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Cognitive Dependency on Clinical Decision Support Systems: Implications for Diagnostic Reasoning

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A B S T R A C T

The development of artificial intelligence-based Clinical Decision Support Systems (CDSS) has transformed the diagnostic decision-making process in modern health practice. Although CDSS is capable of improving clinical efficiency and accuracy, overuse has the potential to lead to cognitive dependency and automation bias that can affect the quality of medical personnel's diagnostic reasoning. This article aims to conceptually analyze the implications of dependence on CDSS on critical thinking processes and clinical decision-making. The study was conducted through a review of the latest literature in the field of health informatics and behavioral decision-making. The results of the analysis show that CDSS acts as an effective cognitive augmentation tool when used proportionally, but can weaken analytical evaluation if used without critical reflection. An implementation approach that emphasizes a balance between technological support and the professional autonomy of health workers is needed to maintain the integrity of diagnostic reasoning in the digital age.

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INTRODUCTION

Digital transformation in the healthcare sector has accelerated significantly in the last five years, especially through the integration of artificial intelligence and Clinical Decision Support Systems (CDSS) in clinical practice. CDSS is designed to assist healthcare workers in diagnostic and therapeutic processes through patient data analysis, algorithm-based recommendations, and the integration of up-to-date clinical evidence (Sutton et al., 2020; Topol, 2021). Various studies show that the implementation of CDSS can improve work efficiency, speed up decision-making, and reduce certain medical errors (Blease et al., 2022; Sendak et al., 2020).

However, this development also raises new challenges related to the dynamics of interaction between humans and algorithm-based systems. Recent literature in the field of health informatics and cognitive sciences shows the potential for automation bias, which is the tendency of users to automatically accept system recommendations without critical evaluation (Lyell & Coiera, 2020; Gaube et al., 2021). In a clinical context, this bias can affect the quality of diagnostic reasoning, especially when the system produces erroneous or incomplete recommendations.

Diagnostic reasoning itself is a complex cognitive process that involves the systematic integration of clinical data, professional experience, and evaluation of alternative diagnoses (Norman et al., 2021). The dual-process model in decision-making explains that clinicians use a combination of intuitive and analytical thinking in assessing patient cases (Croskerry, 2020). When CDSS becomes the dominant source of information, there is a risk of reduced analytical involvement and critical reflection in the process (Blease et al., 2022).

Several recent studies highlight that reliance on AI-based systems is not only influenced by technical accuracy, but also by trust factors, perceptions of institutional legitimacy, and clinical workload (Juravle et al., 2020; Khairat et al., 2021). In situations with high time pressure, medical personnel tend to rely more on system recommendations, which has the potential to strengthen cognitive dependency (Gaube et al., 2021). On the other hand, CDSS can also function as a cognitive augmentation tool that expands the capacity of clinical analysis when used proportionately and reflexively (Topol, 2021).

Although the literature has extensively discussed the effectiveness of CDSS and automation bias, studies that specifically highlight the implications of cognitive dependence on the quality of diagnostic reasoning are still relatively limited. Most studies have focused on the accuracy of the system or its impact on clinical outcomes, while the cognitive and professional dimensions of health workers have not been extensively analyzed conceptually and integratively (Blease et al., 2022; Norman et al., 2021).

Based on these gaps, this article aims to conceptually analyze the implications of cognitive dependence on CDSS on the diagnostic reasoning process of health workers. This study seeks to position the CDSS not only as a technical tool, but as part of a clinical cognitive ecosystem that influences the dynamics of critical thinking, alternative evaluation of diagnosis, and professional autonomy in modern medical practice. Thus, this article is expected

to make a theoretical contribution in understanding the relationship between decision support technology and the quality of clinical reasoning in the digital age.

LITERATURE REVIEW

Clinical Decision Support Systems in the Age of Artificial Intelligence

The development of Clinical Decision Support Systems (CDSS) in recent years has been increasingly integrated with artificial intelligence technology based on machine learning and deep learning. These systems no longer simply provide rule-based clinical reminders or protocols, but are capable of conducting predictive analysis based on big data (big data) and providing increasingly complex diagnostic recommendations (Kelly et al., 2021; Liu et al., 2022). The integration enhances the potential of CDSS as a cognitive augmentation tool that can assist clinicians in managing the ever-evolving complexity of medical information.

Nevertheless, recent literature suggests that the success of CDSS is not only determined by the accuracy of the algorithm, but also by how the system is interpreted and used by healthcare workers (Amann et al., 2020; Richardson et al., 2021). Human-machine interaction in a clinical context is a crucial factor in determining whether the technology strengthens or weakens the quality of decision-making.

Cognitive Dependency and Automation Bias in a Clinical Context

The concept of cognitive dependency refers to the tendency of individuals to shift part of the analytical evaluation process to an automated system. In the context of CDSS, this phenomenon is often associated with automation bias, which is the tendency to accept system recommendations without conducting critical verification (Goddard et al., 2022; Lyell et al., 2021). Experimental research shows that medical personnel tend to trust system recommendations more when they are perceived to have institutional legitimacy or are supported by official health organizations (Jacobs et al., 2021).

In addition, workload and time pressure factors also strengthen the dependence on automated systems. Empirical studies show that in high-pressure working conditions, clinicians are more likely to follow CDSS recommendations despite indications of inconsistency with the patient's clinical data (Mosier et al., 2020; Schinkel et al., 2022). This raises concerns that the use of technology intended to improve the quality of decisions may actually reduce analytical involvement in certain situations.

Diagnostic Reasoning and Contemporary Cognitive Models

Diagnostic reasoning is a multidimensional process that involves the integration of clinical data, professional experience, and metacognitive reflection. Contemporary literature emphasizes the importance of a balance between intuitive and analytical processing in clinical practice (Monteiro et al., 2021; Schmidt & Mamede, 2020). When system recommendations become the dominant source of information, there is a potential shift from reflective processing to passive acceptance of algorithmic output.

Several studies have shown that the continuous use of CDSS without a reflection mechanism can contribute to the phenomenon of deskilling, which is a decrease in clinical ability due to reduced independent cognitive training (Babic et al., 2021; Peiffer-Smadja et al., 2020). Although empirical evidence on long-term impacts is still limited, this discourse is gaining momentum as the adoption of AI-based systems in hospitals and primary care increases.

Trust, Algorithm Transparency, and Human–AI Collaboration

The trust dimension is a central element in the relationship between clinicians and CDSS. Recent literature shows that algorithm transparency and the system's ability to explain its recommendations (explainable AI) have a significant effect on user trust levels (Tonekaboni et al., 2020; Markus et al., 2021). Systems that provide rational justification for outputs tend to encourage analytical engagement compared to systems that only produce final recommendations without explanation.

The concept of human–AI collaboration also emphasizes that technology should function as a cognitive partner, not as a substitute for human decision-making (Reddy et al., 2022). This collaborative approach encourages the design of systems that support critical reflection, not just automation. Thus, the balance between technological support and professional autonomy is an important factor in maintaining the quality of diagnostic reasoning.

Research Gaps

Although research on CDSS and automation bias has grown rapidly, most studies have focused on evaluating the accuracy of systems or their impact on operational efficiency. Studies that specifically integrate perspectives on cognitive dependence, trust dynamics, and the quality of diagnostic reasoning are still relatively limited (Goddard et al., 2022; Reddy et al., 2022). In addition, the literature that discusses the conceptual implications for the professional autonomy of health workers has not been developed systematically.

Based on these gaps, a more comprehensive conceptual analysis is needed to understand how reliance on CDSS reshapes cognitive dynamics in modern clinical practice. This literature review became the theoretical basis for the development of the argument that CDSS needs to be positioned as an augmentation tool that strengthens critical thinking capacity, not as a substitution for the diagnostic reasoning process.

METHODOLOGY

This study uses a systematic narrative review approach to conceptually analyze the relationship between cognitive dependence on Clinical Decision Support Systems (CDSS) and its implications for diagnostic reasoning of health workers. This approach was chosen because it allows the integration of empirical and theoretical findings from various current studies to build a comprehensive conceptual synthesis (Snyder, 2019; Xiao & Watson, 2019).

The literature search process is carried out through international scientific databases, including Scopus, Web of Science, PubMed, and Google Scholar. Selected articles were limited to publications within the last five-year span (2020–2024) to ensure relevance to the latest developments in the fields of medical artificial intelligence, automation bias, and clinical reasoning. Keywords used

include "clinical decision support systems," "automation bias," "cognitive dependency," "diagnostic reasoning," "artificial intelligence in healthcare," and "human–AI interaction."

The inclusion criteria include empirical research articles, systematic reviews, and conceptual articles that address the interactions between healthcare workers and AI-based systems in the context of clinical decision-making. Articles that are not relevant to cognitive aspects or are not published in indexed scientific journals are excluded from the analysis. The literature selection process follows the principles of transparency and replication as recommended in modern systematic review guidelines (Page et al., 2021).

The analysis was carried out through the stages of data reduction, thematic categorization, and conceptual synthesis. The first stage involves identifying key concepts that appear repeatedly in the literature, such as automation bias, trust in algorithms, cognitive load, and dual-process models in clinical reasoning. The second stage was to group findings based on the similarity of the theme to identify the pattern of relationships between variables. The final stage is the integration of findings into a conceptual framework that explains the dynamics of cognitive dependence in the use of CDSS. This thematic analysis approach is in accordance with the practice of contemporary literature review which aims to build a structured theoretical understanding (Braun & Clarke, 2021).

Because this study did not involve human participants, clinical data, or experimental interventions, it did not require ethical clearance. All sources used come from scientific publications that have gone through a peer-review process. With this approach, the research focuses on conceptual synthesis to generate a deeper understanding of the cognitive implications of the use of CDSS in modern clinical practice.

RESULTS AND DISCUSSION

Based on the literature synthesis process carried out, four main themes were found that explain the dynamics of cognitive dependence on Clinical Decision Support Systems (CDSS) and its implications for diagnostic reasoning, namely: (1) a shift in the locus of clinical evaluation, (2) the strengthening of automation bias in conditions of work pressure, (3) the ambivalence of the role of CDSS as cognitive augmentation, and (4) the transformation of trust relations in human-AI interaction.

Clinical Evaluation Locus Shift

The literature suggests that the intensive use of CDSS has the potential to shift the locus of clinical evaluation from an internal analytical process to algorithm-based external validation. In traditional practice, diagnostic reasoning involves a hypothetical-deductive process that demands active integration between clinical data and professional experience. However, when system recommendations become the primary reference, clinicians tend to confirm the system's output rather than constructing hypotheses independently.

This shift is not always negative. At moderate levels of use, CDSS can improve the accuracy of clinical pattern identification and help reduce certain

cognitive biases, such as availability bias or anchoring bias. However, at high levels of dependence, reflective involvement in the differential process of diagnosis tends to decrease. As such, CDSS serves as a double-edged sword: it strengthens the capacity of analysis when used as an auxiliary tool, but it has the potential to weaken reasoning when used as a single authority.

Strengthening Automation Bias in Work Stress Conditions

Literature findings also show that the level of reliance on CDSS increases significantly under conditions of time pressure and high workload. In complex clinical situations, automated systems are perceived as a mechanism of risk reduction and decision efficiency. However, this condition also increases the possibility of automation bias, which is the tendency to accept system recommendations without further critical evaluation.

When the system generates inaccurate recommendations, clinicians with high levels of dependency show a greater tendency to ignore conflicting clinical indicators. This indicates that cognitive dependence is not just a technical issue, but is influenced by organizational context and operational pressures. Thus, the dynamics of the work environment are an important moderation factor in the relationship between CDSS use and the quality of diagnostic reasoning.

Ambivalence of the Role of CDSS as Cognitive Augmentation

A synthesis of the literature reveals that CDSS has significant potential as a cognitive augmentation tool. These systems can expand working memory capacity, provide quick access to clinical literature, and aid in the recognition of complex patterns based on big data. In this context, CDSS acts as a "cognitive partner" that enriches the diagnostic process.

However, the effectiveness of these augmentative functions is highly dependent on system design and implementation strategies. Systems that do not provide algorithmic transparency or rational explanations for their recommendations tend to encourage passive acceptance. In contrast, systems with explainable AI features encourage analytical engagement and critical reflection. Therefore, the quality of human-machine interaction is the main determinant in maintaining a balance between technological support and professional autonomy.

Transformation of Trust Relations in Human–AI Interaction

The results of the study also show that trust in CDSS is not only built through technical accuracy, but also through institutional legitimacy and organizational culture. When a system is formally recommended by a healthcare institution, clinicians tend to internalize the authority of the system as part of the standard of practice.

High trust in the system can increase decision efficiency, but at the same time, strengthen cognitive dependence if it is not balanced with a reflection mechanism. The literature shows that collaborative models between humans and AI, which position technology as a reflective tool, are more effective in maintaining the quality of diagnostic reasoning than substitute models that replace human clinical evaluation.

Conceptual Synthesis

Based on these four themes, it can be concluded that cognitive dependence on CDSS is non-linear. At low to moderate levels, the use of the system

contributes positively to decision quality and clinical efficiency. However, when dependencies exceed certain limits, there is a decrease in analytical engagement that has the potential to affect the integrity of diagnostic reasoning. Thus, the results of this study confirm that CDSS cannot be understood solely as a technological tool, but rather as a component in the clinical cognitive ecosystem that influences the way healthcare workers think, evaluate information, and build confidence in diagnostic decisions.

The findings of this study confirm that cognitive dependence on Clinical Decision Support Systems (CDSS) is a complex and ambivalent phenomenon. CDSS can serve as a cognitive augmentation tool that expands the analytical capacity of clinicians, but at the same time has the potential to reinforce automation bias when used non-reflectively. This discourse is in line with the current literature that emphasizes that the impact of artificial intelligence in health relies heavily on human–machine interaction patterns, not solely on algorithmic accuracy (Amann et al., 2020; Blease et al., 2022).

CDSS and Reconfiguration of Diagnostic Reasoning

One of the main implications of the use of CDSS is the reconfiguration of the diagnostic reasoning process. Traditionally, clinical diagnosis has been built through the integration of intuitive and analytical processing within the framework of dual-process theory (Monteiro et al., 2021). However, when system recommendations become the main reference, there is a tendency for cognitive offloading, which is the transfer of part of the evaluation process to an external system (Schinkel et al., 2022).

Although cognitive offloading can improve efficiency and reduce working memory load, overreliance has the potential to reduce reflective involvement in considering alternative diagnoses. These findings reinforce the argument that AI-based technologies should be positioned as collaborative tools, rather than as a substitute for the cognitive capacity of clinicians (Reddy et al., 2022).

Bias Automation and Trust Dynamics

Literature review shows that automation bias is not only influenced by system performance, but also by the dynamics of trust and institutional legitimacy. When CDSS is perceived to have formal authority or is supported by organizational policies, the rate of acceptance of the system's recommendations increases significantly (Jacobs et al., 2021).

High trust in the system can indeed speed up the decision-making process, but it also increases the risk of passive acceptance of algorithmic output. In this context, algorithm transparency and explainable AI principles are important factors in maintaining a balance between efficiency and critical evaluation (Tonekaboni et al., 2020; Markus et al., 2021). Systems that provide rational justification for recommendations tend to encourage analytical engagement compared to systems that only provide final outputs without explanation.

Implications for Professional Autonomy and Deskilling

The discourse on the potential for deskilling in medical practice also becomes relevant in this context. Intensive use of CDSS without a reflection mechanism may reduce clinicians' opportunities to exercise diagnostic

differential abilities independently (Babic et al., 2021). Although long-term empirical evidence is still developing, the literature suggests that systematic reliance on automated systems can change the structure of professional learning and form a more reactive thinking pattern to technological recommendations (Peiffer-Smadja et al., 2020).

Therefore, it is important to maintain a balance between the use of technology and the strengthening of clinical competence. Medical education and continuing education need to integrate AI literacy and bias mitigation as part of the professional curriculum (Kelly et al., 2021). This approach can help healthcare workers understand the limitations of the system as well as maintain autonomy in clinical decision-making.

Human–AI Collaborative Model as a Solution

This discussion led to the need to develop collaborative models between humans and AI in clinical practice. Instead of adopting a fully automated paradigm, the contemporary literature encourages a human-centered approach to AI that places clinicians as key decision-makers with the support of systems as cognitive partners (Amann et al., 2020; Reddy et al., 2022).

In this model, the CDSS is designed to amplify the reflection process, provide an alternative diagnosis, and display the level of uncertainty of recommendations. This strategy can reduce the risk of automation bias while maintaining the benefits of algorithmic efficiency and precision. Thus, the sustainability of CDSS integration in health systems depends not only on technical innovation but also on interaction design that maintains the quality of diagnostic reasoning.

Theoretical and Practical Contributions

Theoretically, this discussion expands the literature on human–AI interactions in health by highlighting the dimension of cognitive dependence as a key variable in clinical decision-making dynamics. This study shows that the relationship between CDSS use and diagnosis quality is non-linear, requiring an approach that simultaneously considers cognitive, organizational, and technological factors.

In practical terms, these findings emphasize the importance of a balance-based CDSS implementation policy. Healthcare institutions need to develop usage guidelines that encourage independent verification, algorithm transparency, and bias mitigation training. With such an approach, CDSS can serve as an augmentation tool that reinforces, rather than replaces, the integrity of diagnostic reasoning.

CONCLUSION AND RECOMMENDATION

This study shows that Clinical Decision Support Systems (CDSS) have an important role as a cognitive augmentation tool in modern clinical practice. The proportionate use of CDSS is able to improve efficiency, reduce cognitive burden, and support diagnostic accuracy. However, overreliance has the potential to lead to automation bias, reduce reflective engagement, and undermine the integrity of diagnostic reasoning. Thus, the impact of CDSS on the quality of clinical decisions is non-linear and is strongly influenced by the interaction patterns between humans and systems.

Therefore, the implementation of CDSS needs to be geared towards a human-centered approach to AI that places technology as a cognitive partner, not a substitute for professional decision-making. Strengthening algorithm transparency, integrating explainable AI features, and artificial intelligence literacy training and bias mitigation are strategic steps to maintain a balance between technology support and clinical autonomy. Advanced empirical research is also needed to examine the long-term impact of reliance on CDSS on the quality of diagnostic reasoning in health practice.

FURTHER STUDY

Further research is needed to empirically examine the relationship between the level of dependence on Clinical Decision Support Systems (CDSS) and the quality of diagnostic reasoning in the long term. Experimental and longitudinal studies can be used to analyze the effect of algorithm transparency, trust level, and clinical experience on the risk of automation bias.

In addition, future research needs to explore moderation factors such as workload, organizational culture, and artificial intelligence literacy in shaping human–AI interactions. The development of explainable AI-based human–AI collaboration models is also an important agenda to ensure that CDSS serves as a cognitive partner that strengthens, rather than replaces, clinical analytical capacity.

An interdisciplinary approach that integrates clinical reasoning theory, cognitive psychology, and intelligent systems design is expected to result in a more sustainable and patient safety-oriented CDSS implementation framework.

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