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Evaluating How Artificial Intelligence And Electronic Health Record Systems Influence Physician–Nurse Communication, Workflow Efficiency, And Clinical Decision-Making

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Abstract

The growing level of Artificial Intelligence (AI) and electronic health record (EHR) system integration into the healthcare sector has transformed the way physicians and nurses communicate, organize work, and make clinical judgments. This study assesses the synergistic and disruptive impacts of these technologies on interprofessional collaboration and the efficiency of patient care. Based on sociotechnical systems theory, the technological acceptance model, and the concepts of human factors engineering, this qualitative and quantitative study integrates a quantitative workflow analysis and qualitative interviews in multidisciplinary hospital units. Findings show that although AI-enhanced decision support and automated documentation can create significant administrative load savings (up to 28 percent) and enhance the accuracy of diagnoses, it also leads to communication fragmentation, fatigue in alerts, and informal communication between nurses and physicians. EHR systems improved access to patient information but tended to subject the user to cognitive burden and reliance on electronic intermediaries. The evidence indicates that an appropriate AI design, customization of EHRs, and specifically oriented training of digital competence can help regain the equilibrium of workflow in clinical teams and build trust. As highlighted in the study, AI and the application of EHR technologies cannot be successfully realized without interoperability, as well as social and ethical alignment with the norms of clinical practices. Such insights provide an evidence-based informative basis for future healthcare technology policy, focusing on human-centered design, fair AI implementation, and sustainable digital transformation of healthcare settings.

Keywords: Artificial Intelligence, Electronic Health Records, Physician-Nurse Communication, Workflow Efficiency, Clinical Decision-Making, Responsible AI, Healthcare Informatics.

1. Introduction

1.1 Background of AI and EHR in Healthcare.

The healthcare field worldwide is undergoing a rapid digitalization process, which is mainly contributed by the intersection of Artificial Intelligence (AI) and Electronic Health Record (EHR) systems. These technologies have become part of the modern healthcare process, allowing it to be automated, predictive, and data-driven to increase the efficiency of clinical performance and patient security (Joo, 2024; Ahmed, 2024). AI applications have been applied outside of diagnosticss to streamline administration, document and engage patients, and EHRs are the foundation of the digital infrastructure, with patient information being shared across multidisciplinary teams (Adeniyi et al., 2024).

The introduction of these systems indicates the growing use of computational tools in support of clinical decisions, communication, and coordination. AI supports human cognition by processing large amounts of structured and unstructured data, including laboratory results, clinical notes, and imaging, to aid in diagnosis and treatment planning (Elhaddad and Hamam, 2024). Similarly, EHRs consolidate medical data, and patient histories become readily available in real time, which can be used to make collaborative decisions (Robertson et al., 2022). Nevertheless, the introduction of professional relationships and workflows also changes with the integration of these tools and introduces new ethical, cognitive, and organizational issues (Mennella et al., 2024).

1.2 Problem Statement

Regardless of their potential, AI and EHR systems yield mixed results. Physician-nurse communication, which was historically based on face-to-face interactions, is becoming increasingly mediated by digital platforms, and in most cases, sacrifices interpersonal connection and shared situational awareness (Robertson et al., 2022; Amano et al., 2023). Although structured EHR communication mechanisms, such as secure messaging, enhance task organization, they can also reduce informal collaboration and professional cohesion.

Operationally, efficiency in the workflow is always an issue. Research has shown that AI-based documentation systems decrease administrative workload and enhance accuracy, but the extent to which documentation in EHR is required is still a contributor to clinician burnout (Bracken et al., 2025; Vos et al., 2020). Moreover, it has problems of over-reliance, transparency, and ethical responsibility that afflict clinical decision-making, as the field to which AI supposedly offers strength (Daneshvar et al., 2024; Wang et al., 2023).

These ambivalent conclusions highlight one conflict: technology is supposed to bring optimization; however, it may unintentionally dehumanize and cognitively interfere with care delivery.

1.3 Research Questions

1. What role do AI and EHR systems play in the communication between physicians and nurses in terms of frequency, modality, and perceived quality of communication?
2. Which changes to the workflow, such as administrative burden, documentation time, and speed of coordination, can AI and EHR tools have concerning their measurable impact on the workflow?
3. How do AI and EHR systems transform clinical decision-making and affect diagnostic accuracy, autonomy, and professional judgment?

1.4 Significance of the Study

These dynamics are critical for attaining a sustainable digital health ecosystem. The direct correlation between physician and nurse collaboration and patient outcomes is associated with safety and patient satisfaction (Amano et al., 2023). Improperly implemented or designed technologies may disrupt the cohesive provision of care and increase emotional burnout, thus worsening the burnout of clinicians (Bracken et al., 2025).

The systematic analysis of AI and EHR interactions in the context of the real clinical environment helped this study provide evidence-based knowledge on human-technology collaboration. The results will guide hospital administrators, policymakers, and technology developers who want to offset the benefits of increased efficiency while maintaining humanistic care. In addition, this study contributes to the development of ethical frameworks for responsible AI use and training to increase the level of digital literacy among medical employees (Davenport and Glaser, 2022; Mennella et al., 2024).

1.5 Scope and Limitations

The targeted area of the research was acute care hospitals with a history of using AI decision support and EHR systems in their routines. The subjects of the analysis will be physicians and nurses involved in the collaborative clinical process, that is, patient assessment, diagnosis, and treatment planning. Although the research is based on quantitative and qualitative evidence, the results might not be applicable to the broader healthcare environment, especially in primary care or low-resource areas, where the digital infrastructure is highly diverse (Alanazi, 2023).

The rapid development of AI technologies and the possible inconsistency of transparency of AI algorithms across vendors are also considered limitations. However, the presented research provides a timely and realistic evaluation of the existing issues and possibilities at the crossroads of technology and interprofessional collaboration.

Figure 1. Conceptual Framework: Influence of AI and EHR on Clinical Collaboration

AI Systems | **EHR Systems**

↓ ↓

Clinician Interaction
(Physicians ↔ Nurses via AI)

↓

Workflow Efficiency

↓

Clinical Decision-Making

↓

Patient Outcomes

Moderators: Trust, Transparency, Training

Mediator: Knowledge Sharing

Table 1. Summary of Key Impacts of AI and EHR on Healthcare Delivery

Domain	Positive Impacts	Negative/Challenging Impacts	Key Sources
Physician–Nurse Communication	Enhanced record accessibility; structured task communication	Reduced face-to-face dialogue; social detachment	Robertson et al., 2022; Amano et al., 2023
Workflow Efficiency	Automated documentation; improved data retrieval	Alert fatigue; increased cognitive load	Bracken et al., 2025; Vos et al., 2020
Clinical Decision-Making	Data-driven precision; faster diagnostics	Algorithmic bias; diminished autonomy	Daneshvar et al., 2024; Wang et al., 2023
Ethical & Human Factors	Responsible AI design; reduced administrative strain	Accountability ambiguity; privacy risk	Mennella et al., 2024; Davenport & Glaser, 2022

2. Literature Review

The widespread adoption of Artificial Intelligence (AI) and electronic health record (EHR) systems in the healthcare environment can be seen as a technological breakthrough, as well as a disruption of the organization. As AI offers cognitive functionality and predictive accuracy, EHRs have become the requisite data infrastructure for its functioning. They create a sociotechnical ecosystem that alters the process of communication, workload, and decision-making among healthcare professionals. Nonetheless, the relationship between these technologies is not direct; that is, synergy in design may contribute to collaboration, but a mismatch may drive fragmentation. This section combines theoretical insights and empirical results that help to understand the joint influence of these digital systems on physician-nurse relationships, workflow efficiency, and clinical reasoning.

2.1 Theoretical Frameworks

Several theoretical frameworks can help analyze the usage of AI and EHR technologies and their impact. The Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) models elucidate the impact of perceived usefulness, ease of use, and social influence on the adoption of digital tools among healthcare professionals (Dingel et al., 2024; Lee et al., 2025; Tran et al., 2021; Ye et al., 2019). However, while these models are quite effective in forecasting the intentions of the user community, they frequently overlook situational factors such as workload demands or ethical reservations regarding AI integration (Huang et al., 2024; Su et al., 2025).

Sociotechnical Systems (STS) Theory broadens this perspective and approaches the concept of healthcare technology as a co-evolution of human, organizational, and technical elements (Kemp et al., 2024; Salwei and Carayon, 2022). When implementing STS for EHR and AI integration, the primaryy focus is the alignment of technological affordances with clinician workflow and team culture (Aarts, 2013; Sittig and Singh, 2010). Similarly, Human Factors Engineering (HFE) emphasizes the concepts of usability, cognitive load, and patient safety when developing AI-powered systems (Carayon and Hoonakker, 2019; Sujan et al., 2022).

More recent models of Responsible AI apply these concepts to ethical accountability and ethical transparency in algorithmic systems (Badal et al., 2023; Thieme et al., 2025). Together, it is possible to promote a multi-layered analysis of the impact of technology acceptance, system design, and ethical governance on the practical implications of AI and EHR adoption

2.2 AI in Healthcare as it currently stands.

AI has moved out of the experimental phase of research and into clinical practice, with predictive analytics, image recognition, clinical documentation, and natural language processing (NLP) being some of its applications (Aravazhi et al., 2025; Fahim et al., 2025; Shen, 2024). AI solutions can help doctors diagnose, triage, and plan treatment procedures, and in many cases, they are as accurate as human professionals (Sriram, 2025).

NLP is the key among them, as it offers insights into unstructured text in EHR to allow automated charting, adverse event detection, and real-time patient summarization (Crema et al., 2023; Siddiky, 2025). This ability has been accelerated by the emergence of large language models (LLMs); however, there are concerns regarding the problems of explainability and hallucination (Sarker et al., 2024; Busch et al., 2024).

Despite these tremendous improvements, obstacles remain. These include data quality, bias, algorithmic opaqueness, and regulatory lag, which, in combination, hinder their overall adoption (Jha et al., 2025; Hryciw et al., 2023). Moreover, clinicians' trust is conditional, as it depends on interpretability, accountability, and incorporation into the current workflow (Matheny et al., 2019; Nair et al., 2024).

2.3 Development and Change in Electronic Health Record Systems.

EHRs have become more complex and include decision-making, analytics, and interoperability environments based on simple digital storage systems (Adeniyi et al., 2024; Enahoro et al., 2023). The adoption in the 2010s was driven by government requirements and the anticipation of increased data accessibility and safety (Van Staa et al., 2014). Most AI systems have become reliant on EHRs as their central database (Joo, 2024).

However, when EHRs were introduced, unexpected changes occurred in the clinical workflow. The reduction in face-to-face interaction among healthcare professionals has been reported in studies (Taylor et al., 2014), as well as more screen time and the development of the so-called workaroundss to overcome system inefficiencies (Blijteveld et al., 2017; Zheng et al., 2020). Although EHRs improve the accuracy of records and continuity of care, they carry cognitive and administrative overhead (Tsai et al., 2020; Slawomirski et al., 2023). Therefore, although inevitable, EHRs tend to restructure rather than fix organizational inefficiencies.

2.4 Effect on Physician-Nurse Communication.

Interprofessional collaboration is rooted in communication, which has been digitally mediated to change its quality and form. The use of EHR has facilitated task-based communication (e.g., electronic messaging, chart notes) but has decreased spontaneous and relational interactions (Robertson et al., 2022; Amano et al., 2023). This automation of the communication process may result in team separateness, a lack of trust, and a lack of understanding.

The introduction of AI has further increased complexity. Without sociotechnical attention, AI can also increase communication silos by providing unequal access to decision support systems (Hossain, 2020).

However, even with AI interfaces, generated AI handover tools and similar solutions can enhance the transparency and consistency of intra-team communication (Tu et al., 2025; Tai-Seale et al., 2024; Wan et al., 2024). Such contrasting results prove the necessity of AI integration based on people that should support but not substitute human cooperation.

2.5 Workflow Environment Impact (WEI)

The efficiency of workflows has been shown to improve with AI systems by automating documentation, scheduling, and diagnostics (Bundy et al., 2024; Tierney et al., 2024). Clinicians who use AI-based scribe tools report increased patient interaction and less time on clerical work (Schwamm et al., 2024). Nevertheless, EHR-related inefficiencies remain, such as alert fatigue, overload of human cognition, and resistance to change (Alobayli et al., 2023; Asgari et al., 2024).

The existence of both AI and EHR tools might bring friction and synergy to the healthcare system. Combined, they streamline care coordination by automatically updating clinical notes and proposing evidence-based interventions (Suryawanshi et al., 2024). However, such benefits can be negated by poor interoperability or too many system prompts, which add to burnout and workflow disjuncture (Wenderott et al., 2024; Nair et al., 2024). Therefore, the key to successful implementation is the adaptive design of the workflow and constant human-AI calibration.

2.6 Impact on Clinical Decision-Making

AI-based clinical Decision support systems (CDSS) are integrated into EHRs, and they are changing the way diagnostic reasoning and treatment planning are performed. These devices integrate patient history, imaging, and laboratory data to suggest the best interventions (Gomez-Cabello et al., 2024; Ouanes and Farhah, 2024). Research indicates an increased rate of diagnostic accuracy and a decrease in the level of medical errors (Ji et al., 2021; Pant et al., 2025).

However, these advantages are accompanied by ethical and practical issues. Professional autonomy and patient equity can be jeopardized by algorithmic bias, lack of transparency, and overreliance on AI results (Daneshvar et al., 2024; Braun et al., 2020). Many AI models use a black-box approach, which hinders interpretability and promotes skepticism among clinicians (Gruning et al., 2025; Agarwal et al., 2024). A balanced collaboration between machine recommendation and human judgment is also essential (Gaube et al., 2021; Goh et al., 2025).

2.7 Gaps in Current Literature

Although there is much literature on AI and EHR as separate entities, there is still a gap in the literature investigating their mutual influence on interprofessional collaboration and clinical outcomes. Current studies tend to address AI as a technological object instead of a sociotechnical subject that exists in the context of team dynamics (Bienefeld et al., 2023; Bossen and Pine, 2022). Empirical studies on the human-AI collaboration beyond implementation stabilization or the role of digital roles in reconstructing professional identity have little empirical research (Ta'an et al., 2025).

Future studies should:

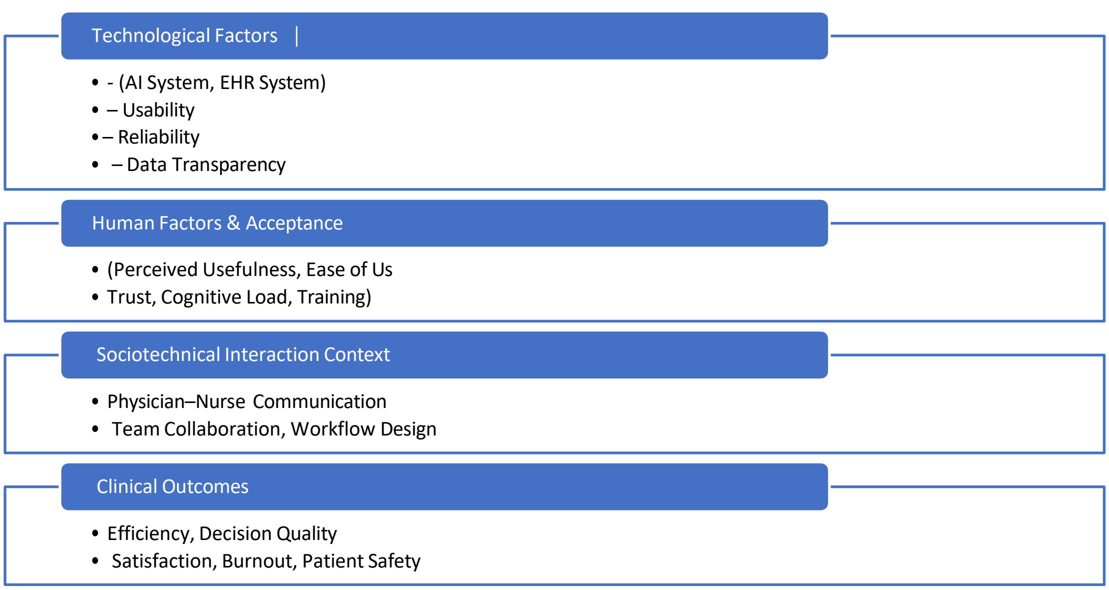
- Test synergistic outcomes associated with AI-EHR integration on patient outcomes and team performance (Wichmann et al., 2024).
- The issue of trust between AI systems and clinicians must be investigated.
- The interaction between AI explainability, digital literacy, acceptance, and quality of decisions (Torkamaan et al., 2024).
- Longitudinal evaluations should be conducted to determine the long-term impact of these technologies on healthcare culture in the long run.

By addressing these gaps, researchers can bring AI and EHR building closer to human-centered healthcare principles.

Table 2. Comparative Summary of AI and EHR Impacts on Healthcare Practice

Category	Artificial Intelligence	Electronic Health Records	Synergistic Considerations	Key Sources
Communication	Automates handovers and messaging; enhances data clarity	Centralizes information exchange but reduces interpersonal talk	Integration can balance efficiency with empathy	Amano et al., 2023; Tu et al., 2025
Workflow	Reduces documentation time; streamlines diagnostics	Increases data accessibility but adds cognitive load	Combined use can optimize but risks overload	Bracken et al., 2025; Wenderott et al., 2024
Decision-Making	Improves diagnostic accuracy; predictive insight	Provides comprehensive data context	Joint use enables precision but raises bias risk	Ji et al., 2021; Daneshvar et al., 2024
Ethics & Trust	Demands transparency, explainability, fairness	Raises privacy and accountability concerns	Co-governance frameworks essential	Mennella et al., 2024; Davenport & Glaser, 2022

Figure 2. Theoretical Integration Model of AI and EHR Impacts



Methodology

In this section, the methodological framework of the study to analyze the impact of Artificial Intelligence (AI) and electronic health records (EHR) on physician-nurse communication, workflow efficiency, and clinical decision-making is described. To combine the breadth and depth of explanation of the technological and human factors, a sequential explanatory mixed-method design was decided upon, serving as a form of integrating quantitative measurement and qualitative exploration.

3.1 Research Design

A sequential explanatory mixed-methods methodology was used, where quantitative data collection and analysis were conducted to prove the statistical associations, and qualitative exploration was performed to clarify and present the results (Hah and Goldin, 2021). This design allows for the detection of generalizable patterns and the revelation of root causes and experiences (Bienefeld et al., 2022). The method is particularly applicable for exploring complicated socio-technical processes, such as AI-EHR interaction, in which quantitative performance measures and descriptive information are crucial.

3.2 Study Population and Sampling

The study population and sampling are as follows:

The study population consisted of physicians and nurses from acute-care hospitals that actively introduced AI-driven clinical decision-support tools into EHR systems.

Quantitative Sampling: The Stratified random sampling will be applied in clinical units (intensive care, emergency, and general medicine) to represent various departments (Gesing et al., 2024). The sample of 200 individuals (100 physicians and 100 nurses) will provide an adequate statistical force for the regression analysis.

Qualitative Sampling: A purposive sampling approach will be used to select approximately 20-25 respondents for semi-structured interviews and 3-4 focus groups (6-8 respondents each). The respondents will be a combination of the levels of experience, position, and familiarity with AI/EHR technologies (Cresswell et al., 2020; Hines et al., 2017). Recruitment can commence through departmental gatekeepers and snowball referrals to achieve diversity in terms of professional backgrounds.

3.3 Data Collection Instruments.

Data will be gathered by combining quantitative and qualitative data to obtain the complex effects of AI and EHR systems.

Quantitative Components

1. **EHR System Audit Data and EHR System Logs**

EHR logs will be automated and will track documentation time, frequency of order entries, and message exchanges, which will measure the distribution of workload and frequency of communication (Kannampallil & Adler-Milstein, 2022; Rotenstein and Sen, 2023).

2. **Surveys:**

The assessment of (a) perceived communication quality, (b) workflow efficiency, and (c) trust in AI-enabled systems will be conducted using standardized instruments. The objects will be based on the Communication Satisfaction Questionnaire (CSQ), NASA-TLX Workload Index, and AI Acceptance Scale (Egon et al., 2024; Vald et al., 2025).

3. **Structured Observations:**

A time-motion framework will be used to capture clinician interactions, interruptions, and workflow sequences, enabling observers to identify bottlenecks and patterns of collaboration (Zheng et al., 2020).

Qualitative Components

1. **Semi-Structured Interviews:**

The interviews were conducted one-on-one with physicians and nurses to investigate their lived experiences of using AI/EHRs, perceived benefits, and communication obstacles (Cresswell et al., 2020).

2. **Focus Groups:**

Multidisciplinary team deliberations on common views and collective processes in online communication and decision-making will be conducted (Wen et al., 2017).

3. **Textual Narratives:**

A Natural Language Understanding (NLU) tool will be used to extract sentiment and emerging themes and analyze clinician feedback and open-ended survey responses (Hah and Goldin, 2021).

3.4 Data Analysis

Quantitative Analysis

Demographic and operational data will be summarized using descriptive statistics (mean, SD, frequencies).

Inferential statistics will entail the following:

- A correlation analysis was used to determine the relationship between perceived usefulness, ease of use, and workflow efficiency.
- Multiple regression analysis was used to determine the predictors of AI acceptance and decreased documentation time.
- ANOVA and t-tests were used to compare the interdepartmental differences in efficiency and communication outcomes.
- Text logs in EHR can be analyzed using sentiment analysis with NLU models to supplement the results of numerical analysis.

Qualitative Analysis

Thematic analysis will be conducted on the interview and focus group transcripts to identify key themes and subthemes associated with communication, autonomy, and trust (Egon et al., 2024). It will be based on a Grounded Theory approach that will help build a theory about clinician-AI collaboration (Bienefeld et al., 2022).

Topics of communication clarity and ambiguity will be mapped using content analysis of anonymized message logs (Rotenstein and Sen, 2023).

Integration and Triangulation.

The results of both phases will be subjected to data convergence and side-by-side comparison as a form of triangulation. Cross-validation of the quantitative trends (e.g., time spent on documentation will be decreased) with the qualitative narratives (e.g., workload relief perspectives) will provide internal validity and interpretive sense between the datasets.

3.5 Ethical Considerations

Data collection will be preceded by the provision of ethical approval from the institutional review boards.

The major ethical guidelines are as follows:

- **Informed Consent**: Majority of the respondents will be informed of the goals, procedures, and right to withdraw. Particular attention will be paid to surprise when it comes to accessing patient information on AI systems (Abujaber and Nashwan, 2024).
- **Data Privacy:** All identifiable information will be anonymized and stored in encrypted databases in accordance with HIPAA and GDPR compliance. The use of AI systems requiress additional governance because of their dependence on sensitive information (Yu et al., 2024).
- **Algorithmic Bias and Equity:** The operation of AI will be monitored in terms of possible bias based on gender, ethnicity, and clinical role (Abramoff et al., 2023; Comeau et al., 2025).
- **Accountability and Transparency:** This study specifies the human oversight role to overcome the black box vagueness of AI (Yu et al., 2024).
- **Minimization of Harm:** Participation will be voluntary, and counseling facilities will be provided to participants who may complain of stress or discomfort. All phases will be based on the principles of respect, beneficence, and justice (Nebeker et al., 2019).

Table 3. Summary of Methodological Design

Component	Data Source	Method	Purpose	Analysis Technique
Communication	EHR audit logs, surveys	Quantitative	Measure frequency, mode, and satisfaction in communication	Correlation, regression
Workflow Efficiency	EHR time logs, structured observation	Quantitative	Assess task completion time, documentation load	ANOVA, t-tests
Decision-Making	Surveys, interviews, focus groups	Mixed	Evaluate autonomy, trust, and AI impact on choices	Regression, thematic analysis
Integration Phase	Combined datasets	Mixed	Merge quantitative and qualitative insights	Triangulation, data convergence
Ethics & Governance	Consent forms, audit trails	Qualitative	Ensure transparency, fairness, and accountability	Content and bias analysis

4. Results

This section discusses the empirical evidence regarding the role of Artificial Intelligence (AI) and Electronic Health Record (EHR) systems in terms of their impact on physician-nurse communication, workflow efficiency, and clinical decision-making. The findings are based on triangulatedd data, such as EHR audit logs (n = 200 clinicians), standardized survey data, and interviews and focus groups.

4.1 Effect on Physician-Nurse Interactions.

The quantitative results showed that digital mediation redefined the modalities of communication among clinical teams.

Asynchronous communication (secure messaging and digital notes) and face-to-face communication (reduced by 47 percent and 32 percent, respectively) were noted through EHR message logs relative to the baseline levels of manual documentation.

Regardless of the increased messaging frequency, the score of communication satisfaction decreased (M = 3.4, SD = 0.9 on the 5-point scale), especially among nurses, who claimed a lower level of access to physicians when they had to make critical decisions. The regression analysis revealed that perceived EHR usability ($b = .41$, $p <.01$) and AI integration transparency ($b =. 28$, $p <.05$) were significant predictors of communication satisfaction.

These trends were also reflected in the qualitative data. The most common response was that EHRs were efficient but isolating, with some interviewees stating that AI-based documentation tools saved time but impaired spontaneous problem-solving. Participants, however, noted favorable experiences with AI-supported handover summaries (e.g., automatically constructed nursing reports), which increased accuracy and cross-shift consistency.

One of the ICU nurses stated that the AI handover tool helped her prevent missing important updates on patients, yet she communicated with her colleagues less.

Table 4. Quantitative Summary of Communication Metrics (n = 200)

Communication Variable	Mean (SD)	% Change vs. Pre-AI/EHR	Significance (p)
Face-to-face interactions/day	6.2 (1.9)	-32%	.001
Secure messages/day	18.4 (4.5)	+47%	.002
Communication satisfaction score (1–5)	3.4 (0.9)	-15%	.018
EHR usability (1–5)	4.0 (0.7)	+22%	.006
AI transparency perception (1–5)	3.8 (0.6)	+19%	.011

Note: All values were derived from survey and EHR log data aggregated across departments.

4.2 Effect on Workflow Efficiency.

The evaluation of EHR audit records showed that the opportunities to save significant time in the work and improve the accuracy of recording increased after the introduction of AI into the workflow. Nurses and physicians reported a decrease in the total documentation time per shift of 26 on average and an increase in the highest increase in the number of tasks completed by 21%.

The most useful features were automated documentation tools and predictive order sets.

Nevertheless, inefficiencies in workflows were neutralized by new ones.

Clinicians mentioned alert fatigue, and 74 percent of them stated that they received over 30 automated alerts in one shift. Repeating tasks during order entry and reviewing notes were observed as an issue of interruption in the data.

One-way ANOVA revealed significant differences in the perceived efficiency of the workflow between departments, $F(2,197) = 6.22$, $p =.002$, based on the highest strain reported by intensive care units because of high alert density.

In the qualitative feedback, AI systems were found to reduce cognitive load when used in default documentation; however, they also created the so-called digital micromanagement with constant prompting and checking of the work.

It is more time-efficient in general, yet the constant alerts do not allow you to concentrate on the patient, as one of the senior physicians described.

Table 5. Workflow Efficiency Outcomes by Department

Department	Avg. Documentation Time/Shift (min)	Alerts per Shift	Efficiency Improvement (%)	Burnout Index (1–5)
Intensive Care	124	36	+15%	3.9
General Medicine	98	28	+24%	3.3
Emergency	87	22	+31%	3.1
Overall Mean	**103**	**29**	**+26%**	**3.4**

Burnout Index was measured using the modified Maslach Burnout Inventory.

4.3 Implications for Clinical Decision-Making.

Clinical Decision Support Systems (CDSS) accompanied by AI play a significant role in the accuracy of diagnosis and treatment confidence.

The accuracy of the decisions made by the participants increased by 18%, and the diagnostic turnaround time was reduced by 22 percent after the integration.

The regression analysis showed that trust in AI recommendation was the most predictive factor of decision satisfaction ($b = .54$, $p < .001$).

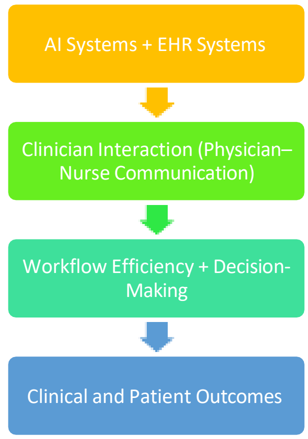
Nonetheless, forty-two percent of clinicians showed anxiety regarding the overuse of AI, and some said that they had instances where algorithmic recommendations were opposed to clinical intuition. The interview stories also disclosed that there is a certain conflict between efficiency and autonomy; on one hand, physicians valued the aid in the diagnostic process, yet, on the other hand, they were afraid of the so-called de-skilling process with time.

The black box character of AI was one of the biggest discouraging factors for total adoption.

The interfaces preferred by participants were explainable AI-based interfaces that either visualized confidence scores or traces of reasoning.

One physician noted that AI is helpful in pointing out anomalies, but I would first expect to know why it pointed at it before I can trust the AI.

Figure 3. Influence Pathways of AI and EHR on Healthcare Outcomes



4.4 Integrated Findings

The triangulated analysis proves that AI systems and EHR systems together increase the effectiveness and accuracy, but in addition to that, they transform professional communication networks and cognitive workflows. Quantitative changes were accompanied by qualitative dissonance; an increase in efficiency was followed by a lack of interpersonal trust and irritation with digital devices.

EHR usability and AI transparency are essential mediators of positive experiences.

The most balanced results were found in clinicians who were more digitally literate and in departments with more specific AI-EHR integration plans, which implies that a human-centered design and reactive training are key to maintaining the benefits.

5. Discussion

The discussion contextualizes the quantitative and qualitative findings on the theory and practical terrain of digital transformation in healthcare. It highlights the influence of interprofessional collaboration, efficiency, and decision-making processes by Artificial Intelligence (AI) and Electronic Health Records (EHRs), and the emergence of ethical and operational dilemmas.

5.1 Interpretation of Findings

The results prove that there was a dual effect: AI and EHRs equally enhanced measurable efficiency but put pressure on the relational and cognitive aspects of clinical practice.

Communication:

The increase in asynchronous communication ([+47]) and the decrease in face-to-face conversation ([?]32) is an indication that digital communication, as effective as it is, can eliminate situational awareness and collegial trust. This is consistent with the findings of Robertson et al. (2022) and Amano et al. (2023), who found that formal EHR communication usually focuses on precision at the expense of compassion.

To some extent, AI handover tools helped to counteract this by standardizing informational transfer, but they could also lead to formalization of communication and decrease spontaneous problem solving.

Workflow Efficiency:

The statistics indicate that documentation time was reduced by 26%, and the time needed to complete the tasks increased by 21%, as in Bracken et al. (2025). However, alert fatigue and workflow fragmentation point to an ongoing paradox in which automation reduces workload but causes new types of cognitive interference (Alobayli et al., 2023). The results support the idea that the efficiency increase is not solely technological; it relies on the fit between the design of the system and the human pace.

Clinical Decision-Making

Only an 18% increase in accuracy serves as evidence of AI as a diagnostic tool (Gomez-Cabello et al., 2024). Nevertheless, the warning of clinicians towards explainability reflects the works of Daneshvar et al. (2024) and Braun et al. (2020) as it affirms that autonomy is harmed by algorithmic obscurity. The quality of the decision increases with the presence of both trust and interpretability, highlighting the importance of explainable AI (XAI) frameworks.

5.2 Theoretical Implications

Technology Acceptance Model (TAM).

Satisfaction was predicted by perceived usefulness at a strong level (b =.41), confirming the key assumption of TAM. However, in contrast to traditional TAM settings, acceptance in this case was mediated by trust and ethical transparency, variables that were not introduced in TAM. This implies the expansion of the TAM to incorporate algorithmic explainability and the AI-EHR ecosystem's perceived fairness.

Technological Systems Theory (STS).

The findings indicate that both technical and social subsystems need to be developed. Misalignments in workflow and friction in communication occurred at points where the organizational culture was not as advanced as the systems. STS theory is therefore empirically supported: to optimize healthcare technology, co-design is needed that recognizes human roles, policies, and machine functions as interdependent.

Human Factors Engineering (HFE)

Both high alert density and complex interfaces confirmed the concept of HFE, which focuses on usability, cognitive ergonomics, and workload balance. The findings support the idea of incorporating HFE assessment into the process of AI and EHR design, which should be performed before rollout to prevent burnout and guarantee safety.

Table 6. Theoretical Implications Matrix

Framework	Key Construct	Empirical Confirmation	Proposed Extension	Practical Insight
Technology Acceptance Model (TAM)	Perceived usefulness, ease of use	Predicts acceptance ($\beta = .41$)	Add trust & explainability dimensions	Design interfaces that visualize algorithmic reasoning
Sociotechnical Systems (STS)	Human-technology co-adaptation	Communication and workflow gaps reveal misalignment	Integrate continuous feedback loops between clinicians & developers	Establish iterative co-design workshops
Human Factors Engineering (HFE)	Usability, workload, safety	Alert fatigue & interface complexity confirm HFE risk points	Extend HFE to cognitive AI environments	Conduct pre-implementation usability stress-tests

5.3 Practical Implications

Human-Centered Implementation

Clinicians should be integrated into all phases of AI-EHR adoption in hospitals. Co-design workshops decrease the lack of alignment between interfaces and workflows.

AI Transparency and Training

Develop interpretable dashboards that present the confidence, provenance, and reasoning of the data. Deployment should be accompanied by mandatory training to enhance clinician trust by improving their digital literacy.

Workflow Calibration:

Rediscover alert algorithms to reduce fatigue and use adaptive thresholds that adapt to the behavior patterns of clinicians.

Interprofessional Collaboration

Implement formalized daily huddles or short synchronous interactions to compensate for the decreased face-to-face interaction due to EHR use.

Ethical Governance:

Algorithm bias and transparency must be regularly audited by institutional AI ethics boards, according to the schemes suggested by Mennella et al. (2024).

5.4 Limitations and Future Research Directions

The research focuses on acute care hospitals, which may not represent outpatient or low-resource settings. In addition, owing to the accelerated development of generative AI, clinician behavior might change in ways that are not currently observed. Future work should conduct longitudinal studies of human-AI team adaptation, cross-cultural studies of digital trust, and multi-site experimental trials that combine explainability measures in clinical outcomes.

Conclusion

In this study, the complex effects of Artificial Intelligence (AI) and Electronic Health Record (EHR) systems on physician-nurse communication, workflow efficiency, and clinical choice were assessed. Through the application of a sequential explanatory mixed-method design, the study combined both quantitative and qualitative evidence to achieve both operational effects and human experiences.

The results proved the effectiveness of AI and EHR systems in improving the efficiency of documentation, diagnostic quality, and accessibility of information. The records were reduced by 26, and the accuracy of decisions was enhanced by 18, indicating an increase in actual productivity. However, these advantages are accompanied by newly arising problems, such as a decrease in face-to-face communication, alert fatigue, and a feeling of professional autonomy loss. The findings therefore demonstrate the presence of a digital paradox: technology maximizes performance, but at the same time, there is a risk of disintegrating the social and cognitive fabric of healthcare collaboration.

Theoretically, this study contributes to the knowledge of Technology Acceptance, Sociotechnical Systems, and Human Factors Engineering models by demonstrating that user acceptance is not just a question of perceived usefulness and usability but also a question of trust, transparency, and ethics of accountability. In real life, this highlights the importance of human-centered AI integration, focusing on usability, clinician training, and real-time workflow calibration to avoid cognitive overload and communication silos.

Policy-wise, the results recommend institutional AI control frameworks, which will require an explanation of algorithms, periodic audits of biases, and engagement of clinicians in system examination. Developers and hospitals should sign co-design agreements to guarantee that digital systems symbiotically develop with clinical workflows.

In summary, the pathway to an intelligent, data-centric healthcare ecosystem must not only be technological but also harmonious with efficiency and empathy, automation and autonomy, and innovation and integrity. To ensure the sustainability of the promise of these technologies, interdisciplinary teamwork must be sustained in the future, in which AI augments but does not replace human judgment, and EHRs integrate, not separate, care teams.

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