Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 1s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

The Impact of Health Information Systems on Clinical Decision Support and Diagnostic Accuracy

Muhammad Obaid M Alotaibi[1]

[1]Health specialist, Master degree

Cite this paper as: M Alotaibi, M. O.. (2025 jan 1). The Impact of Health Information Systems on Clinical Decision Suppo rt and Diagnostic Accuracy. Journal of Neonatal Surgery, 14(15), 1282-1284.

1. INTRODUCTION

Health Information Systems (HIS) have revolutionized modern healthcare by enabling more efficient data management, enhancing clinical workflows, and most importantly, supporting accurate and timely clinical decision-making. Clinical Decision Support Systems (CDSS), often integrated into HIS, use patient data to provide tailored recommendations, flag critical alerts, and reduce diagnostic errors (Osheroff et al., 2007).

Accurate diagnosis is the cornerstone of effective treatment. Misdiagnoses not only harm patients but also strain healthcare resources. In recent years, HIS have been increasingly recognized as tools that can reduce human error, enhance evidence-based practice, and improve patient outcomes. The aim of this research is to examine how HIS influences clinical decision support and diagnostic accuracy.

Key questions include:

- How do HIS and CDSS enhance diagnostic precision?
- What system-level factors affect their performance?
- What challenges hinder their effectiveness?

2. THEORETICAL FRAMEWORK

This research draws on the Technology Acceptance Model (TAM) and the Information Continuum Framework. TAM posits that perceived usefulness and ease of use are critical for adoption of HIS tools like CDSS (Davis, 1989). The Information Continuum Framework suggests that information flows from data to decision to action, highlighting the importance of data quality and system design in achieving diagnostic accuracy (Lippeveld, 2001).

Additionally, HIS can be categorized under the Sociotechnical Systems Theory, which emphasizes that successful implementation requires alignment between technology, people, processes, and the environment (Sittig & Singh, 2010).

3. LITERATURE REVIEW

Research supports the positive correlation between HIS and improved diagnostic outcomes. Bates et al. (2003) demonstrated that electronic clinical alerts reduced adverse drug events in hospital settings. Similarly, Kawamoto et al. (2005) found that CDSS integrated into EHRs improved clinician performance in 68% of randomized controlled trials reviewed.

However, literature also highlights limitations. A study by Berner and Graber (2008) emphasized that while HIS systems can aid diagnosis, over-reliance may cause clinicians to overlook contextual cues. Moreover, poor interface design and information overload may lead to alert fatigue, undermining the intended benefits (Ancker et al., 2017).

In low- and middle-income countries (LMICs), fragmented systems and lack of interoperability reduce the effectiveness of CDSS, especially in primary and emergency care settings (Aqil et al., 2009).

4. METHODOLOGY

This paper adopts a qualitative narrative review methodology. Academic databases including PubMed, Scopus, and Google Scholar were searched using terms such as “Health Information Systems,” “Clinical Decision Support,” “Diagnostic Accuracy,” and “Electronic Health Records.”

Inclusion criteria:

- Peer-reviewed articles published between 2005 and 2024
- Focus on HIS in relation to diagnostic accuracy or CDSS

- English language only

A total of 32 articles were selected, critically reviewed, and synthesized based on thematic relevance. Emphasis was placed on studies evaluating real-world implementations of HIS in hospital and outpatient settings.

5. RESULTS

The review produced the following key findings:

1. Improved Diagnostic Timeliness: HIS systems with embedded CDSS accelerated time-to-diagnosis in emergency and ICU settings (Moja et al., 2014).
2. Reduction in Diagnostic Errors: Systems that flagged abnormal lab values or imaging discrepancies reduced missed diagnoses, especially in radiology and internal medicine (Graber et al., 2012).
3. Data-Driven Insights: Integration of machine learning into HIS enabled pattern recognition for rare or complex diseases (Topol, 2019).
4. Variation by Setting: HIS impact was strongest in structured environments (e.g., tertiary hospitals), but weaker in community clinics due to infrastructure gaps (Amoakoh-Coleman et al., 2016).
5. Barriers Identified: Alert fatigue, poor user training, and interoperability limitations were recurrent barriers to ffectiveness (Ancker et al., 2017).

6. DISCUSSION

The findings confirm that HIS and CDSS substantially contribute to diagnostic accuracy by offering data-driven recommendations, reducing oversight, and standardizing clinical practice. Their greatest value lies in complex or time-sensitive environments where rapid decision-making is critical.

However, technological potential must be matched by human and organizational readiness. The TAM framework supports the idea that clinicians must perceive these systems as both helpful and easy to use for successful adoption (Davis, 1989). Moreover, HIS must be context-sensitive—designed with the end-user in mind and tailored to the local workflow and infrastructure.

Alert fatigue remains a major issue. Studies suggest that clinicians ignore up to 90% of alerts in some systems (Phansalkar et al., 2013), rendering them ineffective. Solutions include tiered alert systems, predictive analytics, and better user interface design.

Lastly, the promise of AI-driven HIS is enormous. Systems that learn from clinical data can continuously improve diagnostic support. However, ethical considerations, data privacy, and the need for transparency must guide future development.

7. CONCLUSION

Health Information Systems, particularly those incorporating Clinical Decision Support, are powerful tools for enhancing diagnostic accuracy and clinical decision-making. When designed and implemented effectively, they can reduce errors, support timely diagnoses, and improve patient outcomes.

Nonetheless, challenges such as poor usability, alert fatigue, and limited adoption in low-resource settings remain barriers to their full potential. Future efforts should focus on improving user-centered design, promoting interoperability, and building clinician trust in data-driven decision tools.

Further research is needed on the cost-effectiveness and long-term impact of HIS in varied clinical contexts, especially in underserved regions.

REFERENCES

[1] Amoakoh-Coleman, M., et al. (2016). Effectiveness of mHealth interventions targeting healthcare workers to improve pregnancy outcomes. JMIR, 18(8), e226. https://doi.org/10.2196/jmir.5533

[2] Ancker, J. S., Edwards, A., Nosal, S., Hauser, D., Mauer, E., & Kaushal, R. (2017). Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. BMC Medical Informatics and Decision Making, 17(1), 36. https://doi.org/10.1186/s12911-017-0430-8

[3] Aqil, A., Lippeveld, T., & Hozumi, D. (2009). PRISM framework: Strengthening routine health information systems. Health Policy and Planning, 24(3), 217–228. https://doi.org/10.1093/heapol/czp010

[4] Bates, D. W., et al. (2003). The impact of computerized physician order entry on medication error prevention. Journal of the American Medical Informatics Association, 10(4), 295–308.

[5] Berner, E. S., & Graber, M. L. (2008). Overconfidence as a cause of diagnostic error in medicine. The American Journal of Medicine, 121(5 Suppl), S2–S23.

[6] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

[7] Graber, M. L., Kissam, S., Payne, V. L., et al. (2012). Cognitive interventions to reduce diagnostic error. Diagnosis, 1(1), 25–32.

[8] Kawamoto, K., et al. (2005). Improving clinical practice using clinical decision support systems: A systematic review. BMJ, 330(7494), 765. https://doi.org/10.1136/bmj.38398.500764.8F

[9] Lippeveld, T. (2001). Routine health information systems: The glue of a unified health system. MEASURE Evaluation Bulletin, 3, 1–5.

[10] Moja, L., Liberati, E. G., Galuppo, L., et al. (2014). Effectiveness of computerized decision support systems linked to electronic health records: A systematic review and meta-analysis. American Journal of Public Health, 104(12), e12–e22.

[11] Osheroff, J. A., et al. (2007). A roadmap for national action on clinical decision support. Journal of the American Medical Informatics Association, 14(2), 141–145.

[12] Phansalkar, S., van der Sijs, H., Tucker, A. D., et al. (2013). Drug–drug interactions that should be non-interruptive in order to reduce alert fatigue in electronic health records. Journal of the American Medical Informatics Association, 20(3), 489–493.

[13] Sittig, D. F., & Singh, H. (2010). A new socio-technical model for studying health information technology in complex adaptive healthcare systems. Quality & Safety in Health Care, 19(Suppl 3), i68–i74.

[14] Topol, E. (2019). Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again. New York: Basic Books.