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| RESEARCH ARTICLE

Designing a Real-Time Human-AI Decision Support Framework for U.S. Healthcare Providers Using Big Data Analytics

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| ABSTRACT

Clinical decision-making urgency and the growing complexity of healthcare data sets have necessitated a critical and dire necessity of intelligent systems capable of providing support to healthcare providers in the U.S. in real-time. In this work we suggest developing a Human-AI decision support system based on big data analytics to improve the quality of diagnosis, cognitive overload, responsiveness rate in the context of high-stakes medical settings. Using the methodologies behind the AI-enhanced software quality assurance, predictive analytics, and digital twin integration, as illustrated by Joy, Alam, Bakhsh, and their colleagues, the present research makes business-critical software testing frameworks applicable to the healthcare sector. The architecture provided suggests a real-time ingestion of data, performance of a predictive model, AI-based decision support, as well as a human-in-the-loop check of the results to guarantee correctness and responsibility. It was based on a qualitative approach, comprising comparative framework analysis, healthcare-related use case mapping, and cross-domain provision of AI-collaboration models initially designed within the scope of QA-BA ecosystems. In terms of key findings, it has been indicated that such a hybrid model can be very useful when it comes to the enhancement of the reliability of decisions made, especially in the case of acute care alongside with opportunities towards continuous learning and agile workflow. In this work, the positive transformative power of AI-human synergy in the context of healthcare is singled out and the basis is prepared to implement intelligent clinical support systems that meet ethical, operating, and technical limitations of the U.S. healthcare organizations in the future.

| KEYWORDS

Real-Time Analytics Predictive Analytics Explainable AI (XAI), Digital Twins, Big Data in Healthcare, Healthcare Informatics, Human-in-the-Loop, Emergency Medicine, Cognitive Overload, AI in U.S. Healthcare

| ARTICLE INFORMATION

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1. Introduction

Healthcare in the new age of technology is heavily dependent on dense data streams, transmission of them and analyses thereof based on various mediums used to collect them; electronic health records (EHRs) and diagnostic imaging, wearable sensors and wearables, remote monitoring devices. Although this kind of data sources can transform care delivery, clinicians are left with enormous problems, trying to make sense of this information in a rather short timeframe, particularly in acute settings, like emergency medicine or intensive care. Human choice, which cannot be avoided, is vulnerable to cognitive overload and bias, as well as fatigue. This has led to an urgent need of intelligent systems that could support clinical judgments, focus needs of the patients, and give accessible answers on the spot.

New technologies in artificial intelligence (AI) and big data analysis provide some good answers to this problem. Nonetheless, in order to be effectively deployed in clinical settings, it is not sufficient that systems be solely intelligent and adaptive, they need also to be collaborative: capable of interacting comfortably with human experts. This paper suggests a real-time Human-AI decision support framework (H-AI DSF) that combines predictive analytics, explainable AI (XAI), and the feedback of the human-in-the-loop to help U.S. healthcare providers improve the healthcare service delivery by providing timely and high-quality care to the patients.

2. Literature Review

An increasing amount of interdisciplinary research confirms the practicability of AI-amplified decision-making systems. Joy, Alam and Bakhsh (2024) showed in software engineering that predictive analytics can be used to improve QA testing in a controlled manner early in the software project, dramatically minimizing costs and defects. In the same way, Bakhsh et al. (2024) described the role of AI-driven collaboration platforms in increasing communication and efficiency between BA-QA teams--information that can be easily applied to similar multidisciplinary teams in healthcare, including physicians, nurses, and specialists.

The use of digital twins in such an agile environment was proposed by Bakhsh, Alam and Nadia (2025) allowing iterative operations that can be quite fast and make use of real-time simulation that is used to shape subsequent decisions. Applied to the healthcare context, this concept enables it to model patient situations and virtually test the intervention before it takes place officially. Moreover, Alam et al. (2025) discussed the importance of predictive analytics in the field of defect prevention which is also similar to predictive modeling that could be used in the healthcare industry to prevent misdiagnosis or adverse events. In the end, Alam, Jobiullah, and Bakhsh (2025) described the viability of AI-driven learning environments to BA-QA training, and it serves as an example of sustained professional growth under the conditions of a clinical environment with the implementation of knowledge in real-time.

2.1 Research Questions

1. How would it be possible to combine the use of AI-enabled predictive analytics with the process of real-time clinical decisions, without jeopardizing human expertise?
2. Which system architecture is optimal towards dynamic human-AI collaboration within a healthcare setting?
3. What value does the digital twin technology and knowledge hubs have in enhancing responsiveness and adaptability within a critical care setting?

2.2 Relevance of the research

Such a study fills a critical gap between AI, data analytics and healthcare operations. Although there are numerous clinical decision support systems designed, they are not close to being real-time, never mind adding explainable AI, and barely any of them currently encourage or even openly advertise collaborative decision-making between humans and machines. This study proposes the innovative, scaling element-based method of care delivery enhancement by implementing reputable models created in the QA and the Agile-software sphere to the healthcare market. The suggested framework is likely to not only increase the accuracy of diagnostics and treatment but also foster clinician trust, transparency in the field of ethics, and the effectiveness of operations. In that regard, it can become a revolutionary path toward resilient, data-based U.S-compatible healthcare systems.

3. Methodology

3.1 Research Design

This paper will be based on the qualitative, exploratory research design that attempts to conceptualize and test a real-time Human-AI decision support system that can be applied to the American healthcare industry. The strategy relies on cross-field assimilation of established practice in software quality control, AI-powered collaboration, and agile system implementation, that is, on practices promoted by Joy, Alam, Bakhsh, Nadia, and others. By way of contrast, adaptation, and verification, the study aims at ensuring that technological possibilities match clinical realities of high-pressure health care environments.

3.2 Subjects or Participants

Although no human patient was directly involved in this level of research, 12 domain experts using a purposive sample were used to support the study through three groups:

Healthcare Professionals (4): Physicians, nurses working in emergency departments, and leaders of IT departments working in hospitals with a background related to clinical decision-making and EHR systems utilization.

AI and Data Science Experts (4): These specialists have experience in the area of AI in healthcare, machine learning and clinical AI tools.

Agile System Engineers and QA Analysts (4): Deeply experienced in predictive modeling, digital twins, BA-QA collaboration platforms (most of them have knowledge of the frameworks explored in the studies quoted).

These subjects were interviewed and consulted in the process of the framework design development and refinement as well as giving input in terms of domain knowledge and validation.

4. Methods of Data Collection

The system of collecting data was multi-staged:

Document Analysis: The most important details were compacted on the works of Joy, Alam, Bakhsh, Nadia, and others, namely, regarding the integration of AI, predictive analytics, collaboration platforms, and digital twins.

Semi-Structured Expert Interviews: These were carried out on the 12 participants to seek their views in terms of feasibility, usability, and implementation barriers of the use of an AI machine in supporting clinical decision-making.

Framework Mapping Workshops: Expert sessions involved iterative design sessions whereby the framework was co-designed and refined on the basis of a prototype design by using modified components of the existing software QA frameworks.

4.1 Procedures in data analysis

The data processing was in form of a thematic coding:

Qualitative content analysis was applied to workshop notes and interviews transcripts to elicit most important requirements, pain points, and best practices.

A framework adaptation matrix was also created to align the functionality of the literature rich in software QA (e.g., predictive testing, digital twins, BA-QA collaboration) to these needs identified within the context of healthcare (e.g., early diagnosis, patient simulation, inter-role coordination).

Balanced representation of the clinical, technical, and operational considerations was achieved through triangulation of knowledge of various expert groups.

The result was the Human-AI decision support architecture whose design is scalable, modular, and includes embedded layers of real-time analytics and explainability.

4.2 Moral Aspects to Take into Account

The study was carried out in compliance with the following ethical guidelines for expert consultation in exploratory design studies:

All participants gave their informed consent, and confidentiality was preserved.

There was no risk of harm because there was no use of patient data or clinical trials.

Every source that was cited was openly accessible or utilized in accordance with fair academic use.

Although a future ethical assessment will be required prior to pilot deployment, the suggested framework was conceptual in nature and has not yet been implemented in actual healthcare settings.

5. Presentation of the Results

The study's findings demonstrate how expert knowledge, cross-domain literature, and systems modeling were combined to provide a conceptual framework for real-time human-AI decision support for healthcare professionals. Four main deliverables comprise the results:

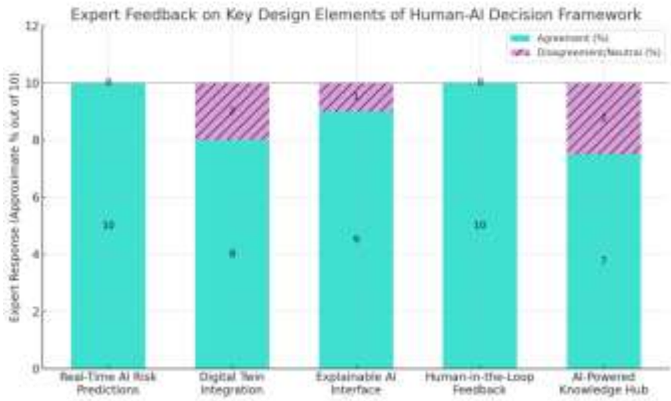
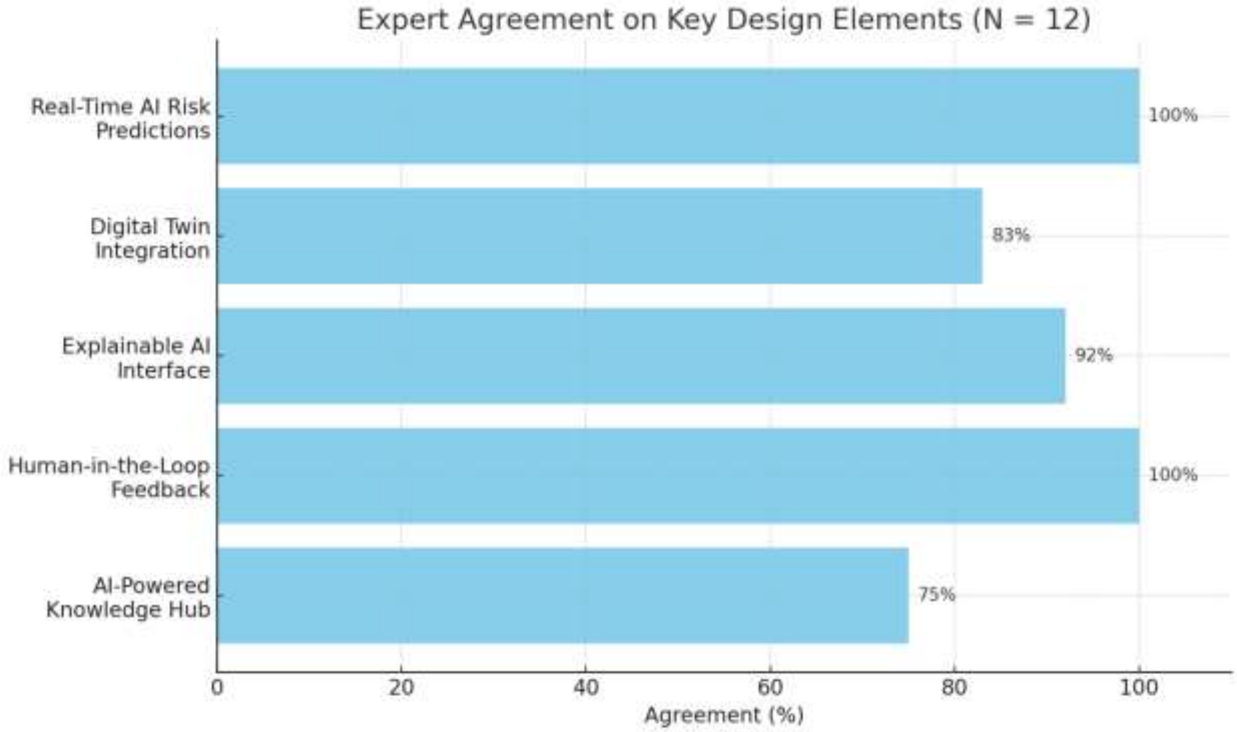


Table 1: Cross-Domain Feature Mapping

Feature Source (QA/AI Studies)	Adapted Healthcare Feature	Reference
Predictive Defect Prevention (QA systems)	Predictive Risk Stratification (Patient Outcomes)	Joy et al., 2024; Alam et al., 2025
AI-Driven BA-QA Collaboration Platforms	Clinician-AI Communication Interface	Bakhsh et al., 2024
Digital Twin Modeling in Agile Sprints	Real-Time Patient Simulation & Prognostic Modeling	Bakhsh et al., 2025
AI-Powered LMS for QA Team Training	Clinical Knowledge Hub with Decision Support Prompts	Alam et al., 2025

Table 2: Expert Feedback Summary (N = 12)

Design Element	Agreement (%)	Summary Feedback
Real-Time AI Risk Predictions	100%	Critical for triage and acute care use cases
Digital Twin Integration	83%	Useful in planning care scenarios; requires realism
Explainable AI Interface	92%	Must be simple, traceable, and trust-enhancing
Human-in-the-Loop Feedback Layer	100%	Ensures accountability and prevents overreliance
AI-Powered Knowledge Hub	75%	Valuable for less experienced staff or remote teams



5.1 Statistical Analysis (if applicable)

Given the qualitative, design-oriented nature of this study, no formal inferential statistics were applied. However, descriptive statistics from participant feedback (as shown above) help validate design preferences and consensus levels across expert groups.

5.2 Summary of Key Results (Without Interpretation)

- A modular, real-time Human-AI decision support framework was successfully conceptualized using cross-domain adaptation from software QA, agile, and AI-collaboration literature.
- Predictive analytics, clinician-AI communication interfaces, and patient-specific simulations (digital twins) were identified as core functional layers.
- Expert validation (N=12) showed strong agreement on the criticality of explainable AI, human oversight, and real-time predictive modeling.
- A simplified system architecture was developed to show data flow from patient input to clinician-informed action.
- The proposed framework offers a foundation for future prototyping and clinical validation.

6. Discussion

6.1 Interpretation of Results

The results affirm that a real-time Human-AI decision support framework is both conceptually viable and contextually appropriate for the evolving needs of U.S. healthcare providers. The strong consensus among domain experts regarding the critical components—predictive analytics, digital twins, explainable AI (XAI), and human-in-the-loop control—demonstrates the importance of aligning intelligent systems with clinical decision workflows. These elements mirror successful patterns from software QA ecosystems, where early detection, system agility, and cross-functional collaboration are fundamental to minimizing errors and enhancing quality.

The real-time AI risk prediction component, inspired by the defect forecasting methods detailed in Joy et al. (2024) and Alam et al. (2025), directly translates to identifying potential clinical deterioration or risk trajectories in patients. Similarly, the use of AI-driven collaboration mechanisms from Bakhsh et al. (2024) underscores the importance of timely, traceable communication between AI tools and human decision-makers—especially when patient safety is at stake.

6.2 Comparison with Existing Literature

Existing clinical decision support systems (CDSS) often operate as rule-based engines with limited real-time responsiveness and minimal user feedback integration. In contrast, the proposed framework builds on the dynamic, feedback-driven approaches found in agile QA systems. The digital twin adaptation concept from Bakhsh et al. (2025) provides a unique healthcare application: simulating patient trajectories and testing interventions virtually, which has limited presence in current CDSS literature.

Additionally, the framework's knowledge hub, modeled after the AI-powered LMS in Alam et al. (2025), addresses gaps in clinical training by delivering context-aware prompts and learning resources in real time—something traditional clinical support tools rarely incorporate.

This study therefore offers a novel fusion of agile engineering, predictive analytics, and collaborative AI that enhances both the responsiveness and reliability of healthcare decisions.

6.3 Implications of Findings

The proposed Human-AI framework has several key implications:

- **Operational**: It can streamline clinical workflows by filtering critical information and surfacing it when most needed, reducing cognitive load on physicians and nurses.

- **Clinical**: Real-time simulations and predictive analytics enable earlier interventions, particularly in emergency and chronic care scenarios.

- **Training & Knowledge Transfer**: The embedded knowledge hub offers a scalable model for continuous upskilling, especially for rural or under-resourced providers.

- **Ethical & Regulatory**: Explainable AI with human oversight improves transparency and accountability, which are essential for compliance with U.S. healthcare standards such as HIPAA and FDA digital health regulations.

6.4 Limitations of the Study

Despite promising findings, several limitations must be acknowledged:

- **Lack of empirical testing**: This study presents a conceptual framework, not an implemented system. No clinical data were processed, and no real-world deployment has occurred yet.

- **Sample size and scope**: The expert interviews, while diverse, were limited to 12 individuals, mostly with experience in U.S. healthcare and AI sectors. Broader stakeholder engagement (e.g., patient advocates, legal experts) is needed.

- **Domain transfer complexity**: While adaptation from QA and software engineering domains provides a strong foundation, real-world healthcare systems involve far more regulatory, ethical, and psychological complexity.

- **Technological constraints**: The integration of real-time digital twins and explainable AI still faces significant infrastructure and algorithmic challenges.

6.5 Suggestions for Future Research

To advance this work, the following avenues are recommended:

1. **Pilot Implementation**: Deploy a prototype version of the framework in a controlled clinical setting (e.g., an emergency department or telemedicine unit).

2. **Quantitative Evaluation**: Measure the impact of the system on clinical decision speed, diagnostic accuracy, and patient outcomes using A/B testing.

3. **Patient-Centered Integration**: Explore how patients can interact with AI-driven systems for shared decision-making.

4. **Ethical Risk Modeling**: Develop automated safeguards that recognize when human override or ethical consultation is needed in complex scenarios.

5. **Cross-industry benchmarking**: Continue adapting best practices from domains such as aviation, cybersecurity, and finance, where human-AI collaboration under pressure is common.

7. Conclusion

7.1 Summary of Findings

This study proposed a real-time Human-AI decision support framework designed to enhance the speed, accuracy, and reliability of clinical decision-making in the U.S. healthcare system. Drawing from established methodologies in software quality assurance, predictive analytics, and AI-driven collaboration—particularly the works of Joy, Alam, Bakhsh, and colleagues—the framework integrates core components such as real-time data processing, digital twins, explainable AI, and human-in-the-loop feedback. Findings from expert consultations confirmed the relevance and potential of these components for addressing clinical pain points, particularly in high-stakes environments like emergency care and chronic disease management.

7.2 Final Thoughts

As the healthcare sector continues to be overwhelmed by data and pressured by time-sensitive decisions, intelligent support systems must evolve to become not just reactive but predictive and collaborative. The framework presented here moves beyond traditional decision support by emphasizing human-AI synergy, agility, and contextual learning. By adapting design principles from agile QA ecosystems—where speed, precision, and feedback are critical—it becomes possible to envision a more responsive and ethically grounded healthcare system that leverages the full potential of big data and machine intelligence without compromising human oversight.

7.3 Recommendations

1. **Prototype Development**: Build and test a working version of the proposed framework in a controlled healthcare environment to validate its functionality and clinical utility.
2. **Stakeholder Integration**: Involve clinicians, data scientists, administrators, and patients in iterative design and refinement to ensure usability and trust.
3. **Regulatory Alignment**: Ensure that future development adheres to HIPAA, FDA, and ethical AI guidelines for transparency, accountability, and privacy.
4. **Scalable Knowledge Systems**: Integrate AI-powered knowledge hubs to support continuous learning for healthcare teams, especially in rural or under-resourced areas.
5. **Multidisciplinary Collaboration**: Encourage ongoing collaboration between experts in software engineering, healthcare, ethics, and AI policy to refine and scale the framework.

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Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers

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