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A Narrative Theoretical Framework for Integrating AI into Electronic Medical Record Management for Allied Health Practice

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Abstract

This conceptual paper investigates the role of artificial intelligence (AI) in advancing human-centered Electronic Health Medical Records (EMRs) to enhance care delivery by Allied Health Professionals (AHPs) from hospital to home care. Anchored in the Technology–Organization–Environment (TOE) review framework, the study explores the enablers and barriers to AI integration into EMRs during an organization's digital maturity journey, with the aim of guiding product and project management to successful deliverables and acceptance to underrepresented Allied Health users. A literature review was conducted using Scopus, EBSCO, and websites of professional bodies. AI is positioned not as an end goal, but as a mediating tool that - when aligned with the nuanced needs of AHPs - can enhance clinical outcomes. This paper proposes a conceptual framework and literature-informed propositions to support future empirical testing in international, digitally diverse healthcare environments, with particular attention to deployment challenges and opportunities in the US and the UK.

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1. Introduction

It is estimated up to 70-80% of health information technology (IT) initiatives fail or partially fail, primarily due to several factors including unclear stakeholder requirements and inadequate project oversight (Gomes and Romão 2019; Hughes et al., 2016). For example, the UK's National Programme for IT (NpIT) was launched to centralize patient records and standardize care delivery, but this failed due to conflicting institutional logics, lack of clinical engagement, and overly centralized governance (Currie and Guah, 2007).

Despite its ambitious £6.2 billion budget, the programme suffered from significant delays, limited adoption, and poor alignment with frontline needs. Many clinicians felt excluded from the design process, and local National Health Service (NHS) Trusts struggled to implement one-size-fits-all systems that were not tailored to their workflows. The initiative was dismantled in 2011, serving as a cautionary example of large-scale digital health transformation efforts. Another example of poor IT Electronic Health Medical Record (EMR) project/product roll out takes place in a major US hospital network using the market-dominant EMR system Epic®, initial user satisfaction rates fell below 70%, largely due to poor documentation design, lack of workflow alignment, and opaque cost structures (Johnson, 2016). In response to IT product and project failure in healthcare, several theoretical models have emerged to guide project and product managers in enhancing EMR systems to better support digitally mature, human-centered data networks that improve both provider and patient experiences.

With the rise of artificial intelligence (AI), the success of digital transformation (DT) initiatives in healthcare increasingly depends on the need for robust product and project management strategy through good stakeholder management, a long accepted high project success factor (Dugbartey, 2024). This paper focuses on exploring the landscape for AI integration within EMRs as used by Allied Health Professionals (AHPs), aiming to support the evolution toward intelligent, interoperable systems.

The concept of DT is often mistaken for merely becoming an IT-enabled organization. However, as Wessel et al. (2021) clarify, DT involves fundamentally redefining an organization's value proposition, whereas IT-enabled organizations only support the existing one through technology. Recent scoping review protocols focused on AHPs emphasize that the rapid evolution of AI significantly impacts research, demonstrating the necessity for consistent review of the digital AI landscape in which AHPs operate. This lack of clarity suggests that organizations choosing to deploy AI-driven products or AI-use projects will inevitably undergo DT - intentionally or not - as they are compelled to reshape practices, values, and operating models around an evolving and uncertain definition of value. As Kuziemycki et al. (2024) note in their rapid umbrella review, there is still no consensus on quality criteria for AI in healthcare, and actual adoption of AI remains limited. This gap constitutes a pressing theoretical challenge. To further elaborate, Raghunathan et al.'s scoping review protocol on the development of AI for AHP use highlights the pace of technological change, reinforcing the need for continuous academic analysis of the environments in which AHPs practice. Accordingly, the purpose of this paper is to address these gaps by proposing a conceptual framework, grounded in the Technology-Organization-Environment (TOE) model (Yang et al., 2022), to guide the integration of AI into EMRs for AHPs across digitally diverse healthcare systems.

2. Approach

This conceptual study employed a narrative literature review strategy to construct a high-level theory-informed framework addressing the integration of AI into EMRs adoption and management by AHPs within the context of health and social care. The methodology followed three key stages: literature identification, thematic synthesis, and framework development, with iterative modifications. The research spans global healthcare research, with prioritized emphasis on UK and US systems in terms of government initiatives, including both public and private from acute hospital care to long-term care in homes and community settings that provide health and social care. It focuses on the continuum of health and social care, where AHPs (e.g., speech-language pathologists, physiotherapists, occupational therapists, therapy assistants, dieticians, and therapy managers) frequently manage complex, multidisciplinary interventions, for neurological rehabilitation and disease management.

A comprehensive search was conducted across academic databases such as Scopus and EBSCO and supplemented by grey literature from professional bodies such as Health Information Management Systems Society (HIMSS), National Health Service (NHS), the Professional Standards Authority, and the UK and the US Governments. The

search focused on literature published between 2004 and 2025 to capture both foundational and emerging perspectives on DT, EMR integration, AI deployment, and project management in healthcare settings. Key words like “AI,” “Allied Healthcare,” and “EMR” were used in variations to select relevant theoretical and empirical studies.

To enhance transparency in the review process, inclusion criteria prioritized peer-reviewed journal articles, systematic or umbrella reviews, preprints of emerging relevance, and authoritative grey literature published between 2004 and 2025. Sources were included if they addressed DT, EMR adoption, AI integration, or project management strategies in healthcare, with particular attention to studies referencing AHPs or transferable organizational contexts. Exclusion criteria encompassed sources lacking methodological detail, non-healthcare-specific industry commentary, or studies without relevance to EMRs or AI adoption. The synthesis followed a narrative review approach, manually thematically grouping evidence under the TOE framework and supported by complementary constructs such as Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Awa et al., 2017; Yang et al. 2022) as shown in Fig 1. Table 1 was co-generated with the assistance of a generative AI tool to support structured summarization, with all content subsequently verified for accuracy by the author.

3. Results and Discussion

The study begins by grounding itself in the TAM and UTAUT, both of which are widely used to understand healthcare professionals' adoption of digital tools (Healthcare, 2021). TAM emphasizes perceived usefulness and perceived ease of use as primary factors influencing user acceptance, while UTAUT extends the model by incorporating Social Influence and facilitating conditions—elements especially relevant in complex, collaborative healthcare environments. These models assist in explaining the variability in EMR adoption, particularly when adapted to specific clinical contexts, and in this study, will serve as moderators to outline how certain factors—whether enablers or inhibitors—can influence implementation and outcomes.

Building on this foundation, this study further employs the TOE framework to conceptualize adoption factors influencing AI-enabled EMRs (Yang et al., 2022). Awa et al. (2017) extend the TOE framework by demonstrating its enriched applicability when combined with UTAUT constructs, showing that technological, organizational, and environmental factors exert a statistically stronger influence on adoption than individual characteristics alone. This expanded perspective reinforces the need for context-sensitive implementation strategies that prioritize institutional readiness, system functionality, and social dynamics within healthcare ecosystems. Accordingly, this paper adopts the TOE lens to identify: (1) Technological factors such as system functionality, data quality, and integration capabilities; (2) Organizational factors including digital readiness, leadership engagement, and institutional culture; and (3) Environmental drivers like national policies and regulatory mandates.

3.1. Technology-driven factors

Technological enablers and inhibitors continue to shape the integration of AI within electronic medical records (EMRs). A persistent barrier to digital maturity is the lack of data standardization and semantic interoperability across EMR systems. Early in EMR development, Lenz et al. (2007) highlighted mismatches in coding frameworks (e.g., XML vs. SNOMED CT), which fragmented patient records and forced clinicians to manually reconcile data—ultimately compromising safety and efficiency. For example, Suter-Crazzolara (2018) emphasized that critical data often remain siloed between structured EMR fields and unstructured clinical notes, such as lab results and narrative rehabilitation reports. This makes natural language processing (NLP) and semantic harmonization essential for enabling AI to function effectively within EMR ecosystems. However, Rahimi et al. (2024) found that most hospital networks face challenges in transitioning from data validation to real-time data integration. Their review revealed that AI adoption remains limited in quality and scope, as only 5 of 1,247 evaluated studies were rated “good” and demonstrated tangible implementation. Their review further indicated that most studies were concentrated in radiology, underscoring the limited attention given to AI research focused on AHPs. Despite this slow uptake, the pipeline of AI-enabled EMR products under development continues to expand, reflecting ongoing efforts to overcome these systemic barriers. New deep learning models continue to be explored in EMR systems; Miotto et al. (2018) demonstrate that such models can extract high-value clinical insights from unstructured data to support risk prediction, treatment recommendations, and disease progression tracking. However, their reliance on large, well-annotated

datasets and their limited generalizability across care settings pose challenges for broad adoption into everyday AHP workflows. Moreover, the usability of EMRs and the speed of system responses significantly influence clinician adoption. Without streamlined interfaces and low cognitive load, even technically capable systems risk underutilization. Therefore, AI implementation success depends not only on system capabilities but on how well those capabilities are designed to accelerate workflows while minimizing friction points that inhibit adoption.

3.2. Organization-driven factors

DT in healthcare extends beyond IT system upgrades; it represents a fundamental redefinition of how healthcare organizations create value, deliver services, and engage stakeholders (Wessel et al., 2021). Within this evolving paradigm, EMRs serve as a central platform through which transformation efforts materialize—both enabling and reflecting an organization’s digital maturity. Philips (2020) outlines a continuum from analog (paper-based) systems to digital (basic electronic documentation), and smart (AI-enabled, interoperable systems). This maturity model aligns with the HIMSS Electronic Medical Record Adoption Model (EMRAM), a globally recognized benchmark for tracking EMR functionality across eight progressive stages as identified through formal assessment (HIMSS, 2024). Despite significant investment, many healthcare organizations, particularly within the US and the UK, remain at or below Stage 5 on the EMRAM scale, lacking capabilities such as real-time decision support, full interoperability, and advanced analytics (Kharrazi et al. 2018; Phiri et al. 2023). Organizational inhibitors such as fragmented governance, change resistance, and limited end-user involvement have repeatedly hindered implementation success.

Deutsch et al. (2010), in their cross-country evaluation of five national EMR programs, found that structural and cultural issues outweighed technical shortcomings in determining digital health outcomes. In a recent study, Snowdon et al. (2024) argue that advancing digital maturity in US hospitals is a critical strategy for enhancing patient experience, emphasizing that organizations with higher levels of digital integration tend to deliver more responsive, coordinated, and person-centered care.

Project delivery models within organizations also act as important organizational enablers or inhibitors. Morsi et al. (2024) compared Agile and traditional approaches in healthcare IT initiatives, reporting that Agile-managed projects achieved 28% faster delivery and 12% higher patient satisfaction, where traditional approaches had 5% better budget adherence. While clinical outcomes did not significantly differ, the enhanced adaptability and user engagement facilitated by Agile methods suggest potential value in aligning project management strategies with end-user needs - an area warranting further empirical investigation.

3.3. Environment-driven factors

In the UK, the NHS Long-Term Plan outlines a vision for community-based transformation of analogue to digital care and expanded use of AI technologies (UK Government, 2025). However, the strategy lacks specific guidance on user-centered design or inclusion of AHP perspectives. In the US, the Department of Health and Human Services (HHS, 2025) similarly recognizes the potential for AI in data-rich environments (e.g., wearables, EHR analytics), but notes the underutilization of AI in complex care transitions - particularly where data is fragmented across hospital, home health, and community care. The United States’ current AI policy environment, as outlined in the current presidential administration’s *America’s AI Action Plan* (2025), reflects a strong national emphasis on accelerating private-sector-led AI adoption across critical sectors, including healthcare. Recognizing that the primary bottleneck to harnessing AI’s potential lies in organizational uptake rather than technological availability, the plan advocates for regulatory sandboxes and domain-specific Centers of Excellence to enable rapid testing and deployment of AI tools in complex systems such as EMRs. Specific attention is given to building public trust, establishing national standards, and fostering productivity assessments to support adoption in healthcare contexts. These efforts are particularly relevant to AHPs, who often rely on EMRs to coordinate multidisciplinary care. Furthermore, the action plan calls for strategic investment in workforce upskilling and AI literacy, which may facilitate smoother transitions for clinicians adapting to AI-integrated workflows. Overall, the plan creates a permissive, innovation-driven policy climate aimed at reducing regulatory friction, enabling experimentation, and promoting robust AI integration into US health systems. These findings illustrate a possible growing tension between top-down policy ambitions and bottom-up adoption

realities. Without effective stakeholder engagement and requirement specification early in the process, even well-resourced digital health initiatives risk low utilization and suboptimal impact.

3.4. *Factors moderating AHPs AI adoption*

The integration of AI into EMRs introduces a new layer of complexity to organizational readiness. Lambert et al. (2023), using UTAUT, identified major barriers to hospital-based clinician adoption of AI tools: fear of losing professional autonomy, poor alignment with existing workflows, lack of transparency, and cognitive overload from alerts. Notably, their review revealed the importance of end users early on in AI development and to offer needs tailored training to build adequate AI use infrastructure.

Feely et al. (2023) examined AHP's responses to a large-scale, "big bang" EMR implementation across three Australian hospitals. Six months post-implementation, they found high user acceptance, with 88% of clinicians reporting they liked using the system and 64% finding it easy to use. However, the study also noted a significant increase in documentation time, suggesting a trade-off between usability and workflow efficiency. AI demonstrates as an opportunity to help reduce noted increased documentation time noted in EMR roll outs.

Hoffman et al. (2025) explored the key barriers and enablers within a hospital in Australia influencing the adoption of AI in allied health clinical practice through a qualitative study. Their scoping review revealed that while AHPs are generally open to AI integration, significant challenges remain, including limited digital literacy, unclear regulatory guidance, and a lack of profession-specific evidence to guide implementation. The authors emphasized the importance of targeted education, transparent communication, and involvement of AHPs in the design and evaluation of AI tools to build trust and usability. The study highlights that successful AI adoption in allied health requires alignment with clinical workflows and organizational support structures (Hoffman et al. 2025) and reveals that more studies with AHPs with use of AI are needed and in various healthcare settings.

Ronquillo et al. (2022) argue that nursing and AHP's are underrepresented in AI research, particularly regarding the integration of social determinants of health and intersectionality data across social care. Despite these professions' rich documentation of patient context, their contributions are often confined to unstructured EMR narratives, limiting their utility in AI development. The study contends that harnessing nursing and allied health data is essential for advancing equitable AI integration in healthcare. However, this requires enhanced EMR infrastructure and the deliberate inclusion of these disciplines in research design. Strategic collaboration between AHP's and interdisciplinary teams is identified as a key enabler of successful AI deployment.

3.5. *Proposed conceptual framework*

The proposed integrated AI-based TOE model for EMR adoption by AHPs (Fig. 1) posits that effective adoption and use require navigating the trade-off between a range of AI enablers and inhibitors. At the same time, the perceived usefulness and ease of AI tools by AHP can accelerate the adoption of EMR for the efficient provision of social care. In addition, individual driven factors such as AHPs cognitive load tolerance, social influence and collaboration within their clinical teams can accelerate the integration of AI tools into the management of electronic health records (EHR) by AHPs for social care delivery. The role of leadership support and capacity building of the AHPs in AI and emerging technologies are equally critical in enhancing the integration of AI in EMR management for efficient delivery of social care.



Fig. 1. An integrated AI-based TOE model of EMR Adoption By AHP.

Table 1. Review results: Sources, contributions, rationale for inclusion, and noted limitations.

Author(s), Year	Focus / Contribution	Inclusion Rationale	Notes on Quality / Limitations
Currie and Guah 2007	Case study of the UK National Programme for IT (NpFIT).	Illustrates risks of large-scale EMR transformation without stakeholder engagement.	Older study; context-specific to UK, but widely cited cautionary case.
Lenz et al. 2007	Semantic integration in healthcare networks.	Identifies technical inhibitor (data fragmentation).	Older; foundational technical relevance.
Deutsch et al. 2010	Critical areas of national EMR programs.	Highlights organizational and cultural inhibitors to EMR success.	Cross-country scope strengthens validity; lacks AI-specific focus.
Hughes et al. 2016	Analysis of causal links in IT project failure.	Adds theoretical depth on failure modes.	Broader IS lens; not AI-specific.
Johnson 2016	Review of Epic® EMR implementation.	U.S. example of poor EMR roll-out tied to usability and cost issues.	Narrow focus on one vendor; valuable real-world case.
Awa et al. 2017	Revisits Technology–Organization–Environment (TOE) theory for enriched applicability.	Provides theoretical foundation for TOE framework used in study.	Conceptual; not healthcare-specific, but transferable to EMR/AI adoption.
Miotto et al. 2018	Deep learning applications in healthcare.	Illustrates AI potential in EMR use.	Requires large datasets; generalizability limited.
Suter-Crazzolara 2018	Mining biomedical big data for outcomes.	Demonstrates role of data integration in AI.	General biomedical scope; not AHP-focused.
Gomes and Romão 2019	Challenges of IS/IT projects in healthcare.	Provides failure factors framing for EMR/AI adoption.	Strongly aligned with health IT; single context study.
NHS England 2019	NHS Long-Term Plan (Version 1.2).	Illustrates national ambitions for digital and AI adoption in UK healthcare.	Policy-driven; lacks detailed user-centered design or AHP focus.
Philips 2020	Future Health Index—digital maturity continuum.	Offers practical digital maturity lens.	Grey literature; industry-driven perspective.
Wessel et al. 2021	Clarifies difference between DT and IT-enabled transformation.	Provides conceptual anchor for digital transformation framing.	Cross-industry scope; applied here to health.
Ronquillo et al. 2022	Underrepresentation of AHP/nursing data in AI research.	Frames equity and inclusivity challenges in AI-enabled EMRs.	Highlights gaps; limited empirical testing.
Yang et al. 2022	TOE-based adoption of AI in healthcare.	Empirical extension of TOE into AI adoption.	Directly relevant; strong methodological alignment.

Lambert et al. 2023	AI acceptance among hospital clinicians.	Adds evidence on barriers to clinician adoption.	Not AHP-specific; useful parallel insights.
Phiri et al. 2023	Digital maturity consulting in healthcare.	Adds contemporary organizational context.	Focused on consultancy perspective.
Dugbartey 2024	Optimizing project delivery through Agile methodologies.	Demonstrates link between project management strategy and health IT outcomes.	Non-peer reviewed; practical relevance but limited empirical rigor.
Professional Standards Authority 2024	Monitoring Report: Health and Care Professions Council 2023/24.	Provides workforce regulation and oversight context relevant to AHPs.	Regulatory focus; not AI-specific.
Health Resources and Services Administration 2024	State of the Health Workforce Report 2024 (U.S.).	Offers workforce data on AHPs for U.S. context.	Workforce statistics; not tied to AI adoption.
HIMSS 2024	EMRAM (Electronic Medical Record Adoption Model).	Benchmark for EMR digital maturity progression across organizations.	Widely used but industry-led; not peer-reviewed.
Kuziemy et al. 2024	Umbrella review on AI quality standards in healthcare.	Frames theoretical challenge: lack of consensus on AI quality criteria.	Current; strong systematic methodology, though not AHP-specific.
Morsi et al. 2024	Agile vs. traditional project delivery.	Provides evidence on project methodology impacts.	Not peer-reviewed; preliminary but relevant.
Snowdon et al. 2024	Digital maturity as a strategy for patient experience.	Links digital maturity with patient outcomes.	U.S.-centric; transferable concepts.
Hoffman et al. 2025	Barriers/enablers to AI adoption in allied health.	One of few AHP-specific AI studies; fills representation gap.	Early-stage; limited generalizability.
Lee et al. 2025	Review of TAM and UTAUT frameworks for healthcare technology adoption.	Expands understanding of psychosocial barriers to adoption and aligns with acceptance theories used in this paper.	Strong theoretical integration; review-based, limited empirical application.
UK Government 2025	Fit for the Future: 10-Year Health Plan for England.	Provides policy vision for community-based digital and AI-enabled care.	High-level strategy; not operational guidance.
US Government 2025	America's AI Action Plan.	Frames national AI policy direction, including healthcare applications.	Broad national policy; healthcare-specific detail limited.
Rahimi et al. (2024)	AI in hospitals review.	Showcases current hospital AI research projects	Recent literature on AI healthcare technology

4. Concluding remarks

This conceptual paper advances a generalized framework intended to guide future empirical research and provide practical insights on the integration of AI into EMRs for AHPs across digitally diverse healthcare systems. With over 330,000 registered AHPs in the UK and more than 875,000 in the US (Health Resources and Services Administration 2024), the scale of this workforce underscores the urgent need for project and product managers to bridge the persistent gap between top-down policy ambitions and the operational realities of care delivery. Several limitations must be acknowledged. First, the conceptual orientation and geographic focus on the UK and the US may restrict generalizability across other health systems and levels of digital maturity. Second, while structured inclusion and exclusion criteria, thematic synthesis, and a results review table were employed to enhance transparency, the use of AI-assisted summarization during coding introduces potential bias and highlights the need for further methodological rigor in future empirical studies. To strengthen the framework's applicability, subsequent research should empirically validate the model across diverse clinical contexts, integrate systematic end-user requirement gathering, and employ reproducible coding strategies, including intercoder reliability and quality appraisal tools. With an integrated, cross-disciplinary approach, AI-enhanced EMRs have the potential to drive efficiency while advancing more equitable, intelligent, and human-centered care globally.

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