section provides a detailed analysis of the findings derived from our SLR on HCI elements that influence CDSSs. By thoroughly examining the 43 articles included for analysis, we aimed to answer the formulated RQs and MQs, thereby delineating the boundaries of this research area.

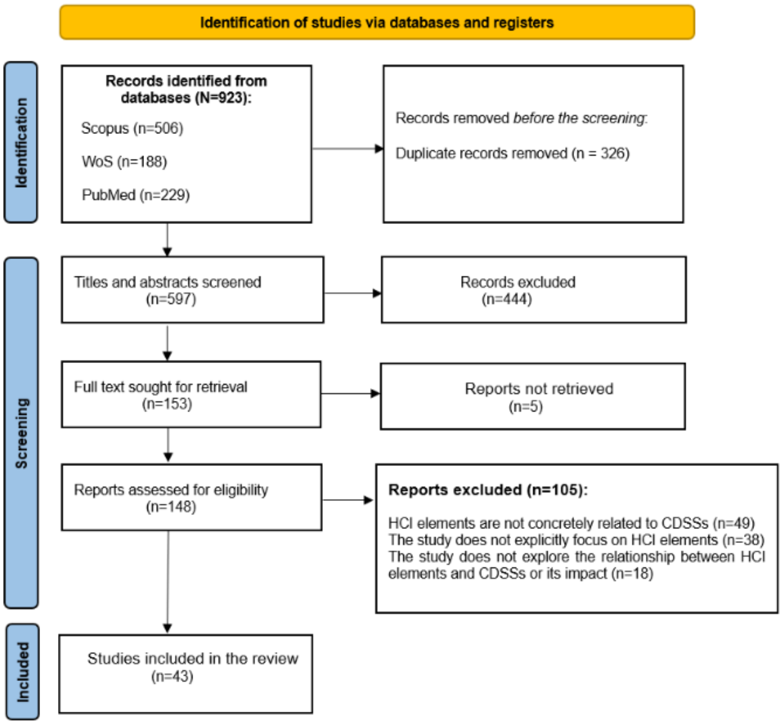
Our RQs focused on identifying the HCI elements that influence medical data management and CDSS functionality (RQ1) and understanding how these identified HCI elements can impact CDSS performance (RQ2). These questions were essential for understanding the relationship between HCI elements and the efficiency, accuracy, and usability of CDSSs.

In addition to these RQs, we formulated several MQs to comprehensively explore the scope and context of the studies. These included understanding the geographic distribution of research efforts in this area, analyzing the temporal distribution of the included studies, and identifying their publication venues. Furthermore, we examined the topic distribution in this SLR to determine the percentage of attention each identified HCI element received across the reviewed studies.

This analysis provides insights into the HCI elements investigated in the studies and how they influence CDSS functionality. This comprehensive overview offers valuable information on how HCI elements can be optimized to enhance the overall performance and effectiveness of CDSSs, ultimately contributing to improved patient care and decision-making within medical settings.

The PRISMA flow diagram [42] illustrates the steps taken to extract the required data (Figure 1).

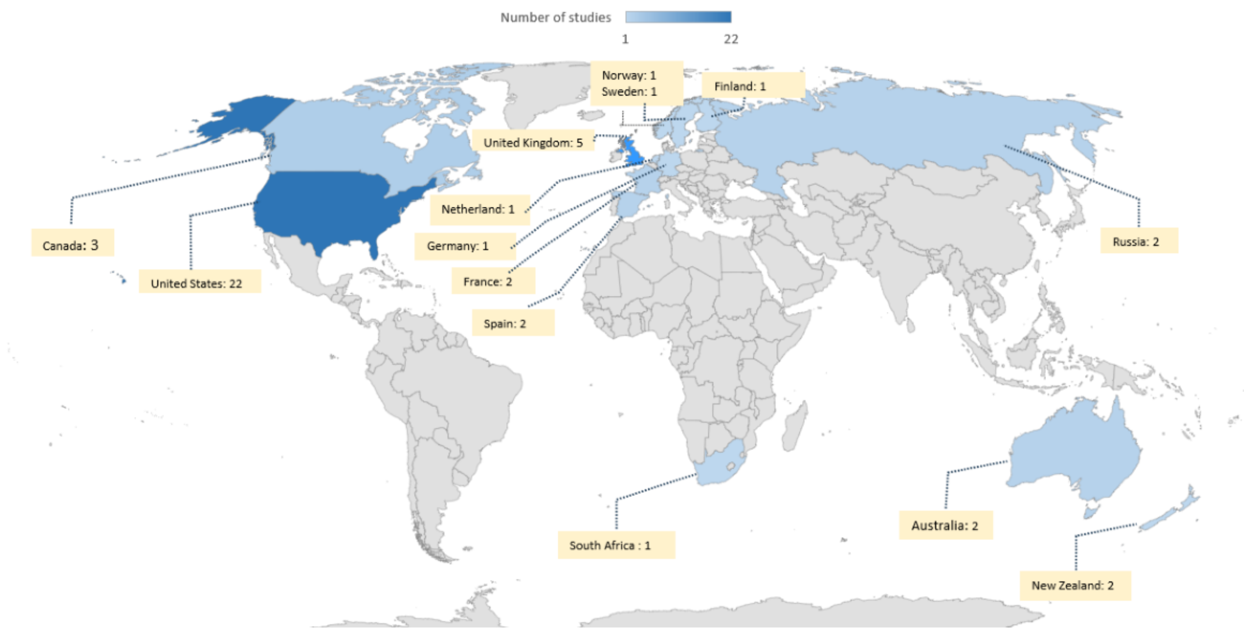
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow diagram showing the number of studies identified, screened, assessed for eligibility, and included in the final analysis. CDSS: clinical decision support system; HCI: human-computer interaction; WoS: Web of Science.



Geographic Distribution of Studies

Our investigation to address MQ1 was carried out by considering the affiliations of all authors. Consequently, a study with authors from Spain, the United Kingdom, and Sweden was attributed to all 3 countries. In total, 43 studies were conducted across 14 countries. As depicted in Figure 2, the geographic distribution reveals a significant concentration of research in the United States and Europe, reflecting global interest in enhancing CDSSs through improved HCI elements. The United States contributed the most publications, with 51% (22/43) of the relevant studies, followed by the United Kingdom with 12% (5/43); Canada with 7% (3/43); and Russia, Spain, France, and Australia with 5% (2/43). The remaining countries—Sweden, South Africa, Norway, New Zealand, Finland, and Germany—each accounted for 2% (1/43) of the studies.

Figure 2. Geographic distribution of the included studies.



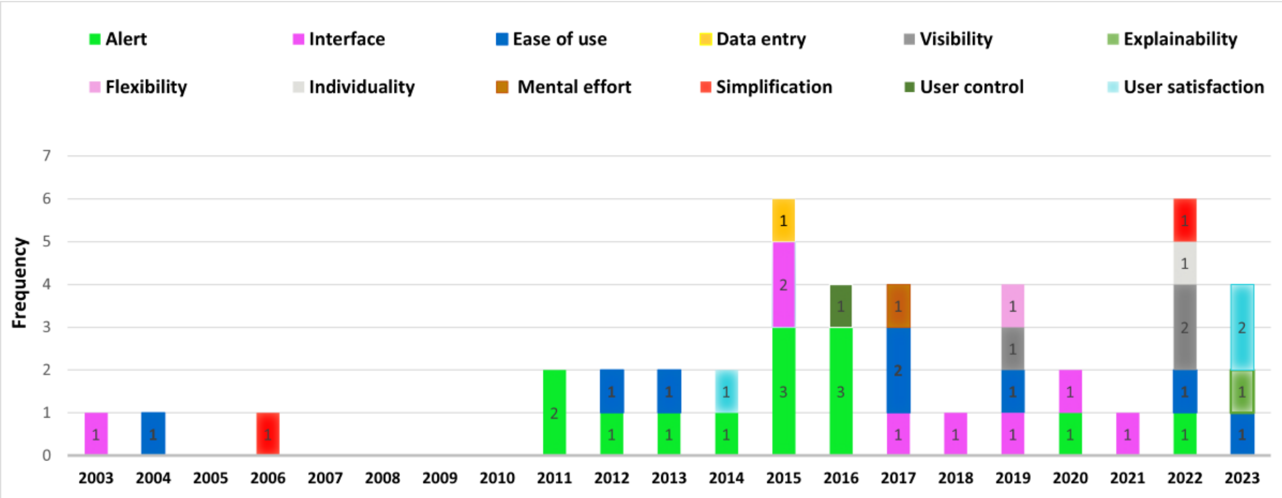
Despite the rapid technological advancements and growing health care needs in Asia, our analysis revealed a notable lack of studies relevant to HCI elements in the CDSS realm from Asian countries. Addressing this discrepancy is crucial for developing cultural and contextual usability solutions to enhance CDSS performance.

Our exploration indicates that the emphasis on distinct HCI elements varies by country based on specific demands, policies, and priorities. In the United States, which has the highest research activity in this field, studies have predominantly investigated HCI elements related to CDSS alerts (9/22, 41%), UI (3/22, 14%), and ease of use (2/22, 9%). Although these core HCI elements are imperative, some specific HCI demands may be considered depending on cultural differences and local needs [85].

Year-Wise Distribution of Studies by Identified HCI Elements

Through the review process, we identified 12 HCI elements. Each included paper primarily focuses on 1 main element, as shown in Figure 3. While some papers discuss multiple HCI elements, the figure presents the dominant HCI element addressed in each paper. The bar graph illustrates which HCI elements related to CDSS received attention each year. Although the gradual formation and evolution of CDSS technology began in 1990 [14], HCI elements have gained significant attention in medical settings since the 1990s, with increasing emphasis on usability, UX, and interface design in health care technology [86]. This study depicts the conjunction of 2 concepts—HCI and CDSS functionality—that have emerged since 2003 and have seen significant advances, especially since 2015. Figure 3 highlights this growth, which is tightly related to MQ2. As shown in Figure 3, an investigation gap existed in this realm between 2006 and 2011, and most studies on this subject were carried out in 2015 and 2022. Since 2011, there has been a growing interest in exploring the relationship between HCI elements and CDSS functionality.

Figure 3. Scattering leverage of human-computer interaction elements in clinical decision support systems over the years.



This trend reflects the increasing comprehension of the importance of UCD in health care technology, aiming to improve the usability and effectiveness of CDSSs in supporting clinical decision-making processes [87].

Publication Venues: Distribution by Study Type (Journal, Conference, or Book Chapter)

Nearly all of the included papers (42/43, 98%) were published in academic journals. This indicates a strong preference for disseminating research findings related to HCI elements in CDSSs through journal publications, which are often peer reviewed and highly regarded in the academic community. Moreover, 1 (2%) of the 43 papers was a book chapter, which provides comprehensive overviews and in-depth discussions on specific topics, contributing valuable insights to the field.

This distribution, as the explicit answer to MQ3, highlights the credibility and rigor of the selected studies, ensuring that the insights and conclusions drawn from this review are thoroughly examined and well substantiated.

Identified HCI Elements That Influence CDSS Functionality and Performance

Overview

As discussed in the previous subsections, regarding our explicit question about HCI or user perspective elements with the potential to impact CDSS functionality, we identified 12 elements after a full-text study of 43 selected papers. These elements were categorized based on their inherent nature, application context, and significance to the UX, particularly from the perspective of medical staff. As illustrated in Table 1, these elements address different HCI concerns. Although HCI elements such as "interface" inherently encompass subelements such as "visibility," "user control," and "data entry," these subelements have been presented independently to highlight their unique roles and distinct contributions to CDSS functionality and usability; for example, "data entry" focuses on minimizing input errors through standardized workflows, whereas "visibility" prioritizes intuitive data presentation—distinct concerns that have been highlighted in studies on clinical efficiency and user trust [60,88].

Table 1. Extracted human-computer interaction (HCI) elements and insights.

HCI elements and topics and addressed concerns	References
Alerts	
Usability flaws	[43,44]
Alert fatigue	[7,45-47]
Alert design recommendations	[48-53]
Barriers (too many alerts)	[54]
Ease of use	
Intention to use	[55]
Understandable	[56]
Customizability	[57]
User-friendly features	[58]
Jargon avoidance	[59]
Consistency of operations	[60]
Goal-directed design	[61]
Facilitators (automating data fetching)	[62]
Interface	
Acceptability	[63]
Information recall issues	[64]
Data presentation	[65]
Visualization	[66]
Interface features	[67]
Physical layout	[68]
Facilitators and barriers to presenting diagnostic information	[69]
Heuristic semantic tags (to improve interface design)	[70]
Visibility	
Error visibility	[71]
Patient status visibility	[72]
Importance-based highlighting	[73]
Simplification	
Removing extraneous information and procedures	[74]
Resolving the conflict between system simplicity and usefulness	[75]
User satisfaction	
Users' expectations and learnability	[76]
Effectiveness, efficiency, and accessibility	[77]
Barriers (mismatch between meaningful-use criteria and physicians' expectations)	[78]
Explainability	
Transparent and informative recommendations	[79]
Flexibility	
Ability to change order and revise data entry	[80]
User control	
Controllability for error prevention	[81]
Data entry	

HCI elements and topics and addressed concerns	References
Accurate and structured data entry	[82]
Individuality	
Individualized and user-centered approach	[83]
Mental effort	
Cognitive load	[84]

This categorization of HCI elements aligns with the International Organization for Standardization (ISO) 9241-11 framework [89], which defines usability as a combination of effectiveness, efficiency, and satisfaction in achieving specific goals within a particular context. We found some studies (3/43, 7%) that directly evaluated CDSSs to assess "user satisfaction," focusing on the outcomes of user-system interaction. These studies align with the satisfaction component of the ISO 9241-11 standard, emphasizing users' subjective experience and acceptance of the system. In comparison, "visibility" supports the effectiveness dimension of this standard by ensuring that users remain informed about the system's status in a timely manner, facilitating accurate decision-making. Conversely, "ease of use" corresponds directly to the efficiency dimension of ISO 9241-11 because it minimizes the cognitive and physical effort required to interact with the system, enabling users to achieve their goals with minimal waste of resources or time. Moreover, "explainability" enhances effectiveness by improving users' understanding of system outputs, while "alerts" contribute to both effectiveness and efficiency, ensuring that critical information is promptly communicated without overwhelming users. Another HCI element, "user control," also strengthens effectiveness by aiding error prevention and recovery, allowing users to rectify mistakes and maintain workflow reliability. As the "interface" element impacts decision accuracy and interaction speed, it is strongly related to effectiveness and efficiency. "Flexibility" and "individuality" primarily support satisfaction because they enable system adaptability to different user needs and preferences, fostering trust and engagement. "simplification" and "mental effort" impact both efficiency and effectiveness because they reduce cognitive load, eliminate unnecessary complexity, and optimize workflow processes. Another HCI element, "data entry," contributes to accurate information for decision-making (effectiveness) and streamlines the input process to save time and reduce effort (efficiency).

The rationale for this categorization is clarified in Table 1, which outlines the main concern addressed by each study and explains how it relates to a specific HCI element. The subsections that follow provide a detailed explanation of each HCI element listed in the table.

Alerts

Overview

Alerts have been identified in this study as a major HCI element. Alerts in CDSSs are essential for enhancing patient safety and clinical efficiency. They provide immediate, actionable information to health care providers. They can warn about potential drug interactions, highlight critical patient allergies, or flag abnormal laboratory results [48]; for instance, an alert might notify a physician about a dangerously high potassium level in a patient, prompting immediate intervention. These alerts help prevent errors, ensure timely responses, and support adherence to clinical guidelines, ultimately improving patient outcomes and streamlining clinical workflows [90].

To explicitly investigate alert-related concerns within CDSSs, it is crucial to differentiate between alerts and reminders because conflating these elements can hinder effective system design. In the context of HCI within CDSSs, alerts and reminders should be discussed separately, given their distinct functions [91]. Alerts are immediate notifications requiring urgent attention, supporting real-time decision-making with minimal cognitive load. Reminders are persistent prompts designed to ensure that critical tasks are not overlooked, thereby improving adherence to clinical guidelines. They are defined as a communication or message to ensure that physicians remember critical tips [92]. Reminders can cause cognitive overload and frustration if they are too frequent or irrelevant—in such cases, they are categorized as barriers. Conversely, when reminders assist physicians, they are considered facilitators [93]. This distinction ensures a more effective optimization of HCI elements in CDSSs, balancing support and usability.

The findings from this SLR demonstrate that 31% (13/43) of the selected papers addressed alert-related topics, while Figure 3 shows that this element was mostly studied between 2011 and 2016 (11/13, 85%), although some studies (2/13, 5%) have been conducted in recent years (2020 and 2022). Research on alerts has focused on 3 main areas. Table 1 presents the studies that have addressed these categories, which are detailed in the following subsections.

Alert Fatigue

Alert fatigue poses a significant challenge for CDSS instruments because users may begin to neglect or override activated alerts due to their frequent occurrence [94]. In 2016, Gong and Kang [47] presented five solutions to address alert fatigue: (1) augmenting alert specificity, (2) tiering alerts based on severity, (3) applying human factors principles (such as format, content, legibility, and color), (4) customizing alerts based on patient attributes, and (5) providing tailored alerts for medical practitioners.

The timing of alerts is crucial because they should be presented at moments conducive to informed medical decision-making. It is important to strike a balance: alerts should be intrusive enough to capture attention, but they should not distract or divert users from the primary care pathway [45]. Maintaining this balance prevents alert fatigue, sometimes referred to as habitual override.

Usability Flaws

Usability flaws relevant to CDSSs that diminish alert performance have been identified as follows [43]:

- The distinguishing visualizations do not illustrate the variety of severity levels in the alerts.
- The information presented within alerts is dense and lacks brevity.
- A low signal-to-noise ratio, reflecting a high proportion of erroneous alerts compared to correct ones, often results from nonupdated or incorrect data.
- Alert content issues stem from missing information relevant to alert goals, data interpretation, or necessary practical recommendations.
- There is a scarcity of transparency regarding the reasons that have led to the triggering of the alert.
- The clinicians are not directed at fixing the problem identified by the alert.
- Adaptability issues point out the insufficient adjustability of the system to accommodate all types of users.
- Workload issues arise when too many tasks need to be performed to correct errors or obtain the required information.

In medical information systems, 2 main types of alert flaws are commonly observed: general and specific. General alert flaws occur when alerts lack specificity or fail to distinguish between different severity levels [44]. Specific alert flaws arise when alerts do not adequately address individual patients' or health care providers' unique contexts or needs, leading to ineffective or irrelevant notifications [95].

Alert Design Recommendations

Alert design recommendations have been addressed across the following aspects to enhance alert effectiveness (Textbox 3). Enhancements in alert functionality within CDSSs can optimize clinical workflows, ensure timely access to relevant information, mitigate alert fatigue, foster user trust, and ultimately contribute to more informed and effective clinical decision-making processes [68].

Textbox 3. Alert design recommendations.

- The visual presentation of alerts can be improved by using different colors, bullet points, and clear textual guidelines [48].
- Alerts should be triggered at appropriate points within the clinical workflow and should align with real-world practices [50].
- False alarms that can occur when the alert's logic is flawed or not based on updated information must be avoided. In some cases, rigid sensitivity calibrations can result in false alarms [49].
- The presentation of alerts should be determined based on their level of importance; for instance, higher-priority alerts may be presented in a way that interrupts the current workflow [50].
- Habituation pertains to repeated exposure to insignificant alerts. This underscores the importance of reducing the occurrence of false alarms, along with adopting an alarm philosophy aimed at minimizing alert overrides [49].
- Consistent terminology emphasizes the use of standardized and predefined words and expressions. This enhances the ability to locate specific words or data on the screen through visual screening and promotes uniformity in the generated data irrespective of geographic location [96].
- Mental models refer to an individual's interpretation of a specific matter that influences their reaction when an alert is triggered; for instance, the color red typically evokes an immediate association with "STOP" [49].
- The content of the alert—the reason for its activation and potential medical consequences—should be kept concise [97], with additional details accessible through related data links [98].
- Font style and size can be used to convey the importance and prioritization of the alert [51,99].
- Alert visibility is a critical HCI component that should be considered in the design of alerts within the CDSS environment [52]. The alert's dimensions as displayed on the screen (target size), luminosity, background contrast, and typography attributes should be carefully considered to quickly capture the user's attention [100,101].
- The degree of workflow interruption must be proportional to the severity of the medical issue that triggered the alert [51]. For high-priority alerts, it may be necessary to interrupt the workflow to prompt immediate user intervention [52].
- To ensure the proximity of decision-making components, decision support tools must be incorporated within the alert; for example, the alert should include hyperlinks to medical reference websites [53].

Excessive and Unnecessary Alerts

Particularly in specific patient populations or under uncommon circumstances, excessive and unnecessary alerts represent a significant barrier to the effective use of alerts within CDSSs. This obstacle can be resolved by grouping similar alerts into a single notification and tailoring alert thresholds and delivery methods based on patient condition and clinical context [54].

Ease of Use

Ease of use was identified as a principal user concern in 19% (8/43) of the selected papers. This element is foreseeable and represents a standard expectation among users, particularly physicians. In this respect, systems should be designed so that users easily understand how to operate the system. This is referred to as perceived ease of use. A positive perceived ease of use is associated with an increased intention to use (IU) [55].

The concept of consistency will augment a system's ease of use. It can be achieved in 2 distinct areas: jargon-free language and consistent operative patterns. Consistent terminology and operation across all system components minimize user confusion and cognitive load, enabling users to quickly and effectively achieve their goals [59].

In essence, a system that is easy to use enhances learnability because users can understand and remember operational procedures more quickly [102].

In a CDSS environment, ease of use can significantly boost system functionality by ensuring that health care professionals can quickly and without complexity access and apply clinical guidelines and decision aids [58]. In this regard, a key facilitator is automated data fetching, which streamlines the retrieval of relevant information, minimizing complexity and allowing users to focus on patient care [62].

Moreover, goal-directed design is a user-centered approach that prioritizes understanding user needs and goals throughout the design process. By engaging end users throughout the design process, goal-directed design ensures that the system effectively supports their tasks and contexts. This alignment directly contributes to ease of use by streamlining interactions and enhancing UX [61].

Interface

Interface, another important HCI element**,** was addressed in 19% (8/43) of the selected papers, especially between 2015 and 2021. While interface design inherently encompasses various HCI elements, the analyzed papers offer unique insights that extend beyond the scope of other discussed elements. These papers provide specific recommendations for interface improvements that can significantly enhance user interaction by optimizing system design and fostering intuitive use.

The interface of a CDSS directly influences acceptability by determining how intuitively users can access and act on clinical information. When the interface aligns with users' workflows and preferences, it increases their willingness to adopt and use the system effectively [63]. Despite recent advances in computerized technologies, the defective design of graphical UIs in clinical settings may lead to frustration among physicians [10]. In the context of CDSSs, the UI refers to the graphical or visual representation through which users interact with the system to access, input, and interpret information [63]. An effective UI should be intuitive, user-friendly, and tailored to health care professionals' specific needs and workflows [64].

Via integration with EHRs, well-designed interfaces within CDSSs can present a list of possible diagnoses associated with medical symptoms, the compatibility percentage of the patient's current medical status, and the factors contributing to the diagnosed illness [65,103]. In addition, effective data visualization enables quick comprehension of complex information, promoting time efficiency by enabling health care professionals to rapidly interpret data without the need for extensive analysis [66].

A responsive and interaction-enabled UI encompasses 2 distinct features: presentation and placement. In terms of presentation, elements such as simplicity, appropriate font size, meaningful colors, acceptable contrast, and bold text enhance readability and user engagement. Regarding placement, information should occupy a prominent position, be localized for easy access, and use multiple presentation layers to facilitate quick comprehension. Together, these interface features facilitate the seamless flow of essential medical data to decision makers [67].

In the interface realm, the physical layout concept refers to the arrangement and organization of screen objects with which users interact. This layout significantly impacts user control, allowing health care professionals to directly manipulate the screen's objects (such as buttons, sliders, and forms). When users have clear control over screen objects, they can more effectively navigate the system, customize their workflow, and respond to patient needs promptly, ultimately improving overall usability and satisfaction with the CDSS [68].

There are some facilitators and barriers relevant to the interface within CDSS environments. One of them is the content-based facilitator that enhances interface usability by presenting clear, concise, and relevant information. In this respect, tailoring content to meet the health care professionals' specific needs and preferences and providing real-time updates on clinical guidelines will enhance the interface. Conversely, inconsistent content within the data presentation and guidelines, potentially leading to confusion and misinterpretation, has been identified as an interface barrier [69].

One reviewed paper introduced the concept of "heuristic tags" to enhance CDSS interface design [70]. The paper describes a container comprising 14 HCI elements relevant to CDSS environments, referred to as semantic tags [70]. These elements are outlined in Table 2.

Table 2. Semantic tags.

Tag	Description
Consistency and standards	All system providers throughout the design must adhere to a unified protocol by maintaining consistency in terminology, sequence of actions, and data localization.
Visibility of the system status	Users should be notified of ongoing processes via suitable alerts and feedback mechanisms.
Match between system and world	Users' perceptions of the system should align with their mental models of how the system is expected to function.
Minimalist design	Any unnecessary information should be eliminated because it acts as a distraction and impedes efficiency.
Minimize memory load	Users should not be required to memorize extensive information to perform routine tasks.
Informative feedback	Users must receive informative feedback regarding their activities.
Flexibility and efficiency	The system should provide resiliency so that users can customize settings and expedite their tasks.
Good error messages	Messages should provide sufficient information for users to comprehend the nature of errors, learn from mistakes, and take corrective action.
Prevent errors	The design should deter errors by preventing incorrect actions.
Clear closure	Users must be explicitly informed when a task has been completed.
Reversible actions	Users should be allowed to recover from errors made by them.
Use user's language	The system language must be comprehensible to the targeted users.
Users in control	Users should not feel in control of the system without encountering unforeseen circumstances.
Help and documentation	The system should offer various forms of help, such as contextual assistance, mission-focused guidance, and alphabetically organized (lexicographically arranged) help topics for easier navigation.

Therefore, interface quality will influence the precision of medical decisions by facilitating intuitive access to relevant information and enhancing user interaction.

Visibility

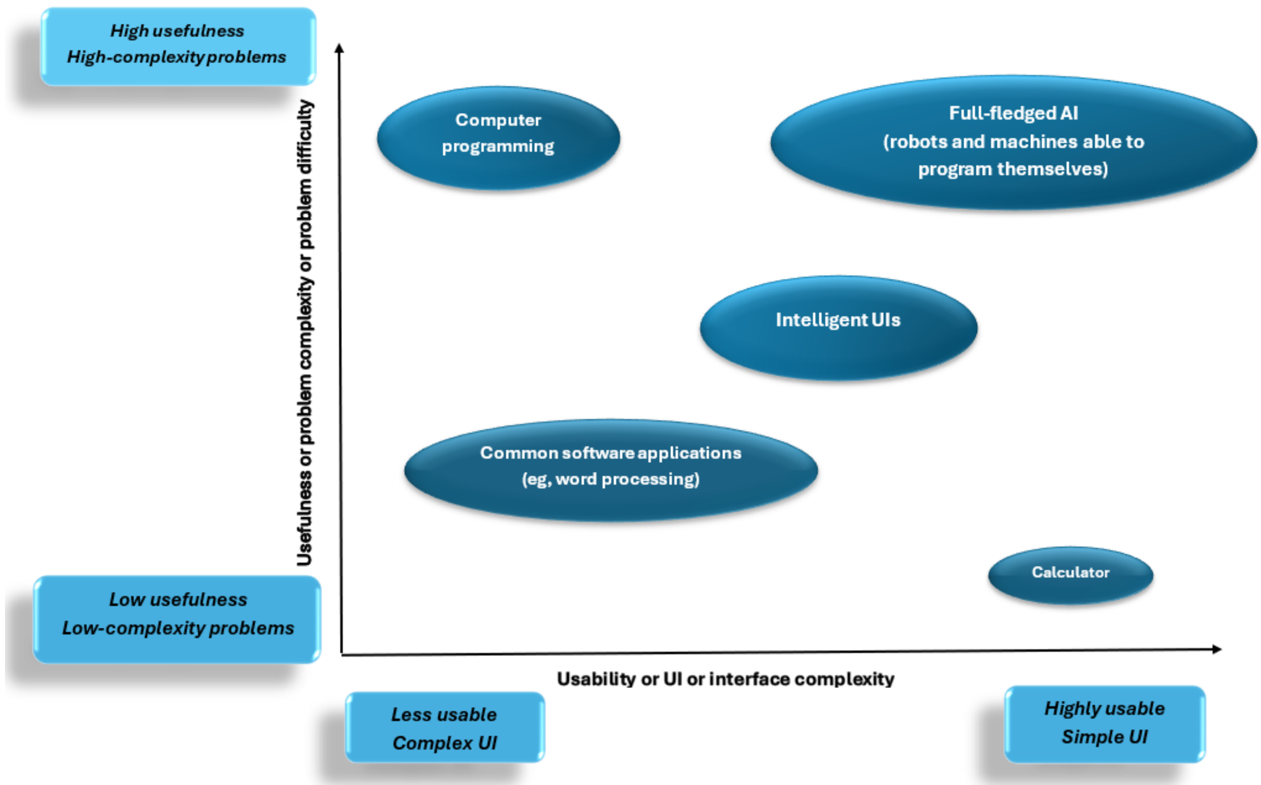
Visibility was addressed in 7% (3/43) of the selected papers, emphasizing that quick access to information requires data to be readily accessible within a short time frame and ensuring that medical data are available at expected locations. This includes the clear and immediate visibility of possible errors or system warnings, allowing users to identify and address issues quickly [71]. Within the treatment cycles pertinent to CDSSs, visibility refers to the clarity and transparency of the workflow stages and progress, meaning that health care providers can easily track and understand the status of the treatment process, including diagnostic tests, medication administration, and patient outcomes [72]. In addition, by visually emphasizing critical information such as high-risk alerts or abnormal laboratory values through color coding, bold text, or other visual cues, clinicians can quickly identify and prioritize important information [73]. As visibility criteria provide a clear and transparent view of the treatment cycle workflow, they enable users to easily monitor the progress of patient care and make informed decisions based on the current stage of treatment, leading to the best possible decision [73].

Simplification

Of the 43 selected papers, 2 (5%) addressed simplification elements. Simplification can be achieved by eliminating unnecessary complexities and providing an optimized workflow congruent with real-world practices [104]. Removing extraneous information and procedures is crucial for achieving this goal [74]. Pantazi et al [75] propounded a theory describing a paradox between simplification a medical system and its usefulness: systems with high usability typically can solve trivial problems, whereas solving intricate problems requires an appropriate level of complexity, which can reduce overall usability.

As shown in Figure 4 [75], some CDSS applications designed for intricate problems have complex UIs with lower usability levels, whereas sections with simpler structures within CDSSs, such as medical calculators, exhibit higher usability levels. Meanwhile, system designers are striving to develop medical AI systems that simultaneously enhance both usability and problem-solving capacity.

Figure 4. The relationship between system complexity and usability. AI: artificial intelligence; UI: user interface.



Nonetheless, while striving for complexity in medical procedures can be inherently beneficial, it is crucial to maintain a balance between usability and necessary intricacy [105]. Striking this balance ensures that procedures are not unnecessarily complex, saves time, and ultimately enables rapid emergency medical decision-making [106,107].

User Satisfaction

User satisfaction was discussed in 7% (3/43) of the selected papers. Recognized as a central focus in HCI research, user satisfaction is paramount to the effectiveness of CDSSs. This concept encompasses aspects such as system acceptability, learnability, memorability, and accessibility [76].

UCD methods are essential for achieving high user satisfaction [108]. By prioritizing the user's needs and perspectives throughout the development process, CDSSs can be tailored to meet their specific requirements [109]. Learnability facilitates users in quickly understanding how to operate the system, which enhances initial engagement [110]. Memorability ensures that the system's functions are easily recalled once learned, reducing the need for repeated training [111]. Accessibility ensures that the required medical information and history are promptly accessible in the system [77]. Incorporating these elements boosts overall user satisfaction, improves efficiency and adoption, and ultimately leads to better patient outcomes in clinical environments.

Conversely, the mismatch between meaningful-use criteria and physicians' expectations represents a significant barrier to user satisfaction within CDSSs. In these cases, the requirements set by system designers do not align with physicians' practical needs and processes, leading to frustration and decreased usability. This misalignment can hinder the effective adoption of CDSSs because physicians may find the systems cumbersome or irrelevant to their clinical workflow. Addressing this gap is essential for improving user satisfaction and ensuring that CDSSs effectively support health care professionals in delivering high-quality patient care [78].

Explainability

Explainability, as identified in 2% (1/43) of the selected papers, is a critical focus in the ongoing discourse surrounding CDSSs and medical AI [112]. Transparency, a cornerstone of explainability, fosters trust between the user and the system [113]. Once the CDSS provides recommendations and solutions, physicians can understand why and how the advice was generated. This understanding augments their clinical expertise and contributes to more informed decision-making over time [79].

Flexibility

Flexibility was articulated in 2% (1/43) of the selected papers. This element requires significantly more attention and could be leveraged to enhance CDSS functionality. Adjustable medical systems typically achieve higher adoption rates, particularly when they meet physicians' need for flexibility [114]. In this context, 3 diverse dimensions related to flexibility concerns have been identified [80]: (1) user tendency to return to previous stages to correct or modify information; (2) data entry in multiple different sequences; and (3) customizable data presentation.

Flexibility is a crucial attribute when designing digital pathways. By aligning flexibility with actual clinical workloads, treatment routes can be tailored to meet physicians' and patients' specific needs and demands [115]. This alignment enhances medical decision accuracy, enhances user satisfaction, and ultimately improves patient outcomes [116].

User Control

User control was addressed in 2% (1/43) of the selected papers, emphasizing the importance of instructions that align with real-world workflows, aiding users in recovering from and preventing errors. Interfaces that are compatible with established practices help users rectify mistakes and reduce the recurrence of common errors, enhancing overall usability and efficiency [81]. In this context, an important framework is the unified theory of acceptance and use of technology (UTAUT). UTAUT is used to predict and understand individuals' acceptance and adoption of new technologies, integrating various factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. By enabling users to recover from mistakes and easily control their interactions, systems can enhance user satisfaction and increase the likelihood of technology adoption, as predicted by the UTAUT model [117].

Data Entry

Data entry was investigated in 2% (1/43) of the selected papers, with a focus on designing systems that minimize potential user errors [82]. Structured data entry management is fundamental in CDSSs, ensuring organized, standardized, and systematic data input. Emerging technologies such as voice recognition technology and natural language processing have facilitated and improved the data entry aspect in eHealth systems. These advancements minimize errors and inconsistencies, ultimately enhancing the reliability and effectiveness of CDSSs in supporting clinical decision-making [118].

Individuality

Individuality was presented in 2% (1/43) of the selected papers. In this area, Klumpp et al [83] discuss the HCI concept as a theory encompassing 4 key issues that shape individuals' interactions with computerized systems. The first factor is the identification of technology, including all technological features applied to the system [119]. The second factor is the assignment, referring to a defined task where the technology used varies depending on the satisfaction and aims of the task [120]. The third factor is context, which can vary depending on the geographic, corporate, or community conditions, meaning that the recommendations should be customized according to the geographic positions and other local conditions [121]. The fourth factor involves human dimensions, such as population characteristics, cognitive abilities, and the attitudes of individuals [122]. In other words, customizability should be based on the intended populations' approaches, attributes, and desires. Concentrating on system individualization and customization can enhance the accuracy of decision-making in CDSSs [83].

Mental Effort

Mental effort was identified as an HCI element in 2% (1/43) of the selected papers. The Rating Scale Mental Effort (RSME), first proposed by Militello et al [84], is designed to accurately measure perceived mental effort during task completion. In other words, it measures the extent to which individuals feel they have exerted mental effort to complete a task. The RSME can be used to gauge how effectively CDSSs aid medical practitioners without overly complicating their decision-making processes. A low RSME score indicates that the CDSS is well integrated into clinical workflows, and CDSS functionality is enhanced without imposing significant additional cognitive complexity on the user [123].

Discussion

Principal Findings

While several studies have explored HCI elements in CDSS environments, each has focused on specific aspects independently. This has left a research gap regarding a comprehensive analysis and categorization of these effective elements. This study attempts to present a scientific framework for CDSS design by identifying HCI elements that influence CDSS functionality across different dimensions. In this respect, after reviewing 43 selected papers in this SLR, we identified and stratified 12 key HCI elements, thereby distinguishing our investigation from the selected studies, which, although they explored the identification and classification of HCI elements, were experimental in nature, with a limited focus on specific, monitored elements.

A common thread among the selected studies is their focus on HCI elements relevant to CDSS applications, which can substantially influence CDSS functionality and performance. Throughout this SLR, the categorization of studies under specific HCI elements depended on the primary focus of each study. While some studies explicitly investigated a single HCI element, others addressed multiple aspects (such as heuristic semantic tags [70]) or offered broad recommendations. In such cases, the main HCI concern emphasized in the study was the selection criterion. This approach ensured that each study was categorized based on its core usability focus, maintaining consistency and relevance in the analysis.

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The interface is considered a distinct HCI element because it serves as the primary medium for user interaction [124]. Although it encompasses visibility, data presentation, and ease of use, its role transcends these components [125,126]. Indeed, the interface functions as the platform that enables the delivery and experience of these elements, making it a distinct and critical component of the HCI context [127]. This distinction is crucial for CDSS environments, where the interface must accommodate complex clinical workflows and user needs to ensure usability and patient safety. Hence, despite its broad scope, the interface has been examined as an independent HCI element in some studies, allowing for a more focused and in-depth evaluation of its inherent contributions to UX and decision-making in CDSS environments [128]. Thus, we considered it a separate HCI element in this study.

The relationship between HCI and UI and UX design further underscores the importance of the interface as an independent element. While UI focuses on the visual and interactive components of a system (eg, buttons, menus, and layouts) and UX encompasses the user-centered experience (including usability, accessibility, and emotional satisfaction), the interface concept (within HCI) is the physical manifestation of these principles [129,130]. As Paneru et al [131] explain, the interface is a visual and interactive layer that enables users to interact with digital products. It is the medium through which all other HCI elements are experienced, making it a foundational component of HCI. However, the interface also extends beyond traditional UI and UX design by incorporating considerations such as workflow alignment, cognitive load reduction, and task efficiency, which are central to HCI. By contrast, Motlagh and Safaei [132] emphasized that, rather than relying solely on UI and UX considerations, HCI evaluation in health care systems should prioritize error prevention, cognitive effort, and information recall. This means that HCI elements promote interfaces that support accurate decision-making and clinical workflow integration.

According to ISO 9241-11, usability measures how effectively, efficiently, and satisfactorily users can achieve their goals with a system in a particular context. This highlights the importance of context and task dependency in evaluating usability because the relevance and effectiveness of HCI elements vary across different environments and user needs [133]. The HCI elements identified in this study align with these usability dimensions but manifest differently depending on task requirements and system context. In frequently used systems such as EHRs in busy hospitals, ease of use, simplification, and task efficiency are paramount HCI elements. Clinicians using these systems need interfaces that minimize cognitive load and streamline workflows because even small inefficiencies can accumulate, leading to frustration and errors. In this context, alerts must be designed to be highly visible but nonintrusive so that they support rather than disrupt workflow [48]. In these circumstances, data entry mechanisms should be optimized for speed and accuracy because frequent use requires efficiency. Conversely, in an infrequently used system (such as a specialized diagnostic tool used only occasionally), HCI elements such as explainability become more critical. Users of such systems will need more guidance and contextual support to navigate the interface effectively. Regarding user control and flexibility, although these elements align with the satisfaction component of the ISO 9241-11 standard, their impact is also context dependent. Experienced physicians may prefer more flexible customization to streamline interactions, while novice users benefit from structured interfaces with clear navigation paths and constraints to prevent errors [80,81]. As shown in Table 1, the identified HCI elements were categorized based on their primary usability contributions; nevertheless, their actual significance in improving CDSS usability depends on the task, frequency of use, and clinical environment.

Two closely related but distinct HCI elements—ease of use and simplification (simplification)—play unique roles in enhancing CDSS usability. Ease of use refers to the system's ability to provide an intuitive and seamless interaction experience, minimizing cognitive and physical effort for users. It encompasses aspects such as jargon avoidance, consistency of operations, and efficient task execution, ensuring that clinicians can navigate the system with minimal frustration [56,58-60]. By contrast, simplification focuses on reducing unnecessary complexity within the system, such as streamlining workflows**,** eliminating redundant steps, and minimizing information overload [74,75]. While ease of use improves UX, simplification optimizes system design by removing obstacles and extraneous procedures that could hinder task completion. Moreover, ease of use is closely tied to user satisfaction and IU. An easy-to-use system facilitates navigation, reduces cognitive efforts, and leads to a more positive UX, ultimately increasing IU and user satisfaction.

This study recognized another prevalent and critical challenge faced by CDSS designers: balancing the paradox between system simplification and maintaining its usefulness in solving complex problems, even if doing so leads to increased complexity. This balance is essential for developing systems with high usability and appeal, ensuring that users can effectively interact with the system without being overwhelmed by its complexity [75]. To reach this equilibrium, designers must adopt a user-centered approach that prioritizes the needs and capabilities of health care professionals. This involves continuous user testing and feedback loops to refine the interface and functionality [59]. In addition, incorporating adaptive interfaces can reduce complexity based on the user's expertise and the specific task to help manage this paradox, resulting in augmented overall satisfaction and higher adoption rates [65].

This study attempted to highlight the HCI elements dedicated to CDSSs, specifically those that address user requirements across various dimensions such as informative notifications [52], aesthetics [61,71], contextual facets [79], unification [70], and psychological aspects [84]. To illuminate all HCI aspects within CDSSs, this study also identified elements that represent challenges in this domain requiring mitigation, such as existing HCI barriers [78], usability flaws [43], user fatigue [7], and the phenomenon of alert override [49]. Although considering the identified HCI aspects is crucial, the final goal is to improve user interaction with the system, enhance ease of use, and anticipate and fulfill user expectations. This approach fosters user satisfaction and promotes a positive UX [74]. This focus on users as major "players" in the design process is now an established principle. Hence, UCD methods are fundamental to the development of CDSSs with high levels of user interaction [134]. Depending on the system's complexity and ease of use, both user interaction with the system and data accuracy can vary, consequently affecting the accuracy of medical decision-making [58].

In summary, this study provides comprehensive insights into the essential HCI elements applicable in the CDSS environment, answering the RQs. It contributes to the field by systematically categorizing these elements and developing a structured framework aimed at improving usability and medical decision-making outcomes.

Conclusions

Of the 923 papers found in 3 databases (PubMed, Scopus, and Web of Science), 43 (4.7%) met the predefined criteria with regard to addressing HCI elements applicable in CDSS environments. This SLR indicates that attention to HCI elements tailored to CDSSs has increased since 2015. In this study, we identified 12 HCI elements. While elements such as "ease of use," "interface," and "alerts" have consistently garnered attention from experts, others such as "user satisfaction," "visibility," and "explainability" have recently received increased focus. This SLR has answered the RQs regarding the HCI elements that can affect CDSS functionality and described how these elements impact CDSS performance. Moreover, the study categorized the identified aspects according to their context and scientific perspectives.

This study identified a gap in current research: the lack of a comprehensive consideration of HCI elements within CDSS design. By leveraging the findings from this investigation, a set of applicable HCI elements for CDSS environments can be established. Consequently, these findings have the potential to enhance the synergistic effect between medical information systems and CDSSs, ultimately leading to improved overall performance.

This research provides the groundwork for generating more structured and reliable datasets to support medical decision-making. Systems designed with these HCI elements are expected to reduce missing data, minimize data redundancies, and improve data clarity. Accordingly, the accuracy and reliability of medical decisions derived from these systems will be noticeably enhanced. Future studies can leverage this framework to develop and examine CDSS systems that improve user interaction and ensure higher data integrity and precision in medical decision-making. This structured approach will advance medical informatics, leading to more efficient, accurate, and user-friendly CDSS solutions.

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Authors' Contributions

AA and FJG-P contributed to conceptualization, methodology, and validation. AA contributed to formal analysis, investigation fulfillment, visualization, and writing—original draft preparation. FJG-P contributed to project administration and writing—review and editing. Both authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[PDF File (Adobe PDF File), 89 KB-Multimedia Appendix 1]

Multimedia Appendix 2

The raw data from this study, including extracted papers from Scopus (506/923, 54.8%), Web of Science (188/923, 20.4%), and PubMed (229/923, 24.8%).
[XLSX File (Microsoft Excel File), 146 KB-Multimedia Appendix 2]

Multimedia Appendix 3

The final set of 43 papers selected for analysis.
[XLSX File (Microsoft Excel File), 26 KB-Multimedia Appendix 3]

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Abbreviations

AI: artificial intelligence
CDSS: clinical decision support system
DSS: decision support system
EHR: electronic health record
EMR: electronic medical record
HCI: human-computer interaction
ISO: International Organization for Standardization
IU: intention to use
MQ: mapping question
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ: research question
RSME: Rating Scale Mental Effort
SLR: systematic literature review
UCD: user-centered design
UI: user interface
UTAUT: unified theory of acceptance and use of technology
UX: user experience

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Annex *B.*

Unpacking the Evaluation Proceeding of Clinical Decision Support Systems: A review of methodological approaches and categories

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Unpacking the Evaluation Proceeding of Clinical Decision Support Systems: A review of methodological approaches and categories

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Abstract

Medical personnel must utilize Clinical Decision Support Systems (CDSS) to enhance clinical decision-making, minimize mistakes, and improve patient outcomes. Accurately evaluating the performance of CDSS is essential to avouch their effectiveness and efficiency. We have reviewed the literature to provide insights into evaluating CDSS, along with the criteria that need to be assessed, such as accuracy, usability, and efficiency. Researchers are instructed to pick an acceptable technique depending on their research aims and the situation in which they will analyze Clinical decision support systems after considering potential obstacles and constraints within the procedure. By conducting these types of research projects, we will be able to improve the quality of the decision-support systems and enhance their utility in clinical practice. This article provides valuable intuition for researchers, healthcare professionals, and decision-makers seeking to evaluate the performance of CDSS in healthcare settings.

Keywords: Clinical Decision Support Systems, Evaluation, Methodology

1. Introduction

Computer programs to boost medical decision-making have long been anticipated by physicians with both curiosity and accuracy [1]. It has been widely recognized that evaluating clinical decision support systems is both a vital component of the larger area of medical computing and a challenging and diverse topic unto itself [2] and has been considered a must [3], hence, to ensure that the Clinical Decision Support Systems (CDSS) have been effective at improving patient care and safety, raising the standard of care, lowering healthcare costs, and boosting healthcare providers' productivity, evaluation is crucial [4]. In other words, evaluation is not only exploited to assess the effectiveness of a program but can also be applied to measure the program's evolution over time [5].

Now that it is obvious why the CDSS evaluation must be done, to guarantee the results' reliability and validity and allow for the generalizability of findings to different contexts, it is imperative to employ the proper evaluation methods [6][7]. These methods, analyses of their comparative effectiveness, and their use have gradually evolved in various studies [8]. According to the predefined aims, the CDSS evaluation can be carried out in two main aspects: usability evaluation and accuracy evaluation, although some other categories have been recommended.

This paper mentions some of the principal methods to evaluate clinical decision support systems. These methods have been classified regarding the nature of the assessment and its purpose into two major categories: usability assessment and evaluating accuracy level. The fruitful methods included in each of the mentioned categories will be described. After getting familiar with the available methods, we will conclude. Since this type of classification of the CDSS assessment has not been performed so far, this study can contribute to future research projects.

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2. Evaluation of Clinical Decision Support systems

Nowadays, the authors may be focusing on measurement considerations rather than reporting this in their study or using methods of unknown assessment [9] opting for the optimum methodology for evaluating CDSS is a critical point in investigating these systems properly and perfectly and in different dimensions. The main aspects which have been addressed in the studies include usability, accuracy level, reliability, and validity.

2.1. Usability methods

Usability is the quality of a user's experience when interacting with products or systems, including websites, software, devices, or applications[3]. Some studies employ a single method and others combined methods to assess usability. In this article, both single and combined methods have been explained.

2.1.1. Single-one methods

The main (single) methods to evaluate the usability facets have been addressed as the following:

Think Aloud: A direct observational method of user testing where users are asked to think aloud while completing a task. Users are asked to say what they are looking at, thinking, doing, and feeling at any moment [10]. This technique is particularly useful for determining user expectations and identifying confusing aspects of the system [11].

Near live: During "Near Live" testing, participants can interact naturally with patient actors. Every participant demonstrates the same workflow regarding the order of events [12].

Heuristic evaluation: Nielsen and Molich [13] introduced a new method for evaluating user interfaces called heuristic evaluation. In this method, a small group of usability experts evaluates user interfaces against a set of guidelines, noting the severity and presence of each usability problem. Andrea et al. [14] applying this method, have reinforced the CARTIER-IA platform pertaining to incorporating medical data (both structured data and images) through actuating Artificial Intelligence algorithms.

Cognitive walkthrough: The cognitive walkthrough is a usability inspection method that evaluates the design of a user interface for its ease of exploratory learning based on a cognitive model of learning and use [15].

Pluralistic usability walkthrough: The multidimensional usability walkthrough adapted the traditional usability walkthrough to include representative users, product developers, product team members, and usability experts in the process[16]. This is defined by her five characteristics:

- Inclusion of representative users, product developers, and human factors professionals.
- The application's screens are presented in the same order as they appear to the user.
- All participants are asked to assume the role of the user.
- Participants write down what actions they, as users, would take for each screen before the group discusses the screens.
- When discussing each screen, the representative users speak first.

Formal usability inspections: A formal usability test reviews a user's potential task performance by an interface designer and their peers. As with multidimensional usability walkthroughs, this involves stepping through the user's tasks [8]. However, because the reviewers are made up of human factors experts, the review can be quicker, more thorough, and more technical than a multidimensional walkthrough. The aim is to identify the maximum number of errors in the interface as efficiently as possible.

Quick and dirty usability testing: John Brooke [17] has claimed in his study that each tool or system's usability must be evaluated in terms of the context in which it is used and its suitability for that context. He explained that, generally, it is impossible to characterize a system's usability without first identifying its intended users, the tasks they will carry out with it, and the features of the physical, organizational, and social environments in which they will use it. He has explained that SUS is a Likert scale. It is usually assumed that a Likert scale is just a type of forced-choice question, where the responder is asked a statement and is then asked to rate how much they agree or disagree with it on a scale of 5 (or 7). He has suggested a questionnaire including 10 questions to measure the system usability scale. In this method, the SUS score will be calculated as follows: first, sum the score contributions from each item. Each item's score contribution will range from 0 to 4. For items 1,3,5,7 and 9, the score contribution is the scale position minus 1. For items 2,4,6,8 and 10, the contribution is 5 minus the scale position. Multiply the sum of the scores by 2.5 to obtain the overall value of SU. SUS scores have a range of 0 to 100.

2.1.2. Multimodal Methods

Based on the research necessities, several methods have been formed to assess the system´s usability in various dimensions and in a stricter manner. In this section we have addressed two multimodal ones:

Development and design approaches (mixed methods): In this paper conducted by Horsky et al.[18] has been addressed with a set of useful suggestions and references to resources that may be utilized to guide the development of Clinical Decision Support Systems, to achieve the best possible human-computer interaction properties. They have claimed that the optimal design approaches for CDSS developers comprise iterative development, user-centered design, collaborative design teams, usability inspection, clinician interviews, log analysis, and cognitive walkthrough, as the principal components.

Since in this study, several aspects have been pointed out to evaluate the CDSS, it is considered a mixed method.

Integrating think-aloud and near-live: In [19] has been innovated a usability method through integrating two other methods, including "near-live" and "think-aloud," which have been discussed above. In this study, the two phases of evaluation have been explained before establishing the deployment of the integrated clinical prediction rules and clinical decision support. Phase I involved usability testing associated with "think-aloud" protocol analysis to evaluate human–computer interaction as the healthcare providers performed specific tasks for invoking the CDSS [20], [21]. Phase II involved a "near-live" clinical simulation in assessing how stakeholders interact with the CDSS while interviewing a simulated patient [22]. They have demonstrated that both types of testing offer various insightful perspectives essential for the successful development and integration of CDSS in Electronic Health Records.

2.2. Accuracy level methods

Another perspective that can be investigated in CDSS is the accuracy and reliability level. By assisting with tasks like diagnosis, decision-making, and ordering tests and treatments, accurate CDSS may cut down on wasteful spending and boost the standard of care. They serve as a (basic) support system, but experts continue to have the final say in all decisions [23]–[25].

Statistical analysis for happened errors: In [26] Chantal et al. proposed a statistical method to compare the error cases that have taken place to calculate a risk score manually and by CDSS. In this research, a retrospective analysis was exploited to determine the degree of correlation for the score criteria: hypertension, diabetes, thromboembolic disorders (cerebrovascular accident, transient ischemic attack, long embolus, and deep venous thrombosis), heart failure, symptomatic arteriosclerosis in the legs and symptomatic coronary disease. In this study, A Bland-Altman plot and regression analysis has been used to visualize the agreement between two different interventions (automated CDSS, which is called aCDSS, and manual CDSS, which is called mCDSS). This study demonstrated that calculations performed by an aCDSS might be more accurate and time efficient than a manual calculation.

Positive and Negative predictive value: In this method, some of the monitoring and critical values have been defined to calculate accuracy, sensitivity, and specificity and to review other screening performance characteristics, including positive and negative predictive values (PPV and NPV). PPV and NPV are true positive and negative results of a diagnostic test, respectively [27]. In other words, in a certain diagnosis process by the test, predictive values explain how probable it is for the diagnosis to be correct. Safari et al. [28] have managed a study and defined some expressions to clarify the accuracy measurement as the following:

- True positive (TP)= the number of cases correctly identified as patient
- False positive (FP) = the number of cases incorrectly identified as patient
- True negative (TN) = the number of cases correctly identified as healthy
- False negative (FN) =the number of cases incorrectly identified as healthy

Altman and Bland [29] proved that positive predictive value is the proportion of cases giving positive test results which are already patients. They have expressed that it is the ratio of patients truly diagnosed as positive to all those with positive test results (including healthy subjects who were incorrectly diagnosed as patients). These criteria will be able to predict how likely it is for a person to truly be patient in case of a positive test result and has been formulated in this study as below:

$$\textit{Positive predictive value (PPV)} = \frac{TP}{TP+FP} \qquad \textit{Negative predictive value (NPV)} = \frac{TN}{TN+FN}$$

Robert Trevethan [30], in another article, has determined the mentioned criteria but with to some extent different expressions. He has utilized the expressions “sensitivity” and “specificity” and explained them:

Sensitivity*:* The sensitivity of a screening test will be described in various manners, often such as sensitivity being the ability of a screening test to detect a true positive, being based on the true positive rate, reflecting a test’s ability to correctly identify all persons who have a circumstance, or, if 100%, identifying all persons with a condition of interest by those people testing positive on the test.

Specificity*:* The specificity of a test is defined in a variety of manners, usually such as specificity being the ability of a screening test to detect a true negative, being based on the true negative rate, correctly identifying the persons who do not have a circumstance or, if 100%, identifying all patients who do not have the condition.

Robert Trevethan has concluded that Sensitivity and specificity must be emphasized as having different origins, and purposes, from PPVs and NPVs. All four metrics should be considered substantial when explaining and evaluating a screening test’s adequacy and usefulness.

Comparison with Golden Standard: This method defines a golden standard for a specific test to compare other automated medical functionalities with the ideal one. In other words, an expert-prepared "gold standard" for making diagnoses was verified in an earlier investigation [31]. The mentioned manner has been exploited in the research project by Helena et al [32].
Indeed, this study was Cross-sectional descriptive with a quantitative approach. In this investigation, The Wilcoxon nonparametric test was employed to compare two paired samples and is considered the number of differences (between the gold standard and the data extracted).
These kinds of methods need to be ascertained as a golden standard by the experts obsessively and precisely otherwise, the evaluation proceeds and its result will not be reliable.

3. Discussion and Conclusion

It can be claimed that assessing Clinical Decision Support Systems is a crucial undertaking that necessitates careful consideration of the most effective assessment techniques. Usability and accuracy assessment, the two main components of CDSS evaluation included in this study, are essential for assuring the successful application of CDSSs in healthcare settings, and experts in this field must carefully consider and choose assessment techniques that are appropriate for the CDSS being assessed. In other words, if CDSSs are assessed successfully, will lead to widespread acceptance and improved patient outcomes. These kinds of studies, by collecting various evaluation methods, categorizing, and comparing their exclusive attributes, will help the assessors to opt for the most optimized option according to the circumstances and limitations of the study.

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Annex *C.*

Combating User Attrition: Remedies for improving Human-Computer Interaction within CDSS ambient

Combating User Attrition: Remedies for improving Human-Computer Interaction within CDSS ambient

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Abstract: In contemporary healthcare, the integration of advanced technological features via cloud facilitators has significantly bolstered the accessibility, availability, and security of computerized medical systems, notably Clinical Decision Support Systems (CDSS). However, these advancements are often undermined by persistent barriers that curtail physician interaction and impede optimal patient outcomes. This study identifies critical usability obstacles within CDSS by leveraging insights from a systematic literature review (SLR) that focused on extracting available Human-Computer Interaction (HCI) elements merely at the CDSS ambient. During this study we attempt to isolate negative HCI factors, aiming to devise effective mitigation solutions. We discussed the identified barriers, and their impacts on CDSS functionality, and reviewed recommendations from existing research to enhance user engagement and system efficacy. The findings of this study are poised to streamline medical decision-making processes, enabling the strategic utilization of recent technological advancements to enhance the accuracy of medical decisions and reduce treatment costs.

Key Words: Human-Computer Interaction, CDSS, HCI barriers, Systematic review, User fatigue

1 Introduction

The significant growth in diverse biomedical data facilitates innovative large-scale studies, necessitating custom computational solutions tailored to specific needs [1] and fostering a seamless and user-friendly interaction with the designed system [2]. Despite the widespread adoption of Electronic Health Records (EHR) as the CDSS prerequisite, physician resistance toward its development is evident [3–5] and stems from diverse usability issues and not adequately paying attention to the user's needs and circumstances [6,7]. The purposes of the CDSS design have before concentrated on the effectiveness, error prevention, and medical recommendations rather than the usability concerns within the designed system [8,9]. CDSS occasionally encompasses complexities requiring users to precisely consolidate poorly structured, uncertain, and potentially conflicting information from diverse sources [10]. Poorly designed Graphical User Interfaces (GUIs) in these systems can lead to frustration among physicians who struggle with using computerized technologies [11]. To smooth the user way on the CDSS usage path, it is crucial to identify the available HCI barriers and the raised reason to assist the CDSS designer in redacting or mitigating the detected problems [12]. Regarding the paucity of research explicitly addressing HCI barriers within the context of CDSS, our study aims to fill this gap by identifying and categorizing these barriers. By shedding light on HCI challenges unique to CDSS environments, we seek to enhance understanding of the difficulties and, consequently, usability improvement in CDSS design.

During our investigation, we explore various dimensions of the obstacles outlined in the existing literature, extracting the prominent insights from the carried out SLR [13] (performed

SLR to extract HCI elements that can affect CDSS functionality) and aiming to gain a comprehensive and applicable perspective. We discuss the alert fatigue issues in the second section, and in the third section, the workload difficulties generated within CDSS will be addressed. The fourth section will express Inadequate system design as the CDSS bottleneck. The mental efforts will be referred to in the fifth section. After that, the challenges and the acquired results will be discussed, and finally, we will conclude the necessary clues and probable modifications to approach the rectified CDSS and worthy outputs.

2 Alert fatigue

Medical alerts are defined as one of the prominent tools to warn physicians about the critical tips that must be considered before making medical decisions [14], and depending on the importance level, it will be able to generate an interruption in the physician's working processes [15]. The raised alarms are triggered by the predefined rules, considering the different circumstances and various philosophies [16,17]. From the physician's perspective, the engendered alarm occasionally seems unbearable and out of their ordinary patience and leads to an emerging phenomenon called alert fatigue [18]. Alert fatigue poses a significant risk as it may lead to overlooking critical alerts, signaling potential harm to patients amidst the influx of bothersome or clinically irrelevant alerts [19]. Launching the desolate alerts frequently causes another grave issue ***called the override*** [20], and the abandoned alarm will continue to grow if the system doesn't meet the actual physicians' needs [21] and simultaneously has the potential to engender various unintended and undesirable consequences for the patient's output [22,23]. Hence, the ***override rate*** is considered one of the primary criteria for assessing the CDSS meaning that a lower rate demonstrates higher effectiveness in begetting the probable inaccurate medical decision [20].

Table 1. Alert fatigue categorization and attributes

Category	Description	Key discrepancy
Cognitive Overload [24]	It occurs when too many alerts saturate a physician’s cognitive capacity, leading to decreased attention to each alert.	Focuses on the overall mental burden from multiple alerts
Desensitization [25]	Develops over time as clinicians become accustomed to frequent alerts, potentially causing important alerts to be overlooked	Involves a reduction in responsiveness due to familiarity.
Habituation [26]	A form of desensitization where the response to repeated alerts diminishes, leading physicians to ignore even critical alerts.	Specific to the diminishing response to repeated exposure.
Interruptive Alerts [27]	Alerts that disrupt workflow significantly, possibly leading to frustration and the ignoring of alerts if they are perceived as obstructive.	Emphasizes the disruptive nature of alerts on daily tasks.

The user attrition stemming from the scanty alarm design has been classified into five categories. As illustrated in Table 1, their identities vary depending on the cause that launched the alarms.

Variant ***solutions*** have been proposed to reduce the discussed problem, including: 1) enhancing the specificity of alerts; (2) categorizing alerts based on their severity; (3) incorporating principles of human factors into the design of alerts and focusing on including only high-severity alerts in the alert set; (4) adapting alerts to the specific characteristics of patients; (5) personalizing alerts for individual physicians [28].

Efforts to mitigate alert fatigue enable physicians to focus on triggered alarms adequately and benefit from various types of alerts, such as interruptive, informative, and those predicated on potential future scenarios and requirements [29].

3 Workload Adversity

In the context of the CDSS, the workload that the user acknowledges and complains about impedes the user satisfaction sensation with the designed system [30] and typically originates from two different reasons: *A)* High-volume workload imposed on the user and *B)* Incompatibility of defined work processes with the real world [31,32].

The workload of medical group members using CDSS is primarily determined by factors such as the amount of data entry required, the frequency of raised alarms, accessibility to user guides, and the degree of system simplification, which can vary significantly across different domains [32–34].

Several solutions proposed in the literature were considered, and we aimed to highlight some of the key ones:

- By implementing various methods, such as integrating subsystems, user tasks can be significantly reduced, enhancing the system's acceptability [35].
- Designing data forms that prevent redundant or duplicated patient data entry [34,36].
- Utilizing inventive methods for auto-populating medical data fields [37].
- Customizable Alerts: Tailor alerts to individual user preferences and relevance to minimize unnecessary interruptions [38].
- User-centered design of CDSS aims to align the system's functionalities with users' actual needs and expectations, ensuring that the defined workflows closely reflect real-world processes and user preferences [39].

Excessive workload not only prevents the efficiency of the healthcare systems but also causes error occurrence and, in some cases, leads to attention loss to the critical points of the treatment plan. Hence, attending to the physicians' working capacity is crucial to determine the assigned tasks within the CDSS ambiance regarding the mentioned elements. In a scenario where an intensive user workload is required to enter critical data into the CDSS, or where such efforts enhance the CDSS output, it becomes imperative to justify to the users the necessity of the elevated exertion and elucidate the valuable advantages stemming from this imposed pressure. By establishing transparent communication regarding the rationale behind intensified workload and its tangible benefits, user engagement, and acceptance can be boosted, resulting in the mitigation of workload adversity on CDSS interaction and performance.

4 System Design Defects

Inadequate system design implies deficiencies or weaknesses in the system structure or system layout within the CDSS environment stemming from different aspects such as the interface, navigation, functionality, and usability [40]. These flaws impede the user from interacting with the system and lead to confusion, frustration, and decision-making errors, ultimately compromising patient care quality and safety [41]. The flaws cause user attrition and keep the user from system engagement. In these circumstances, the physicians prefer to bypass the system and decide without system intervention.

The CDSS experts have presented a methodology to recuperate the identified system design defects. Goal-directed design (GDD) is a methodology that engages end users in developing systems tailored to meet their goals [42]. This approach integrates persona-driven and scenario-based design techniques to ensure alignment with user goals and needs[43,44]. A persona is a profile representing a hypothetical individual, embodying characteristics typical of the intended users of an information system, and scenario-based design concentrates on the tasks and information requirements of the individuals who will interact with an information system, prioritizing user needs over system features or technological capabilities [42]. By exploiting GCD, the designed system will be closer to the user's needs and expectations, resulting in mitigating user attrition and, on the contrary, elevating user satisfaction [45].

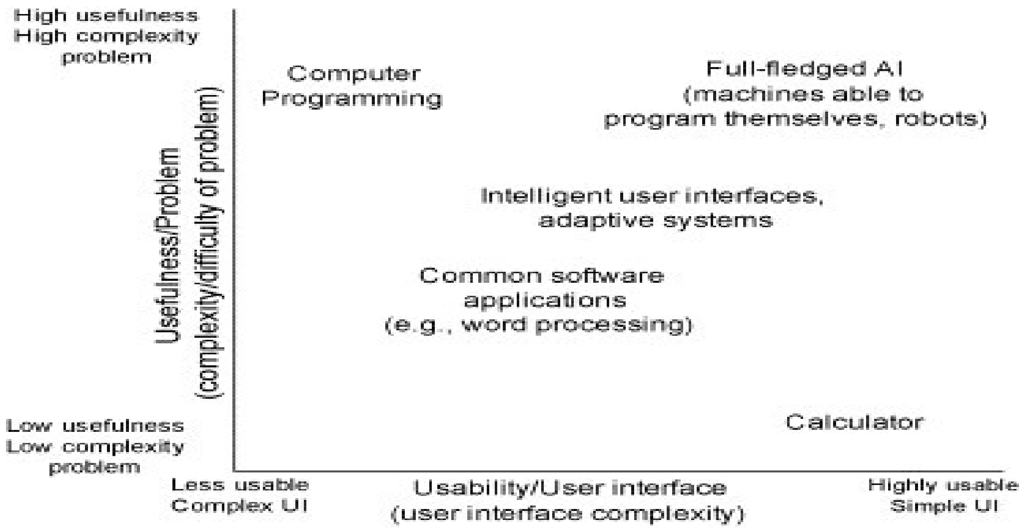

Figure1. reverse relationship between the system complexity and usability [46]

Although to alleviate user attrition, the system must be designed simply, Stefan et al. [46] have rendered a theory that claims there is a kind of paradox between usable user interfaces and having helpful information systems, signifying that one system with a simple design is merely able to solve trivial problems and for solving complex problems we need complex systems. This allegation about the relationship between usability and usefulness is illustrated in Figure 1. As shown, although previous generations of computer programs could solve complex problems, their usability level was lower. The calculators are other instances of high-level usability tools but along with low-level usefulness (capability of solving simple problems). The recent advancements in CDSS realms and artificial intelligence (Medical AI) have simultaneously achieved high-level usability and high-level usefulness.

Despite such a contradiction, it is pivotal to establish the necessary conditions to augment the user satisfaction level and consequently diminish user attrition. For this purpose, the designers consistently need to be informed of the user feedback and recommendations. Several methodologies, such as agile methodology, are being exploited throughout system development, prioritizing incorporating user feedback into the design process and consistently applying the physicians' opinions to design a CDSS with high-level usability [47]. Considering the above concerns and the pertinent solutions, the well-system design will assist the user in interacting efficiently with the system and mitigating user attrition.

5 Mental Efforts

The scientific expression of *mental efforts* is used to ascertain to what extent it is difficult for someone to try specific tasks or activities [48]. In the context of HCI, it refers to the cognitive workload or mental exertion required by users when interacting with a system. It encompasses attention, memory, decision-making, problem-solving, and learning [49]. This HCI concept aims to simplify the tasks within the CDSS environment, making it easier for users to interact with the system during their work processes, meaning that high-level mental efforts in such systems signify a kind of HCI incapacitation.

The CDSS designers have evermore considered mental efforts a critical element even by more details. Siyuan et al. [50] attempted to measure the user's mental efforts through eye activity and even blinking activities. They could illustrate the relationship between eye movement, blinking numbers, and detected mental effort.

One aspect of mental model research related to interaction design is the slower comprehension of equivocal statements. Interaction designers are concerned with the ease of use and the ability to learn, making mental models valuable. Discussions on the conveyance of system causality represent another pertinent topic.

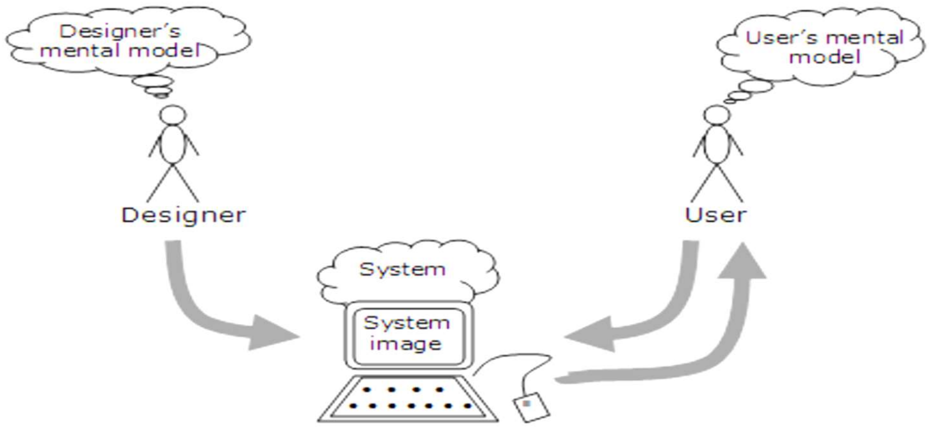

Figure 2. Corresponding the user's mental model to the designer's model

Utilizing mental models gained prominence within the HCI and interaction design field through Donald Norman's publication "The Design of Everyday Things" [51]. Norman utilized mental models to clarify the process of a system, which is conceptualization and execution, based on the designer's cognitive framework. The model is applied to justify the user perception of the system content and to prognosticate the system comportment.

In other words, the designer embodies their conceptual design in a tangible form, such as a computer system, serving as the primary vehicle for communicating their vision to users [52]. This notion is depicted in Figure 2 to convey the pointed-out implications.

Mental models represent the cognitive constructs individuals hold in their minds, shaping their interactions with various systems and tools. Designers aim to overwhelm systems with conceptual models that align with users' mental models, enhancing comprehensibility and coherence. When a designer successfully aligns the conceptual model with the mental model, it theoretically results in a seamless user experience [53].

Ultimately, it is undoubtedly affirmed that mental effort plays a pivotal role in human-computer interaction in CDSS, shaping the extent of user engagement with the system [48].

Higher-level mental effort signifies a heavier cognitive burden on users, reducing interaction with the CDSS. This highlights the significance of developing CDSS interfaces that reduce mental endeavors to improve user involvement and system performance [54].

6 Discussion

In some scientific contexts, rather than solely focusing on the latest advancements and technologies, it is crucial to identify existing obstacles and potential drawbacks to effectively reach predetermined objectives and ensure seamless user interaction with the system. In the current study, we tried identifying multi-dimensional HCI challenges within CDSS, including alert fatigue, workload difficulties, system design flaws, and mental efforts. These alluded elements converge to hinder user engagement and the system's effectiveness, and it seems crucial to be familiar with them as the usual dark points. By tackling the recognized adverse user experiences, it is feasible to greatly enhance the system's performance.

Although the diverse cognitive abilities of the users, and their mental efforts during the engagement with the system vary, the system learnability plays a crucial role in relieving cognitive load, thereby fostering closer interaction with the system. In essence, it could be argued that there exists an inverse correlation between system learnability and user attrition [55].

Despite facing persistent challenges and the contradiction raised in this study between the system's usefulness and complexity, the CDSS designers struggle to meet user expectations and operational requirements [48]. By analyzing these obstacles in detail, our research expands the understanding of Human-Computer Interaction dynamics in CDSS, recommending customized interventions to improve user interaction and enhance system performance [50]. Undertaking these kinds of studies will assist the CDSS experts in providing the ambiance without the addressed defects.

7 Conclusion

Nowadays, user attrition is known as a part of HCI knowledge. In this respect, HCI experts tend to identify these negative axioms to provide a more convenient and attractive system for users to enhance their interaction with the system. Some of these HCI elements are exclusively pertinent to the CDSS environment; hence, recognizing the mentioned gaps requires a more rigorous investigation. In this study, we attempted to gather findings from other studies relevant to user attrition and render the appropriate solutions.

Our evidence illustrates that if one CDSS triggers timely medical alarms with a suitable severity and sensitivity, besides the adequate workload in the system that has been designed considering a proper balance between complexity and usefulness. Finally, the user does not need high-volume mental efforts to do the assigned tasks, which means that such CDSS is eligible for the high-level HCI criteria.

In future research endeavors, the focus will likely shift towards developing strategies aimed at fostering seamless interaction with CDSS so that the user feels live communication, thereby relieving the presence of user attrition. This entails delving deeper into the root causes of user attrition and exploring innovative approaches to enhance user engagement and satisfaction within CDSS environments. Additionally, there is a need to investigate the dynamic nature of user attrition and its impact on long-term user behavior and system performance. By addressing these challenges, future studies aim to pave the way for a more user-centered and effective CDSS that fosters optimal decision-making and healthcare outcomes.

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Annex *D.*

A Synergistic Bridge Between Human–Computer Interaction and Data Management Within CDSS

data

MDPI

Article

A Synergistic Bridge Between Human–Computer Interaction and Data Management Within CDSS

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Abstract: Clinical Decision Support Systems (CDSSs) have become indispensable in medical decision-making. The heterogeneity and vast volume of medical data require firm attention to data management and integration strategies. On the other hand, CDSS functionality must be enhanced through improved human–computer interaction (HCI) principles. This study investigates the bidirectional relationship between data management practices (specifically data entry management, data transformation, and data integration) and HCI principles within CDSSs. Through a novel framework and practical case studies, we demonstrate how high-quality data entry, driven by controlled workflows and automated technologies, is crucial for system usability and reliability. We explore the transformative positive impact of robust data management techniques, including standardization, normalization, and advanced integration solutions, on the HCI elements and overall system performance. Conversely, we illustrate how effective HCI design improves data quality by reducing cognitive load, minimizing errors, and fostering user engagement. The findings reveal a synergistic relationship between HCI and data science, providing actionable insights for designing intuitive and efficient CDSSs. This research bridges the gap between technical and human-centric approaches, advancing CDSS usability, decision accuracy, and clinician trust for better patient outcomes.

Keywords: data management; HCI; CDSS; data quality; data integration; data entry

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1. Introduction

Clinical decision-making systems are helping medical practitioners more and more throughout medical treatment [1]. The rapid evolution of healthcare systems, along with massive and diverse medical data, has highlighted the importance of data management. The systems need to control and steer the data flow [2]. Medical data must be managed in different phases, including data generation, fetching, tagging, and processing [3,4]. Integrating heterogeneous, low-quality data from diverse subsystems for medical decision support emphasizes the significance of robust data management practices [5]. Data entry and generation are significant aspects of data management that require profound investigation as human–computer interaction (HCI) elements because they form the foundation of user–system interactions in healthcare environments [6]. The medical data generated by user–system interactions and fetched data from other systems must be scrutinized as a data management field within Clinical Decision Support Systems. In other words, high-quality data provided for Clinical Decision Support Systems (CDSSs) functionality stems from medical data management and integration [7,8]. Accurate and timely data entry supports clinicians by ensuring access to consistent and reliable information during critical decision-making [9]. For instance, poorly managed data entry systems often lead to increased mental workload, user frustration, and potential medical errors [10,11].

Despite numerous studies exploring data integration and management within CDSSs, a significant gap persists in understanding the role of human–computer interaction in this process. Existing studies focus on optimizing data accuracy, consistency, and integration, while HCI research in CDSSs primarily addresses usability, user experience, and cognitive workload. However, the interplay between these two domains (how data management directly influences HCI elements and, consequently, CDSS functionality) remains unexplored. Investigating these HCI aspects can bridge the gap between system designers and end-users, facilitating smoother user adoption of CDSSs. The current study discusses why data entry management must be investigated as an HCI element and how it can impact CDSS functionality. Furthermore, it will illustrate how data integration improves HCI factors relevant to CDSS environments, introducing a beneficial and bilateral cycle between data management and HCI elements within CDSSs. The primary contribution of this article is establishing a scientific framework that connects HCI factors to data management strategies, offering a roadmap to reach more intuitive and effective CDSS environments.

To achieve our objectives, we employ a qualitative research approach, synthesizing existing studies on data entry management, standardization, and integration within CDSSs to construct a framework that integrates data management with HCI principles. To reinforce the proposed framework, we incorporate empirical findings from previous case studies that examine the real-world application of these components. These studies evaluate how specific data management strategies affect data quality, system usability, and decision-making accuracy. The metrics such as data completeness, error frequency, process efficiency, and alignment with active clinical workflows are benchmarks to assess the framework's practical relevance. This dual approach (literature synthesis and empirical grounding) ensures that the framework is both conceptually robust and contextually applicable.

This paper is organized into sections that collectively address the critical role of data management and integration within CDSS environments, highlighting their impact on HCI elements. In the upcoming sections, at the first step, we delve into data entry management and control, examining existing features for its implementation. In the next section, we will articulate the significance of data standardization and normalization within CDSSs and their concurrent role in enhancing HCI. The subsequent section will address data integration within CDSSs, exploring its diverse forms. The discussion section expands on these foundations by examining real-world standardization and implementation challenges, human-centered design considerations, system limitations, and practical deployment strategies. Finally, we conclude how their collective effect elevates data quality and improves CDSS accuracy.

2. Data Entry Management and Control

After surgery, surgeons commonly note rare medical cases in the surgery reports utilizing professional expressions like "*unicornuate uterus with a rudimentary horn*". Another surgeon might use varying terminology like "*rudimentary horn anomaly*" to describe the same medical condition. This inconsistency in medical terminology can pose challenges when researchers attempt to identify and analyze specific cases. If researchers aim to investigate the prevalence or characteristics of a particular rare condition, they may encounter difficulties in finding surgical reports that include the intended terms and expressions. These challenges can even impact the accuracy level of this research project and, consequently, the obtained results, highlighting the importance of medical data entry.

Data entry is still discussed as a significant bottleneck in electronic health record (EHR) platforms, and in many cases, it hinders optimizing the full potential of EHRs [12]. In other words, data entry difficulties push the medical staff away from interacting with the system, causing user attrition and frustration [13–16]. One of the significant concerns among medical system designers is whether data entry will be carried out correctly to ensure accurate data entry and enhance the quality of the recommendations [17]. Minor data entry errors may impact the treatment plan results and sometimes deceive the physicians [18]. Considering HCI principles is crucial for mitigating many user challenges [19]. Medical practitioners frequently express concerns about the prevalent error from a lack of appropriate user interaction with the medical systems [20]. High-quality and accurate data entry significantly improves the precision of CDSS data and better medical results [21]. In this section, two methods to control medical data entry will be introduced.

2.1. Data Range Control

In medical information systems, a reasonable data range must be defined for some data fields to impede data entry beyond acceptable limits. This restriction applies to augment the reliability of provided data for CDSSs, resulting in more accurate data analysis and decision-making [22]. The mentioned data range is mutable, and medical practitioners can determine the specific values and modify them whenever necessary. In some cases, the color of the data entry field will change to provide visual feedback to the user. As shown in Figure 1, if a value is entered outside the normal range (too low or too high), the field might turn red to alert the user about the problematic value [23]. This color change indicates potential data entry errors or data abnormalities.

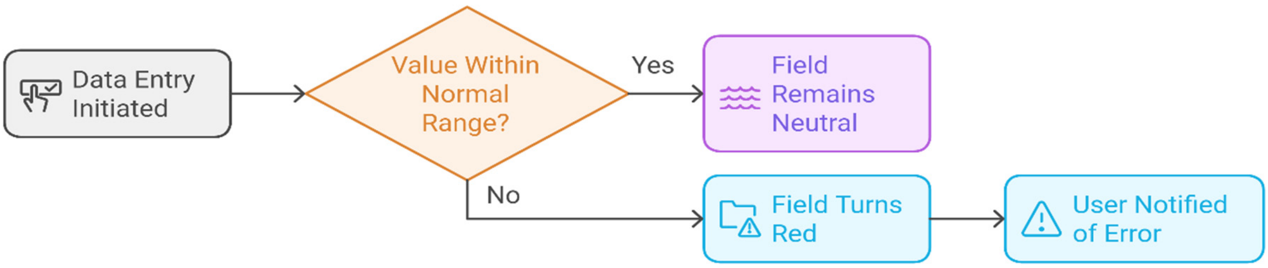

Figure 1. Visual feedback for out-of-range data entry.

Data entries that fall outside the expected range can significantly deviate between research findings and clinical decision-making. Studies have demonstrated that such anomalous data can undermine the validity and reliability of statistical analyses and the accuracy of clinical predictions and outcomes [24]. Hence, it is essential to identify and control out-of-range data entries for data reliability and subsequent data analyses.

Data entry errors usually occur in circumstances such as transcription mistakes, inaccuracies in lab measurements, or reference range misinterpretation. Studies emphasize the need for data quality control processes and validation assessment to detect and refine out-of-normal range data entries [25]. These controls promote more reliable data in healthcare systems.

2.2. Data Entry Obligations Controlling

The mandatory medical data fields are pivotal in guaranteeing data completeness and reliability. This obligation prevents data-missing phenomena, meaning blank data fields and incomplete medical records will be firmly diminished [26,27]. As depicted in Figure 2, the medical systems equipped by the data entry obligation technology are implemented in this way: they adhere to this compulsion seriously so that the medical data forms are arranged sequentially, and medical staff will not be able to complete the following forms unless the mandatory medical records have been filled within the current form.

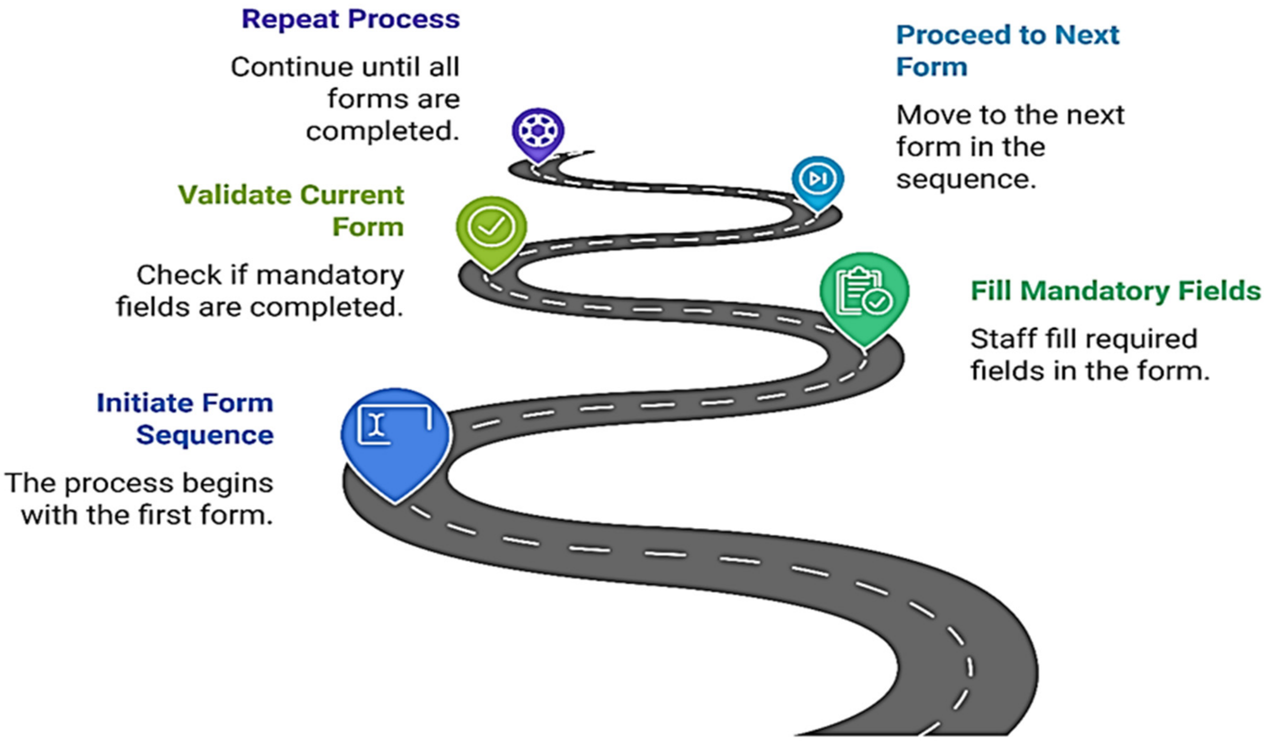

Figure 2. Sequential and mandatory data entry in medical forms.

The implementation of data entry compulsion promotes significant advantages within healthcare systems. First, it vouches for data completeness and inclusion of all necessary information to assist the physicians on the treatment path. Second, the mandatory data entry method allows medical practitioners to fill out specific data fields determined by the physicians. Hence, the risk of errors and data inconsistencies will be firmly reduced. Third, exploiting this method leads to a streamlined medical workflow. When healthcare providers have timely and proper data, they can make accurate medical decisions, ultimately improving patient outcomes [28].

2.3. Leveraging Automated Text Generation for Accurate Data Entry Management

Building upon data entry concepts discussed in the previous sections, we conducted another empirical study [29] to implement a novel technology to resolve data management concerns. The designed platform meets the needs of professionals, such as sonographers, radiologists, and surgeons, to emit medical reports in text format. At the same time, the data entry process can be entirely managed. First, the user fills in data fields within medical forms by forcing the system's policy during the data entry. Then, the medical text (report) derived from data fields will be generated automatically. By exploiting this technology, the data entry process can be managed and controlled record by record, hindering missed or out-of-range data. This feature eliminates the reliance on manual report writing, which is prone to errors and inconsistencies, and produces standardized and reliable documentation.

One of the prominent features of this system is its data range control mechanism. For every data field, predefined acceptable ranges are established, and any value outside these ranges triggers immediate feedback. Additionally, through mandatory data entry requirements, the system ensures that users cannot save or submit records until all essential fields have been completed. This enforcement guarantees comprehensive data entry and helps capture accurate medical data. However, the system is not rigid; physicians maintain complete authority over clinical decisions. They can manually edit the generated medical text when necessary, ensuring that rare or exceptional cases are appropriately documented.

Additionally, embedded text boxes within the system allow practitioners to input specific details that may not fit the predefined structured fields. These features provide flexibility while preserving data accuracy and completeness.

Another innovative aspect of the mentioned technology is its focus on user-centric design. The interface is intuitive and minimally disruptive to clinicians' workflows. It allows the user to perform data entry without excessive cognitive load. Consequently, physicians can focus on patient care instead of text typing. Furthermore, the system's policies regarding data field obligations and raised alarms have been designed with built-in flexibility. Medical professionals can modify these data entry rules without requiring specialized technical expertise, allowing them to adjust defined data constraints to match evolving clinical needs.

To evaluate the effectiveness of this technology, a comparative examination was conducted involving 10 physicians across 150 surgeries (including three different surgery types). The study analyzed 4200 patient records, comparing traditional manual text entry with the automated text generation system. Quantitative metrics were measured, including data completeness, out-of-range error frequency, and accuracy. Statistical analyses revealed that the automated approach eliminated missing data (0%) compared to 6.67% blank entries in the manual text-based method ($\chi^2 = 280.82$, df = 1, $p < 0.001$). Additionally, the system prevented out-of-range data entries altogether, whereas 1.55% of entries in the manual approach fell outside the acceptable range ($\chi^2 = 73.86$, df = 1, $p < 0.001$). These findings confirm that automated text generation can be a ***supportive tool*** rather than a restrictive mechanism, reinforcing clinical decision-making by providing accurate and complete data.

This study compared missed and out-of-range data in two text-based (traditional) and automated text-generating approaches, demonstrating that recent technology significantly reduces data corruption, improving accuracy and reliability. Beyond preventing documentation errors, the system is an intelligent assistant, providing physicians with complete, structured, high-quality patient data to boost medical decision-making. Rather than enforcing a rigid treatment framework, it enhances decision-making clarity, minimizing the risk of errors due to incomplete or inconsistent records. Physicians retain complete authority, leveraging the system's structured data entry as a protective mechanism against potential medical errors rather than as a limitation on their professional expertise.

3. Data Standardization and Normalization

Data standardization and normalization are critical processes in managing the complexity of medical data within Clinical Decision Support Systems. The principal mission of these processes is to govern the consistency attribute regarding data derived from different sources, such as laboratory systems, radiology reports, the patient's medical history, and wearable devices [30]. They assist the system in interpreting and analyzing medical data properly. Considering these procedures, coherent results will be acquired in the same medical circumstances, even in different systems and platforms [31].

The CDSS environments can provide physicians with a more consistent and reliable experience by standardizing and normalizing medical data. Exploiting the mentioned procedures, the CDSSs will be ameliorated in several HCI dimensions:

- **Improved user interface:** Standardized data formats and consistent terminology make user interfaces more straightforward to learn and navigate [32];
- **Reduced cognitive load:** Normalized data structures simplify data entry and retrieval processes, reducing physicians' cognitive burden [33,34];
- **Enhanced decision-making:** Consistent data representation across different platforms and systems allows for more accurate and reliable clinical decision-making [24];

- **Increased system interoperability:** Standardized data formats facilitate seamless integration with other healthcare systems, improving data sharing and collaboration [30].

Ultimately, by investing in data standardization and normalization, healthcare organizations can empower clinicians with a more efficient, effective, and user-friendly CDSS.

Data Transformation Pipeline

The raw data from medical environments must be in a standard available format to feed the data into CDSSs. Standardization and normalization procedures would enable data processing in such a context [35]. To be more precise, this is a data transformation pipeline consisting of several operations on transforming the raw, heterogeneous, and often incomplete medical data into structured and standardized formats usable by CDSSs [36]. This process addresses inconsistencies and significant issues relevant to data gaps, which can compromise decision accuracy.

From an HCI perspective, this pipeline is deeply tied to usability and user interaction with CDSSs. The systems' usability level depends on their potential to present clean, standardized, and interpretable data to end-users [37,38]. This pipeline helps physicians receive reliable and actionable information (without manually interpreting or adjusting inconsistent data inputs) by resolving data gaps and transforming data into a structured and consistent format. In this manner, cognitive load, as one of the most prominent HCI elements, will be mitigated, and the user can focus on clinical decision-making rather than system navigation or data troubleshooting [39]. The functionality of the data transformation pipeline consists of several stages [40–42], as shown in Figure 3. These stages are described as the following:

➢ **Data collection:**
  - **Sources:** Data are gathered from multiple sources, such as electronic medical records (EMRs), laboratory systems, radiology databases, wearable health devices, and patient-reported outcomes;
  - **Challenge:** Data often arrives in different formats, with missing fields or irregular entries.

➢ **Data cleaning:**
  - **Operations**: Handles erroneous, incomplete, or irrelevant data through imputation (filling in missing values), outlier removal, and error correction;
  - **Focus on gaps**: Missing data due to human error, system inefficiencies, or disconnected subsystems are resolved here. Techniques like predictive imputation, default values, or physician-driven corrections are applied.

➢ **Data standardization:**
  - **Purpose**: Converts diverse terminologies, units, and coding schemas into a unified framework—for example, ICD-10 codes and SNOMED CT terminology;
  - **Impact on gaps**: Standardization ensures that gaps caused by mismatched terminologies are bridged, making datasets interoperable.

➢ **Data normalization:**
  - **Process**: Scales data into consistent ranges (e.g., blood pressure in mmHg) or formats (e.g., dates in "YYYY-MM-DD");
  - **Addressing gaps**: Normalization identifies outliers and irregularities that may hint at gaps in understanding or reporting.

➢ **Data integration:**
  - **Objective**: Combines data from multiple sources into a single, unified repository;

- **Role in gaps**: Integration resolves gaps caused by data fragmentation across subsystems, creating a comprehensive view for decision support.

➢ **Data analysis and enrichment:**
- **Techniques**: Applies advanced analytics, predictive modeling, and enrichment using external datasets (e.g., population health statistics);
- **Gap insights**: Identifies systemic gaps by analyzing patterns and generating recommendations for future improvements.

➢ **Data presentation:**
- **Focus**: Presents clean, consistent, and actionable data to users via dashboards or alerts in the CDSS;
- **HCI element:** Assists in making the output comprehensible and prevents user fatigue and system override.

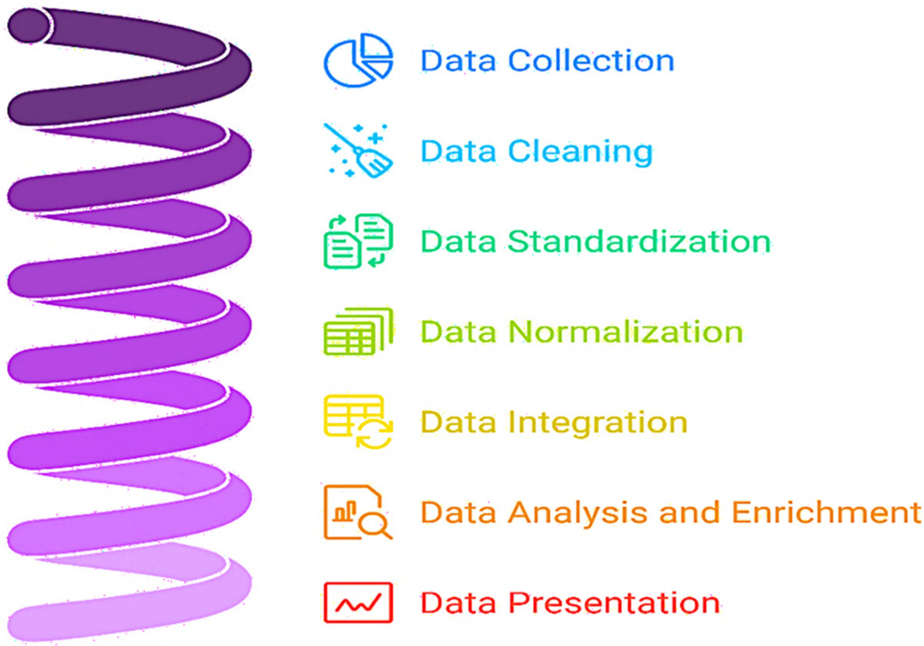

Figure 3. Healthcare data transformation pipeline.

The data after passing this route will be ready for decision proceedings, and the probable *data gaps* will be detected in several aspects:

➢ **Incomplete data**: Missing entries in key fields, such as medication history or lab results, can severely degrade decision-making processes. Research shows that healthcare systems often face challenges with data incompleteness, impacting clinical outcomes [43];

➢ **Inconsistent data**: Variations in data representation, like "hypertension" vs. "HTN", introduce inconsistencies that hinder practical analysis. Some methods can handle inconsistencies in prediction models [44];

➢ **Fragmented data**: Data spread across isolated systems without integration leads to care fragmentation, which is associated with adverse outcomes and higher costs [45];

➢ **Outdated data**: Relying on outdated information affects decision-making accuracy and relevance [46].

Since this pipeline plays a profound role in recuperating the different data gaps, it diminishes CDSS problems in some dimensions:

❖ **Clinical risk:** Missing or erroneous data in a CDSS can directly impact patient outcomes by compromising the quality of diagnoses and treatment plans [47]. For instance, incomplete lab results, missing imaging studies, or gaps in medication history can prevent healthcare providers from identifying critical clinical patterns that may delay lifesaving interventions. Moreover, inaccurate or incomplete records can lead to physicians' inability to identify contraindications, allergies, and comorbidities and provide poor treatment options. These risks underlie the importance of having a robust integrated data pipeline that will ensure the CDSS systems present the clinician with a complete and accurate patient profile for decision-making [24];

❖ **User dissatisfaction:** Users' trust in a CDSS is considerably breached if incomplete or unreliable data come up with questionable recommendations [48]. Generally, physicians depend on timely, accurate, and complete data for precise medical decisions. Suppose either data gaps or inconsistencies provide a CDSS output. In that case, healthcare providers may avoid investing more time in manually verifying information or searching for missing details across systems. This can also raise the cognitive load, break workflows, lower efficiency, and lead to frustration; this diminishes the system's perceived value. These experiences, over time, decrease user confidence in CDSS usage, limiting its adoption and effectiveness within clinical environments [49];

❖ **Algorithm bias:** Machine learning algorithms in CDSSs require complete and representative data for reliable predictions. When datasets contain the mentioned data gaps (due to incomplete records, underrepresented populations, or inconsistent data integration), bias can be introduced to the model. In some cases, if some demographic groups or clinical variables are underrepresented, the system may generate predictions that advantage one subset of patients at the expense of others, thereby undermining fairness and equity in care [50]. Additionally, missing data degrade model stability and decrease its predictive accuracy, leading to unreliable recommendations that can hinder clinical decision-making. These biases can only be resolved by robust data integration approaches and efficient handling of incomplete records for CDSS tools to provide fair and consistent outcomes [51,52].

The data as the primary feed for CDSSs must be presented coherently and consistently, although they may be gathered from various resources [24]. The prerequisite for this data consistency is the data transformation process. The mentioned transformation pipeline significantly boosts the data integration procedures within CDSSs. In this circumstance, the system's reliability level and, consequently, system usability will be elevated [48].

4. Data Integration Within Clinical Decision Support Systems

Data integration combines data from multiple sources into a unified and coherent format. Within CDSSs, data integration is crucial in furnishing relevant, timely, and accurate information to assist healthcare providers in making purposeful decisions [53]. Medical data often originate from separate systems, such as electronic health records, laboratory systems, radiology reports, and real-time monitoring devices. Integrating these diverse data enables a *comprehensive view* of the patient and impedes ignoring critical patient data [54].

Since fragmented, inconsistent, or missing data can significantly compromise decision-making accuracy, the importance of data integration in CDSSs has been increasingly highlighted. In other words, enhancing data integration assists medical practitioners by enabling seamless communication between different systems and improving the precision of medical recommendations [55].

4.1. Bridging Data Integration with Human–Computer Interaction

Data integration significantly enhances the user experience and system usability by presenting the required data to physicians in a unified and merged manner [56]. The integration function can be executed in two aspects: data integration and interface integration.

Although these aspects are intertwined, as illustrated in Figure 4, each plays a disparate role in enhancing the system's usability and user experience [56,57]. When physicians can make medical decisions based on the data derived from various data sources, they can trust the system's veracity and comprehensiveness. On the other hand, if physicians interact with a seamless user interface instead of separate platforms, the necessary information will be considerably more accessible, leading to increased user satisfaction.

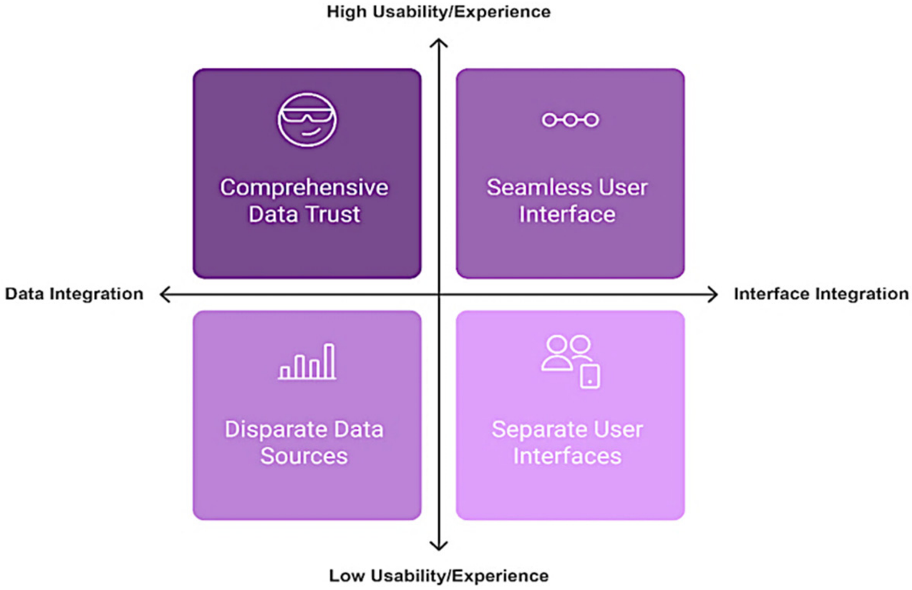

Figure 4. Enhancing usability and user experience through integration.

According to the undeniable importance of this approach in both data and interface integration, nowadays, system designers in the medical context attempt to unify the available systems by exploiting recent cloud technologies. Some dedicated services like iPaaS (Integration Platforms as a Service) provide a range of integration capabilities, including data integration, application integration, and API (Application Programming Interface) management [58,59]. The integration process impacts HCI within CDSSs in the following ways:

- **Improved data presentation**: Integrated and standardized data allow for precise, user-friendly interfaces that present medical information efficiently. Physicians can access patient records, test results, and diagnostic recommendations without navigating fragmented data sources [60];
- **Enhanced trust and engagement**: Since physicians receive reliable, comprehensive, and accurate data during interaction with the system, they can trust CDSSs. When clinicians acquire consistently desired results based on integrated data, they are more likely to engage with and rely on the system for decision-making [61].

As a result, data integration within CDSS, by providing a unified platform for data and user interaction and ensuring more reliable data collection, empowers physicians to achieve more accurate medical decisions and, ultimately, better patient outcomes.

4.2. Categorizing Data Integration to Enhance Usability and Functionality of Clinical Decision Support Systems

In the CDSS context, effective data integration is critical for enhancing clinical workflows, supporting evidence-based decision-making, and improving patient outcomes. To address the diverse needs of healthcare professionals, categorizing data integration based on content types (such as EHRs, genomic data, and medical imaging) provides a structured framework to evaluate their unique contributions to system functionality and usability [62].

The depicted categorization in Table 1 illustrates that integration strategies empower HCI principles such as reducing cognitive load, improving data accessibility, and supplying interface consistency.

Table 1. Different data integration types within CDSSs.

Data Integration Type	Description	References
Electronic health record integration	Incorporating patient data from EHRs into CDSSs	[63]
Genomic data integration	Incorporating genomic information into CDSSs	[64]
Medical imaging integration	Incorporating imaging data (e.g., X-rays, MRIs) into CDSSs	[65]
Laboratory data integration	Incorporating lab results into CDSSs	[66]
Pharmacy data integration	Incorporating medication data into CDSSs	[67]
Wearable device data integration	Incorporating data from patient wearables (e.g., heart rate monitors) into CDSSs	[68]
Social determinants of health (SDOH) data integration	Incorporating socioeconomic and environmental data into CDSSs	[69]
Research data integration	Incorporating the latest clinical research findings into CDSSs	[70]
Patient-reported data integration	Incorporating data directly reported by patients (e.g., symptoms, outcomes) into CDSSs	[71]
Administrative data integration	Incorporating administrative information (e.g., billing, scheduling) into CDSSs	[72]

Each data integration type alone has the potential to impact HCI elements and, consequently, decision-making capabilities. In this regard, EHR integration elevates accessibility to comprehensive patient data and reduces manual data entry, although well-designed workflows must be considered to prevent cognitive load [63]. Genomic data integration introduces personalized care options but demands advanced visualization tools to manage its inherent complexity [64]. Medical imaging integration enhances diagnostic precision by linking imaging and textual data, requiring intuitive interfaces for seamless navigation [65]. Since lab results have become prerequisites for disease diagnosis in recent years, laboratory data integration boosts decision-making speed and accuracy through real-time lab results [66]. On the other hand, pharmacy data integration improves medication safety but should strive to prevent alert fatigue through thoughtful interface design [67]. Wearable device data integration facilitates real-time monitoring, generating accurate and non-intrusive alerts to assist physicians and patients [68]. SDOH data integration combines non-medical factors (e.g., income, housing) with health data to understand broader health influences. Utilizing this data integration, the explainability and individuality aspects of the system will be enhanced, leading to improved health outcomes and equitable care [69]. Research data integration supports evidence-based activities and concentrates on streamlined filtering among medical data [70]. Patient-reported data integration promotes patient-centered care but requires user-friendly input and easy-to-use interfaces to gather essential medical data [71]. Although administrative data integration does not directly influence medical decision-making, it can mitigate the work burden by facilitating the administrative processes, leading to more concentration on the main medical processes [72].

As demonstrated above, data integration in different shapes ameliorates HCI factors, causing better CDSS functionality and more accurate medical decisions.

4.3. Empirical Case Studies About Data Integration Impact on Decision Accuracy and Human–Computer Interaction in Clinical Decision Support Systems

Several empirical studies have investigated the relationship between data integration, data accuracy, and HCI factors within medical settings.

Liyuan et al. [73] implemented a data integration project embedding one of the best practice databases into a CDSS. Their study demonstrated that real-time access to evidence-based clinical guidelines (stemming from data integration) significantly improved diagnostic precision and reduced time-to-diagnosis. This integration allowed physicians to retrieve relevant information without disrupting their workflow, elevating decision accuracy. Some other studies concerning the user interface discuss that focusing merely on data retrieval without addressing user interface design limits the full potential of the medical systems [73,74]. They underscore that systems with poorly integrated interfaces often increase cognitive load, causing frustration among clinicians.

Another study [75] presented a successful implementation of data integration within a Medical Decision Support System (MDSS) framework designed to enhance end-user confidence through ubiquitous IOT (Internet of Things) devices. This study demonstrates to what extent data integrating from diverse data stems from IOT devices leads to significant improvement in system performance.

To illustrate the practical benefits of data integration within medical information systems, we draw on our prior empirical research [76], which investigated the impact of integrating a personnel attendance subsystem from a Management Information System (MIS) into a Hospital Information System (HIS), forming an integrated HMIS. This study aimed to assess how such integration affects the accuracy of performance evaluation reports and, by extension, decision-making reliability. The methodology involved a comparative analysis of reception staff performance before and after integration, focusing on a key metric in medical environments called "reception rate".

This expression is applied to count the number of admitted patients in hospitals and is calculated as below:

$$\textit{Reception rate} = \textit{number of admitted patients} \div \textit{number of useful working hours}$$

In 2019 (pre-integration), the reception rate (RR_19) was calculated using patient admissions data from the HIS and working hours data from the MIS, which were separate systems at the time. In 2020 (post-integration), the reception rate (RR_20) was derived entirely from the HMIS, unifying both variables under one system. The sample comprised 21 reception personnel (15 females, six males, aged 25–37), consistent across both years to control for demographic factors (e.g., age, education). Data were extracted from system reports: in 2019, the MIS provided 152,878.75 total working hours (average 16,803.75 $\pm$ 2488 SD), and the HIS reported 151,539 admitted patients (average 5673.95 $\pm$ 1658.39 SD); in 2020, the HMIS recorded 156,793.22 working hours (average 17,520.82 $\pm$ 1308.82 SD) and 156,392 admitted patients (average 7447.25 $\pm$ 1759.84 SD).

Statistical analysis employed the Mann–Whitney U Test due to non-normal data distribution (Shapiro–Wilk Sig. < 0.05). The results showed a significant difference between RR_19 (0.3468 $\pm$ 0.1153) and RR_20 (0.4298 $\pm$ 0.10909), with a Mann–Whitney U = 14,900, $Z = -2.866$, and $p = 0.004$ (<0.05), rejecting the null hypothesis of no difference. Notably, admitted patients increased by 31.24% in 2020, while working hours rose by only 4.2%, suggesting RR_20's higher accuracy stemmed from capturing "active" working hours (time logged into the HMIS) rather than total presence, unlike RR_19, which relied on less precise MIS data (e.g., arrival/exit times without activity context).

These findings highlight those manual errors and untracked inactive hours (e.g., breaks) skewed RR_19, underestimating actual performance before integration. After integration, the HMIS enabled seamless cross-checking of patient records against active hours, reducing errors, streamlining workflows, and enhancing decision-making precision. For instance, managers could now distinguish productive time, improving staff evaluations and resource allocation. This aligns with broader CDSS goals: integrating subsystems like attendance tracking with clinical data mitigates data discrepancies, directly supporting accurate reporting and informed medical decisions, as seen in reduced cognitive load for users interpreting unified outputs.

The elevated accuracy level from the mentioned integration cases enhanced the system's reliability and user acceptance, increasing user interaction. Hence, the system is improved in some identified HCI aspects, such as user satisfaction [77], ease of use [78], and data entry issues [19]. Therefore, these empirical studies revealed how data integration in medical settings can positively impact HCI status.

5. Discussion

The current study has delved into a critical but often overlooked aspect of healthcare technology: the intersection of data management and human–computer interaction in the CDSS environment. By examining data entry management, standardization practices, and the integration of diverse medical subsystems, this research investigates an underexplored area in healthcare technology: bridging data science and HCI.

While other studies have emphasized the technical aspects of data management and integration, a few have explored how these considerations directly impact the user interaction with the systems. Data entry issues focusing on error reduction have often been discussed in this context. In contrast, the mental efforts stemming from improper data presentation as one HCI element have rarely been addressed [79,80]. Hence, the mentioned area is considered a research gap. Although the automated text generator technology described in the current study significantly reduces manual error, it also alleviates physicians' frustration and cognitive load when typing repetitive and complex data. Systems equipped with these features make the system smarter, facilitate user interaction, and prevent interoperability challenges arising from terminology diversity [29,81].

To indicate the consequential relationship between data management and HCI, Table 2 presents a framework illustrating how data management aspects enhance HCI elements, subsequently improving CDSS functionality. This table is introduced to clarify the cascading effects: effective data management practices directly improve HCI components, which in turn elevate the technical performance of CDSSs. The table addresses the research gap identified earlier by systematically linking these domains, offering a structured perspective on mutual reinforcement. This approach aligns with the study's objective of establishing a scientific framework that connects data management strategies to HCI factors, ultimately fostering more intuitive and effective CDSS environments.

Table 2. Consequential effects of data management on HCI elements and CDSS functionality.

Data Management Aspects	Impacted HCI Elements	Improvements in CDSS Functionality	References
Data range control (validity)	Error feedback, system reliability	Minimizes invalid data entries, enhancing algorithmic precision	[22,23,29]
Data entry obligations (completeness)	Structured interaction flow, task efficiency, usability	Ensures complete dataset availability, reducing query failures	[26,29,82]
Data consistency (terminology)	Lower interpretive ambiguity, interface clarity	Enhanced reasoning algorithms, improving natural language processing	[32,81,83,84]

Table 2. *Cont.*

Data Management Aspects	Impacted HCI Elements	Improvements in CDSS Functionality	References
Data standardization (interoperability)	Predictable interface behavior, workflow integration	System interoperability enables cross-system data synchronization	[30,31,85–87]
Data normalization (units/ranges)	Visual consistency, reliable data interpretation, minimized user confusion	Optimizing automated anomaly detection, accurate alerts	[88–90]
Data integration	Data accessibility, seamless multi-source data flow	Consolidates data streams, accelerating real-time analytics	[53–55,91]
Data presentation	Information visualization, decision clarity	Enhances graphical rendering, faster decision-making, improving predictive accuracy	[92–94]

5.1. Real-World Standardization Challenges

Despite recent advancements in data management technologies, several constraints remain in CDSS design. The variety in medical jargon is a severe limitation in this context. Inconsistent terminology complicates data entry and retrieval, impacting research accuracy and clinical decision-making [83,95]. Although the range control and obligatory data fields have been proposed as potential solutions, these modules require consistent updating with recent medical modifications [29]. On the other hand, the standard discrepancies among different countries present significant constraints on data formats. This limitation hinders standardization and normalization through a structured data transformation pipeline [81]. Moreover, healthcare institutions often use region-specific coding systems and documentation styles, making data interoperability a persistent challenge. To address these discrepancies, adopting widely recognized interoperability standards, such as HL7 FHIR (Fast Healthcare Interoperability Resources) and OMOP (Observational Medical Outcomes Partnership), can provide a structured approach to harmonizing medical data across institutions and regions [96,97].

Additionally, AI-driven terminology mapping and natural language processing (NLP) techniques can aid in translating disparate terminologies into unified medical vocabulary, reducing inconsistencies across different systems [84,98]. A phased, modular approach (starting with critical datasets like lab results and expanding via adaptable adapters) offers flexibility, allowing institutions to adopt standards incrementally without requiring extensive infrastructure upgrades [99]. This strategy mitigates resistance from regions with entrenched coding practices, enhancing data reliability and supporting cross-border research and care coordination [100].

5.2. Implementation Challenges

Implementing these data management solutions in CDSSs entails challenges, notably data privacy and interoperability with legacy systems. Data integration across systems with varying security policies raises privacy concerns, as sensitive patient information may be exposed during aggregation from diverse sources with inconsistent credential protocols (e.g., single sign-on vs. multi-factor authentication) [101]. Robust encryption (e.g., AES-256) and standardized access controls are essential to safeguard privacy [102]. Moreover, integrating with legacy systems (often built on outdated data architecture) poses additional challenges, necessitating the implementation of robust encryption protocols and standardized interfaces to ensure secure and seamless interoperability [103,104].

On the other hand, wearable devices and medical Internet of Things (IoT) solutions generate vast amounts of real-time data, such as vital signs, activity levels, and sleep patterns. While these integrations can enhance continuous patient monitoring and early warning systems, they bring significant challenges. One of these challenges is high-volume data, which can complicate CDSS functionality and make it harder for physicians to reach rational solutions. Furthermore, the lack of standardization in IOT data formats and device protocols entangles seamless integration into existing CDSSs [105]. In data integration, another challenge arises with alert sensitivity and the specified rules that trigger them. Specifically, medical alerts containing similar concerns originating from separate subsystems before the integration process negatively impact the system's usability and lead to alert abandonment [106,107].

5.3. Human-Centered Design Considerations

Human-centered design (HCD) optimizes the data management–HCI bridge by prioritizing clinician needs. For data entry, real-time text previews and auto-suggestions reduce cognitive load and errors, allowing physicians to focus on patient care rather than manual input [108]. For standardization, unified dashboards displaying normalized data (e.g., vital trends in consistent units) improve comprehension and are designed with clinician input to highlight actionable insights [109]. For integration, customizable alert settings (adjustable to workflow preferences) mitigate fatigue, reflecting HCD's emphasis on adaptability [110]. These designs, grounded in principles of empathy and simplicity, enhance usability and foster user trust. This enhancement is achieved through iterative usability testing with clinicians, ensuring alignment with the demands of clinical practice [111]. Such approaches elevate CDSS adoption by addressing human factors often neglected in technical solutions.

5.4. Implementation Constraints

While this study offers a novel framework bridging data management and HCI to enhance CDSS functionality, several limitations must be acknowledged. First, the proposed data processing strategies (such as automated data validation, normalization, and integration) may introduce computational overhead. These mechanisms require real-time performance, particularly in high-volume environments like emergency departments or intensive care units, which may challenge system responsiveness and scalability [112].

Second, the framework's adaptability to diverse healthcare environments is not yet fully validated. Healthcare settings vary significantly in digital maturity, infrastructure availability, and staff training levels, which can influence the adoption and effectiveness of this framework. For instance, institutions with limited IT support or reliance on paper-based records may face more significant barriers in implementing standardized data structures and advanced interface designs [113].

Moreover, despite advancements, constraints persist in inconsistent medical jargon, complicating data entry and retrieval and impacting accuracy and decision-making [114]. Range control and obligatory fields need regular updates to reflect evolving standards [115]; however, cross-national format discrepancies hinder structured data transformation [116]. Although HL7 FHIR, OMOP, and NLP offer solutions [117,118], regional coding and resource disparities remain challenges, necessitating tailored strategies to ensure broad applicability [119].

5.5. Practical Implementation Guidelines

A structured, evidence-informed approach is recommended to operationalize the proposed framework across real-world healthcare environments. First, automated text generation tools should be deployed alongside structured clinician training programs, ensuring adoption and alignment with clinical documentation standards. These tools have demonstrated the potential to reduce manual errors and alleviate cognitive load, particularly in high-frequency data-entry tasks [115]. Second, interoperability should be pursued incrementally through the phased implementation of widely accepted standards such as HL7 FHIR. To address compatibility challenges with legacy systems, interfacing solutions (such as middleware or adapters) can be employed, with an initial focus on high-impact clinical domains like diagnostics and laboratory systems [117]. Third, human-centered design principles should guide interface development, emphasizing iterative usability testing involving clinicians. Tailored dashboards, alert configuration, and workflow-specific adaptations should be continuously refined through participatory design methods to ensure alignment with end-user needs and clinical efficiency [111,120]. Finally, pilot studies in controlled clinical environments are recommended before full-scale deployment. These pilots can help identify context-specific barriers and validate the framework's effectiveness in enhancing CDSS usability, integration, and performance across diverse institutional settings [121].

Despite the mentioned constraints and obstacles to bridge between data management and HCI concepts, their mutual relationship cannot be denied. The proper data management and integration streamline the user interaction with the system through consistent data presentation and providing reliable medical data. On the other hand, enhancing the system usability and HCl aspects impedes data entry errors and missed data, leading to the supply of suitable data for medical decisions and empowering data management aspects. As depicted in Figure 5, this synergistic and bilateral effect can lead to a positive loop: improved HCI empowers data management by ensuring high-quality data, and reciprocally, effective data management enhances HCI by providing a seamless and user-friendly experience.

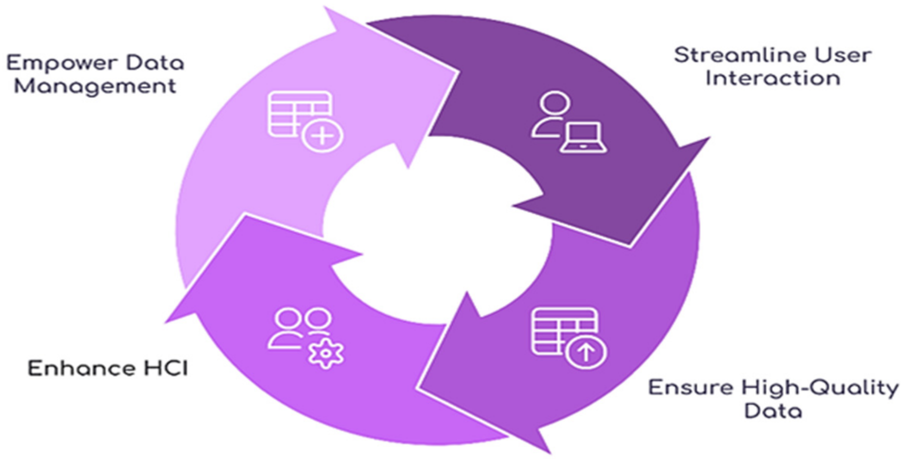

Figure 5. The synergistic cycle of data management and HCI.

This study offers several scalable solutions like 'automated text generation' to mitigate data entry challenges, resulting in reduced user workload. Moreover, by integrating data management techniques with HCI principles, as illustrated in Table 2, this research highlights how effective data practices can enhance user satisfaction and elevate CDSS performance. This way, the system usability in different HCI aspects will be elevated, bringing tangible benefits for clinical outcomes.

Future research should focus on advanced NLP tools to address terminology inconsistencies and provide real-time harmonization of medical terms. Developing globally standardized data formats is essential for seamless interoperability across systems and regions. Enhanced training protocols will empower healthcare providers to effectively utilize complex, integrated systems. Advancing these areas will drive innovation and ameliorate CDSS functionality and patient outcomes.

6. Conclusions

This study has successfully bridged the gap between prominent human–computer interaction concepts and foundational data science principles, including data management, transformation, and integration, within the CDSS context. By delving into practical scenarios, we have demonstrated the mutual impact of data entry management and data integration on HCI elements such as usability, cognitive load, and user satisfaction (and vice versa). These analyses highlight the symbiotic relationship between data science and HCI, emphasizing how thoughtful system design can enhance data quality and user interaction.

Our findings underscore that prioritizing HCI principles significantly improves data accuracy and consistency, which is critical for effective medical decision-making. High-quality data stemming from data flow control and seamless integration enhances CDSS reliability and functionality, leading to the desired patient outcomes. By introducing this scientific framework, we contribute to a deeper comprehension of how integrating HCI into data practices can elevate the performance and adoption of advanced healthcare technologies.

Consistent attention to this interplay between data-driven and human-centered approaches will be crucial to advance healthcare systems further.

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Annex *E*.

Aligning EMR Structure with Treatment Cycles: Enhancing Data Management and CDSS Functionality

applied sciences

MDPI

Article

Aligning EMR Structure with Treatment Cycles: Enhancing Data Management and CDSS Functionality

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Abstract: Electronic medical records (EMRs) are fundamental to clinical decision support systems (CDSS). Conventional EMR structures still fail to capture the cyclical nature of treatment plans, leading to fragmented data representation and reduced decision accuracy. This study addresses this gap by proposing a cycle-based EMR framework that systematically integrates treatment cycles, enabling structured, sequential data organization. Treatment cycles categorize patient data into iterative phases, reflecting disease progression and repeated interventions, ensuring data continuity and analytical precision. A dataset inspired by MIMIC-III was developed to empirically evaluate this approach, incorporating treatment cycle fields to enhance data continuity and analytical precision. The results indicate that cycle-based structuring preserves critical variations in patient responses, improves treatment outcome predictions, and strengthens CDSS recommendations. While this approach offers substantial benefits, challenges such as workflow adaptation, usability, and interoperability must be addressed to facilitate seamless integration into clinical practice. Despite these challenges, this study establishes a scientifically validated foundation for cycle-based EMRs, aligning data structures with real-world clinical workflows. By rectifying data organization, this approach elevates diagnostic accuracy, optimizes treatment planning, and enhances patient outcomes, contributing to the future of precision medicine.

Keywords: electronic medical records (EMR); clinical decision support systems (CDSS); treatment cycle; data management; data tagging

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1. Introduction

The inherent complexity of medical settings has highlighted the importance of system design concerns. This sensitivity increases exponentially when medical decisions are made using data processed by clinical decision support systems (CDSS) [1]. This complexity has increased due to the growing volume and diversity of patient data, necessitating advanced tools like CDSS to manage and support decision-making in these complicated clinical environments [2]. Recent studies highlight the critical role of CDSS in improving clinical practice across diverse fields such as nursing, pediatrics, and oncology, emphasizing their practical usability and widespread applicability in addressing complex healthcare challenges globally [3]. The successful implementation of CDSS depends on their seamless integration into healthcare providers' existing workflows and decision-making processes [4,5]. Usability experts have emphasized that effective system design significantly enhances usability and ensures physician adoption of CDSS [6]. Unlike interface design, which concentrates on a system's visual and interactive aspects, system design encompasses the structural, functional, and operational frameworks of CDSS. It addresses how data is organized, retrieved, and presented to users, ensuring that the system is compatible with medical professionals' real-world needs and workflows [7,8]. Poor system design hinders the fulfillment of physicians' needs and may lead to overwhelm and dissatisfaction. It ultimately can negatively impact patient care [9].

One significant deficiency in the prevalent system design is incompatibility with current medical processes [10]. Among the deficiencies mentioned, the cyclical nature of the treatment plan can be firmly perceived as the prominent requirement. A treatment cycle often contains a sequence of distinct chain phases (diagnosis, treatment plan, and result evaluation), and the existing system designs within medical information systems still do not address the cyclical nature of these phases [11]. Electronic medical records (EMRs), as the principal platforms for medical data collection, are no exception to this. Since they are considered data providers for CDSS, this compatibility with real-world needs must be observed for EMR system design [12]. In contemporary system design, medical data are frequently presented in isolated fragments, which reduces physicians' ability to comprehensively comprehend the patient's medical history and current treatment needs. In other words, the treatment cycle to which the registered data belong is not explicit. This ambiguity reduces the necessary transparency for data analysis [13].

This problematic situation highlights a critical research gap: how can CDSS be designed to align with the inherent cyclical nature of treatment plans? Existing system designs often prioritize medical data entry and retrieval within EMRs, regardless of how data categorization and labeling affect the next-step data analysis and medical decision accuracy [14,15]. To the best of our knowledge, no prior research has explicitly investigated the impact of a cyclical treatment approach on the design of CDSS that integrate with EMR data. Addressing this gap is essential for several reasons. First, enhanced clinical decision-making hinges on our ability to understand and incorporate the cyclical nature of treatment plans into CDSS design. Second, concentrating on cyclical data tagging and organization within EMRs streamlines data retrieval and analysis, elevating the quality of patient care. Finally, this study aims to fill the gap in the existing studies regarding the relationship between the cyclical nature of treatment plans and CDSS design, establishing a foundation for future research and innovation in this critical area. To address this gap, the current study proposes a cycle-oriented approach to CDSS design, investigating different aspects of this approach. In this regard, the upcoming sections are defined as follows.

This study initially delves into a comprehensive review of accomplished studies on cyclical approaches within medical information systems (not limited to the treatment cycle concept with CDSS, but also encompassing medical outcome evaluation, the iterative nature of diagnostic processes, and the application of cyclical methodologies in calculating treatment costs). Separately, we review the articles investigating how the systematic organization of medical data within EMRs and the use of data tagging techniques contribute to more precise medical decision-making. To establish a theoretical foundation, we define the concept of treatment cycles and discuss their necessity in medical applications. A comparative analysis is then conducted to contrast traditional EMR system designs with the proposed cyclical approach, highlighting their advantages and limitations. The implementation of this model is detailed through both technical considerations and the implications for data retrieval and analysis. We further present an empirical evaluation demonstrating how the cyclical model improves the accuracy of medical decision-making. In addition, we discuss implementation feasibility, usability concerns, and ethical implications related to data privacy and decision transparency. Finally, we conclude that integrating cyclical methodologies into EMR structures can significantly enhance the accuracy and reliability of medical decision-making within CDSS.

2. Related Works

The recent and rapid growth in EMR usage due to today's technological advancements has eliminated paper-based processes within healthcare systems [16]. In this realm, proper system design enhances systems' user adoption and data quality, elevating the accuracy level of medical decisions [17]. In this regard, the success of system design strongly depends on its compatibility with ongoing medical processes [18]. From the physicians' perspective, the treatment plan encompasses a series of medical functions that may result in the cure or non-cure of a patient's condition [19]. Throughout the stages of system design, it is essential to consider all physicians' needs, including those related to the treatment cycle, to improve system usability and medical decision-making. To comprehensively understand existing approaches, we review studies emphasizing the importance of cyclical methodologies across different facets of medical information systems. Then, we delve into studies investigating system design solutions that address the challenges of medical data arrangement and labeling within EMRs. Considering these factors, the accuracy and reliability of medical decisions supported by CDSS will be improved.

2.1. Literature Review on Cyclical Approaches in Medical Information Systems

CDSS have become central in enhancing clinical workflows by providing timely recommendations that integrate patient data with evidence-based guidelines. Several studies indicate that embedding iterative feedback loops into CDSS design can significantly improve performance. For instance, cyclic frameworks such as the Plan–Do–Study–Act (PDSA) system have been applied to continuously refine CDSS outputs, ensuring that the system adapts to evolving clinical needs and minimizes errors in real time [20]. The iterative nature of such cycles allows developers to test changes on a small scale, study the outcomes, and then act by modifying the system. On the other hand, the diagnostic process in clinical settings is intrinsically iterative. Diagnostic workflows often require repeated data collection cycles, hypothesis testing, and reinterpretation as new patient information becomes available. Studies in the field have demonstrated that the cyclical approach (in which clinicians and systems repeatedly "loop" through stages of assessment and re-evaluation) can significantly enhance the diagnostic accuracy [21]. Mark Smith et al. [22] emphasized that continuous learning processes in medical systems are essential in ensuring both clinical safety and cost-effectiveness. In this view, the cyclical approach is fundamental because it allows systems to respond dynamically to the complexities of real-world healthcare. Similarly, Loeb [23] found that incorporating iterative diagnostic cycles into CDSS improved the timeliness and accuracy of diagnoses, highlighting the inadequacy of a single, static implementation when patient data change rapidly.

Beyond diagnosis, cyclical approaches have proven valuable in outcome evaluation and cost management. Laka et al. [24] pointed out the limitations of static assessments, arguing that they fail to capture the ongoing benefits of system refinements over time. They recommended conducting repeated outcome assessments to accurately reflect the evolving nature of clinical practice and technological performance within the CDSS environment. White et al. [25] claimed that iterative cost recalibration enables more accurate resource utilization tracking. This guarantees that financial evaluations remain reflective of real-world operational conditions.

Furthermore, Cavour and Chui [26] demonstrated in their study that continuous monitoring provides essential feedback for effective care coordination across the diagnostic process. This aligns with the "continuum of care" concept, emphasizing seamless and integrated healthcare delivery across different stages and settings. This cyclical model supports continuous learning and the refinement of diagnostic processes by providing clinicians with consistent feedback on their diagnostic reasoning and outcomes [27]. The iterative nature of diagnostic processes, as described in the context of diagnostic paths, underscores the importance of cyclical approaches. By continuously gathering and integrating information, clinicians can refine their working diagnoses and improve the diagnostic accuracy over time [28,29].

2.2. Literature Review on System Design Solutions for Medical Data Arrangement and Labeling in EMRs

System design in medical settings, such as CDSS and EMRs, plays a vital role in managing the flow and quality of data that drives medical decision-making [30]. A crucial aspect of this process involves data tagging (or labeling), where raw data are organized and annotated to enhance their usability across systems. Proper data arrangement and labeling in EMRs are fundamental in enabling adequate clinical decision support [31]. While numerous studies explore system design and data flows, we attempt to collect different perspectives to articulate and compare them within the medical domain.

Gustav and Jan [32] analyzed data flows within EMR systems, emphasizing the difficulties posed by unstructured data. They highlighted that the absence of robust tagging mechanisms makes retrieving specific patient information inefficient and prone to errors. On the other hand, Luis et al. [33] delved into the issue from a system integration perspective, emphasizing standardized data tags to streamline interoperability between EMRs and CDSS. These studies highlight the importance of tagging in two different aspects. Gustav and Jan investigated probable internal data flaws, while Luis et al. were concerned with external data compatibility during communication between two medical platforms.

Chih-Hsun et al. [34] explored tagging automation, introducing AI-powered tools that classify and annotate data during entry. Their study demonstrated that automated tagging significantly reduced the manual workload and enhanced the data consistency. Meanwhile, Mohamed et al. [35] investigated tagging from a user interface perspective, showing that user-friendly tagging systems improved the data entry accuracy and reduced clinician frustration. These findings underscore the interplay between technological advancements and user-centric design in optimizing tagging practices.

Structured tagging, such as labeling treatment cycles, enables the systematic organization of critical patient data, which is significant in generating actionable insights in clinical workflows [36]. In this respect, cyclical approaches (like the Plan–Do–Check–Act model) have successfully improved the timeliness and quality of EMR documentation by embedding iterative feedback loops into data entry processes, thereby aligning tags with evolving clinical phases [37]. Advanced frameworks, such as patient similarity-based EMR systems, leverage tagged diagnostic and demographic data to dynamically update treatment recommendations, illustrating how structured tagging supports adaptive decision-making [38]. Similarly, efforts to convert unstructured EMR text into standardized formats (like using BART-based models for entity extraction in lung cancer records) highlight the role of semantic tagging in harmonizing data for analytics [36].

However, challenges persist in psychiatric EMRs, where unstructured narrative data dominate. In such cases, hybrid tagging strategies will be needed to balance clinical nuance with computational usability [39]. These insights underscore that cyclical tagging and structured arrangement enhance data interoperability and drive predictive accuracy and clinical safety in CDSS applications [38,40].

3. Overview of the Treatment Cycle

Like many processes across diverse sectors, medical care follows a cyclical pattern. Treatment plans often involve repeating phases over time, like administrative, industrial, and financial operations that can be optimized for efficiency [41,42]. This section will delve especially into the context of "treatment cycles" within medical settings. A clear definition of this term and its significance in medical practice will be provided. By understanding the cyclical nature of treatment, we can identify opportunities to improve data organization and retrieval within EMR systems.

3.1. Definition of Treatment Cycle in Medical Settings

A treatment cycle is a structured process that consists of repeated sequences of therapy interspersed with rest periods, which may include either no treatment or alternative therapies. For example, one cycle may involve one week of active treatment and three weeks of rest. When this cycle is repeated consistently over time, it constitutes a comprehensive course of therapy, often referred to as a treatment plan [43].

This cyclical framework is integral to treatment plans, which outline the timing, dosage, and sequence of interventions tailored to individual patient needs. Clinical pathways (standardized, evidence-based protocols) guide these cycles by specifying diagnostic, therapeutic, and monitoring steps for specific patient populations, ensuring consistency while allowing adaptability to clinical progress [44].

The medical process comprises several sequential steps that must be executed. As illustrated in Figure 1, each stage has its priorities and specific position within the overall framework. The diagnosis and the chosen treatment plan will be assessed based on the preceding steps.

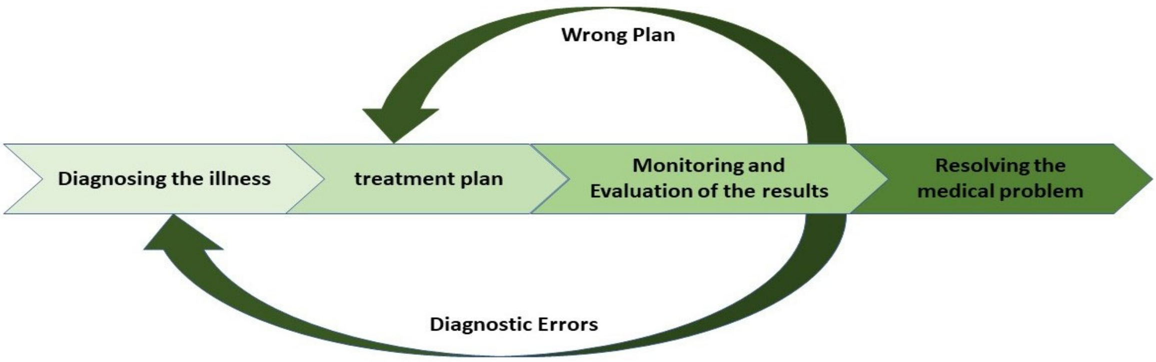

Figure 1. Medical process overview with treatment cycle focus.

3.2. The Importance of a Cyclical Approach in Medical Processes

As indicated in Figure 1, a set of activities is typically performed for the diagnosis step and the treatment plan. Medical processes often require frequent review and re-assessment [45]. Continuous evaluation and improvement during the treatment process are essential, leading to the development of a cyclical approach within the therapeutic framework. Clinical pathways are prescriptive models outlining the standard medical steps required to treat specific patient populations [46]. Clinical pathways represent a patient's diagnostic and treatment journey [47]. This implication highlights the importance of a cyclical approach, facilitating continuous evaluation and improvement. This iterative process enhances patient outcomes and optimizes data analysis by allowing for the integration of feedback and adjustments at each stage of care [48].

Treatment plans typically consist of distinct phases that recur over time. The cyclical approach enables the linkage of data points to specific phases within a treatment cycle, enhancing data organization. This facilitates progress tracking, the identification of trends, and the comparison of data across different cycles [49].

4. Two Different Approaches Within EMRs for the Patient Treatment Process

EMR systems have reached a pivotal stage in their adoption and utilization. As healthcare professionals become more proficient in leveraging these systems, their potential to enhance clinical decision-making and patient outcomes grows consistently [50]. EMR system architectures must be designed with transparency and efficiency to maximize these benefits, ensuring that physicians can generate meaningful reports and make well-informed medical decisions. This section examines existing and proposed approaches to structuring medical processes within EMRs, evaluating their effectiveness and potential improvements.

4.1. Conventional Approach

Healthcare professionals increasingly leverage EMRs to streamline clinical workflows, with advancements such as smart forms enhancing functionality [51]. One of the primary advantages of EMRs is their ability to support clinical decision-making by providing software solutions tailored to individual patient needs [52]. Given the central role of electronic data forms in EMRs, optimizing their structure and functionality across multiple dimensions is crucial.

A key consideration is ensuring that EMR data entry processes align with real-world medical workflows while maintaining transparency in medical reports and, ultimately, in clinical decision-making. Physicians document relevant medical information within designated data forms when patients visit a hospital or medical center. As the treatment progresses, they continuously input updates into the data fields embedded within the EMR system. After treatment, the outcomes are recorded to facilitate a comprehensive evaluation.

For medical teams to assess both the initial diagnosis and the effectiveness of the chosen treatment path, a structured and accessible data framework is essential. Regardless of whether a treatment is successful, the recorded medical data and outcomes remain valuable for the individual patient and similar future cases. The critical limitation of the current EMR approach is the absence of a well-defined treatment cycle structure, leading to fragmented data entry where each data point is recorded in isolation, without considering its relationships with other relevant forms. This scattered approach impairs the ability to track and evaluate treatment progression effectively. The prevalent data entry workflow among physicians, which illustrates these challenges, is depicted in Figure 2.

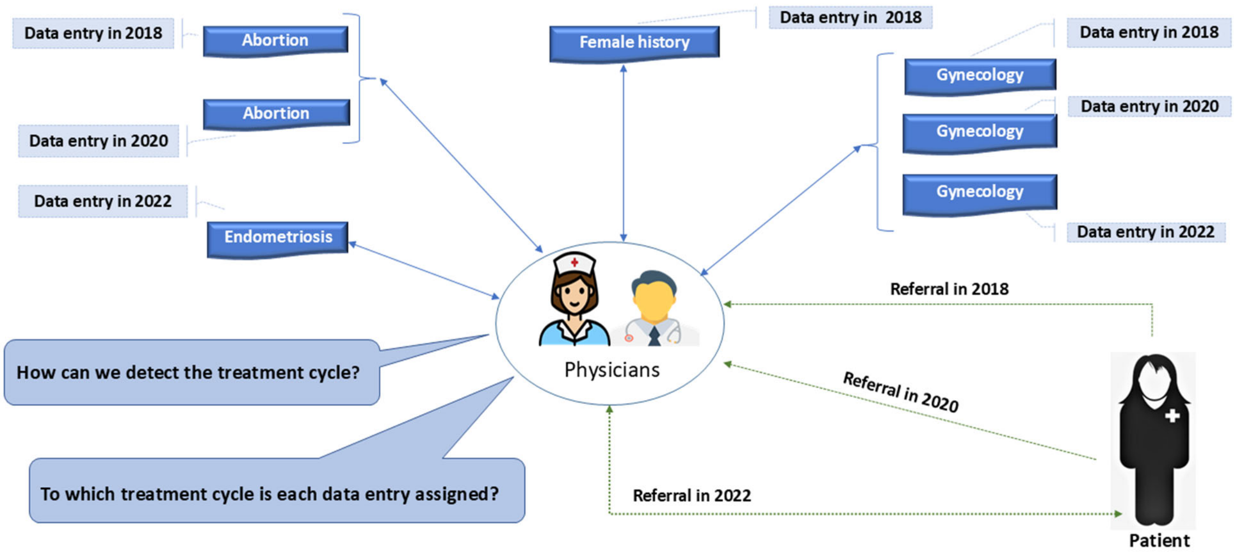

Figure 2. Ambiguity in current EMR systems for assigning data entries to treatment cycles.

In the conventional EMR data entry approach, inconsistencies arise due to the lack of a structured treatment cycle framework. A crucial issue is that certain data forms may be filled out multiple times during a patient's treatment course, while others (equally relevant to the case) may only be completed once. This irregularity creates ambiguity for physicians when tracking and analyzing a patient's treatment route. Physicians struggle to determine whether a set of records represents a single continuous treatment plan or multiple fragmented encounters without a standardized cycle-based structure.

A well-defined treatment cycle should include a consistent set of core data forms for every patient referral, ensuring that each treatment iteration is comprehensively documented. However, in the current system, these essential forms are not systematically present across each patient's visit. This inconsistency is exemplified in Figure 2, where the number of completed data forms does not align with the number of patient referrals. In the given case, a patient underwent three separate treatment attempts due to unsuccessful outcomes in prior visits. Despite this, some key data forms were only utilized once or twice rather than being completed systematically for each referral.

This fundamental flaw (the absence of a structured and clearly defined treatment cycle) leads to critical gaps in medical documentation, making it challenging to evaluate treatment progress, identify patterns, and ensure data completeness for clinical decision support. To address this issue, we propose a novel EMR model that systematically integrates treatment cycles, ensuring that each cycle is adequately defined, structured, and consistently documented across all patient encounters.

4.2. Treatment Cycle Approach Within EMRs

The effective utilization of EMRs is pivotal in promoting physician engagement with these systems, as it provides significant incentives for adoption while enforcing penalties for non-compliance [53,54]. However, to maximize the usability and clinical value of EMRs, it is essential to ensure that the data entered during the treatment process are structured in such a way that aligns with real-world medical workflows. Recognizing this necessity, we have introduced an innovative cycle-based approach that redefines how medical processes are documented and analyzed within EMRs. This proposed model systematically segments the entire treatment process into distinct cycles, allowing for a more structured and transparent representation of a patient's progression. By explicitly defining treatment stages and outcomes within the EMR, this approach enhances the ability of physicians and medical decision support systems to track treatment effectiveness, recognize iterative patterns, and optimize patient care strategies. Ultimately, the cycle-based framework bridges the gap between digitalized medical data and practical clinical needs, offering a more intuitive and analytically powerful solution for the management of treatment histories within EMRs.

As illustrated in Figure 3, the proposed model establishes a structured sequence for data form arrangement, ensuring that, except for the initial form, each subsequent form has prerequisite entries before it can be accessed or completed. In this framework, the priority of data entry is a fundamental principle, with numbered data forms appearing sequentially based on their designated order of precedence. While each data form is associated with a specific department and utilized independently by its users, the model maintains interdependence and continuity, effectively linking them like a chain.

This structured approach resolves the imbalance between the number of treatment cycles and the corresponding data forms used in the current system. By enforcing a logical sequence, the proposed model enhances data integrity and ensures a more coherent representation of the treatment process. To further illustrate the application of this method, Figure 3 presents a data field for intrauterine fetal demise (IUFD) as an example of a structured treatment cycle.

In this model, each IUFD data field per referral is assigned a unique cycle number, distinguishing treatment cycles. For instance, IUFD data from 2020 are separable from IUFD data from 2022 through the cycle number. This patient underwent two treatment cycles, each with a different path and outcome. The cycle number field in medical reports helps medical teams to identify the corresponding treatment cycle for each data entry, allowing for a more precise evaluation of treatment progress and effectiveness. Additionally, this model provides flexibility in defining treatment cycles, enabling medical personnel to include multiple data forms as needed. The cycle structure and its components can be modified based on medical requirements, ensuring adaptability to different treatment scenarios. An empirical evaluation is conducted to validate this approach, comparing it with the conventional EMR design and demonstrating its advantages in structuring and analyzing medical data.

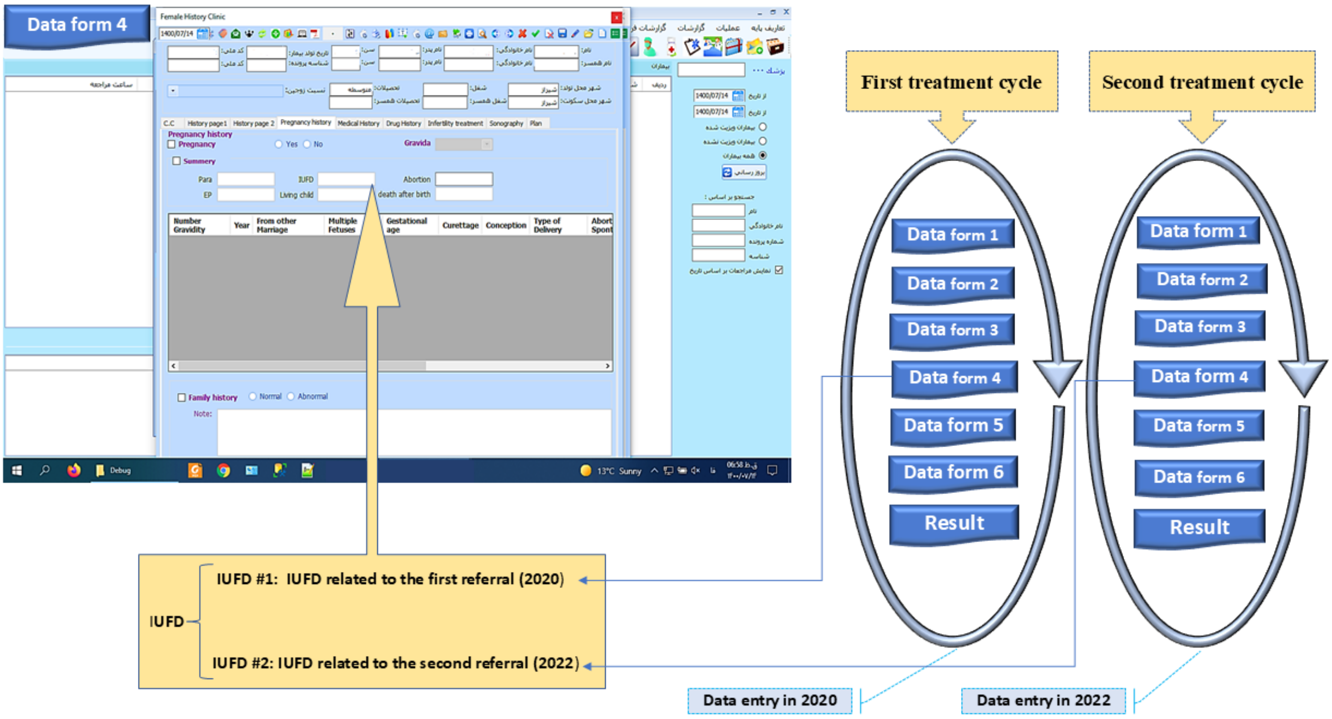

Figure 3. Cyclical structure for organizing data forms in EMR treatment cycles.

5. Implementing the Proposed Model

Digitalization has become a fundamental aspect of modern healthcare, transforming traditional medical practices into digital formats. This transition involves utilizing electronic systems to collect, store, and analyze patient data, ultimately enhancing efficiency, accuracy, and accessibility in medical processes [55]. Moreover, AI-driven data collection, analysis, and assessment are increasingly integrated into healthcare, enabling more precise and reliable outcomes [49,50]. As discussed in the previous section, the cyclical approach is essential in structuring medical records. Therefore, integrating this approach into EMRs is a crucial consideration. Digitalization sometimes necessitates modifications to existing processes to ensure optimal implementation.

During EMR deployment, IT specialists frequently encounter a recurring request from physicians: "We need to determine which referral (treatment cycle) a specific data field (e.g., lab results, medical item) belongs to in the patient's treatment". Addressing this requirement is essential to prevent medical errors and ensure data integrity. To resolve this issue, our study proposes a structured model of sequential data forms that delineates treatment cycles within EMRs, enhancing clarity and decision-making.

5.1. Technical Considerations

EMR systems can enhance patient data retrieval, organization, and analysis by integrating treatment cycle-based data tagging. Employing unique cycle identifiers during data entry can significantly improve the data's integrity, transparency, and traceability. This section discusses this framework's technical aspects of data entry design, management, and retrieval.

5.1.1. Data Entry Design

The data entry design integrates cycle identifiers into form templates, automatically tagging each form with its respective treatment cycle. This ensures accurate and consistent data tagging while providing a user-friendly interface for healthcare providers to minimize errors and streamline the data entry process. These cycle-based form templates are implemented in the following way.

- Each data form (f1, f2, . . . , fn) within a treatment cycle is designed to include a field for a cycle identifier (flag).
- The form templates are pre-configured to automatically assign the appropriate treatment cycle flag according to the patient's current treatment stage.
- For instance, during the first treatment cycle, forms will be tagged with "Cycle 1". If the patient begins a new cycle, subsequent forms will be tagged with "Cycle 2".

The system employs automated flagging to ensure that the cycle identifier is consistently applied to all relevant forms without manual input, reducing the risk of errors.

5.1.2. Data Management

Data management exploits a robust database schema that includes treatment cycle identifiers for each entry. This maintains data integrity and prevents the mixing of cycle information, with strict validation protocols and regular audits ensuring the accuracy and reliability of patient records. The data management concern has been considered in two axioms.

Database Schema: The database schema is designed to include a column for the treatment cycle identifier, ensuring that each data entry is associated with the correct cycle. An example of the mentioned schema is as follows.

As demonstrated in Table 1, the database schema includes columns for the patient ID, form ID, data, and treatment cycle. This structure ensures that each data entry is accurately linked to its treatment cycle. The patient with Patient ID 12004 has undergone two distinct treatment cycles in this example. In the first treatment cycle, forms F1 and F2 were used. Hence, both were tagged with "Cycle 1". This tagging ensures that all data related to the first cycle are easily identifiable and can be retrieved or analyzed without confusion.

Table 1. Database structure in the cycle model.

Patient ID	Form ID	Data	Treatment Cycle
12004	F1	. . .	Cycle 1
12004	F2	. . .	Cycle 1
12004	F1	. . .	Cycle 2
12004	F3	. . .	Cycle 2

Subsequently, the same patient began a second treatment cycle, during which forms f1 and f3 were used, now tagged with the "Cycle 2" identifier. This demonstrates the model's flexibility in reusing forms across different cycles while maintaining a clear separation between the data entries of each cycle.

Data Integration: The model is designed to integrate seamlessly with existing EMR systems, ensuring that the tagging process does not disrupt current workflows. In this regard, interoperability standards are adhered to, facilitating the exchange and management of tagged data across different healthcare information systems.

The flexibility of the cyclical model, allowing physicians to modify forms, directly impacts data integration. This adaptability necessitates dynamic data mapping and integration processes. When physicians can alter the structure or content of forms, it implies that the data structure is dynamic, meaning that the data model must be adaptable to accommodate changing form layouts and data elements.

5.2. Data Retrieval and Analysis

Effective data retrieval and analysis are essential in leveraging the benefits of the treatment cycle-based data tagging model. Advanced query functions enable healthcare providers to filter and access patient data based on treatment cycle identifiers, facilitating precise and relevant data retrieval. Clinicians can easily track a patient's treatment history and analyze outcomes across different treatment cycles, with clear distinctions between different treatment cycles maintained by the system via the anticipated queries and analytical tools.

Query Functions: The EMR system incorporates advanced query functions that allow healthcare providers to filter and retrieve patient data based on treatment cycle identifiers. In this case, the system can provide the required data through various queries like the following:

SELECT ∗ FROM Patient Records WHERE Patient ID = 12004 AND Treatment Cycle = 'Cycle 1'.

Reporting and Analytics Tools: Reporting tools are developed to generate insights and reports based on treatment cycle data, helping clinicians to analyze the treatment efficacy across different cycles [56]. Cyclical data tagging facilitates pattern recognition and trend analysis, enabling data-driven insights for improved healthcare outcomes and resource allocation. Tools like SQL 2019, Python 3.10 (with libraries like Pandas 1.5), or specialized healthcare analytics platforms (e.g., Tableau 2023.1 or Power BI) can extract insights from tagged data. For instance, analyzing treatment cycle data can reveal optimal treatment pathways or identify patient subgroups that respond better to specific therapies.

6. Empirical Evaluation of the Cycle Approach's Utilization in EMRs

To investigate the efficacy of a cyclical approach within EMRs for data management and analysis, we constructed a synthetic dataset comprising 750 rows inspired by real-world clinical data and tailored to emphasize iterative treatment cycles and data tagging. This dataset, titled "CycleDiabetes750", is available at https://bit.ly/MIMIC-Cycle750 (accessed on 4 March 2025), is rooted in the structure of the Medical Information Mart for Intensive Care III (MIMIC-III) database, a widely recognized public dataset sourced from Beth Israel Deaconess Medical Center and accessible via PhysioNet [57]. MIMIC-III was selected due to its comprehensive coverage of clinical variables pertinent to diabetes care, including patient demographics (e.g., subject_id, age, gender), laboratory measurements (e.g., glucose), medication administrations (e.g., treatment_type), diagnoses (e.g., diagnosis), and admission details (e.g., admission_type). These data fields align closely with the study's requirements, providing a robust framework for the simulation of diabetes treatment scenarios.

To specifically address the cyclical nature of treatment plans and enable the detailed analysis of iterative interventions, we augmented the MIMIC-III-inspired dataset with custom fields not natively present in the original database. These included "treatment_cycle", "cycle_tag", "cycle_outcome", "treatment_start_date", "treatment_end_date", and "total_cycles". The "treatment_cycle" field distinguishes successive treatment phases (Cycle 1, 2, 3), while "cycle_tag" categorizes patient glucose states (Initial_VeryHigh, Followup_Moderate) to reflect the clinical severity and progression. The "cycle_outcome" field (Improved, Stable) evaluates the treatment efficacy related to each cycle, and the temporal fields (the treatment_start_date, the treatment_end_date) track intervention durations. Finally, "total_cycles" indicates the number of cycles per patient, facilitating longitudinal analysis. These modifications transform the static, single-event focus of traditional EMR datasets like MIMIC-III into a dynamic, cycle-based framework, enabling us to explore features and analytical capabilities unique to this design.

To ensure that incorporating treatment cycle fields does not introduce bias, the dataset's construction followed rigorous validation protocols, aligning with established guidelines for synthetic dataset development in medical research [58,59]. The statistical distribution of patient characteristics was preserved to reflect real-world clinical settings, minimizing artificial distortions. Cycle assignments were structured based on predefined glucose thresholds rather than arbitrary labeling, preventing systematic misclassification. Additionally, confounding variables such as patient demographics and admission types were analyzed to confirm that cycle-based grouping did not disproportionately affect treatment cycle categorization [60]. Lastly, potential observer bias was mitigated by maintaining transparency in variable definitions and ensuring that treatment cycle classifications were based on objective glucose level thresholds rather than subjective clinical interpretations. These precautions collectively enhanced the study's internal validity, ensuring that the findings were robust and not driven by dataset modifications.

The primary objective of this empirical analysis is to demonstrate enhanced analytical precision and multifaceted insights afforded by the cyclical approach in EMRs, which are inaccessible without such a design. The dataset comprises patient records with variables such as treatment dates, treatment cycles, post-treatment metrics, and success rates. To assess the effect of treatment cycles, we compared the results obtained from analyses considering cycle tagging with those obtained from studies that ignored cyclic patterns.

6.1. Data Preparation and Cleaning

The dataset was first in an Excel file and inspected for consistency, missing values, and outliers. Variables considered in this study (such as treatment_cycle, post_treatment_glucose, and treatment_success_rate) were identified and cleaned to ensure uniformity. Any erroneous entries were corrected, and the data were tagged based on the treatment cycle, creating a structured approach for subsequent analyses.

6.2. Cycling vs. Non-Cycling Approaches

In this regard, we conducted a detailed analysis of treatment outcomes by comparing metrics across treatment cycles, conducting statistical tests, and visualizing the results. The studies mentioned were performed within the Python environment, and the provided codes are available at the Zenodo repository (Metrics Comparison in cyclic and non-cyclic approaches, accessed on 18 March 2025).

The cyclical and non-cyclical analyses were conducted using the same dataset, including identical patient records, variables, and outcome definitions. The only difference between the two approaches lies in the additional fields that we introduced to support treatment cycle identification (e.g., treatment_cycle, cycle_tag). These enhancements enabled data tagging that facilitated cycle-based analysis, without altering the underlying data.

Cyclical analysis: Rather than treating all patient records as part of a uniform dataset, entries were grouped based on their corresponding treatment cycles (e.g., Cycle 1, Cycle 2, Cycle 3), as defined by the treatment_cycle field. This cyclical approach enabled an evaluation of variations across individual cycles by calculating summary statistics (mean, standard deviation) and visualizing cycle-specific distributions. Such categorization allows for the detection of meaningful patterns and clinical insights that could be overlooked in aggregate-level analyses.

Table 2 shows that the data can be broken down by treatment cycle by exploiting the cyclical approach. For each cycle (for example, Cycle 1, Cycle 2, etc.), we calculated multiple metrics, such as the mean, standard deviation, median, minimum, maximum, and count for post-treatment glucose levels, alongside similar statistics for the treatment success rate. Each row corresponds to a treatment cycle, and each column shows a specific metric. For instance, regarding the cell in row [2, 1] of this table, it represents the value of the first metric (typically the post-treatment glucose mean) for the treatment cycle listed in the second row (which here corresponds to, e.g., Cycle 2). This cell gives a quick snapshot of this cycle's average post-treatment glucose value, providing insights into how the treatment outcomes may vary from one cycle to another.

Table 2. Cycle-based metrics.

Treatment Cycle	Post_Treatment Glucose_Mean	Treatment_Success Rate_Mean	Treatment_Success Rate_Std	Treatment_Success Rate_Min	Treatment_Success Rate_Max
1	8238.71	14.26	11.62	0	25
2	8172.4	13.67	9.94	5	25
3	6672.6	25	0	25	25

Non-cyclical analysis: For comparison, an overall analysis was performed by treating the dataset as a single group, disregarding cycle information. This approach provides an aggregated view of the treatment outcomes, helping to highlight the potential loss of granularity when treatment cycles are not considered.

Table 3 demonstrates that the conventional approach aggregates all data without considering the treatment cycles. It computes the same metric types (mean, standard deviation, median, etc.) for the entire dataset. Essentially, it gives a single, overall view of the post-treatment glucose levels and treatment success rates for the whole patient population. This approach is practical when we require an aggregate metric. Still, as our further analysis shows, it hides any differences or variability across treatment cycles.

Table 3. Overall metrics (non-cyclical approach).

Treatment Cycle	Post_Treatment Glucose_Mean	Treatment_Success Rate_Mean	Treatment_Success Rate_Std	Treatment_Success Rate_Min	Treatment_Success Rate_Max
Overall	8158.12	14.53	11.15	0	25

In summary, the cycle-based table reveals nuances between individual treatment cycles (highlighted by values such as cell [2, 1] for Cycle 2's average post-treatment glucose level). In contrast, the overall table provides a single, unified benchmark. This two-pronged approach illustrates that significant differences between information stemming from treatment cycles might be lost if one only looks at the global (non-cyclical) summary.

6.3. Statistical Analysis

To rigorously assess the impact of the cyclical approach on treatment outcomes, we conducted a statistical evaluation using analysis of variance (ANOVA) [61]. This method was chosen because it allows us to compare means across multiple treatment cycles and determine whether the observed differences are statistically significant. Unlike simple pairwise comparisons, which increase the risk of Type I errors [62], ANOVA efficiently tests for variations across all cycles simultaneously, ensuring a more reliable interpretation of the treatment effects.

According to the structure of our dataset (where each treatment cycle may involve a distinct treatment plan tailored to evolving clinical judgments), we considered each cycle an independent analysis unit. While some individual patients may have undergone multiple cycles, the treatment strategy in each cycle was often adjusted depending on patient-specific responses. Therefore, treatment cycles were not strictly repeated measures of a fixed protocol but potentially distinct interventions with unique clinical contexts.

Given the independent nature of the treatment cycles in our study, ANOVA was selected as the most suitable statistical method, as it effectively evaluates the variance across cycles without assuming systematic correlations within patients. The frequent adjustments in treatment plans reinforce this choice. These adjustments minimize the dependency between treatment cycles. As a result, the assumptions of a mixed-effects model become less applicable. At the same time, ANOVA ensures the delivery of robust and clinically relevant insights into cycle-specific outcomes [63].

ANOVA determines whether the means of multiple groups differ significantly by comparing the variance within groups to the variance between groups. The test statistics (F-statistic) are calculated as follows:

$$F = \frac{\text{Variance between groups}}{\text{Variance within groups}}$$

ANOVA works by comparing two types of variances.

Variance between groups (treatment cycles): This specifies how much the average values (means) of different treatment cycles differ from the overall mean of all cycles combined. If the treatment cycles are firmly different, their means should be spread apart. Conversely, if they are not, their means will be close together.

Variance within groups (individual patients in the same cycle): This specifies how much individual patient outcomes vary within each treatment cycle. If a treatment cycle is consistent, individual patients will have similar results, and this variance will be low. Otherwise, much variation within the same treatment cycle might indicate external factors affecting treatment.

The first ANOVA test examined post-treatment glucose levels across different cycles. The results are as follows:

F-statistic: 64.6814, p-value: 0.0.

It is interpreted that, since the p-value is zero, we reject the null hypothesis and conclude that glucose levels significantly differ across treatment cycles. This suggests that the treatment effectiveness is not uniform across cycles and that iterative interventions are critical in stabilizing glucose levels.

Similarly, an ANOVA test was conducted to analyze the treatment success rates across cycles. The results obtained are as follows:

F-statistic = 14.4841, p-value = 0.0.

In this case, the very small p-value indicates that the treatment success rates significantly differ between cycles. This confirms that the treatment success rates also vary between cycles, reinforcing the importance of tracking treatment progress over the mentioned cycles rather than evaluating overall outcomes.

Although some minor within-patient dependency may exist, the magnitude of the observed differences (evidenced by extremely small p-values) indicates that the main findings are robust. The strong statistical significance and clinical rationale for cycle independence support the use of ANOVA as a reliable and interpretable method in this context.

These findings highlight the necessity of incorporating a cyclical approach into EMRs, unlike traditional EMRs, which often treat patient visits as isolated events and miss critical trends in the treatment response. The cycle-based structure provides deeper insights into patient progression, enabling more personalized and adaptive treatment strategies.

6.4. Results

6.4.1. Success Rate Evaluation

The results from the statistical analysis highlight the significance of adopting a cyclical approach in EMRs for the evaluation of treatment effectiveness. To illustrate the impact of a cyclical approach in treatment analysis, we visualized the treatment success rates from two different perspectives. This visualization (Figure 4) compares the treatment success rates under cyclical and non-cyclical conditions.

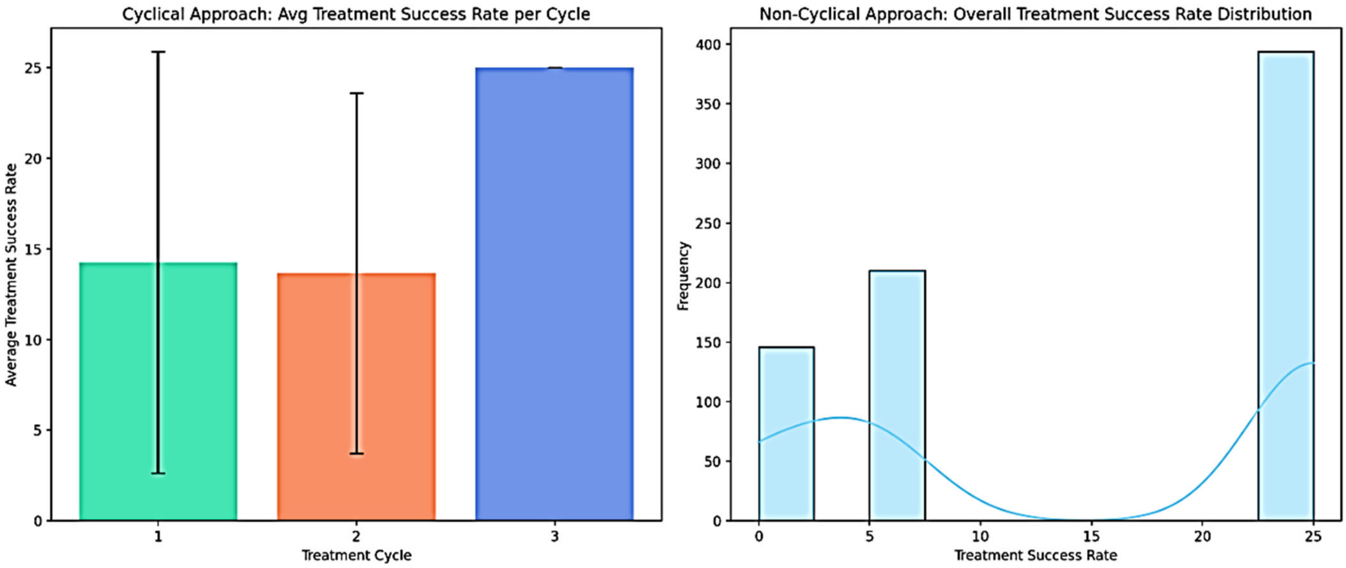

Figure 4. Treatment success rate evaluation using different approaches.

The left panel in Figure 4 presents a bar plot illustrating the average treatment success rate per cycle, with the error bars indicating standard deviations. This visualization highlights a progressive improvement in the success rate as the treatment cycles advance. The observed trend suggests that treatment responses are not uniform across cycles, reinforcing the importance of capturing cyclical data structures in EMRs. Different colours are used for each bar (Cycle 1, Cycle 2, and Cycle 3) to visually distinguish the treatment cycles, enhancing the clarity of the progressive success rate trend. The third cycle exhibits the highest success rate, indicating that iterative treatments may yield cumulative benefits over time. Conversely, the right panel depicts a histogram with a kernel density estimate (KDE) overlay [64], showing the overall distribution of the treatment success rates across all patients, irrespective of cycle classification. Without the cyclical structure, the distribution appears heterogeneous, failing to differentiate the impacts of successive treatment phases. This limitation underscores the loss of critical insights when treatment cycles are not explicitly incorporated into the analysis.

These findings demonstrate that incorporating a cyclical approach enables a more nuanced treatment success analysis, distinguishing patterns hidden in traditional, non-cyclical datasets. The Python code used to generate these visualizations is available in the Zenodo repository at https://zenodo.org/records/15066593 (accessed on 21 March 2025), allowing further exploration of this approach.

6.4.2. Information Loss Analysis

To examine the impact of the cyclical approach, we analyzed the post-treatment glucose levels across different treatment cycles and compared them to a non-cyclical perspective. The left panel of Figure 5 presents a box plot illustrating the post-treatment glucose levels for each treatment cycle. In contrast, the right panel displays a histogram accompanied by a KDE representing the overall post-treatment glucose distribution without consideration of cycle distinctions.

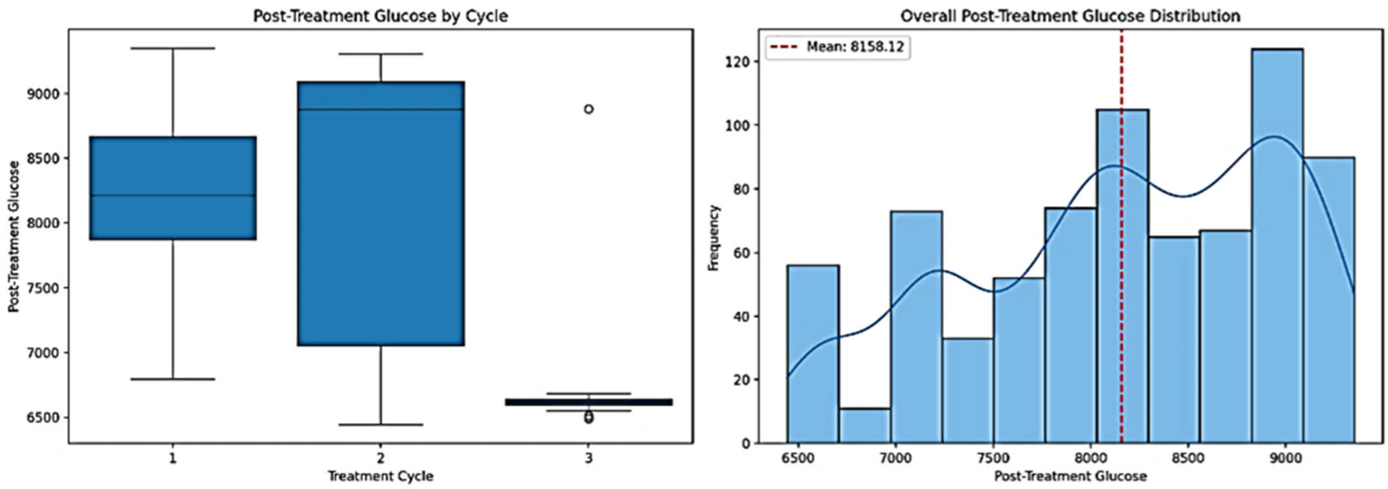

Figure 5. Post-treatment glucose evaluation using different approaches.

As depicted in the left panel of Figure 5, the post-treatment glucose levels fluctuate significantly across treatment cycles. The box plot shows that Cycle 3 has substantially lower post-treatment glucose levels than Cycles 1 and 2, indicating a potential trend where the glucose levels decrease as the treatment progresses. This suggests that successive cycles contribute to more effective glucose regulation, an insight that would be overlooked without cycle-specific analysis. Additionally, the variation in glucose levels, as indicated by the interquartile ranges and whiskers, differs significantly among cycles, underscoring the importance of evaluating treatment phases separately.

The right panel of Figure 5, which aggregates all data without accounting for cycles, provides a significantly less detailed view. The histogram shows the overall distribution of the glucose levels but does not reveal whether specific cycles are responsible for higher or lower values. The red dashed line indicates the mean glucose level. Still, without distinguishing between treatment cycles, assessing whether this average is influenced by specific cycles performing better or worse is impossible.

A quantitative analysis further supports these findings. By incorporating treatment cycles, we can observe distinct differences between the cycles. These variations are lost without this distinction, as shown in the overall distribution, leading to a less precise understanding of glucose trends. Specifically, our analysis shows that 14.96% of the variance in the post-treatment glucose levels can be explained by the treatment cycles. This means that, by ignoring the cyclical nature of treatment, we lose about 15% of the relevant information, potentially overlooking significant patterns in the patient response.

A similar trend is observed in the treatment success rates. The grouping of the data by cycle explains 37.31% of the variance, meaning that over one-third of the variation in treatment outcomes is directly related to the treatment cycle structure. Without tracking the treatment cycles separately, the mentioned information will be lost, leading to an incomplete or potentially misleading interpretation of the treatment efficacy.

These percentages originate from our ANOVA test, which quantifies how much of the total variance in the dataset is explained by differences between treatment cycles. Specifically, the ANOVA partitions the variance into two components:

Variance between treatment cycles—how much the mean values differ across cycles.

Variance within cycles—how much individual values vary within each treatment cycle.

The proportion of the variance explained by the treatment cycles, known as the eta-squared (η^2), is calculated as the ratio of the between-group variance to the total variance [65]. This metric quantifies the extent to which treatment cycles contribute to variations in the post-treatment glucose levels and treatment success rates. The obtained values suggest that incorporating treatment cycles is essential in accurately assessing glucose regulation and treatment efficacy, as it accounts for a significant portion of the observed variance.

These findings reinforce the importance of a cyclical EMR design, demonstrating that a non-cyclical system fails to capture crucial variations in patient outcomes. A complete set of Python codes for statistical analysis and visualization is available in the Zenodo repository at Metrics Comparison in cyclic and non-cyclic approaches (accessed on 18 March 2024) for further exploration and validation.

7. Discussion

This study highlights the importance of integrating a cyclical approach into EMRs to improve clinical data management and enhance the effectiveness of CDSS. Traditional EMRs primarily rely on independent, event-driven data entry, often neglecting the iterative nature of treatment plans. Our findings address this critical research gap by demonstrating how treatment cycles impact medical decision-making and the quality of predictive analytics within CDSS.

The current study's findings align with existing studies investigating the role of structured data organization in EMRs. Hripcsak et al. [66] found that longitudinal data structuring in EMRs enhances predictive analytics for chronic diseases, particularly diabetes management. However, their approach focused on temporal event sequences rather than explicitly modeling treatment cycles. Similarly, Batavia et al. [67] examined the benefits of structured data entry in EMRs, finding that predefined templates improve consistency in medical documentation and facilitate better AI-driven decision-making. While their study reinforced the value of standardization, it did not address the need for a cyclical framework. Moreover, Gifford et al. [68] investigated the effectiveness of repeated intervention tracking in EMRs and found that tracking sequential medical interventions improved treatment predictions. However, their study primarily analyzed repeat hospital admissions rather than structured treatment cycles within a single disease management framework. Our research provides a more granular approach by demonstrating how each treatment cycle uniquely contributes to the overall effectiveness of medical interventions.

A quantitative analysis of the proposed cyclical framework confirms that incorporating treatment cycles significantly enhances the precision of clinical assessments. Specifically, we observed that 14.96% of the variance in post-treatment glucose levels and 37.31% of the variance in treatment success rates could be attributed to the cyclical structure of treatments. These findings suggest that ignoring treatment cycles leads to substantial information loss, making capturing patterns in patient responses challenging over time. Without a cycle-based framework, crucial insights regarding treatment efficacy and disease progression may be overlooked, ultimately reducing the accuracy of CDSS recommendations. Although the potential benefits are evident, implementing this model in real-world practice requires addressing several critical considerations. Key topics include practical implementation strategies, usability impacts, ethical concerns, and opportunities for future research.

7.1. Implementation Challenges in Real-World EMRs

The proposed cyclical framework is currently undergoing pilot implementation in two infertility centers. This domain is particularly well suited to a cycle-based structure, given the complex and multi-staged nature of infertility treatments, which involve different levels of intervention (from prescribing medication to suggesting surgical procedures). At the end of each treatment cycle, clinical outcomes are carefully evaluated based on all practical medical elements and the patient's exclusive medical history, highlighting the critical importance of sequential data tracking.

The initial implementation phase leverages existing medical forms to mitigate workflow disruption and prevent system overload. Retaining their established structure, these forms are strategically grouped into treatment cycles through sequential sorting. Data form and field revisions will be introduced systematically only after stabilization at this stage. This gradual, structured approach facilitates a seamless transition, enabling the integration of the cyclical method into EMRs without overwhelming users.

The cyclical approach may be incompatible with existing EMR processes, which primarily support independent, event-based data entry rather than iterative, cycle-oriented documentation. To overcome these challenges, physicians and system designers must collaboratively define standardized treatment cycles, specifying structured data forms, mandatory fields, and sequence requirements to ensure alignment with clinical decision-making needs. Furthermore, flexibility in modifying treatment cycles is crucial, as protocols may evolve due to advancements in medical knowledge, patient-specific considerations, or administrative regulations. Adapting to these dynamic requirements will require continuous evaluation and refinement, ensuring that structured cycle-based data entry enhances workflow efficiency rather than impeding it.

Implementing this model requires economic, temporal, and human resource investments during the transition phase. However, by providing structured data for the evaluation of outcomes per cycle, this approach ultimately supports cost-saving through better decision-making, more efficient resource allocation, and the precise calculation of treatment cycle expenses, which is not achievable with non-cyclical models.

7.2. Usability and Clinician Adoption Concerns

Despite the revealed advantages of this approach, implementing a cycle-based framework in EMRs presents several challenges that must be carefully addressed. One of the primary concerns in implementing a cycle-based framework within EMRs is usability, which, according to ISO 9241-11 [69], encompasses effectiveness, efficiency, and user satisfaction. While the cyclical approach enhances effectiveness by improving data accuracy and supporting better clinical decision-making, it may also introduce complexity in data entry workflows. The structured nature of cycle-based documentation imposes stricter data entry protocols, which could reduce efficiency and satisfaction among healthcare providers accustomed to more flexible data input methods.

Several features and technologies proposed in prior studies can be applied to mitigate the potential documentation burden introduced by the cyclical approach. These include automated text generation (e.g., automatically generating textual reports like sonography or radiology reports from structured data inputs), default data values, and data fetching from external medical sources [70,71]. These enhancements can improve efficiency and user satisfaction, aligning with the ISO 9241-11 standard.

Moreover, the usability of the cyclical model will be systematically evaluated using the think-aloud method [72]. During the pilot project, physicians will provide real-time feedback through this technique, facilitating the identification of usability challenges and iterative system refinements. By incorporating clinician insights early in the process, we aim to elevate the usability level of the cyclical approach and foster greater acceptance among end-users.

7.3. Ethical Implications of Cycle-Based EMRs

Implementing a cyclical data structure in EMRs introduces significant ethical considerations that must be carefully addressed. A primary concern is balancing the need for standardized cycle templates (which enable cross-institutional learning and enhance clinical decision-making) with the imperative to safeguard patient confidentiality and ensure data privacy. While some structured elements of treatment cycles (such as generalized data forms and standardized fields) can be shared across systems to enhance collective medical knowledge and improve decision support, it is crucial to ensure that only non-private, non-identifiable information is used for broader applications. Data anonymization and selective filtering must be employed to protect patient confidentiality before sharing data [73,74].

Furthermore, transparency in CDSS recommendations derived from cyclical data is essential. Physicians must explicitly understand how patient data across treatment cycles shapes AI-driven or system-generated recommendations, mitigating the risk of over-reliance on automated outputs. It is crucial to underscore that the ultimate responsibility for medical decisions rests with the physicians [75,76]. The proposed approach is intended to support clinicians by offering structured insights that improve the decision-making accuracy while preserving the primacy of professional judgment.

Finally, the growing structure and data-driven nature of EMR systems necessitate continuous evaluation to ensure that patient safety, data privacy, and data ownership rights are fully respected in all implementation and data utilization stages [77].

7.4. Future Research Directions

This study establishes a foundation for several vital directions in future research. Expanding upon our findings, subsequent investigations could focus on developing machine learning models trained on cyclical treatment data to refine personalized treatment recommendations by capturing the iterative nature of patient responses more effectively. Such models could significantly improve AI-driven care, particularly for rare diseases and atypical conditions, where conventional static data structures often fail to identify nuanced response patterns.

Future research should prioritize a thorough and systematic evaluation of the usability of cycle-based frameworks. Employing iterative user feedback throughout different stages of system design and implementation (guided by established scientific usability evaluation frameworks) will be essential. This approach will help to continuously refine the system based on real-world physician experiences, enhancing its effectiveness, efficiency, and user satisfaction.

Moreover, a critical research direction entails the development of standardized treatment cycles customized for specific medical domains. Academic efforts aimed at defining and validating cycle templates for fields such as infertility treatment, oncology, and chronic disease management would ensure that cyclical documentation aligns with the clinical practices of these specialties while preserving system interoperability and adaptability. These initiatives would significantly enhance the practical utility and adoption potential of cycle-based EMRs across diverse healthcare settings.

8. Conclusions

This study introduces a scientifically grounded definition of cyclical treatment structures and explores their implications for EMRs and CDSS. A comprehensive review of existing studies identified a critical gap in how treatment cycles are represented in EMRs, which often fail to capture the iterative nature of medical interventions. We proposed a structured, cycle-based approach to EMR design to address this issue, outlining its necessity in improving data organization and supporting more precise clinical decision-making.

Beyond the conceptual foundation, we examined the practical implementation of this approach, detailing how cyclical treatment structures can be integrated within EMRs to enhance the accuracy and relevance of stored medical data. We empirically demonstrated its advantages by analyzing structured treatment cycles, showing that this method preserves crucial variations in patient responses that would otherwise be overlooked. The findings indicate that incorporating treatment cycles accounts for a substantial portion of the variance in both post-treatment glucose levels and treatment success rates, reinforcing the value of this structured approach in medical decision-making.

By aligning EMR data structures more closely with real-world clinical workflows, this study provides a framework that meets physicians' needs for structured, context-aware data analysis. The proposed approach ensures that patient records reflect the actual progression of treatment, aiding physicians in evaluating past interventions and optimizing future treatment strategies. This is particularly critical in complex and long-term conditions where treatment plans evolve.

Moreover, this research contributes to the ongoing evolution of medical data management by proposing a structured methodology that balances data granularity with usability. While workflow integration and user adoption must be addressed, this study establishes a foundation for future research into AI-driven analytics, predictive modeling, and personalized medicine.

In conclusion, the current study provides a theoretical and empirical basis for the integration of cyclical treatment structures into EMRs, offering a scientifically validated solution to a pressing challenge in CDSS design. As medical data systems evolve continuously, adopting this structured approach will improve diagnostic accuracy, refine treatment plans, and ultimately enhance patient care.

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Annex *F.*

Private Health Record system: Improving the patient's medical knowledge with an e-learning approach

Private Health Record System: Improving the Patient's Medical Knowledge with an e-Learning Approach

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Private Health Record System: Improving the Patient's Medical Knowledge with an e-Learning Approach

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Abstract. The recent circumstance related to the COVID-19 pandemic has highlighted the healthcare issues and medical internet systems. A more prominent tip is the role of education in treating and preventing medical problems through the internet. Now consider that this training is completely tailored to the patient's unique medical needs. In this direction, this paper initially presents the Personal Health Record concepts, related works, and best practices to prepare the best manner for the PHR platform. It also outlines the proposal for PHR in which the patient will receive the necessary educational tips depending on their specific medical needs which are determined based on available information in Electronic Medical Records including the patient's medical history, lifestyle, type of habits, and behavior, medication history, surgeries performed in previous years, accurate diagnosis and medical advice. Based on the proposed model, the paper concludes by providing directions toward achieving several solutions to implement an e-learning platform embedded in PHR. Its content will be compatible with each patient's circumstances exclusively so it will lead to delivering targeted training instead of some general medical advice.

Keywords: Private Health Record (PHR) · e-learning · EMR · eHealth

1 Introduction

Numerous e-Health systems and apps have been created as a result of the constant requirement for collecting, managing, and utilizing patient health-related data [1]. A hospital's administrative, financial, and clinical components are managed through a hospital information system (HIS), which is an extensive, integrated information system. [2]. The significance of these systems stems from their crucial role in maintaining all types of patient data and information, including vital information about the patient and other comprehensive medical data. They also play a crucial role in keeping track of all medical services provided to the patient, including investigations, diagnoses, treatments, follow-up reports, and crucial medical decisions [3]. A collection of computerized tools known as the Personal Health Record (PHR) have been described as enabling people to access, organize, and make relevant portions of their lifelong health information

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available to others who need them [4]. Although there are many potential advantages to using personal health records (PHRs), including more patient participation, poor usability is still a major deterrent to people using PHRs [5]. Despite their advantageous characteristics, such PHRs' inefficient, unproductive, and convoluted designs result in disgruntled consumers who stop using them [6].

Maintaining a PHR creates more emphasis on communication between the patient and the providers as well as enhanced personal involvement in healthcare. The development of a PHR offers healthcare professionals the chance to inform patients about personal health issues and offers a tool for enhancing health literacy. Patients' capacity to participate in decision-making is improved as they grow more skilled at communicating with their caregivers and documenting crucial health information. The PHR can be modified to meet the needs of the individual through the assessment of health literacy and functional competence. Early identification of family members or other important people is crucial, and teaching efforts should start right away [7].

Some facilities and expressions, like telemedicine and PHR, will eventually need to be combined as we work to create a more interactive environment for patients and caregivers. This will increase user acceptance and usability and, in turn, enable us to provide patients with high-quality training [8].

The ability of patients to manage their health and the healthcare system by making sense of increasingly complicated information is restricted in clinical settings. Videos for patient education may assist to convey important information, but they are frequently impersonal and time-consuming to develop or update with new research [9].

Different levels of patient activation can be accommodated with individualized support and education strategies. These tactics might be used in a variety of clinical contexts and circumstances, including the use of health coaching, targeted care transition techniques, and collaborative decision-making [10]. Patients who had access to their inpatient personal health records, which allowed them to examine their hospital prescriptions and obtain information about their medical issues, expressed a high level of satisfaction with these features. Patients expressed a wish to access instructional materials regarding their post-acute rehabilitation and receive daily progress updates about their hospital stay [11] EMRs keep track of a variety of patient data that is digitally structured, including demographic information, medical history, radiography, and laboratory findings [12]. Although many articles and conferences have discussed the benefits of PHR and also there are lots of papers about learning the patients via the internet (e-learning), the targeted training for the patient which is based on the detected need through existing information in EMR is considered a kind of shortage among these studies, hence we have attempted to address this important issue. Indeed, in this paper, we will study how can we design a PHR associated with the facility to educate the patients according to their specific needs and of course in a user-friendly, interactive, targeted, and customized environment.

In the rest of this paper, first, we have addressed some related works, that have pointed to PHR and its role in patient learning, in the next sections, in order, we will talk about learning the patients through PHR, the role of EMR in e-learning, and we will compare the patient's e-learning approach via the PHR and without it. In the end, we will conclude the mentioned issues.

2 Related Works

The implementation of patient portals in the United States will allow authorized professionals (EPs) to communicate with patients via secure electronic messages, "allowing patients to view, download, and submit their health information online." is increasing due to reasonable use standards that require that Within 4 business days of the information becoming available to EP" [13]. The use of e-health components including electronic health records (EHR), health information exchange (HIE), telemedicine, and personal health records (PHR), despite the fact that e-health has been shown to enhance healthcare quality, is either minimal or nonexistent in European nations. This is partially caused by elements that influence people's perceptions, obstacles and difficulties faced by health professionals, and how professionals learn to embrace this new system and subsequently make it accessible to the infrastructure [14]. PHRs can be untethered (stand-alone) or tethered (linked) to an electronic medical record (EMR) run by a healthcare system or provider [15]. Because they have a better grasp of their health and associated issues, patients using PHRs may be more likely to participate actively in their care. There is more pressure on hospitals and doctors to give PHRs to their patients. PHR adoption is advantageous since it enables the correction of inaccuracies in medical records and offers patients access to the data for sharing with other healthcare professionals. In contrast, it's possible that every practitioner uses a unique system, which makes it challenging for patients to use. The typical healthcare consumer would find it extremely difficult to manually maintain data integrity across many PHRs offered by retail pharmacies, insurance providers, hospitals, doctor offices, and patient-generated systems Melissa et al. [16]. As expounded by Yaser et al. [17] Numerous nations have set a goal for the creation of a national infrastructure that will improve the safety, quality, and provision of healthcare. They addressed the fact that such infrastructure is necessary for allowing and sustaining safe access to health-related information from multiple EHR systems across several areas of a nation during their study. The implementation of nationally integrated ePHRs will be aided by this integration of various EHR systems, according to their declarations, which promises a host of advantages for all parties involved in healthcare, including patients, providers, professionals, and the healthcare system as a whole. The PHR Adoption Model identifies four variables that might affect behavior and potentially modify outcomes: Personal, technological, environmental, and chronic disease-related elements Melanie et al. [18]. Personal health records (PHRs) connected to hospitals can offer reliable data, but if the hospital does not create and distribute PHRs, the information is not available electronically. Additionally, we discovered a number of challenges to overcome in order to consolidate health data [19]. Today's medical environment makes extensive use of hospital information systems, including electronic medical record (EMR) systems, radiology information systems (RIS), laboratory information systems (LIS), pharmacy systems, and others. Different types of databases, such as Oracle, MySQL, etc., may be used in these heterogeneous systems. Tables and fields may have varied designs. Different databases' interpretations of the same filed name are possible. It is incredibly difficult and time-consuming to extract and transform data from diverse systems. Thankfully, data table interfaces or integrative platforms have also been used to completely develop the integration environment [20]. In another study, Sharon et al. [21] expounded that in the present healthcare environment, e-learning choices utilizing web-based technology are quickly supplanting or replacing more conventional face-to-face types of professional development training for health professionals.

A prominent study about the role of PHR in e-learning has been conducted by Luis et al. [22] explained that the participants most commonly emphasized usability while discussing the needs for the eLearning platform. The participants highlighted that the platform should pay special attention to the needs of older persons. In terms of content, instructions for using the PHR, knowledge of its principles, and access authorization were mentioned.

F. J. García-Peñalvo et al. [23] have pointed out that creating user-friendly interfaces for the health sector might simplify complex procedures and save up time for doctors. This issue has been investigated by Saeideh [24] from another angle and she has expressed that as a novel training approach, e-learning for patients is now easier to use and more appealing when combined with text, voice, picture, and video. However, despite the numerous benefits of e-success learning in self-care, it has been noticed in practice that professional people's performance in clinical settings and even in educational contexts is inappropriate for patient education. Line et al. [25] suggest multimedia and interactive elements in patient education to augment more traditional methods of disseminating health information. Additionally, their research expands their understanding of the creative design process of digital tools and how to incorporate several viewpoints, i.e., using patients', health professionals', and professionals' professional experience and knowledge of communication and digital learning in the design.

3 The Patient's e-Learning Through PHR

To improve health care outcomes, physicians must spend more time with patients [26]. This study explains that the teaching related to the physician's interaction with the patient must be enthusiastic, motivated, and responsive to the individual patient's needs. Timothy et al. [26] clarify that for individual members of our society to realize the benefits of physician's health education, there is a need for a robust, hearty engagement between patients and physicians. Although training the patient via the internet helps the curing trend, shrinking the training circle along with targeting them increases the efficiency of the education. It means that the patient ac-cording to his/her characteristics, age, gender, habits, medical history, drug history, and even doctor's advice and prescription can receive the necessary training and employ them to cure optimally. This is exactly why patient education must be placed in his/her profile as a part of PHR. As it has been indicated in Fig. 1, e-learning can be one of the beneficial sections of the PHR environment.

Patients after logging in his/her profile will be able to access the necessary educational material consisting of web pages, pdf files, and video files whole of them have been considered for the patient by the medical personnel and certainly according to the registered data in EMR.

Fig. 1. Personal Health Record components

In this study, to better perceive, we assume that an infertile couple in the infertility center has entered the e-learning section of their PHR. As it will be illustrated in Fig. 2, they will encounter what they need to be taught in the cure plan. These education materials are presented completely considering their characteristics and treatment method.

Fig. 2. e-Learning section in PHR

As has been indicated in the above figure, the necessary educational content according to the needs of the patient and categorized will appear in the e-learning section and the patient can exploit them during his/her treatment.

Even in some cases and on-demand, the medical personnel will be able to control whether these educational parts have been utilized by the patient or not. These types of control about the patient's use of the educational content intended for her/him often are crucial for the nurses, doctors, or other medical personnel while it cannot be controlled by training the patient out of the PHR (or another dedicated environment). So the implementation of e-learning as a new member of the PHR body will lead to some advantages like this which be mentioned above.

4 The Role of EMR in e-Learning of the Patients

The benefits of facilitating patient access to the EMR through web-based, PHR portals may be substantial; foremost is the potential to enhance the flow of information between patients and healthcare practitioners [27]. This study has emphasized that the benefits of improved communication and transparency of care are presumed to be a reduction in clinical errors, increased quality of care, better patient management of disease, and better disease and symptom comprehension. When physicians intend to provide targeted education to their patients, EMR can be considered a suitable and reliable resource for this purpose. It means the physicians through utilizing the available information in EMR including medical historical data, curing processes, the patient's living habits, diagnosis of the medical problem, and treatment plan will be able to select the best educational package for the patient.

For instance, when an infertile couple refers to the infertility center and the necessary data related to them has been entered in the data forms of EMR, the assigned nurse according to the information available in EMR that it indicates the man is a smoker and fat person with normal sperm and with a previous history of high blood pressure and for example, the treatment plan specified for him is the plan which is called TP26 so the best educational package is P2 and also for his wife who is thin, (alcohol) drinker, with history of abortion and because of the doctor's diagnosis will have surgery in the next month and her treatment plan is TP34 so the best educational package for her is P7. Considering the patient's conditions in the different dimensions the best educational package will select and place in the PHR. To clarify the issue, we have proposed a model in Fig. 3 which represents the scenario that takes place to choose the most useful package related to the patient's e-learning. It has indicated that a part of the mentioned processes has been placed inside of HIS (Hospital Information System) and another part is out of HIS and accessible through the internet.

We review the scenario steps that occurred in this model:

- whole educational files have been categorized by the medical specialist and depending on the needs of each patient in his/her unique situation.
- For example, package num.3 (P3) belongs to the patients who are male, their age is between 30–50, are not smokers, their treatment plan is TP10 and they are diabetic.
- The medical personnel, by reviewing the summary information they have on the data form, selects the most suitable educational package and assigns it to the patient. The mentioned data form will be shown just the significant and key factors which are effective in the choice of the educational package.

- The assigned packages will be stored in the HIS server which is communicated to the PHR server via the cloud services.
- When the patient as an active user logs in to his/her PHR portal, in the e-learning section, can access the assigned educational materials.

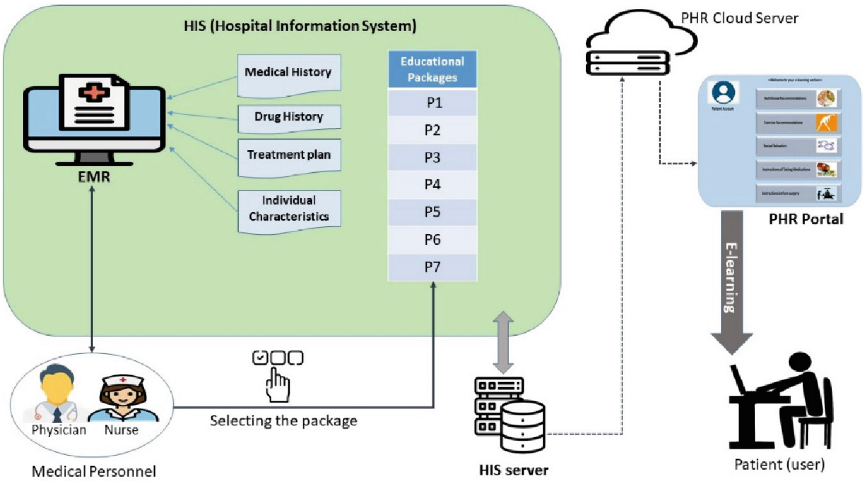

Fig. 3. The patient's e-learning model via EMR and PHR

5 Comparison of the Patient's e-Learning Approach via the PHR and Without It

Commonly, when the nurses and physicians want to advise the patient to exploit the educational resource, they use some prevalent ways such as paper guidelines, Oral explanations, or addressing some internet resources. They recommend the web pages through the URL or presenting the QR codes, etc. But in this paper, we have proposed a model of medical e-learning which is completely different and undoubtedly has several advantages compared to the current e-learning style. To clarify this difference, we have compared the patient's e-learning in Table 1 and two statuses: via the PHR portal and the current one (just through the internet).

Table 1. Comparison of patient's e-learning in two different approaches

attributes	e-learning embedded in PHR	e-learning out of the PHR portal
Being Personalized	The educational materials personalized for the patient	The educational material is not dedicated to the patient
Confusion	Just the necessary training is accessible for the patient	Finding the patient's educational materials is confusing
Usage control	Medical personnel will be able to control the extent to which patients use educational materials	The level of use of educational material is not controllable
Interactivity	The patient can contact the medical group to clear up any ambiguity about the educational content	Interactive features are not provided for this purpose
Sequence of the content	The priority for the display of the educational materials is controllable	The order in which educational content is displayed cannot be controlled
The patient adoption	When the patient knows that the educational content is prepared dedicatedly, will easily adapt to it	Due to the scattering of educational materials, the patient may not be able to adapt to them

6 Conclusions

Like other realms, in the medical field, integration of information systems and also platforms will be along with vast advantages, indeed the physicians will be able to reap the result of the made efforts in implementing some essential infrastructure like HIS and EMR. When digital data forms have been designed based on data science, they are comprehensive and cover whole health needs and data entry has been performed by the medical personnel, why we should not employ the prepared infrastructure to meliorate the medical services?

Regarding the proposed model in this study, whereas the patients will receive the targeted training, in addition to the benefits listed in Table 1, they will feel that they have received the attention of medical personnel and they are monitoring the patient's treatment process and certainly, it leads to evokes a live environment for the patient.

In future studies, we can investigate the role of this kind of e-learning (embedded in PHR) for the patients in evaluating the effectiveness of educational materials provided to the patients and also how can the medical personnel get the patient's feedback for improving this platform and its educational material.

We hope that by conducting these kinds of studies and promoting better suggestions, we manage to play even a small role in the improvement of patients.

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Annex *G.*

Resumen Extendido:

El rol de la ciencia de datos en las historias clínicas electrónicas.

¿Cómo se puede mejorar la toma de decisiones médicas basándose en un historial médico electrónico completo?

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Tesis doctoral

Programa de doctorado en Ingeniería Informática

Departamento de Informática y Automática

Autor: Ali Azadi

Director: Prof. Dr. Francisco José García-Peñalvo

Diciembre 2025

Resumen extendido

Las historias clínicas electrónicas (HCE) se han consolidado como el principal canal de entrada de datos para los Sistemas de Apoyo a la Decisión Clínica (CDSS, por sus siglas en inglés), desempeñando un papel cada vez más central en la gestión de información médica y en la generación de recomendaciones clínicas [1]. Pese a que conceptos técnicos como "dirigido por datos" (en inglés, *data-driven*) y "toma de decisiones asistida" se han convertido en pilares del desarrollo tecnológico en salud, la interacción entre los profesionales sanitarios y los sistemas digitales sigue presentando desafíos significativos [2]. En particular, la falta de atención a los principios de Interacción Persona-Ordenador (IPO) limita la eficacia, la eficiencia y la adopción de los CDSS en entornos reales [3].

Aunque existen estudios que abordan elementos de IPO en aplicaciones médicas generales, pocos se centran en el contexto específico de los CDSS, donde la complejidad de las decisiones clínicas, la sensibilidad de los datos y la presión asistencial exigen enfoques adaptados. Esta omisión es crítica, ya que los CDSS deben integrar conocimiento médico complejo, cumplir con protocolos clínicos estrictos y minimizar la carga cognitiva del usuario. En este sentido, los elementos de IPO (como la explicabilidad, la visibilidad de los datos, el diseño de alertas o la estructura de entrada de información) no deben considerarse accesorios, sino componentes esenciales que influyen directamente en la calidad de las decisiones clínicas y en la experiencia del usuario.

Para abordar esta brecha, la investigación se ha estructurado en torno a tres objetivos principales: (i) identificar y categorizar los métodos de evaluación utilizados en aplicaciones CDSS, con el fin de comprender cuáles son los más adecuados para valorar los elementos de IPO en distintos contextos; (ii) examinar los elementos específicos de IPO que influyen en la funcionalidad y los resultados de los CDSS, analizando cómo contribuyen al rendimiento del sistema y a la satisfacción del usuario; y (iii) investigar el impacto de estos elementos sobre la eficacia y eficiencia de los CDSS, determinando en qué medida afectan los procesos de toma de decisiones clínicas y los resultados en pacientes.

La presente investigación aborda esta brecha mediante un enfoque metodológico mixto que combina revisión sistemática, análisis cualitativo y evaluación empírica. Para ello, se ha realizado una revisión sistemática de la literatura (SLR, por sus siglas en inglés) bajo las directrices propuestas por Kitchenham [4], [5], con el objetivo de identificar y categorizar los métodos de evaluación aplicados a elementos de IPO en entornos de CDSS. Esta revisión permitió establecer la novedad del enfoque propuesto y sentar las bases para el análisis posterior.

Complementariamente, se ha aplicado un análisis cualitativo que incluye técnicas de análisis de contenido y síntesis temática [6], [7], con el fin de extraer patrones, relaciones y matices contextuales que enriquecen la comprensión de los elementos de IPO y su impacto en la funcionalidad de los CDSS. Este enfoque permitió identificar tanto los facilitadores como las barreras de IPO, así como proponer directrices metodológicas adaptables a distintos entornos clínicos.

Finalmente, se ha incorporado una fase empírica basada en la evaluación cuantitativa de modelos y estructuras de datos. Para ello, se han utilizado los conjuntos MIMIC-IV y MIMIC-III, ampliamente reconocidos en la comunidad científica, junto con un conjunto sintético desarrollado específicamente para esta tesis (MIMIC-Cycle750), que incorpora ciclos de tratamiento y dinámicas temporales [8], [9]. El modelo cíclico propuesto organiza los datos clínicos en fases de tratamiento, lo que mejora la trazabilidad, la explicabilidad y la alineación con la lógica clínica. Los resultados obtenidos proporcionan evidencia robusta de que este enfoque mejora la precisión diagnóstica y se ajusta mejor a los flujos de trabajo reales, subrayando la relevancia del diseño de interfaces y de la experiencia del usuario en el apoyo a la toma de decisiones médicas.

Las metodologías seleccionadas permiten una investigación rigurosa y matizada de los elementos de IPO en entornos de CDSS. La SLR proporciona una base sólida mediante la síntesis sistemática del conocimiento existente; el análisis cualitativo enriquece esta base con perspectivas contextuales detalladas; y la evaluación empírica valida el marco propuesto, conectando el rendimiento técnico con consideraciones clave de IPO. Esta combinación metodológica permite abordar las preguntas de investigación desde múltiples ángulos y ofrecer conclusiones sólidas tanto para futuras investigaciones como para aplicaciones prácticas en el diseño de sistemas clínicos centrados en el usuario.

En el marco de esta investigación, se ha actualizado y ampliado la literatura hasta la preparación de la versión final de la tesis en octubre de 2025. Esta revisión ha permitido consolidar una base de conocimiento más sólida y actualizada sobre los elementos de IPO aplicables en CDSS. En total, se identificaron 1042 publicaciones científicas a partir de las bases de datos Scopus, Web of Science y PubMed. Tras eliminar los registros duplicados, se procedió a una primera fase de cribado mediante la lectura de resúmenes, lo que permitió reducir el conjunto a 708 artículos. De estos, 188 fueron seleccionados para su lectura completa. Finalmente, tras un análisis exhaustivo del contenido y la aplicación de criterios rigurosos de inclusión, exclusión y evaluación de calidad, se seleccionaron 68 estudios para el análisis final. El examen detallado de estos trabajos permitió identificar doce elementos clave de IPO que inciden de forma directa en la funcionalidad, la eficiencia y la usabilidad de los CDSS. Los resultados obtenidos a través de esta revisión han respondido de forma clara y estructurada a las preguntas planteadas en las fases iniciales del proyecto. Se ha logrado establecer qué elementos de IPO son más relevantes en el contexto clínico, cómo influyen en la calidad de las decisiones médicas y de qué manera pueden integrarse en el diseño de sistemas para mejorar su eficacia, eficiencia y aceptación por parte de los usuarios. Esta contribución resulta especialmente valiosa en un momento en que la digitalización de los procesos clínicos exige soluciones tecnológicas que no solo sean funcionales, sino también comprensibles, intuitivas y adaptadas a las necesidades reales del personal sanitario.

Uno de los hallazgos más significativos del estudio fue la identificación de ***doce elementos*** clave de IPO: satisfacción del usuario, flexibilidad, individualidad, visibilidad, explicabilidad, control del usuario, facilidad de uso, ingreso de datos, alertas, simplificación, esfuerzo mental e interfaz [10], [11]. Estos elementos fueron alineados con el marco ISO 9241-11, que define la usabilidad en términos de eficacia, eficiencia y satisfacción [11]. Esta clasificación permitió comprender que ciertos elementos refuerzan la eficacia del sistema al facilitar la comprensión de las recomendaciones clínicas (como la visibilidad y la explicabilidad), mientras que otros optimizan la eficiencia al reducir la carga cognitiva y agilizar la navegación (como la facilidad de uso y la simplificación). Finalmente, componentes como la satisfacción del usuario, la flexibilidad y la individualidad contribuyen a mejorar la aceptación del sistema y su adaptabilidad a distintos perfiles profesionales.

Cabe destacar que algunos elementos tienen un impacto transversal, influyendo simultáneamente en varias dimensiones de la usabilidad. Por ejemplo, el ingreso de datos estructurado no solo mejora la precisión de las decisiones, sino que también facilita la integración del sistema en los flujos de trabajo clínicos [12]. El diseño de alertas, cuando se implementa correctamente, proporciona información crítica sin saturar al usuario, lo que mejora tanto la efectividad como la eficiencia del sistema [13],[14]. Asimismo, la interfaz actúa como puente entre el usuario y el sistema, siendo determinante para la calidad de la interacción y la comprensión de los contenidos clínicos [15].

Desde una perspectiva geográfica, el análisis reveló que Estados Unidos ha sido el país con mayor producción científica en este ámbito. Las contribuciones estadounidenses se han centrado especialmente en elementos como el diseño de alertas, la facilidad de uso, la explicabilidad, la satisfacción del usuario, la interfaz, el esfuerzo mental, el control del usuario, la visibilidad y la individualidad. Esta concentración temática refleja una clara orientación hacia el diseño centrado en el usuario y la mejora de la experiencia clínica mediante soluciones tecnológicas adaptadas. Además, se observó una notable evolución temporal en la literatura, con un incremento significativo en los últimos años, especialmente en torno al elemento de satisfacción del usuario. Esta tendencia pone de manifiesto el creciente reconocimiento del diseño centrado en el usuario (en inglés, *User Center Design*) como componente esencial en el desarrollo de tecnologías sanitarias [16].

El énfasis en la satisfacción del usuario no es casual. En un entorno clínico cada vez más digitalizado, la aceptación de los sistemas por parte de los profesionales sanitarios depende en gran medida de su experiencia de uso. Sistemas que no consideran adecuadamente los principios de IPO pueden generar frustración, errores en la introducción de datos y una baja adopción, lo que compromete su utilidad clínica [17]. Por el contrario, sistemas diseñados con

Una orientación clara hacia la usabilidad y la experiencia del usuario puede facilitar la toma de decisiones, mejorar la calidad de los datos registrados y, en última instancia, contribuir a mejores resultados clínicos [18].

La revisión también permitió identificar patrones de publicación y distribución temática. Se observó que la mayoría de los estudios se publicaron en revistas científicas de alto impacto y que los congresos internacionales han comenzado a incorporar sesiones específicas sobre IPO en sistemas clínicos. Esta evolución refleja una madurez creciente en el campo, así como una mayor conciencia sobre la necesidad de integrar perspectivas multidisciplinares (como la ergonomía, la psicología cognitiva y la ingeniería de software) en el diseño de soluciones médicas digitales.

En conjunto, esta revisión sistemática ha permitido construir un marco conceptual sólido para el diseño de CDSS centrados en el usuario. Los elementos identificados no deben considerarse componentes aislados, sino piezas interdependientes que, integradas adecuadamente, pueden transformar la experiencia clínica digital. La evidencia recopilada ofrece una guía práctica para investigadores, diseñadores y profesionales sanitarios interesados en desarrollar sistemas más fiables, comprensibles y adaptados a las necesidades reales del entorno médico. Esta contribución no solo responde a una necesidad científica, sino que también tiene implicaciones directas en la práctica clínica, al facilitar la adopción de tecnologías que realmente apoyen la toma de decisiones médicas de forma segura, eficiente y humana.

La interacción persona-ordenador constituye un eje central en el diseño y la funcionalidad de los CDSS, ya que determina en gran medida cómo los profesionales sanitarios interactúan con estas herramientas digitales en su práctica diaria. ***Evaluar los elementos de IPO*** en el contexto de los CDSS no solo es relevante desde una perspectiva técnica, sino que resulta indispensable para garantizar que estos sistemas realmente contribuyan a mejorar la atención médica, optimizar los flujos de trabajo clínicos y facilitar la toma de decisiones informadas y seguras [19],[20].

En entornos clínicos, donde las decisiones deben tomarse con rapidez y precisión, la integración adecuada entre el sistema y el usuario humano es crítica. Un diseño que no contemple los principios de IPO puede derivar en errores, ineficiencias operativas, frustración del usuario y, en última instancia, en una disminución de la calidad asistencial. Por ello, la evaluación de estos sistemas debe incluir no solo métricas de rendimiento técnico, sino también indicadores de experiencia del usuario, adaptabilidad y facilidad de uso [21].

La importancia de evaluar los aspectos de IPO en los CDSS se acentúa aún más si se considera la diversidad de contextos clínicos en los que estos sistemas se implementan. Las condiciones de uso, el perfil del usuario, el tipo de decisión clínica que se apoya y el entorno organizativo son variables que influyen directamente en la interacción con el sistema. En este sentido, seleccionar el método de evaluación adecuado se convierte en una decisión estratégica que debe considerar factores como el tiempo disponible para el usuario, el propósito de la investigación, el tipo de sistema evaluado y los elementos específicos de IPO que se desean analizar [22],[23].

Dentro del alcance de esta tesis, se plantea como objetivo examinar cómo la atención a los elementos de IPO puede influir en el rendimiento global de los CDSS. Para ello, es necesario identificar y aplicar los métodos de evaluación más adecuados, lo que exige un conocimiento profundo de las metodologías disponibles y de su aplicabilidad en el contexto clínico.

A pesar de que diversos estudios han abordado los factores de IPO y su impacto en la funcionalidad de los CDSS, la literatura científica carece de una clasificación sistemática de los métodos de evaluación disponibles, especialmente en función de las circunstancias específicas que se presentan en estos sistemas. En muchos casos, los estudios mencionan brevemente el método utilizado sin justificar su elección ni analizar su adecuación al contexto clínico. Esta carencia metodológica limita la posibilidad de replicar los estudios, comparar resultados y avanzar hacia estándares de evaluación más sólidos. La mencionada categorización relacionada con los métodos de evaluación de IPO aborda dicha laguna mediante la propuesta de una taxonomía comprensiva de métodos de evaluación de IPO aplicables en entornos CDSS. Esta clasificación se basa en los resultados obtenidos en la SLR descrita, en la que se analizaron los estudios más relevantes centrados en el entorno CDSS. A partir de esta revisión, se identificaron los métodos de evaluación utilizados en los trabajos seleccionados, lo que permite establecer un marco para seleccionar las técnicas que mejor abordan los elementos de IPO identificados.

En el ámbito de la usabilidad, se han identificado varios métodos individuales que permiten analizar cómo los usuarios interactúan con el sistema, qué dificultades encuentran y cómo perciben la experiencia de uso. Entre los más destacados se encuentra el método *"Think Aloud"*, una técnica de observación directa en la que los usuarios verbalizan sus pensamientos mientras realizan tareas específicas. Esta técnica permite detectar expectativas, confusiones y patrones cognitivos durante la interacción, proporcionando información valiosa sobre la facilidad de uso y la comprensión del sistema [24],[25].

Otro método relevante es el *"Near Live Testing"*, que consiste en simular situaciones clínicas reales mediante la participación de actores que representan pacientes. Los usuarios interactúan con el sistema en condiciones similares a las del entorno clínico, lo que permite evaluar la naturalidad de la interacción y la adecuación del sistema al flujo de trabajo médico [26]. Una variante más colaborativa es el *"Pluralistic Usability Walkthrough"*, que incorpora a usuarios representativos, desarrolladores y expertos en factores humanos en el proceso de evaluación. Los participantes asumen el rol de usuario y proponen acciones para cada pantalla antes de discutirlas en grupo, lo que permite integrar múltiples perspectivas en el análisis de la interfaz [27]. También se han identificado métodos más estructurados como las inspecciones formales de usabilidad, en las que expertos en diseño de interfaces revisan el desempeño potencial del usuario en tareas específicas. Este enfoque permite detectar errores de forma rápida y técnica, optimizando el proceso de evaluación [28].

Por otro lado, el método "*Quick and Dirty Usability Testing*", propuesto por John Brooke [29], utiliza el cuestionario SUS (en inglés, *System Usability Scale*) para medir la percepción de usabilidad mediante una escala Likert. Este enfoque es especialmente útil en contextos donde se requiere una evaluación rápida y cuantificable de la experiencia del usuario.

Además de los métodos individuales, se han desarrollado enfoques multimodales que combinan varias técnicas para obtener una visión más completa de la interacción. Por ejemplo, el estudio de Horsky et al. [30] propone un enfoque mixto que incluye diseño iterativo, entrevistas clínicas, análisis de registros, inspección de usabilidad y *walkthrough* cognitivo. Esta combinación permite abordar la evaluación desde múltiples dimensiones, adaptándose a las necesidades específicas del sistema. Otro ejemplo de integración metodológica es el uso combinado de *Think Aloud* y *Near Live Testing*, como se describe en el estudio de Li et al. [31]. En este caso, se aplican ambas técnicas en fases sucesivas para evaluar la interacción del usuario con el sistema, primero mediante verbalización de pensamientos y luego en simulaciones clínicas. Esta estrategia permite obtener perspectivas complementarias sobre la usabilidad y la adecuación del sistema al entorno clínico [32],[33],[34].

En cuanto a la evaluación de la precisión del sistema, se han identificado métodos que permiten medir *la fiabilidad de las decisiones generadas* por el CDSS. Uno de ellos es el análisis estadístico de errores, como el propuesto por Chantal et al. [35], que compara puntuaciones de riesgo calculadas manualmente y por el sistema mediante análisis de regresión. Este enfoque permite visualizar el grado de concordancia entre diferentes métodos de cálculo y evaluar la eficiencia del sistema automatizado.

También se han utilizado métricas como los valores predictivos positivos y negativos (PPV y NPV), que permiten evaluar la precisión diagnóstica del sistema. Estas métricas se basan en la proporción de verdaderos positivos y negativos respecto al total de resultados y se complementan con indicadores como la sensibilidad y la especificidad [36],[37],[38]. Estos métodos son especialmente útiles para determinar la fiabilidad del sistema en la identificación de condiciones clínicas específicas. Además, en algunas ocasiones se ha aplicado el método de comparación con estándares de oro, en el que los resultados del CDSS se contrastan con diagnósticos establecidos por expertos. Este enfoque, utilizado por Helena et al. [39], permite validar la precisión del sistema mediante pruebas estadísticas como la prueba de Wilcoxon [40], evaluando las diferencias entre ambos conjuntos de datos.

En conjunto, estos métodos de evaluación ofrecen un abanico de posibilidades para analizar los elementos de IPO en CDSS desde distintas perspectivas. La elección del método más adecuado dependerá del objetivo del estudio, del contexto clínico y del elemento específico que se desea investigar. Al aplicar estas metodologías de forma estratégica, se contribuye a mejorar la calidad de los sistemas, aumentar su aceptación por parte de los profesionales sanitarios y optimizar su impacto en la atención médica.

Comprender ***los obstáculos*** que dificultan la interacción entre el usuario y el sistema es tan esencial como identificar los elementos que la favorecen. En el contexto de los CDSS, donde las decisiones clínicas deben tomarse con rapidez y precisión, cualquier fricción en la experiencia del usuario puede tener consecuencias directas sobre la calidad asistencial. A pesar de los avances tecnológicos que han mejorado la accesibilidad, disponibilidad y seguridad de los sistemas médicos informatizados, persisten barreras que limitan la participación de los profesionales sanitarios y comprometen los resultados clínicos [41].

Uno de los desafíos más recurrentes es ***la fatiga por alertas***, fenómeno que se produce cuando el sistema genera notificaciones excesivas, muchas de ellas irrelevantes o poco ajustadas al contexto clínico. Aunque las alertas tienen como objetivo advertir al médico sobre situaciones críticas, su uso indiscriminado puede saturar la capacidad cognitiva del usuario, provocar desensibilización y llevar al abandono sistemático de las advertencias, incluso cuando son pertinentes [42]. Esta situación, conocida como *override* (omitir las alertas), representa un riesgo significativo para la seguridad del paciente y se ha convertido en un indicador clave para evaluar la eficacia de los CDSS [43]. Cuando las alertas no responden a las necesidades reales del profesional, se convierten en una fuente de frustración y rechazo [44], lo que puede derivar en consecuencias clínicas no deseadas [45].

Otro obstáculo importante es ***la adversidad relacionada con la carga de trabajo***. Esta puede originarse tanto por el volumen de tareas impuestas por el sistema como por la falta de alineación entre los flujos definidos por el CDSS y los procesos clínicos reales [46]. Los profesionales sanitarios suelen señalar que el sistema exige una entrada de datos excesiva, interrumpe con frecuencia su actividad y carece de orientación intuitiva [47]. Además, la incompatibilidad entre las tareas del sistema y las rutinas clínicas genera una percepción de ineficiencia que afecta la aceptación del CDSS [48]. Para abordar esta dificultad, se han propuesto medidas como la integración de subsistemas para reducir tareas redundantes [49], el diseño de formularios que eviten la duplicación de datos [48], el uso de técnicas de autocompletado [48] y la personalización de alertas según las preferencias del usuario [50]. Asimismo, el diseño centrado en el usuario permite adaptar los flujos del sistema a las necesidades reales del entorno clínico, mejorando la percepción de utilidad y la satisfacción [50].

Las deficiencias en el diseño del sistema representan otro punto crítico. Interfaces mal estructuradas, navegación confusa o funcionalidades poco intuitivas pueden dificultar la interacción, generar errores en la toma de decisiones y comprometer la calidad asistencial. En estos casos, los usuarios tienden a evitar el uso del sistema, lo que reduce su impacto clínico [51]. Para superar estas limitaciones, se ha propuesto el enfoque de diseño orientado a objetivos (en inglés, *Goal-Directed Design*), que incorpora perfiles de usuario (personas) y escenarios de uso para alinear el sistema con las metas y expectativas del profesional [52], [53]. Este enfoque permite construir sistemas más comprensibles, útiles y adaptados al contexto clínico.

Sin embargo, existe ***una paradoja entre la usabilidad del sistema y su capacidad*** para resolver problemas complejos. Como señalan Pantazi et al. [54], los sistemas altamente usables tienden a ser menos potentes, mientras que aquellos capaces de abordar desafíos clínicos sofisticados suelen presentar interfaces más difíciles de manejar. Esta tensión entre simplicidad y funcionalidad plantea un reto constante para los diseñadores, que deben encontrar un equilibrio entre ambos extremos.

Por otro lado, ***el esfuerzo mental*** requerido para interactuar con el sistema es otro factor que puede limitar la participación del usuario. Este concepto engloba la carga cognitiva asociada a tareas como la atención, la memoria, la toma de decisiones y el aprendizaje [55], [56]. Un sistema que exige un esfuerzo mental elevado puede resultar inaccesible o poco atractivo para el usuario, especialmente en contextos de alta presión. Investigaciones recientes han explorado métodos para medir este esfuerzo, como el análisis de la actividad ocular y el número de parpadeos durante la interacción [57]. El uso de modelos mentales, introducido por Norman [58], [59], permite alinear la conceptualización del sistema con la forma en que los usuarios entienden y procesan la información. Cuando el modelo conceptual del diseñador coincide con el modelo mental del usuario, la interacción se vuelve más intuitiva y eficaz [60]. Esta alineación mejora la comprensión del sistema, reduce la carga cognitiva y favorece una experiencia de usuario más fluida.

En conjunto, estos elementos (fatiga por alertas, carga de trabajo, defectos de diseño y esfuerzo mental) conforman el lado oscuro de la IPO en los CDSS. Ignorarlos puede comprometer la utilidad del sistema, su adopción por parte de los profesionales y, en última instancia, la calidad de la atención médica. Por ello, es fundamental reconocer estos obstáculos, analizarlos en profundidad y proponer soluciones que permitan construir sistemas más eficaces, humanos y centrados en el usuario.

Después de abordar los elementos negativos de la IPO, se profundiza en cómo estos mismos elementos, cuando se optimizan adecuadamente, pueden influir positivamente en ***la calidad de los datos*** y en la gestión de la información dentro del entorno de la CDSS. Estos sistemas están diseñados para asistir a los profesionales sanitarios mediante el uso de la ciencia de datos, interpretando grandes volúmenes de información y proporcionando recomendaciones clínicas accionables. No obstante, el éxito de los CDSS depende en gran medida de la calidad de los datos, la integridad de la información introducida y la forma en que el usuario interactúa con el sistema [61].

Cuando *el diseño de un CDSS incorpora elementos eficaces de IPO*, se mejora la experiencia del usuario y, como consecuencia directa, se incrementa la precisión de los datos introducidos, lo que repercute positivamente en la calidad de la atención médica [62]. En este sentido, se establece una conexión entre los elementos de IPO aplicables en entornos CDSS y los aspectos fundamentales de la ciencia de datos, como la calidad de los datos, la exploración de la información y la interpretabilidad de los modelos. Cada elemento de IPO puede potenciar dimensiones específicas de la calidad de los datos, lo que justifica su integración en el diseño de sistemas clínicos.

Uno de los elementos más destacados es el diseño de las alertas clínicas. Estas alertas, cuando se implementan de forma cuidadosa y contextualizada, permiten notificar al profesional sanitario sobre información crítica o acciones necesarias, mejorando así la calidad de los datos clínicos y el proceso de toma de decisiones. Desde la perspectiva de la ciencia de datos, el diseño de las alertas influye directamente en la recolección de datos, la reducción del ruido informativo y la interpretabilidad de los modelos predictivos [63].

Otro componente esencial son ***los facilitadores de IPO***, entendidos como las funcionalidades que los diseñadores del sistema incorporan para facilitar la interacción del usuario con el CDSS. Estos facilitadores permiten superar barreras previamente identificadas [64], promoviendo una mayor implicación del usuario, especialmente en tareas de entrada de datos. Cuando se logra esta implicación, los datos generados están mejor preparados para ser analizados mediante técnicas de aprendizaje automático, lo que incrementa su valor clínico [65].

La visibilidad es otro atributo clave que incide directamente en la calidad de los datos. Este elemento garantiza el acceso rápido a la información necesaria y asegura que los datos médicos estén disponibles en los puntos donde el usuario espera encontrarlos. Esta transparencia en la presentación de la información permite que la entrada de datos se realice sobre una base clara y en tiempo real, lo que refuerza la fiabilidad de los procesos posteriores dentro del CDSS [66]. Desde el enfoque de la ciencia de datos, la visibilidad mejora la calidad de los datos utilizados en distintos niveles del sistema.

Por último, ***la facilidad de uso*** representa un factor determinante en la calidad de los datos. Este elemento, cuando se incorpora adecuadamente en el diseño del sistema (mediante una navegación intuitiva, la eliminación de jerga técnica innecesaria y el fomento de la intención de uso), permite que el usuario introduzca datos de forma más precisa y eficiente. Un diseño centrado en la facilidad de uso puede mejorar significativamente la calidad de los datos en múltiples dimensiones, lo que repercute directamente en la eficacia de los algoritmos de análisis clínico [67], [68].

En conjunto, se demuestra que las decisiones médicas generadas por los CDSS serán más precisas y confiables cuando los datos proporcionados cumplan con los criterios de calidad exigidos por la ciencia de datos. Se evidencia que la calidad de los datos está *estrechamente vinculada al nivel de interacción del usuario* con el sistema y que la incorporación de los elementos de IPO descritos permite generar datos más completos, estructurados, etiquetados adecuadamente y listos para su análisis. Esta mejora en la calidad de los datos conduce, de forma natural, a decisiones clínicas más precisas, que constituyen el objetivo principal de los CDSS.

Dado que se ha reconocido la importancia de considerar los elementos de IPO en los sistemas de apoyo a la decisión clínica y su impacto directo en ***la calidad de los datos médicos***, se ha explorado cómo estos datos pueden ser ***controlados, gestionados, integrados y estandarizados*** para mejorar la funcionalidad del sistema y la precisión de las decisiones clínicas. Los CDSS desempeñan un papel cada vez más relevante en la asistencia a los profesionales sanitarios durante el proceso de atención médica, especialmente en un contexto donde los sistemas de salud generan volúmenes crecientes de datos complejos que requieren una gestión eficaz para garantizar decisiones fiables y oportunas [69], [70]. Este proceso implica múltiples fases, como la generación, recuperación, etiquetado y procesamiento de datos, todas ellas sujetas a exigencias de precisión [71], [72].

La integración de datos heterogéneos y de baja calidad provenientes de subsistemas diversos refuerza la necesidad de aplicar prácticas sólidas de gestión de datos [73]. La entrada y generación de datos constituyen aspectos fundamentales de esta gestión y, al mismo tiempo, representan elementos clave de IPO, ya que configuran la base de la relación entre el usuario y el sistema en entornos clínicos [74]. La calidad de los datos médicos, ya sean introducidos por el usuario o extraídos de otros sistemas, influye directamente en el rendimiento de los CDSS [280], [281]. Cuando los datos se introducen de forma fiable y en el momento adecuado, los profesionales sanitarios acceden a información coherente y útil durante decisiones críticas [75]. Por el contrario, sistemas mal diseñados pueden aumentar la carga cognitiva, generar frustración y provocar errores clínicos [76], [77].

Aunque numerosos estudios han abordado la gestión e integración de datos en CDSS, el papel de IPO en estos procesos ha sido frecuentemente ignorado. Abordar esta omisión resulta esencial para mejorar la usabilidad del sistema y fomentar su adopción por parte de los profesionales. Por ello, se ha planteado la necesidad de tratar ***la gestión de la entrada de datos*** como una preocupación central en el ámbito de IPO, y se ha explorado cómo la integración de datos puede mejorar aspectos relacionados con la experiencia del usuario en los CDSS.

La entrada de datos médicos sigue siendo uno de los principales puntos críticos en los sistemas clínicos. ***Las inconsistencias terminológicas***, como las que se producen en informes quirúrgicos al describir una misma condición con expresiones distintas, dificultan la identificación de casos específicos y comprometen la validez de los análisis clínicos [78]. Para abordar estos desafíos, se han implementado mecanismos como el control de rangos, que permite definir límites aceptables para ciertos campos. Si un valor excede el rango establecido, el sistema proporciona retroalimentación visual inmediata, alertando al usuario sobre posibles errores [23]. Este tipo de control mejora la fiabilidad de los datos y reduce la probabilidad de errores clínicos derivados de información anómala [79], [80].

También se ha incorporado *el control de obligatoriedad en la entrada de datos*, que garantiza la completitud de los registros médicos. Los formularios se estructuran de manera secuencial, impidiendo avanzar si los campos obligatorios no han sido completados [81], [82]. Esta estrategia asegura que la información crítica esté presente, optimiza el flujo de trabajo clínico y reduce inconsistencias [83]. Además, se ha desarrollado una tecnología basada en ***la generación automática de texto médico***, que transforma los datos introducidos en informes clínicos estandarizados. Este sistema combina control de rangos, obligatoriedad de campos y flexibilidad para editar manualmente el texto generado, permitiendo documentar casos excepcionales sin perder precisión ni estructura [84]. En un estudio comparativo con más de 4000 registros, se demostró que esta tecnología eliminó por completo los datos faltantes y redujo significativamente los errores fuera de rango, mejorando la calidad y fiabilidad de la documentación clínica.

La estandarización y normalización de datos permiten que los CDSS interpreten correctamente la información, ofreciendo resultados consistentes incluso en plataformas distintas. La estandarización convierte terminologías, unidades y esquemas de codificación en un marco unificado, mientras que la normalización ajusta los datos a rangos y formatos consistentes [85], [86]. Estas prácticas reducen la carga cognitiva del usuario, simplifican la navegación por la interfaz y mejoran la precisión de las decisiones clínicas [87], [88], [89]. Desde la perspectiva de IPO, estos procesos están estrechamente vinculados a la usabilidad del sistema. Un CDSS que presenta datos limpios, estandarizados e interpretables permite al usuario centrarse en la toma de decisiones sin distraerse por inconsistencias o errores de formato [90], [91], [92].

El flujo de transformación de datos incluye etapas como la recolección, limpieza, estandarización, normalización, integración, análisis y presentación [93], [94], [95]. Este proceso permite detectar y corregir problemas como datos incompletos, inconsistentes, fragmentados o desactualizados, que pueden comprometer la precisión diagnóstica y la seguridad del paciente [96], [97]. La calidad de los datos es el pilar sobre el cual se construyen las recomendaciones clínicas en los CDSS. Cuando los datos son completos, consistentes y bien integrados, el sistema puede ofrecer decisiones más precisas y confiables. Por el contrario, los datos incompletos o erróneos pueden aumentar el riesgo clínico, generar insatisfacción entre los usuarios y provocar sesgos en los algoritmos de aprendizaje automático [98], [99], [100].

La integración de datos consiste en combinar información de múltiples fuentes en un formato coherente y unificado. En el contexto de los CDSS, esta integración es esencial para proporcionar una visión completa del paciente y evitar que se omita información crítica [101], [102]. La fragmentación de datos entre sistemas aislados puede generar errores clínicos, aumentar los costes y reducir la eficiencia del tratamiento [103]. La integración impacta directamente en la experiencia del usuario y la usabilidad del sistema. Cuando los datos se presentan de forma unificada y accesible, los profesionales confían más en el sistema y lo utilizan con mayor eficacia [104]. Esta integración puede abordarse desde dos dimensiones: *la integración de datos* propiamente dicha y *la integración de interfaces*, ambas necesarias para mejorar la interacción con el sistema [105].

El uso de tecnologías como iPaaS (*Integration Platform as a Service*) permite unificar sistemas mediante servicios dedicados de integración de datos, aplicaciones y gestión de API (*Application Programming Interface*) [106], [107]. Estas soluciones no solo mejoran la presentación de datos, sino que también reducen la carga cognitiva, aumentan la eficiencia del flujo de trabajo y fortalecen la confianza del usuario en el sistema. La implementación de estrategias de gestión de datos basadas en principios de IPO permite reducir estos riesgos, mejorar la experiencia del usuario y aumentar la adopción del sistema. En este sentido, se establece una relación sinérgica entre la gestión de datos y la IPO, donde cada dimensión refuerza a la otra para alcanzar entornos clínicos más intuitivos, eficientes y centrados en el usuario.

Respecto a la importancia de la calidad de los datos médicos y los desafíos en la gestión de la información clínica, se propuso ***el modelo cíclico*** como una solución estructural que permite mejorar la organización de los datos médicos, optimizar la entrada de información y reforzar la transparencia en las decisiones clínicas mediante elementos enriquecidos de interacción persona-ordenador. En el contexto actual de la atención sanitaria, el diseño de los sistemas médicos desempeña un papel decisivo en la configuración de una interacción eficaz entre el usuario y el sistema, lo que repercute directamente en la funcionalidad y utilidad del sistema [10]. Un sistema diseñado con elementos avanzados de IPO no solo fomenta la participación del usuario, sino que también facilita la navegación y la organización de los datos médicos [108].

Durante el proceso de entrada de datos, generación de información médica e interacción con el sistema, es imprescindible priorizar ***la calidad de los datos*** y su preparación para el análisis. Incluso si los datos médicos introducidos son completos, si no están organizados adecuadamente ni etiquetados de forma efectiva, no se obtendrán decisiones clínicas precisas ni resultados deseables [109],[110]. Uno de los principales problemas detectados en los diseños actuales es ***la incompatibilidad con los procesos médicos contemporáneos*** [111]. En particular, la naturaleza cíclica de los planes de tratamiento se presenta como una necesidad crítica. Estos planes suelen incluir fases específicas como el diagnóstico, la planificación del tratamiento y la evaluación de resultados, pero los sistemas actuales no contemplan esta estructura repetitiva [112].

Los registros médicos electrónicos (EMR), que constituyen la plataforma principal para la recopilación de datos clínicos, también presentan esta deficiencia. Al actuar como fuente de datos para los CDSS, es esencial que su diseño esté alineado con las necesidades reales del entorno clínico [113]. En los sistemas actuales, los datos médicos se encuentran dispersos en secciones fragmentadas, lo que dificulta que los profesionales sanitarios obtengan una visión integral del historial del paciente y de sus necesidades terapéuticas. En otras palabras, no queda claro a qué ciclo de tratamiento pertenece cada dato registrado, lo que reduce ***la transparencia necesaria para el análisis clínico*** [114].

Una ventaja adicional de optimizar la IPO es la posibilidad de ofrecer ***contenido personalizado para la formación del paciente***, adaptado a sus necesidades médicas específicas. Esto puede lograrse mediante la categorización de contenidos informativos, permitiendo que cada paciente reciba información relevante en su registro personal de salud (PHR, por sus siglas en inglés, *Personal Health Record*) [115]. Para ello, los datos médicos relacionados con la formación del paciente deben ser etiquetados adecuadamente en el EMR, lo que facilita a los profesionales seleccionar el paquete informativo más adecuado para cada perfil [116].

Los diseños actuales de sistemas suelen centrarse en la entrada y recuperación de datos médicos sin considerar cómo ***la categorización y el etiquetado de datos*** influyen en el análisis posterior y en la precisión de las decisiones clínicas [117],[118]. Esta omisión limita el potencial de los CDSS para ofrecer recomendaciones precisas y adaptadas al contexto clínico. Al considerar los elementos de IPO y las necesidades reales de los profesionales en el diseño de sistemas médicos, se puede influir directamente en la calidad de los datos y en su análisis, mejorando así los resultados clínicos.

El enfoque propuesto destaca la importancia de integrar la naturaleza cíclica de los planes de tratamiento en las aplicaciones de CDSS. Al aplicar un ***etiquetado cíclico*** de los datos dentro de los EMR, la organización de la información se adapta mejor a las necesidades de médicos y pacientes, lo que facilita el análisis clínico y mejora la trazabilidad de los tratamientos. Este modelo permite que los datos médicos se estructuren en ciclos claramente definidos, lo que mejora la identificación de patrones, la comparación entre ciclos y la evaluación de la eficacia terapéutica [119].

La implementación del modelo cíclico en los EMR permite que cada ciclo de tratamiento esté documentado de forma coherente, con formularios de datos organizados secuencialmente y vinculados entre sí. Esta estructura garantiza que cada fase del tratamiento esté representada de manera clara, desde el diagnóstico hasta la evaluación de resultados. Por ejemplo, en el caso de pacientes con antecedentes de IUFD (*Intrauterine Fetal Death*), cada ciclo de tratamiento puede identificarse mediante un *número de ciclo único*, lo que permite distinguir entre diferentes intentos terapéuticos y evaluar su evolución de forma precisa [120].

Este modelo no solo mejora la organización de los datos, sino que también refuerza la ***explicabilidad de las decisiones clínicas***, al permitir que los médicos comprendan con mayor claridad la evolución del tratamiento y los resultados obtenidos. La posibilidad de modificar la estructura del ciclo según las necesidades médicas ***garantiza la adaptabilidad del sistema*** a distintos escenarios clínicos [121]. En la evaluación empírica realizada, se comparó el modelo cíclico con el diseño convencional de EMR, demostrando sus ventajas en la estructuración y análisis de los datos médicos, así como en la mejora de la precisión diagnóstica.

En la evaluación empírica realizada, se aplicó el modelo cíclico a un conjunto de datos clínicos simulados, inspirado en MIMIC-III [8], con el objetivo de comparar su rendimiento frente al diseño convencional de EMR. Se incorporaron campos específicos de ciclos de tratamiento para organizar los datos de forma secuencial y estructurada. Los resultados mostraron que el modelo cíclico permitió preservar variaciones críticas en las respuestas de los pacientes, facilitó la identificación de patrones clínicos y mejoró la precisión en la predicción de resultados terapéuticos. Además, se observó una mejora significativa en la capacidad del sistema para generar recomendaciones clínicas más coherentes y contextualizadas, lo que confirma que este enfoque no solo optimiza la organización de los datos, sino que también potencia la funcionalidad de los CDSS al alinearse con los flujos reales de trabajo clínico [122].

Otro beneficio destacado del enfoque cíclico es su aplicación en ***la formación del paciente***. Al categorizar los datos médicos mediante ***etiquetas específicas***, los profesionales pueden seleccionar el contenido educativo más adecuado para cada paciente, teniendo en cuenta su historial clínico y sus necesidades particulares. Esta personalización del contenido dentro del PHR mejora la comprensión del paciente sobre su tratamiento y promueve una participación más activa en su proceso de atención [116].

Además, el modelo cíclico permite establecer una ***relación directa entre los datos clínicos y las fases del tratamiento***, lo que facilita la evaluación longitudinal de los resultados y la identificación de tendencias clínicas. Esta capacidad de vincular datos con momentos específicos del proceso terapéutico no solo mejora la calidad del análisis, sino que también permite una mejor comunicación entre los distintos profesionales implicados en la atención del paciente.

En conjunto, el modelo cíclico propuesto permite superar las limitaciones de los sistemas actuales, ofreciendo una solución estructural que mejora *la calidad de los datos*, la organización de la información y la transparencia en la toma de decisiones clínicas. Al integrar elementos avanzados de IPO en el diseño de los sistemas médicos, se establece una base sólida para el desarrollo de entornos clínicos más intuitivos, eficientes y centrados en el usuario. Este enfoque no solo optimiza la funcionalidad de los CDSS, sino que también contribuye a mejorar los resultados clínicos y la experiencia del paciente en el sistema sanitario. Además, al facilitar la trazabilidad de los tratamientos y la personalización de la información, se promueve una medicina más precisa, adaptada y sostenible.

Para implementar el enfoque cíclico propuesto, deben considerarse cuidadosamente las ***limitaciones éticas y organizativas*** que acompañan el uso de datos clínicos en sistemas inteligentes. Aunque el modelo demuestra un claro potencial científico para mejorar la fiabilidad del sistema, la adopción por parte de los usuarios y los resultados clínicos, su aplicación práctica exige abordar dimensiones más amplias. En particular, ***el uso de datos médicos*** para entrenar modelos de aprendizaje y alimentar algoritmos de decisión plantea desafíos relacionados con la gobernanza de datos, el consentimiento informado y el cumplimiento de normativas como ***el Reglamento General de Protección de Datos (GDPR)***. A pesar de que se aplican técnicas de anonimización y protocolos de cifrado para proteger la confidencialidad, el uso secundario de datos clínicos requiere una atención rigurosa a los marcos regulatorios, especialmente cuando se trata de **la integración y transformación de datos** entre instituciones o países. Además, aunque el sistema busca mejorar la explicabilidad, la transparencia y la confianza del usuario, los médicos siguen siendo ***legal y éticamente responsables*** de las decisiones clínicas finales, lo que exige mantener ***la auditabilidad*** de cada paso del proceso.

Desde una perspectiva institucional, la adopción de rediseños centrados en IPO implica un proceso complejo que abarca estructuras de gobernanza, procedimientos de licenciamiento y aprobaciones administrativas. Antes de su implementación en entornos reales, los sistemas deben superar revisiones regulatorias, obtener certificaciones oficiales y demostrar conformidad con las políticas institucionales y gubernamentales. Estos pasos son especialmente relevantes para sistemas integrados que gestionan el intercambio y la transformación de datos médicos a nivel nacional o internacional. Solo mediante una gobernanza robusta, el respeto a los derechos de los pacientes y la transparencia en el diseño y despliegue, los diseñadores de sistemas médicos podrán aprovechar plenamente el potencial de los CDSS avanzados para lograr mejoras significativas en la toma de decisiones sanitarias.

A modo de conclusión, la presente tesis ha explorado la aplicación de IPO en entornos de CDSS, investigando cómo los principios de diseño orientados a la usabilidad pueden mejorar la estructura, la interpretabilidad y la funcionalidad de los entornos clínicos digitales. En este sentido, se plantea ***la hipótesis de que la integración de elementos de HCI en los CDSS*** *puede mejorar aspectos específicos de su funcionalidad* (en particular, la capacidad de explicar las decisiones médicas y la fiabilidad de los resultados del sistema).

Para explorar esta hipótesis, se realizó primero una SLR que recopiló los estudios existentes sobre IPO en entornos de CDSS. Esta revisión permitió identificar ***doce elementos distintos de IPO*** que influyen en el rendimiento de los CDSS, revelando tanto los aspectos positivos de la IPO (como la explicabilidad, la visibilidad y la facilidad de uso) como los factores negativos o perjudiciales, entre los que se incluyen la fatiga por exceso de alertas, la carga de trabajo y la sobrecarga cognitiva. Estos elementos no solo se catalogaron, sino que también se contextualizaron dentro del panorama más amplio de la informática clínica, revelando sus funciones tanto facilitadoras como inhibidoras en los procesos de toma de decisiones [10].

Una de las principales contribuciones de esta tesis reside en la clasificación de los métodos de evaluación de la IPO. Mediante el análisis de cómo se aplican estos métodos en diferentes estudios, se desarrolló una taxonomía que distingue entre enfoques *basados en expertos, basados en usuarios e híbridos*. Esta clasificación ayuda a futuros investigadores y diseñadores de sistemas a seleccionar estrategias de evaluación que se ajusten a sus objetivos, limitaciones y contextos de usuario [23].

Más allá de la identificación y clasificación, la tesis se centró en las implicaciones prácticas de los elementos de la IPO (en particular, su impacto en la calidad de los datos médicos y la experiencia del usuario). Se ha demostrado que la introducción de datos estructurados y con un propósito definido, cuando *se alinea con los flujos de trabajo clínicos*, puede mejorar la claridad, la trazabilidad y la interpretabilidad de los registros médicos. En consecuencia, mejora la capacidad de explicación de los resultados de los sistemas de apoyo a la decisión clínica, haciéndolos más transparentes y fiables para los médicos [123].

Para implementar estas ideas, se propuso y evaluó un ***modelo cíclico de diseño de registros médicos electrónicos***. Este modelo organiza la introducción de datos en torno a los ciclos de tratamiento, lo que permite a los médicos asociar cada dato con una fase específica de la atención. El modelo se probó empíricamente utilizando el conjunto de datos público MIMIC-III y los resultados demostraron que la estructuración de los datos por ciclos da lugar a patrones de distribución distintos y a una mejor interpretabilidad, así como a indicadores clave de una mayor capacidad de explicación [122].

Al adoptar un enfoque cíclico, el sistema se adaptó para reflejar las necesidades y prácticas reales de los profesionales de la salud, garantizando que su estructura se ajuste al razonamiento clínico y a la lógica del flujo de trabajo. Esta alineación no solo mejora la usabilidad de la interfaz, sino que también refuerza la confianza en los resultados del sistema. ***La fiabilidad de las recomendaciones clínicas*** se ve reforzada al organizar los datos médicos en fases de tratamiento claramente definidas, lo que permite a los médicos interpretar las sugerencias dentro de un marco familiar y contextualizado. En definitiva, estas mejoras contribuyen a una interacción más eficaz con el sistema de apoyo a la toma de decisiones clínicas, lo que se traduce en una mayor ***satisfacción del usuario***.

En resumen, la combinación de los hallazgos de la SLR, los análisis empíricos y la validación del modelo nos permite afirmar que ***se han alcanzado tanto el objetivo principal como sus subobjetivos derivados***. A la luz de estos resultados, ***la hipótesis*** planteada al inicio de esta tesis se considera ***válida***.

Con vistas al ***trabajo futuro*** y a *las líneas de investigación emergentes*, esta tesis abre el camino hacia múltiples direcciones innovadoras en el ámbito de los sistemas clínicos digitales. A medida que la atención médica incorpora tecnologías impulsadas por inteligencia artificial, especialmente aplicaciones conversacionales, se vuelve imprescindible integrar IPO para crear entornos más interactivos, personalizados y atractivos. Estas aplicaciones pueden mejorar significativamente la interacción entre profesionales y pacientes al ofrecer interfaces adaptables, retroalimentación en tiempo real e información accesible. Sin embargo, para que estos sistemas sean eficaces, es fundamental que los elementos de IPO estén diseñados para proporcionar ***una experiencia de usuario satisfactoria***, mitigando barreras como la frustración, la desconfianza o el rechazo tecnológico, y contribuyendo así a mejores resultados clínicos. En particular, futuras investigaciones deberán centrarse en cómo mejorar

la explicabilidad de los CDSS, desarrollando estrategias de diseño que permitan a los usuarios comprender con mayor claridad *el razonamiento detrás de las recomendaciones clínicas*. Este enfoque no solo fortalecerá ***la confianza del usuario***, sino que también facilitará una adopción más amplia de estos sistemas en la práctica clínica.

El enfoque cíclico propuesto en esta investigación representa un marco sólido para integrar los elementos de IPO en futuras aplicaciones médicas basadas en ***IA (Inteligencia Artificial)***. Al organizar los datos médicos en ciclos recurrentes, este método permite comprender con mayor profundidad cómo los usuarios interactúan con los sistemas inteligentes. Esta estructura no solo mejora la organización y el análisis de datos, sino que también facilita el desarrollo de aplicaciones capaces de adaptarse dinámicamente a las necesidades cambiantes de pacientes y profesionales. En este contexto, el uso continuo de datos permite que los sistemas aprendan de las interacciones, ofreciendo soporte relevante y oportuno. Además, con la creciente incorporación del ***procesamiento de lenguaje natural (PLN)*** en los sistemas clínicos, será necesario investigar cómo los elementos de IPO (como el control del usuario, la explicabilidad, la retroalimentación y la individualización) pueden mejorar la interacción con herramientas basadas en PLN. Las futuras investigaciones deberán centrarse en desarrollar ***marcos de evaluación de IPO*** adaptados a estas tecnologías, contribuyendo al diseño de sistemas de apoyo clínico más eficaces, centrados en el usuario y alineados con los desafíos de una atención médica cada vez más digitalizada.

A lo largo del desarrollo de esta investigación doctoral, se han publicado diversas ***contribuciones científicas*** con el objetivo de validar y difundir los hallazgos derivados de los enfoques propuestos. Estas publicaciones han permitido recibir retroalimentación valiosa por parte de expertos en informática médica e IPO, lo que ha contribuido directamente al perfeccionamiento de las ideas centrales del estudio. Como ***resultado de la tesis***, se han generado *4 artículos revisados por pares en revistas indexadas y 3 ponencias presentadas en congresos internacionales*, lo que refleja la relevancia y el impacto académico del trabajo en múltiples plataformas científicas.

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