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The Role of Health Information Professionals in AI-Enabled Healthcare Transformation: Emerging Competencies, Digital Literacy, and Professional Practice Redesign

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ABSTRACT: Artificial intelligence (AI) is reshaping how health data are generated, interpreted, and used, yet the contribution of health information professionals to this transformation is seldom examined. This narrative review synthesizes literature published between 2017 and 2024 on the changing role of health information managers, clinical coders, informaticians, data stewards, and knowledge specialists in AI-enabled care. We describe how AI reconfigures core information functions, identify emerging competency domains, examine digital and AI literacy as enabling conditions, and discuss governance, bias, and safety responsibilities. We then propose a model for redesigning professional practice, supported by two tables and two figures. Evidence indicates that routine tasks are being automated while demand grows for data stewardship, algorithm oversight, and educational leadership. Realizing this potential requires curriculum reform, clear accountability structures, and sustained investment in workforce development.

1. INTRODUCTION

Healthcare systems are generating data at a scale and speed that exceed the capacity of manual processing. Electronic health records, imaging archives, genomic platforms, wearable devices, and administrative systems feed analytical tools that increasingly rely on machine learning, natural language processing, and, more recently, generative language models. Authoritative reviews describe a transition in which AI moves from experimental research into routine clinical and operational

use, with implications for diagnosis, risk prediction, documentation, and health system management (Topol, 2019a; Yu et al., 2018; Rajpurkar et al., 2022). Whether this transition improves care depends not only on algorithmic performance but also on the quality, governance, and interpretation of the underlying information.

These are the traditional concerns of health information professionals (HIPs). For the purposes of this review, the term refers to the broad community responsible for creating, curating, classifying, protecting, and communicating health information, including health information managers, clinical coders, health and clinical informaticians, data stewards, privacy and compliance officers, health librarians and knowledge specialists, and data analysts. Their work spans the data lifecycle, from capture and classification through storage, exchange, and secondary use, and it has historically been organized around records, standards, and regulation (Stanfill & Marc, 2019).

AI challenges this arrangement in two ways. First, it automates functions that have defined HIP roles, such as abstracting, coding, and indexing. Second, it creates new needs that map closely onto HIP expertise, including data provenance, bias detection, model documentation, and post-deployment monitoring. Despite this, discussions of AI in healthcare are dominated by clinician and data scientist perspectives, and the workforce, educational, and governance implications for information professionals are comparatively underexplored (Sapci & Sapci, 2020; Charow et al., 2021).

This narrative review addresses that gap. It aims to (a) outline the AI landscape relevant to health information work, (b) describe how AI reconfigures HIP functions, (c) identify emerging competencies and the role of digital and AI literacy, (d) examine governance, ethical, and safety responsibilities, and (e) propose a framework for redesigning professional practice. The sections that follow address each aim in turn, and the paper closes with challenges, recommendations, and conclusions.

2. REVIEW APPROACH

A narrative review design was selected because the topic is interdisciplinary, evolving rapidly, and poorly suited to quantitative synthesis. The review draws on peer-reviewed articles, scoping and systematic reviews, consensus statements, and policy documents published between 2017 and 2024 that address AI in healthcare, health information management, informatics workforce development, digital literacy, and AI governance. Sources were selected purposively according to relevance, recency, and contribution to understanding the HIP role. No formal search protocol, risk-of-bias assessment, or quantitative pooling was undertaken, and selection bias is therefore possible.

Because the evidence specific to HIPs is limited, the review also draws on literature concerning related professions, such as nursing and medicine, and on studies of AI implementation in general. Where inferences are extended from these domains to information professionals, this is stated explicitly. The competency and practice-redesign frameworks presented in Tables 1 and 2 and Figures 1 and 2 are interpretive syntheses developed by the author and are not validated models.

3. THE AI LANDSCAPE RELEVANT TO HEALTH INFORMATION WORK

3.1 From Narrow Prediction to Embedded Decision Support

Early healthcare AI concentrated on narrow tasks, particularly image interpretation and risk prediction. Deep learning applied to electronic health record data demonstrated that models could predict outcomes such as mortality and readmission across large hospital datasets, albeit with considerable data preparation effort (Yu et al., 2018). Broader appraisals describe AI applications across clinical care, operations, administration, and patient engagement, and they emphasize that the main barriers to adoption are no longer purely technical but concern data access, integration with workflow, trust, and organizational readiness (Davenport & Kalakota, 2019; Bajwa et al., 2021). Topol (2019a) argued that the benefits of AI depend on its convergence with human expertise and on rigorous prospective evaluation, a point that has direct implications for professionals who manage the data on which evaluation depends.

Regulators have responded to this expansion. A comparative analysis of approvals in the United States and Europe documented rapid growth in AI-based medical devices, concentrated in imaging and differing between regulators in the transparency of supporting evidence (Muehlematter et al., 2021). Approved status therefore does not guarantee that performance will generalize to a particular institution, and local validation and monitoring remain necessary. These tasks require data infrastructure, documentation, and information governance capabilities that sit within HIP portfolios.

3.2 Generative AI and Large Language Models

The arrival of large language models has widened the relevance of AI to information work, because these systems operate directly on text, the dominant medium of health records. Lee et al. (2023) examined the capabilities of an advanced language model in medical contexts and noted potential for documentation support, summarization, and question answering, while also warning of fabricated content and inconsistent reliability. A broader review of language models in medicine similarly identified opportunities in administrative and educational tasks alongside risks relating to accuracy, bias, privacy, and accountability (Thirunavukarasu et al., 2023). Meskó and Topol (2023) called for regulatory oversight proportionate to the potential for harm, noting that existing frameworks for medical devices were not designed for general-purpose generative systems.

Ambient documentation tools illustrate how quickly such technology is entering practice. An early deployment report from a large integrated health system described the use of ambient AI scribes to reduce the burden of clinical documentation and reported favorable clinician experience, although the evidence arose from quality-improvement data rather than controlled trials (Tierney et al., 2024). For information professionals, such tools raise immediate questions about the legal status of AI-generated notes, the accuracy of the resulting record, consent for audio capture, and the downstream effects on coding and data quality.

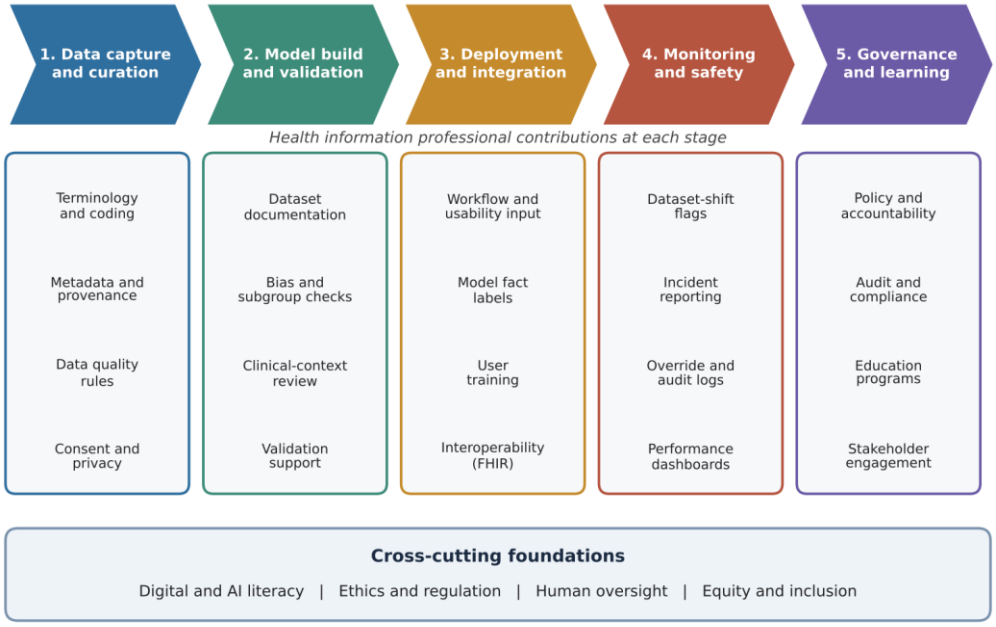
3.3 Why the Information Layer Matters

Across these developments, a consistent message is that the performance of AI in practice is constrained by the information layer that surrounds the model. Models trained on data from one institution may behave differently elsewhere because of differences in documentation habits, terminologies, and workflows, and the literature repeatedly identifies data availability, quality, and integration as central determinants of success (Rajpurkar et al., 2022; Davenport & Kalakota, 2019). This observation reframes the role of information professionals. Rather than being peripheral to AI projects, they manage the very resources that determine whether models are valid, fair, and sustainable, and their absence from project teams is a risk factor that organizations can address at relatively low cost.

4. HOW AI RECONFIGURES HEALTH INFORMATION FUNCTIONS

Health information work can be understood as a sequence of data lifecycle stages, each of which AI changes in different ways. Figure 1 depicts a five-stage AI lifecycle and the contributions that HIPs can make at each stage, together with the cross-cutting foundations that support them.

Figure 1. Health Information Professional Contributions across the AI Lifecycle



Note. FHIR = Fast Healthcare Interoperability Resources.

4.1 Clinical Coding and Classification

Clinical coding is perhaps the clearest example of an information function exposed to automation. Computer-assisted coding systems use natural language processing to suggest classification codes from clinical documentation. A narrative review of this technology concluded that it may improve productivity but that evidence on accuracy was mixed and that its adoption shifts the coder's role toward validation, auditing, and quality assurance rather than eliminating it (Campbell & Giadresco, 2020). More recent work on automated coding has made progress with deep learning, but it highlights continuing difficulties with rare codes, variability between institutions, and limited explainability (Dong et al., 2022).

These findings suggest that coders and classification specialists will increasingly act as supervisors of algorithmic output, requiring skills in error analysis, sampling and audit methods, and communication with clinicians about documentation quality. The shift also carries a workforce risk: if routine coding experience diminishes, the pathway through which novices develop expertise may be weakened, which in turn could undermine the capacity to supervise the algorithm.

4.2 Unstructured Data and Natural Language Processing

A large proportion of clinically valuable information resides in free-text notes. Systematic review evidence indicates that natural language processing has been applied to extract information on chronic diseases from clinical notes, with unstructured text containing details often absent from structured fields, although studies are heterogeneous and generalizability across sites is limited (Sheikhalishahi et al., 2019). HIPs contribute by curating terminologies, defining annotation standards, ensuring that training corpora are representative and legally usable, and validating outputs against reference standards. These responsibilities connect directly to professional knowledge of clinical language and documentation practice.

4.3 Interoperability, Standards, and Knowledge Services

AI systems require data that are comparable across settings. Systematic review evidence shows growing use of the Fast Healthcare Interoperability Resources (FHIR) standard for integrating data in health research and care, while also noting that implementation varies in maturity (Vorisek et al., 2022). Information professionals who understand data models, terminologies, and exchange standards are therefore well positioned to prepare datasets and to support integration of AI tools into existing systems. Related disciplines face similar changes. Thought leaders in academic librarianship anticipated that AI would alter library work by automating discovery and metadata tasks while elevating roles in information literacy, curation, and ethical guidance (Cox et al., 2019). Although that study concerns academic libraries, the implications plausibly extend to health librarians and knowledge specialists who support evidence retrieval and critical appraisal.

4.4 Clinical Decision Support and Workflow

AI-enabled decision support inherits both the benefits and the problems of earlier clinical decision support. Sutton et al. (2020) described how well-designed systems can improve guideline adherence and safety, while poorly designed ones generate excessive alerts, undermine trust, and impose workload. Documentation and electronic record burdens are themselves associated with clinician stress and burnout, with design and usage features such as inefficient interfaces and extensive data entry demands linked to adverse outcomes (Kroth et al., 2019). For HIPs, the implication is that AI deployment cannot be separated from workflow redesign. Professionals with informatics training can contribute usability evaluation, alert governance, and structured feedback loops that help organizations avoid replicating legacy problems with newer technology.

4.5 Generative AI and the Integrity of the Health Record

Generative tools introduce a distinctive concern for record integrity. When a language model drafts a note, summarizes a chart, or proposes a patient message, the resulting text may be fluent and plausible yet contain omissions or fabrications that are difficult to detect on casual review (Lee et al., 2023; Thirunavukarasu et al., 2023). Records are legal documents, sources of evidence for care continuity, and the raw material for coding, quality reporting, and research, so errors introduced at the point of documentation propagate widely. Information professionals have established methods for record audits, authentication, and amendment, and these will need to be adapted to address provenance (who or what authored the text), review attestation, and version control for AI-assisted entries.

Organizations should therefore define policies specifying when AI-generated content is acceptable, how clinicians must review and attest to it, and how the use of such tools is recorded. Information professionals can lead the development of these policies,

drawing on records management principles, and can monitor the effect of ambient and generative tools on documentation quality, coding specificity, and downstream analytics. Early adopters would also be wise to collect baseline data on documentation quality so that effects can be measured rather than assumed (Tierney et al., 2024).

5. EMERGING COMPETENCIES FOR HEALTH INFORMATION PROFESSIONALS

5.1 Evidence From Competency Frameworks and Reviews

Competency frameworks for health informatics have been developed internationally for some time, and the Technology Informatics Guiding Education Reform (TIGER) initiative offers an example of a multinational effort to define informatics competencies for education and practice (Hübner et al., 2018). Systematic and scoping reviews of digital health competencies among healthcare professionals have since identified a wide range of competency domains, but they also reveal conceptual inconsistency, variable terminology, and limited assessment of outcomes (Longhini et al., 2022; Jimenez et al., 2020). Nursing scholars have argued that the profession must adapt to a digital future by embedding informatics competencies, leadership, and digital literacy into education and practice (Booth et al., 2021), and similar arguments apply to information professions.

The Topol Review, commissioned for the National Health Service in England, projected that digital technologies including AI would affect almost all roles in the health workforce and recommended investment in digital literacy, understanding of data and AI, and continuing education (Topol, 2019b). Although it addresses the workforce broadly, its argument that technology should free time for human tasks resonates with the HIP context, where automation may release capacity for higher-value analytical and governance activities.

5.2 Competency Domains

Synthesizing these sources and the functional changes described in Section 4, seven competency domains appear particularly salient for HIPs in AI-enabled environments. They are summarized in Table 1. The first, data governance and quality, extends existing strengths: HIPs have long been responsible for ensuring that records are accurate, complete, and appropriately accessed, and these capabilities become critical when algorithms learn from the record. Second, terminology and interoperability expertise underpins the construction of coherent datasets and the integration of AI into clinical systems (Vorisek et al., 2022).

Third, AI and data science literacy refers to the ability to understand how models are trained and evaluated, to interpret performance metrics, and to recognize limitations such as overfitting and dataset shift, without necessarily developing algorithms. Reviews of AI education for health informatics students found that formal AI content was limited and called for integration of machine learning concepts into curricula (Sapci & Sapci, 2020). A scoping review of AI education programs for healthcare professionals likewise found that offerings were heterogeneous, frequently short, and seldom rigorously evaluated (Charow et al., 2021). Fourth, ethics, privacy, and regulatory competence involves applying principles of fairness, transparency, and accountability and navigating legal requirements for data protection and medical device regulation.

Fifth, workflow and human factors competence supports the integration of AI into care processes, and sixth, evaluation and safety surveillance competence allows professionals to participate in validation, monitoring, and incident analysis. Seventh, communication, education, and leadership capabilities enable HIPs to translate technical concepts for clinicians and managers, train colleagues, and contribute to strategic decisions. A scoping review of AI in medical education reported a growing but largely descriptive evidence base dominated by small studies, which underlines the need for more rigorous evaluation of educational interventions (Gordon et al., 2024).

Table 1. Emerging Competency Domains for Health Information Professionals in AI-Enabled Healthcare

Competency domain	Description	Illustrative professional tasks	Supporting sources
Data governance and quality	Ensuring that data used by algorithms are accurate, complete, traceable, and appropriately accessed	Data quality rules; provenance and metadata standards; missingness audits; access control	Stanfill & Marc, 2019; Gianfrancesco et al., 2018

Terminology and interoperability	Applying classification, terminology, and exchange standards to build coherent datasets	Terminology mapping; FHIR-based integration; dataset preparation	Vorisek et al., 2022; Sheikhalishahi et al., 2019
AI and data science literacy	Understanding model training, evaluation, and limits without necessarily building models	Interpreting performance metrics; recognizing overfitting and dataset shift	Sapci & Sapci, 2020; Charow et al., 2021
Ethics, privacy, and regulation	Applying principles of fairness, transparency, and accountability within legal requirements	Privacy impact review; consent policy; participation in governance committees	Jobin et al., 2019; Price & Cohen, 2019; World Health Organization, 2021
Workflow and human factors	Integrating AI tools into care processes while limiting burden and automation bias	Usability evaluation; alert governance; user feedback loops	Sutton et al., 2020; Kroth et al., 2019; Gaube et al., 2021
Evaluation and safety surveillance	Participating in validation, monitoring, and incident analysis of AI systems	Version and override logs; drift flags; linkage of outputs to outcomes	Wong et al., 2021; Finlayson et al., 2021; Magrabi et al., 2019
Communication, education, and leadership	Translating technical concepts and guiding organizational change	Staff training; model documentation; strategic advice	Hübner et al., 2018; Booth et al., 2021; Gordon et al., 2024

Note. HIP = health information professional; FHIR = Fast Healthcare Interoperability Resources.

5.3 Developing and Assessing Competence

Listing competencies is easier than developing them. Reviews of digital health competencies describe heterogeneous approaches to assessment, ranging from self-report questionnaires to performance-based tasks, and they highlight the lack of validated, widely accepted measures (Longhini et al., 2022; Jimenez et al., 2020). Educational strategies that show promise in related disciplines combine foundational instruction with applied, interprofessional learning, so that information professionals, clinicians, and data scientists learn to work together on realistic problems. Such approaches are consistent with the argument that AI education should address both technical content and the professional judgment needed to apply it (Gordon et al., 2024; Charow et al., 2021).

A further consideration is the sequencing of competence development. Individuals entering the profession may benefit from early exposure to data science concepts, whereas experienced practitioners may need targeted upskilling that builds on their domain knowledge of classification, records, and regulation. Organizations can support this through mentoring, rotations with analytics teams, and participation in AI governance committees, which provide experiential learning in context. Without structured support, the burden of acquiring new skills may fall disproportionately on individuals and risk widening disparities within the workforce.

6. DIGITAL LITERACY AND AI LITERACY AS ENABLING CONDITIONS

6.1 Digital Health Literacy

Digital literacy underpins every competency described above, yet it is unevenly distributed within the health workforce. A study of healthcare staff found variable levels of digital literacy and a relationship between literacy and attitudes toward information systems, suggesting that capability and acceptance are intertwined (Kuek & Hakkennes, 2020). Digital health literacy has also been conceptualized as a determinant of health in its own right, interacting with social and economic conditions in ways that can either reduce or exacerbate inequity (van Kessel et al., 2022). The Lancet and Financial Times Commission on governing health futures 2030 similarly framed digital determinants of health as requiring attention to literacy, access, and governance, so that the benefits of digital transformation are shared fairly (Kickbusch et al., 2021).

HIPs occupy a dual position in this landscape. They need strong digital literacy to perform their own roles, and they are frequently called upon to support the digital literacy of others, whether clinicians learning to use a new record system, managers interpreting dashboards, or patients accessing portals. Their educational function should therefore be recognized and resourced explicitly rather than treated as an informal extension of technical support.

6.2 AI Literacy and Calibrated Trust

AI literacy extends digital literacy to include understanding what AI can and cannot do. It involves knowledge of how training data shape model behavior, familiarity with measures such as sensitivity, calibration, and positive predictive value, and awareness of failure modes. Its importance is illustrated by evidence on human responses to AI advice. In an experimental study, clinicians were influenced by diagnostic advice whether it was attributed to an AI system or to a human, including when the advice was incorrect, which indicates that automation bias is a real risk even among experts (Gaube et al., 2021). Trust must therefore be calibrated rather than maximized. Nundy et al. (2019) argued that maintaining trust between patients and physicians in the era of AI requires transparency about how algorithms are used and clarity about human responsibility for decisions.

Information professionals can contribute to calibrated trust by producing accessible documentation of AI tools, including intended use, training population, performance characteristics, and known limitations. Concise labeling approaches modeled on nutrition labels have been proposed to communicate such information to clinical end users (Sendak et al., 2020). Providing and maintaining these documents, and educating users about them, is a natural extension of HIP responsibilities for metadata and record standards. Literacy initiatives should be tailored to role, with differentiated expectations for frontline staff, specialist analysts, and leaders, and they should be accompanied by assessment so that outcomes can be tracked.

6.3 Equity and Patient-Facing Literacy

Digital and AI literacy are not only workforce concerns. As patients gain access to portals, remote monitoring, and conversational tools, differences in literacy and access can translate into differences in the ability to benefit from AI-enabled services. Health information professionals often manage patient portals, consent processes, and release of information, and they are therefore well placed to design accessible communication about how AI is used in care. Commission-level analyses emphasize that digital transformation should reduce rather than widen inequalities, which implies attention to language, disability, age, and connectivity (Kickbusch et al., 2021; van Kessel et al., 2022).

7. GOVERNANCE, DATA QUALITY, BIAS, AND SAFETY RESPONSIBILITIES

7.1 Data Quality and Algorithmic Bias

Algorithms reflect the data used to develop them. Gianfrancesco et al. (2018) identified several mechanisms through which electronic health record data may introduce bias into machine learning, including missing data, small samples for some groups, misclassification, and measurement variability that differs by patient characteristics. A frequently cited example showed that an algorithm used to manage population health relied on health care costs as a proxy for health need, and consequently underestimated the needs of Black patients compared with White patients with similar levels of illness (Obermeyer et al., 2019). Rajkomar et al. (2018) proposed that fairness in machine learning should be addressed throughout model design, evaluation, and deployment, with attention to the equity of outcomes rather than technical performance alone.

These examples demonstrate that bias often originates in data definitions and documentation practices, which are the domain of information professionals. Coding conventions, missingness patterns, and variable definitions may encode differential access to care or differing documentation habits. HIPs with deep knowledge of how data are produced can therefore identify risks that data scientists working from extracted datasets may overlook, particularly if they collaborate early in model development.

7.2 Validation, Dataset Shift, and Patient Safety

External evaluation of a widely implemented proprietary sepsis prediction model in hospitalized patients found poor discrimination, with the model missing about two thirds of patients who developed sepsis while generating alerts for nearly one in five hospitalized patients (Wong et al., 2021). The case shows that deployment without local validation can create both safety risks and alert burden. Finlayson et al. (2021) explained that clinicians and organizations must also anticipate dataset shift, whereby changes in practice, patient populations, equipment, or coding systems degrade model performance over time, and

they noted that transitions in classification standards can be a source of such shift. Because HIPs manage and understand these structural changes, they are well placed to flag them to model owners.

The international working group on evaluating AI in clinical decision support stressed that evaluation must extend beyond technical accuracy to include clinical impact, usability, and ongoing surveillance after deployment (Magrabi et al., 2019). Information professionals can support this by maintaining logs of model versions and overrides, linking outputs to outcomes, and contributing to incident reporting systems that capture AI-related events.

7.3 Ethics, Privacy, and Regulation

A review of global AI ethics guidelines found convergence on principles such as transparency, justice and fairness, non-maleficence, responsibility, and privacy, though interpretation and implementation varied considerably (Jobin et al., 2019). The World Health Organization (2021) set out six principles for AI in health: protecting autonomy, promoting human well-being and safety, ensuring transparency and intelligibility, fostering responsibility and accountability, ensuring inclusiveness and equity, and promoting responsive and sustainable AI. Reddy et al. (2020) proposed a governance model addressing fairness, transparency, and trustworthiness across the AI lifecycle, emphasizing that governance should operate at the levels of regulation, organizational policy, and clinical practice.

Privacy raises particular challenges. Price and Cohen (2019) observed that AI and large linked datasets can weaken traditional deidentification safeguards and that existing legal frameworks do not cover all data flows relevant to medical big data. Information professionals who administer consent, access, and disclosure policies therefore need to update practice in light of reidentification risk, secondary use, and data sharing with commercial partners. Their familiarity with regulatory requirements positions them as essential members of AI governance committees alongside clinicians, data scientists, ethicists, legal counsel, and patient representatives.

7.4 Institutional Structures for AI Assurance

Principles become effective only when translated into institutional structures. Organizations adopting AI increasingly need standing committees or review pathways that evaluate proposed tools before purchase or deployment, specify monitoring requirements, and define criteria for suspension. Governance models emphasize that these bodies should be multidisciplinary and should address the lifecycle from procurement to decommissioning (Reddy et al., 2020; World Health Organization, 2021). HIPs can contribute to intake assessments by examining data requirements, interoperability, and documentation, and by maintaining an inventory of AI tools in use, which is a prerequisite for oversight that is often missing.

Monitoring is the area in which long-term commitment is most needed. Performance may drift as data sources, workflows, and populations change, and without routine review such drift may go unnoticed (Finlayson et al., 2021; Magrabi et al., 2019). Assigning clear responsibility for surveillance, using agreed indicators, and linking findings to a process for action are therefore as important as the initial approval. Information professionals who are accustomed to audit cycles and compliance reporting can adapt these routines to the monitoring of AI systems.

8. REDESIGNING PROFESSIONAL PRACTICE

8.1 A Staged Model of Role Evolution

Taken together, the evidence implies that HIP roles will not simply be replaced or preserved but will be reconfigured. Figure 2 presents a four-stage model in which professionals progress from foundational digital and AI literacy, through data stewardship excellence and AI governance and assurance, to strategic leadership and co-design. The model does not imply that every professional must reach the final stage; rather, it shows how capabilities accumulate and how organizations might plan development pathways. It is an interpretive synthesis of the literature and has not been empirically validated.

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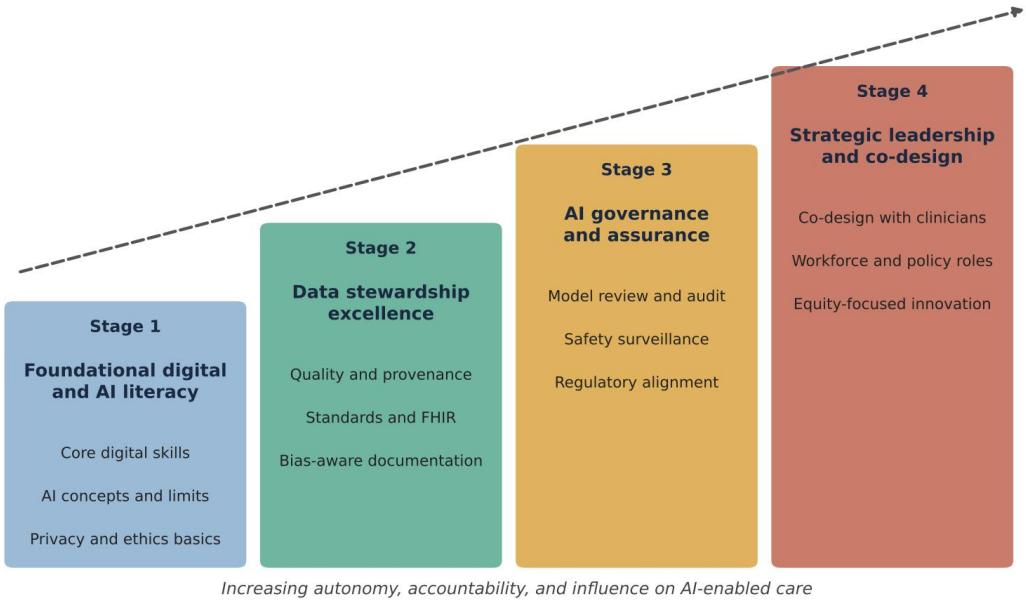
Figure 2. A Staged Model of Professional Practice Redesign



Note. FHIR = Fast Healthcare Interoperability Resources.

8.2 Redesigned Functions

Table 2 contrasts traditional functions with their AI-enabled redesign. The common pattern is a shift from performing tasks to supervising, auditing, and improving automated processes, and from custodianship of records to stewardship of data as an asset used by algorithms. Coding specialists become auditors of automated coding, quality managers become designers of data quality rules that are consumed by models, and privacy officers become participants in algorithmic risk assessment. Knowledge specialists extend their role from retrieval to critical appraisal of AI-generated summaries and evidence.

Table 2. Redesign of Health Information Functions in AI-Enabled Practice

Traditional function	AI-enabled redesign	Enabling conditions and risks	Supporting sources
Clinical coding and classification	Auditing and validating automated code suggestions; error analysis; feedback to developers and clinicians	Training in audit methods; risk of eroded apprenticeship pathways	Campbell & Giadresco, 2020; Dong et al., 2022
Record and data quality management	Designing quality rules consumed by models; monitoring dataset shift and missingness	Cross-team collaboration; documented definitions and versions	Gianfrancesco et al., 2018; Finlayson et al., 2021
Clinical documentation integrity	Reviewing AI-assisted notes; defining attestation, provenance, and version control	Clear policy on AI-generated content; baseline quality measures	Lee et al., 2023; Tierney et al., 2024
Privacy, access, and disclosure	Assessing reidentification and secondary-use risks; sitting on AI governance committees	Updated legal knowledge; authority within governance structures	Price & Cohen, 2019; Reddy et al., 2020

Library and knowledge services	Appraising AI-generated summaries; supporting evidence retrieval and information literacy	Investment in new skills; extrapolation from academic libraries	Cox et al., 2019; Thirunavukarasu et al., 2023
Analytics and reporting	Preparing datasets, validating models locally, and communicating limits to managers	Access to data science expertise; local validation resources	Wong et al., 2021; Vorisek et al., 2022
User education and support	Delivering role-specific digital and AI literacy; maintaining model fact labels	Assessment of learning outcomes; protected learning time	Sendak et al., 2020; Kuek & Hakkennes, 2020; Charow et al., 2021

8.3 Implementation and Organizational Conditions

Redesign cannot succeed through individual effort alone. A scoping review of frameworks for implementing AI in healthcare found that existing frameworks were limited in scope, and that few offered comprehensive guidance across stages from planning to sustainment (Gama et al., 2022). Practical lessons from clinical decision support suggest that engagement of end users, attention to workflow, and iterative evaluation are needed (Sutton et al., 2020). Organizations should define role descriptions that recognize new responsibilities, protect time for learning, and establish career pathways that do not penalize staff whose routine tasks are automated. Without such measures, automation may be experienced as deskilling rather than as an opportunity.

Education systems also need to change. Curricula for health information management and informatics should integrate data science fundamentals, AI ethics, and governance, with applied projects using real datasets and collaboration with clinical and technical students (Sapci & Sapci, 2020; Gordon et al., 2024). Continuing professional development should be modular and role-specific, and credentialing bodies could incorporate AI-related competencies into standards. Evaluation of these programs should extend beyond satisfaction to include knowledge, behavior, and organizational outcomes, as called for in the review of AI education programs (Charow et al., 2021).

8.4 Professional Identity, Accountability, and Ethics

Practice redesign also raises questions about professional identity and accountability. When an algorithm proposes a code or flags a record, responsibility for the final decision must remain unambiguous. Ethical analyses of machine learning in medicine emphasize that human accountability cannot be delegated to systems and that organizations need to clarify who is answerable for errors (Reddy et al., 2020; World Health Organization, 2021). Professional bodies should update codes of ethics and practice standards to address AI-related duties, such as disclosing automated processing, escalating concerns about biased data, and refusing to certify outputs that cannot be verified.

Professional identity may evolve from that of a record keeper or technician to that of a data steward and trusted adviser. This transition may be welcomed by some and resisted by others, particularly where roles have been defined by task completion and productivity metrics. Leaders should therefore communicate a credible vision, involve staff in redesign, and align performance measures with the new emphasis on quality, oversight, and learning. Such change management is likely to determine whether the redesign described in Table 2 is realized or remains aspirational (Gama et al., 2022).

9. CHALLENGES AND LIMITATIONS

Several challenges temper this analysis. The first is the thinness of evidence specific to information professionals. Much of the literature addresses clinicians or the technology itself, and conclusions about HIP roles therefore rely partly on extrapolation from adjacent fields and on conceptual argument. Empirical research, including workforce surveys, task analyses, and evaluations of redesigned roles, is scarce. Second, the pace of change, especially with generative AI, means that evidence ages quickly, and some claims in this review may be outdated by the time they are read.

Third, professional boundaries and terminology differ across countries and health systems, which complicates generalization. Roles described in one context may be distributed differently in another, and regulatory environments vary. Fourth, the potential

for workforce displacement should not be underestimated. Although the literature suggests redeployment toward higher-value tasks, such transitions depend on investment and policy and may not be evenly achieved, particularly in resource-constrained settings. Finally, enthusiasm for AI can obscure unresolved problems in data quality, interoperability, and clinician burden that existed before AI and may be amplified by it (Kroth et al., 2019; Rajpurkar et al., 2022). As this review used a purposive rather than systematic approach, it may have overlooked relevant studies.

A further limitation concerns measurement. There are few agreed indicators for assessing whether HIP involvement improves AI outcomes, and the outcomes themselves, such as data quality, equity of performance, and clinician burden, are multidimensional. Without suitable metrics, organizations may default to easily counted productivity measures that reward speed over oversight. Developing balanced scorecards that reflect quality, safety, and learning would help to ensure that redesigned roles are evaluated on the dimensions that matter (Magrabi et al., 2019; Sutton et al., 2020).

10. RECOMMENDATIONS AND FUTURE DIRECTIONS

On the basis of the evidence reviewed, several recommendations may be offered. For organizations, HIPs should be included formally in AI governance structures and in the design, validation, and monitoring of AI tools, with accountability for data quality and documentation clearly assigned. Organizations should invest in role-specific AI literacy programs and adopt transparent documentation practices such as model labels (Sendak et al., 2020; Reddy et al., 2020). For educators and professional bodies, curricula and credentialing should integrate the competency domains in Table 1, building on existing frameworks (Hübner et al., 2018) and on lessons from other professions (Booth et al., 2021).

For researchers, priorities include empirical studies of how AI changes HIP workload, skill requirements, and error patterns; evaluation of competency-based training; and comparative research across jurisdictions. Studies should examine whether HIP involvement improves the safety, equity, and effectiveness of AI deployment, since the argument advanced here remains plausible but largely untested. For policymakers, workforce planning should anticipate shifts in demand for information roles, and regulation should clarify accountability for AI-generated content in health records (Meskó & Topol, 2023; World Health Organization, 2021).

For individual practitioners, a pragmatic starting point is to build literacy through short, applied learning, to seek involvement in local AI projects, and to document the data issues encountered so that organizational learning accumulates. Professional associations can support this by curating learning resources, convening communities of practice, and sharing case studies of redesigned roles. Such grassroots activity complements formal reform and can help build the evidence base the field currently lacks.

11. CONCLUSION

AI is changing the information environment of healthcare in ways that directly implicate health information professionals. Routine functions such as coding and abstraction are increasingly supported by automation, while demands grow for stewardship of data quality, oversight of algorithms, attention to bias and privacy, and education of colleagues. The competencies required are extensions of existing professional strengths, combined with new knowledge of AI, ethics, evaluation, and leadership.

Realizing this potential is not automatic. It requires deliberate curriculum reform, institutional recognition of new responsibilities, investment in digital and AI literacy, and research that tests whether the proposed roles improve outcomes. If these conditions are met, health information professionals can serve not as bystanders to AI-enabled transformation but as essential custodians of the trustworthiness on which safe and equitable AI depends.

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دور أخصائيي المعلومات الصحية في التحول الصحي المُمكَّن بالذكاء الاصطناعي: الكفاءات الناشئة، ومحو الأمية الرقمية، وإعادة تصميم الممارسة المهنية

الملخص

يعيد الذكاء الاصطناعي تشكيل كيفية توليد البيانات الصحية وتفسيرها واستخدامها، غير أن مساهمة أخصائيي المعلومات الصحية في هذا التحول نادراً ما تُفحص. تستعرض هذه المراجعة السردية الأدبيات المنشورة بين عامي 2017 و2024 حول الدور المتغير لمديري المعلومات الصحية، والمدوّنين السريريين، وأخصائيي المعلوماتية، وأمناء البيانات، وأخصائيي المعرفة في الرعاية المُمكَّنة بالذكاء الاصطناعي. ونصف كيف يعيد الذكاء الاصطناعي تشكيل الوظائف المعلوماتية الأساسية، ونحدد مجالات الكفاءات الناشئة، ونبحث محو الأمية الرقمية ومحو الأمية في الذكاء الاصطناعي كشروط مُمكِّنة، ونناقش مسؤوليات الحوكمة والتحيز والسلامة. ثم نقترح نموذجاً لإعادة تصميم الممارسة المهنية، مدعوماً بجدولين وشكلين. وتشير الأدلة إلى أن المهام الروتينية تُؤتمت بينما يتزايد الطلب على إدارة البيانات، والرقابة على الخوارزميات، والقيادة التعليمية. ويتطلب تحقيق هذا الإمكان إصلاح المناهج الدراسية، وهياكل مساءلة واضحة، واستثماراً مستداماً في تطوير القوى العاملة.

الكلمات المفتاحية: أخصائيو المعلومات الصحية؛ الذكاء الاصطناعي؛ محو الأمية الرقمية؛ كفاءات القوى العاملة؛ المعلوماتية الصحية