ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

Healthcare Institutions and Artificial Intelligence

Olivia Johnson
Asst Professor

Abstract

Artificial Intelligence (AI) is positioned to transform healthcare services and operations into intelligent systems, delivering innovative solutions to improve the quality of care while containing rising costs. However, AI readiness at all levels of the healthcare ecosystem must be examined in combination with real-world implementations that deliver actual transformation. Readiness is commonly defined as the state of being fully prepared for something. In a healthcare management context, readiness refers to the state of a healthcare organization in determining whether the required capabilities exist for the successful adoption of a new technology or concept. Towards AI integration in healthcare, the concept applies at three levels—technological, data, and skills readiness—and can be assessed using maturity frameworks that provide an indication of progress and direction, as well as stakeholder analysis.

While Technology Adoption Models assess potential uptake of AI solutions by health practitioners, these validations assess preparedness to adopt and/or innovate in AI solutions within the healthcare ecosystem. Emerging AI applications covering clinical needs from radiology to mental health support, or from product development to operational management, present recognition and acceptance challenges requiring stakeholder engagement. Stakeholder impact on the success of AI solutions can be assessed using readiness levels, grouping stakeholders into three categories: IDPC leaders responsible for implementation, users at the point of care who interact directly with patients, and patients, the users of the healthcare system and the ultimate beneficiaries or sufferers from the role out of the AI solution.

Keywords : AI readiness assessment, Digital health infrastructure,Clinical workflow integration,Health data interoperability,Electronic health record (EHR) maturity,Data governance frameworks,Ethical AI in healthcare,Workforce AI competency,Change management in healthcare,Clinical decision support systems,Health information security,Regulatory compliance for AI,Algorithm transparency,Patient data quality,Organizational readiness for AI,AI adoption barriers,Health system innovation capacity,Human–AI collaboration,AI-enabled care delivery,Implementation science for AI in healthcare.

1. Introduction

AI technologies possess the potential to revolutionize healthcare participation through disparate access to tools and services. However, AI adoption necessitates considerable modifications to health enterprises. Addressing delivered care systems readiness for full-scale AI implementation remains an urgent and extensively investigated imperative. Evaluations of health enterprises readiness are plentiful and employ multiple frameworks and methodologies with differing enumerations of examined dimensions. This essay provides a comprehensive overview of the academic literature for readiness by assessing the definition and scope of readiness, outlining the main frameworks and methodologies for investigation, and synthesizing typical research findings and reported trends. Research shows that, while AI adoption tends to remain superficial and duration-intensive, enterprise-wide readiness evaluations point to a more favorable picture across the examined dimensions.

Readiness is the degree to which a system—technology, organization, or community—can assimilate a given innovation. Its practical essence draws on preparations that enable successful future execution of major initiatives. In healthcare, readiness typically refers to just-in-time conditions that support the introduction or expansion of a

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

designated element. Readiness evaluations seek to identify observed strengths and weaknesses, thereby guiding allocation of funding and resources to areas of greatest impact. For AI, these dimensions may be optimally considered together using a common evaluatory framework.

Fig 1: Augmented intelligence in medicine

1.1. Background and Significance

Recent advances in Artificial Intelligence (AI) have raised hopes that it can help address the significant challenges faced by health systems globally, including rising costs, inadequate access to care and unsatisfactory organizational performance. Moreover, it is forecast that AI will have a profound impact on business processes in general and, accordingly, that it will create huge opportunities in multiple sectors. Yet, questions remain regarding the readiness of health systems to embrace AI.

Readiness pertains to the extent to which stakeholders in a specific area are prepared for a major change in business practices and supporting data infrastructure. Readiness can be assessed from a technology perspective as well as from a data governance perspective.

Equation 1: Technological Readiness: TRL (1–9) as an ordinal "technology maturity" variable

Step 1 — Define the TRL variable

Let:

- $\mathrm{TRL} \in \{1,2,\ldots,9\}$

Step 2 — Convert TRL to a normalized readiness score (0 to 1)

A standard way to make TRL usable in indices:

$$T_{\mathrm{TRL}} = \frac{\mathrm{TRL}-1}{9-1} = \frac{\mathrm{TRL}-1}{8}$$

- If TRL = 1 ⇒ $T_{\mathrm{TRL}} = 0$
- If TRL = 9 ⇒ $T_{\mathrm{TRL}} = 1$

Step 3 — If you have multiple AI systems, aggregate them

If a hospital has n AI solutions each with TRL_i:

$$T = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{TRL}_i - 1}{8}$$

This produces a single **Technological readiness score** $T \in [0,1]$.

(You'll see the **TRL summary table** rendered above from the article's TRL descriptions.)

2. Conceptual Foundations of Healthcare AI

Conceptual Foundations of Healthcare AI Research initiatives focusing on artificial intelligence (AI) in healthcare tend to be unbalanced and concentrated in specific areas, often overselling a narrow range of applications while ignoring issues that remain unaddressed. Well-intentioned hype around avenues such as medical diagnosis, medical imaging, and drug discovery, along with a plethora of technical feasibility demonstrations, puts such initiatives at risk of being viewed as technology in search of a problem, draining research funds from areas with less glitzy appeal. At the same time, fears over overhyping AI technologies in healthcare risk overshadowing other, equally important, readiness factors that must be addressed in order for AI to deliver value. Attention is therefore urgently

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

needed for these readiness gaps and honing the understanding of all conceptual foundations necessary for AI in healthcare.

In the context of health care, research initiatives exploring the readiness of health care systems for the successful introduction and use of AI tools are particularly relevant. Readiness determines when a system is prepared to integrate the novel technology into its operations and appears well defined in the literature. Scholars and practitioners have positioned the concept as a predictor of the likelihood of successful introduction and use. The nature of readiness changes over time, and AI presents not only a wave of new technology but also a new process for the development and introduction of health care technologies: the prospect of data-driven discovery.

2.1. Definitions and Scope

Three-dimensional printing consists of digital 3D models, usually created by computer-aided design (CAD) software or through 3D scanning equipment, and code that controls the 3D printer as raw materials are deposited in a variety of ways to create a part with little to no manual effort. Common materials that can be readied into the desired shape with a 3D printer include metals, plastics, ceramics, resins, biomaterials, waxes, glass, and during the past few years foods such as chocolate or dough. Additive manufacturing methods used for three-dimensional print include draughting, inkjet printing, electron-beam melting, laser sintering, lamination, and continuous liquid interface production.

Three-dimensional printing (3DP) has received global recognition because it has the potential to redefine production processes. The memorable phrase “You print it, I’ll eat it” is often used to describe how 3DP will change the approach to logistics of food supplies and delivery. As 3DP food printers become commercially available, the growing hype associated with food-3D printing cannot be ignored. Food-3D printing brings more excitement compared to other applications because food is essential for human survival, and production of food is a task with which everyone in society can identify. However, because the volume of work addressing the food-3D printing area is relatively small, understanding of the field has not matured.

2.2. Historical Development and Current Landscape

The use of AI in healthcare is not new; the application of AI-based decision-support systems started more than four decades ago [38]. Research on using AI in healthcare has increased exponentially in recent years. Over the last decade, more than 85,000 research articles have been published on the topic, with the number exceeding 6,000 annually by the end of the decade. AI remains a dominant theme in publications because it promises to assist healthcare in improving patient care, reducing costs, and coping with the increase in demand driven by population growth, disease burden, ageing, and other factors.

Healthcare stakeholders are keen to reimagine and transform care delivery through generative AI. However, while innovative AI products and services are being launched across the world, excitement about AI's potential must be tempered by concerns provided by a rising trend in assessing healthcare organisations’ readiness to implement AI systems. To continue the discussion on readiness, it is essential to demystify data aspects and examine the computing resources required to put machine-learning models into production, and these need to support diverse AI models, including AI-driven general-purpose large-language models.

Equation 2: Data Readiness & Governance: measurable “data fitness” score

Step 1 — Define measurable sub-scores (each 0–5 Likert, or 0–100)

Let the data pillar have k components (example aligned to the paper):

- d_1: data quality
- d_2: completeness
- d_3: interoperability/accessibility

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

- d_4: governance & compliance (privacy/security/regulatory)

Assume each d_j is rated on a **0–5** scale (typical readiness questionnaire).

Step 2 — Normalize each component to 0–1

$$d'_j = \frac{d_j}{5}$$

Step 3 — Aggregate into a single data readiness score

With weights α_j such that $\sum_{j=1}^{k} \alpha_j = 1$:

$$D = \sum_{j=1}^{k} \alpha_j \, d'_j$$

So $D \in [0,1]$ becomes the **Data readiness & governance score**.

3. Readiness Frameworks for AI in Healthcare

Technological readiness serves as a prerequisite for innovation adoption, with a mature infrastructure acting as a foundation for proceeding with technological adoption. The integration of advanced technologies such as AI requires particular attention to the readiness of critical technological components. Multiple technological readiness assessments have focused specifically on AI in healthcare. This emerging body of work highlights the importance of computing resources, data quality, data policies, and data ecosystems—spanning the entire AI life cycle from development to deployment.

Data quality is a well-established prerequisite for any data-driven technology. Poor-quality data in training sets can lead to biased AI models and inaccurate predictive results. Several readiness evaluations have cited the necessity of investing in the collection, governance, and maintenance of high-quality datasets. Sound data governance frameworks are similarly essential, ensuring the ethical use of data and building public trust in AI technologies. Accordingly, stakeholder voices are important for allay concerns over data security, privacy, and ownership, and for enabling the transparent and trustworthy creation of AI solutions. Moreover, some readiness assessments have highlighted the need for cross-system healthcare data integration to enhance the training of national-scale AI models. Such investments support the wider ecosystem of image-sharing services across the healthcare industry.

The extraction of knowledge concealed in the copious quantities of clinical data already collected is critical to support the development of safer and more effective health AI applications. Guidelines and initiatives, such as the Health AI Consortium in the UK, advocate the secure and liable use of electronic health data during model training. Data custodians must ensure a definite process to analyse prospective AI projects and monitor any use of the data. However, custodians typically lack the necessary knowledge and experience to carry out these assessments effectively. It has thus been argued that dedicated health-data administrators should be established to empower custodians, creating a concordat that defines the roles and responsibilities of all stakeholders and allows proper functioning with data-sharing regulations.

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

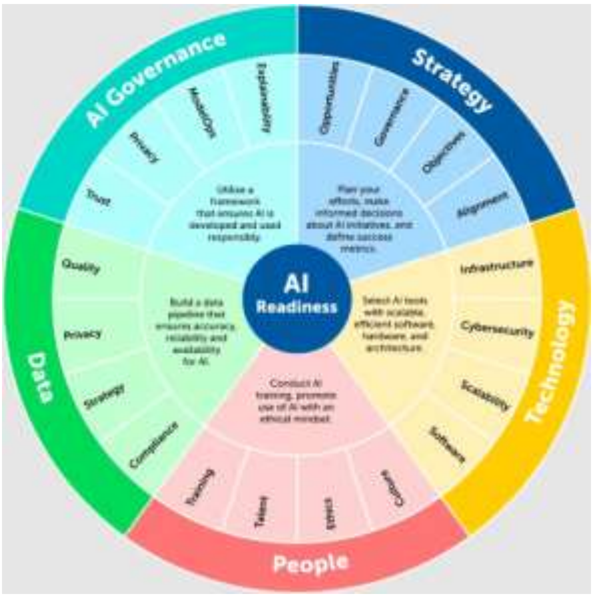


Fig 2: AI Readiness Framework

3.1. Technological Readiness

Technological readiness is the availability of synthesizing components, that were previously validated. Assessment of technology readiness is useful for complex endeavors. Various means of investment scoping can be leveraged such as technology readiness level (TRL) assessments. The TRL scale is from 1 to 9, where 1–3 indicates invention or academic proof-of-concept. Level 4 means validation of the technology piece, while 5 means validation of the integrated technology component. Level 6 means a system has been externally tested, while 7 means validated in an environment close-to-operational. Level 8 defines operating in an expected environment and 9 means the operating system of interest is validated in operational environments. For AI, TRL largely refers to data training and testing in pre-production systems or full and final production roll-out.

Medical technology, algorithm-based technology and robotics in healthcare can also be assessed for readiness through the healthcare TRL+ (HTRL+) Scale. Factors for assessing technology readiness are culture and collaboration processes; science and technology strategy; systems architecture; programme management; operations support; external factors and resources/capabilities. Issues that have to be considered include investigative medicine; trans-disciplinary biotechnology; engineered treatments for neurodegeneration; clinical biology for development; human-centric interactions; functionality-centric patients; precision and metabolic medicine; and validation by necessity.

Equation 3: Skills / Workforce Readiness: measurable competency capacity score

Step 1 — Define workforce components (example)

Let:

- s_1: ML/AI literacy among clinicians
- s_2: data engineering / MLOps capacity
- s_3: change management & workflow redesign skills
- s_4: interdisciplinary collaboration maturity

Each on 0–5 Likert.

Step 2 — Normalize

$$s'_m = \frac{s_m}{5}$$

Step 3 — Aggregate

With $\sum \beta_m = 1$:

$$S = \sum_m \beta_m \, s'_m$$

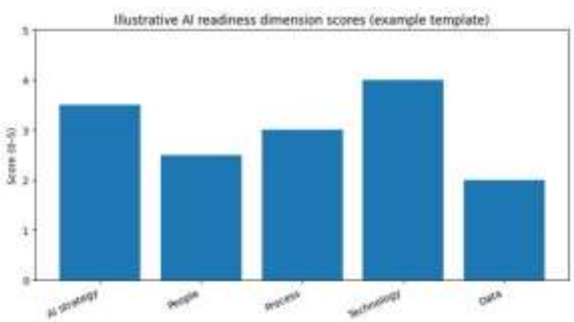
So $S \in [0,1]$ is the **Skills readiness score**.

3.2. Data Readiness and Governance

A review of recent literature reveals that the incorporation of AI in healthcare requires high-quality, adequately labelled training data that is often challenging to source and secure, thus creating bottlenecks for clinical adoption. Readiness

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

frameworks therefore often incorporate an assessment of the volume, completeness, quality, and accessibility of healthcare data within a given jurisdiction, in conjunction with imperatives for appropriate data governance tools. Proper regulation, legislation, and GDPR-like frameworks are unavoidable since data pools comprise highly sensitive private information. Local data administrators must verify that the set goals of data pooling are lawful, legitimate, and justifiable, protecting individual rights while maintaining public safety, health, and interest. Beyond oversight, stakeholder cooperation between data custodians and AI researchers is indispensable to develop policies and guidelines for accessing and sharing data. Furthermore, suggested transparent and realistic data-sharing guidelines might lessen collaborators' concerns about legal liabilities.



4. Methodologies for Assessing Readiness

Two prominent methodologies for assessing readiness are maturity models and stakeholder analysis, both of which, though applied to different domains, have proven applicable to the category of AI readiness in healthcare context. Maturity models typically involve the development of a maturity scale with ordinal levels, against which the development of the specific entity can be analysed to guide investments and activities towards resources, processes, or components that may hold highest impact or potential.

A second well-established methodology for determining readiness is stakeholder theory, which posits that successful performance of an organization requires consideration of the interests of multiple parties, including not only shareholders or owners of the organization but also employees, customers, business partners, government controls or regulators, and society at large.

4.1. Maturity Models

Maturity models offer a widely accepted framework for evaluating organizations' readiness for the integration of novel technologies, including AI. Many such models have been produced specifically to assess health systems' readiness for AI adoption. For instance, one model examines five dimensions: AI strategy (availability and alignment); people (skills, education, hiring, and collaboration necessities); process (alignment with process management, use-case development, execution); technology (infrastructure, steps for implementation, algorithms); and data (quality, availability, security, and ethical concerns). This model can assess AI readiness from differing stakeholder perspectives by tailoring specific questionnaires for each of the five dimensions.

Similarly, another AI readiness-maturity model identifies three levels—foundational, emerging, and predictive—across seven areas, including data quality, people and capabilities, strategy, use case development, technology and infrastructure, governance and risk mitigation, and partnerships. Yet another model for AI impact assessment maps five stages of maturity against the seven elements of the Digital Health Innovation Framework, targeting vendors, healthcare systems, and payers. In the United Kingdom, a second-tier maturity model for assessing readiness and potential for AI implementation uses four stages—strategic validation, investment decision, delivery, and value realisation—aligned with artificial intelligence's three phases of development and testing. These diverse models can guide organizations' technology adoption journeys.

Equation 4: The paper's "3-level readiness" → a single composite Readiness Index

Let:

- T = technological readiness (0–1)

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

- D = data readiness & governance (0–1)
- S = skills/workforce readiness (0–1)

Choose weights $w_T, w_D, w_S \geq 0$ with $w_T + w_D + w_S = 1$.

$$R = w_T T + w_D D + w_S S$$

That gives $R \in [0,1]$, a single **AI integration readiness index**.

(Above, I included a **bar diagram** example for the 3 pillars and showed how R is computed with example weights—purely as a *template*, since the paper doesn't provide numeric data.)

4.2. Stakeholder Analysis

Stakeholder analysis is another technique for assessing a healthcare system's readiness for AI adoption and deployment. Since AI technologies require collaboration between stakeholders across different sectors, the ability of a region to harness these partnerships is vital to realizing the potential benefits and achieving ethical outcomes. Building genuine partnerships is challenging, however, as it requires the alignment of stakeholder interests and is often complicated by power asymmetries. Stakeholders in an AI network in healthcare commonly include institutions and organizations from the public, private, and third sectors such as healthcare institutions, industry partners, regulators, AI specialists, health information technology suppliers, research institutions, universities, and foundations.

The stakeholder analysis method assesses relationships, motivations, interests, capabilities, and funding sources that can either enhance or hinder the establishment of partnerships. The output is a framework that highlights the overarching consensus among stakeholders involved in AI projects that alleviating clinician workloads should be prioritized, strengths and weaknesses across stakeholders in terms of capabilities and resources, the relatively low funding levels available for AI projects given their multidisciplinary nature, power imbalances with local private AI companies, the need for private-sector participation to allow AI to develop towards self-financing, and the inclusion of community members and health consumers in the partnership discussion and planning processes across multiple aspects of AI projects.

5. Infrastructure and Data Ecosystems

Assessing readiness necessitates understanding either the structural components needed to facilitate the desired integration or the conditions of a specific aspect of a healthcare ecosystem that support AI's successful adoption. Data and technology ecosystems must inform an analysis of readiness. Whereas technology readiness analysis involves assessment of infrastructure-related components, data ecosystem analysis emphasizes elements of data quality, interoperability, and usability.

Data Quality, Interoperability, and Standards

Interoperable, high-quality health data availability has emerged as the primary requirement for AI applications; indeed, some argue that "health AI is a challenge of data." To this end, Hor et al.'s review of literature published in English through 2020 identifies key factors for the successful integration of AI into EHRs. Among the salient variables loaded or emerged in the other factors were patient privacy, data usability and interoperability, data quality, AI data availability, and AI trusts, along with the necessary legal framework.

Computing Resources and Cloud Governance

The successful integration of AI into hospitals and the healthcare sector as a whole is not feasible without the requisite computational resources. Hor et al. thus describe and recommend the use of cloud governance and cloud computing, as well as edge computing, as data from various Internet of Medical Things devices may be collected and stored.

Equation 5: Mapping maturity models described in the paper into equations

Let dimension scores (0–5):

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

- x_1=strategy, x_2=people, x_3=process, x_4=technology, x_5=data

Normalize:

$$x'_i = \frac{x_i}{5}$$

Aggregate:

$$M_5 = \sum_{i=1}^{5} \gamma_i x'_i, \quad \sum \gamma_i = 1$$

B) Convert a numeric maturity score to levels

If you want an ordinal maturity label:

- Foundational if $M_5 < 0.40$
- Emerging if $0.40 \leq M_5 < 0.70$
- Predictive if $M_5 \geq 0.70$

Those cutoffs are a standard rubric; the paper names levels (foundational/emerging/predictive) but doesn't specify numeric thresholds.

(Above, I also rendered a **bar chart** example across the five dimensions as a reporting-friendly "readiness dashboard".)

Fig 3: Ecosystem for AI in healthcare

5.1. Data Quality, Interoperability, and Standards High-quality, interoperable data are essential for AI applications in healthcare. Poor quality, heterogeneous, or fragmented datasets hinder the development of sophisticated AI models, which, in turn, can lead to eroding public trust and reluctance to accept AI interventions. Consequently, the absence of data-driven and systematic approaches to datasets, including data collection, preparation, sharing, and reuse, undermines the envisaged transformation and added value of AI.

With healthcare data requirements spanning a multitude of tasks, sectors, and boundaries, increasing interoperability holds the key to addressing disparate datasets and supporting sensitive data-related AI tasks. The introduction of AI-ready datasets and model zoos for the healthcare domain can facilitate research and deployment while reducing testing and training costs. Several quality requirements for clinical text data have been proposed that can focus AI research activities and help assess the quality of clinical natural language processing resources and applications. Determination of trustworthiness for COVID-19-related datasets supports trust in the enormous amount of data generated during the pandemic. Moreover, appropriate data sharing and reuse practices can help in building public trust in data-driven models and enable sensitive AI tasks. It is also important to keep track of the quality and information contained in these shared datasets, such as their construction process, ethical and legal issues, and so forth.

5.2. Computing Resources and Cloud Governance AI-powered applications often rely on costly resources for training, inference, and deployment. Consequently, a robust IT infrastructure must be available, or cloud capability must exist for large model-driven applications. Decisions on the use of cloud-based services, deployment pipelines, storage, and resources are essential for ensuring that such platforms can effectively deliver these services to wide-ranging consumers. A distributed large language model designed for general use necessitates the availability of powerful clusters supporting low-latency setups on GPUs connecting institutions worldwide. Utilization of dedicated edge solutions for vision-based applications improves workload distribution, data privacy, and operational latency. Ideally, guidelines must govern the use of public cloud platforms where sensitive information resides. Native cloud ecosystems generally retain and enhance such aspects for

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

their consumer user community with continual upgrades and advancements for existing applications and expansion to new domains. Governance guidelines specific to cloud-based services should manage data transfer, purpose, usage patterns, and access so that cloud resources are deployed only for the desired purpose with the least risk and overhead possible.

Cloud-driven solutions on available first-party clouds (such as the Google Cloud Platform for Google applications) highlight simple user experiences through seamless integration. By using casing APIs, state-of-the-art models can be called on minimal latency without the need for dedicated resources supporting the models. Given sensitive data, stakeholders must engage and work continually with cloud service providers to reduce risks and identify sensitive landmarks to support specific usage. Native cloud ecosystems hold distinct advantages. Siloed or public cloud models may suit forensic AI applications where speed of retrieval, visualisation, and exhaustive analysis of critical information take precedence over privacy.

6. Workforce and Skill Implications

Skill gaps, particularly in machine learning and data engineering, challenge AI integration in healthcare. Addressing these gaps is essential to nurture a workforce capable of executing AI projects and ultimately adopting AI-based processes. Consequently, collaboration between academic centers, hospitals, and other relevant institutions should facilitate the design and establishment of AI-focused training and educational programs.

Healthcare AI research remains largely fragmented, often with limited integration of clinical needs, thus challenging the realization of clinically useful applications. Building teams and networks of researchers with different skills, including computer scientists, engineers, and medical professionals, is vital to the successful development and deployment of AI technologies in clinical settings. Such collaborations can connect different stakeholders, fostering a constructive dialogue and understanding of clinical needs and challenges.

Equation 6: Stakeholder readiness (implementation leaders, point-of-care users, patients)

A practical way to quantify stakeholder readiness is to score each stakeholder group across readiness factors:

Let stakeholder groups:

- $g \in \{\text{Leaders,Clinicians/Users,Patients}\}$

Let readiness factors (example):

- trust, usability/workflow fit, perceived benefit, training/support, risk concerns

Score each factor (0–5), normalize, then:

$$R_g = \sum_f \lambda_f \left(\frac{r_{g,f}}{5}\right)$$

Then summarize stakeholder alignment as:

- **minimum readiness** (bottleneck):

$$R_{\min} = \min_g R_g$$

- or **weighted adoption likelihood**:

$$R_{\text{stake}} = \sum_g \pi_g R_g, \quad \sum \pi_g = 1$$

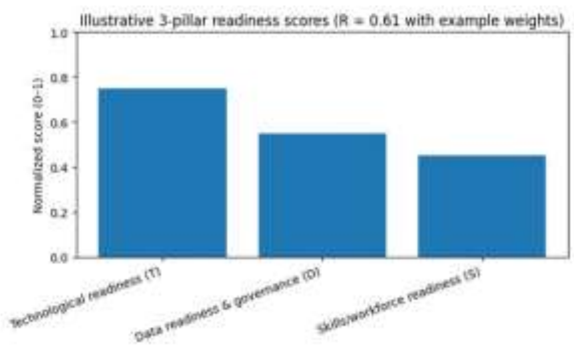
This is useful because in real deployments, the least-ready stakeholder group often limits adoption.

6.1. Skill Gaps and Training Programs

Artificial Intelligence (AI), an increasing presence in the present world, is reported to have a significant and sometimes negative impact on jobs. In healthcare, where AI has many applications, augur and developers are optimistic about future improvements in the quality of the healthcare system. However, AI technologies require provisioning and preparation, among other things. These preparations must include a skilled workforce tailored to preparing, using, and supporting such AI end products. Primarily, there is a need to identify the human skill gap for effective AI integration, and then the workforce can be prepared accordingly.

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

While academic conversations revolve around training next-generation skilled professionals prepared to work hand-in-hand with AI technologies to solve complex issues, research demonstrates how organizations perceive AI from a human-resources perspective. AI Pose survey respondents reported that the most sought-after Type-2 and Type-3 disruptive skills for enterprise AI are critical-thinking, analytical, troubleshooting, attention-to-detail, and project-management skills. All these skills fall under the Category-1 "fundamental skills" of the AI Computation Skills Matrix. Meanwhile, the students surveyed perceived project and stakeholder-management skills as important for integrating AI-driven solutions in business. Training programs in Malaysia were also recommended to educate the workforce seeking careers in AI technology; a report on Chinese education recommended prioritizing the training of teachers to help students adapt to the Age of AI.



6.2. Interdisciplinary Collaboration

Historically, artificial intelligence research has typically required sub-areas of expertise such as advanced mathematics and statistics, state-of-the-art programming skills, knowledge about optimization techniques, neural network architecture design skills, and natural language processing. Although these requirements remain true in research, their relevance has diminished in the deployment of AI applications. As L. D. Ratner stated: "One of the main barriers for adoptions of AI methods in many industries are the lack of domain experts who can get close to the problem domain and use these methods to derive business value." It is important to understand that the complexity of too many areas of AI is confusing and too much specialized knowledge is needed for its successful usage. Implementation of AI applications becomes much easier with abstraction.

The major skills needed for the success of current AI applications are related to the business domain in which the AI application is being used; e.g. customer insight in retail, human resource management in finance, call center operations in telecom, and shipping operations in logistics. Consequently, organizations should aim to train employees in student friendly and developer friendly tools, custom made for their business domains. Such user-friendly tools target business users rather than data science specialists. However, taking a longer view toward the AI skills point-of-view means that many more AI specialists will be needed over time.

7. Conclusion

The digitization of healthcare offers great promise; however, poor healthcare preparedness is seen as a possible reason for failure. The preparedness of the health ecosystem for the adoption of Artificial Intelligence (AI) into healthcare has yet not been explored. This research addresses the readiness of the healthcare ecosystem for the adoption of AI as a component of the digital transformation journey while considering AI adoption across management processes, specialist functions, and administrative functions. It proposes a framework for critical success factors related to Data quality & governance, IT infrastructure readiness, workforce competency preparation, and the functional preparedness of the healthcare ecosystem.

Healthcare ecosystem leaders are urged to assess and enhance the efficaciousness of these success factors that have been defined with respect to their ecosystem and the adoption levels of the participating entities and felt stakeholders before embarking upon the AI journey. The "hype-cycle" of AI and its envisaged transformation impact has received considerable attention for technology-centric stakeholders and applications. Although there have been artefacts on the readiness of the technology ecosystem along

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

the lines of the TAM or for AI models, there are no known studies that directly address the readiness of the healthcare ecosystem for hardware-centric AI adoption beyond similar information systems and e-health more generally.

7.1. Emerging Trends

Currently, the integration of Artificial Intelligence (AI) into the healthcare system hinges on the preparation of the insurance, health service sectors, and specifically the hospitals, for its implementation. This process is framed within an incremental evolution approach, where continuous progress in AI will lead to a gradual increase in its application, until the moment when the current top AI models can be used in everyday situations. AI is expected to be increasingly used in hospitals, both in its assistance functions and in generating diagnostic options, treatment proposals, risk profiles, research needs, training, and the like. However, the successful development of these systems will depend, among other factors, on the AI-related capacities that need to be in place. To identify the specific needs, focus, qualitative nature and degree of required capacities at hospitals, a readiness framework for their AI integration is presented.

The readiness framework builds on the concept of technological readiness, commonly used for evaluating the capacity of institutions and regions to develop and implement high-technology industries. It has been adapted for districts, cities, and the country. In addition to being adapted, the analysis has been extended to the requirements for data, AI infrastructure, skills available in the local environment and hospitals themselves, and the nature and degree of the AI integration needs. The latter incorporates specific information from techniques and approaches being considered for implementation, therefore encompassing AI integration especially in the hospital sector. GUI standards appear key for fostering data interoperability, encouraging the use of data lakes, cloud computing, cyber security protection standards, computer cyber-resilience, intelligent alerts and smart contracts, with testing and training not being directly included.

8. References

1. Antes, A. L., Burrous, S., Sisk, B. A., Schuelke, M. J., Keune, J. D., & DuBois, J. M. (2021). Exploring perceptions of healthcare technologies enabled by artificial intelligence: An online, scenario-based survey. BMC Medical Informatics and Decision Making, 21, 236.
2. Aung, Y. Y. M., Wong, D. C. S., & Ting, D. S. W. (2021). The promise of artificial intelligence: A review of the opportunities and challenges of artificial intelligence in healthcare. British Medical Bulletin, 139(1), 4–15.
3. Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: Transforming the practice of medicine. Future Healthcare Journal, 8(2), e188–e194.
4. Inala, R. (2022). Engineering Data Products for Investment Analytics: The Role of Product Master Data and Scalable Big Data Solutions. International Journal of Scientific Research and Modern Technology, 155-171.
5. Bakker, L., Aarts, J., Uyl-de Groot, C., & Redekop, K. (2021). How can we discover the most valuable types of big data and artificial intelligence-based solutions? A methodology for the efficient development of the underlying analytics that improve care. BMC Medical Informatics and Decision Making, 21, 336.
6. Brnabic, A., & Hess, L. M. (2021). Systematic literature review of machine learning methods used in the analysis of real-world data for patient-provider decision making. BMC Medical Informatics and Decision Making, 21, 54.
7. Goirand, M., Austin, E., Rumney, P., & Sibbald, B. (2021). Implementing ethics in healthcare AI-based applications: A scoping review. Science and Engineering Ethics, 27, Article 50.
8. Möllmann, N. R. J., Mirbabaie, M., & Stieglitz, S. (2021). Is it alright to use artificial intelligence in digital health? A systematic literature review on ethical considerations. Health Informatics Journal, 27(4).
9. Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

intelligence in healthcare: A structured literature review. BMC Medical Informatics and Decision Making, 21, 125.

10. Aitha, A. R. (2024). Generative AI-Powered Fraud Detection in Workers' Compensation: A DevOps-Based Multi-Cloud Architecture Leveraging, Deep Learning, and Explainable AI. Computer Fraud and Security.
11. Soellner, M., & Koenigstorfer, J. (2021). Compliance with medical recommendations depending on the use of artificial intelligence as a diagnostic method. BMC Medical Informatics and Decision Making, 21, 236.
12. Gama, F., Tyskbo, D., Nygren, J., Barlow, J., Reed, J., & Svedberg, P. (2022). Implementation frameworks for artificial intelligence translation into health care practice: Scoping review. Journal of Medical Internet Research, 24(1), e32215.
13. Garvey, K. V., Craig, K. J. T., Russell, R., Novak, L. L., Moore, D., & Miller, B. M. (2022). Considering clinician competencies for the implementation of artificial intelligence-based tools in health care: Findings from a scoping review. JMIR Medical Informatics, 10(11), e37478.
14. Chomutare, T., Tejedor, M., Svenning, T. O., Marco-Ruiz, L., Tayefi, M., Lind, K., Godtliebsen, F., Moen, A., Ismail, L., Makhlysheva, A., & Ngo, P. D. (2022). Artificial intelligence implementation in healthcare: A theory-based scoping review of barriers and facilitators. International Journal of Environmental Research and Public Health, 19(23), 16359.
15. Čartolovni, A., Tomičić, A., & Lazić Mosler, E. (2022). Ethical, legal, and social considerations of AI-based medical decision-support tools: A scoping review. International Journal of Medical Informatics, 161, 104738.
16. Liao, F., Adelaine, S., Afshar, M., & Patterson, B. W. (2022). Governance of clinical AI applications to facilitate safe and equitable deployment in a large health system: Key elements and early successes. Frontiers in Digital Health, 4, 931439.
17. Inala, R. (2021). A New Paradigm in Retirement Solution Platforms: Leveraging Data Governance to Build AI-Ready Data Products. Journal of International Crisis and Risk Communication Research, 286-310.
18. London, A. J. (2022). Artificial intelligence in medicine: Overcoming or recapitulating structural challenges to improving patient care? Cell Reports Medicine, 3(5), 100622.
19. Mudgal, S. K., Agarwal, R., Chaturvedi, J., Gaur, R., & Ranjan, N. (2022). Real-world application, challenges and implication of artificial intelligence in healthcare: An essay. Pan African Medical Journal, 43, 3.
20. Terry, A. L., Kueper, J. K., Beleno, R., Brown, J. B., Cejic, S., Dang, J., Leger, D., McKay, S., Meredith, L., Pinto, A. D., Ryan, B. L., Stewart, M., Zwarenstein, M., & Lizotte, D. J. (2022). Is primary health care ready for artificial intelligence? What do primary health care stakeholders say? BMC Medical Informatics and Decision Making, 22, 237.
21. Lambert, S. I., Madi, M., Sopka, S., Lenes, A., Stange, H., Buszello, C.-P., & Stephan, A. (2023). An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. npj Digital Medicine, 6, 111.
22. Li, L. T., Haley, L. C., Boyd, A. K., & Bernstam, E. V. (2023). Technical/Algorithm, Stakeholder, and Society (TASS) barriers to the application of artificial intelligence in medicine: A systematic review. Journal of Biomedical Informatics, 147, 104531.
23. Hogg, H. D. J., Al-Zubaidy, M., & colleagues. (2023). Stakeholder perspectives of clinical artificial intelligence implementation: Systematic review of qualitative evidence. Journal of Medical Internet Research, 25.
24. Aravind, R., Deon, E., & Surabhi, S. N. R. D. (2024). Developing cost-effective solutions for autonomous vehicle software testing using simulated environments using AI techniques. Educational Administration: Theory and Practice, 30(6), 4135-4147.
25. Sauerbrei, A., Kerasidou, A., Lucivero, F., & Hallowell, N. (2023). The impact of artificial intelligence on the person-centred, doctor-patient relationship: Some problems and solutions. BMC Medical Informatics and Decision Making, 23, 73.
26. Sezgin, E. (2023). Artificial intelligence in healthcare: Complementing, not replacing, doctors and healthcare providers. Digital Health, 9.

ISSN: 3050-9696
E-ISSN: 3050-970X
EUROPEAN ADVANCED JOURNAL FOR SCIENCE & ENGINEERING
Volume: 03 Issue: 02
RECEIVED: APRIL 25 REVISED: MAY 09 ACCEPTED: MAY 28 PUBLISHED: JUNE 23

27. Wubineh, B. Z., Deriba, F. G., & Woldeyohannis, M. M. (2024). Exploring the opportunities and challenges of implementing artificial intelligence in healthcare: A systematic literature review. Urologic Oncology: Seminars and Original Investigations, 42(3), 48–56.
28. Kamel Rahimi, A., Pienaar, O., Ghadimi, M., Canfell, O. J., Pole, J. D., Shrapnel, S., van der Vegt, A. H., & Sullivan, C. (2024). Implementing AI in hospitals to achieve a learning health system: Systematic review of current enablers and barriers. Journal of Medical Internet Research, 26, e49655.
29. Preti, L. M., Ardito, V., Compagni, A., Petracca, F., & Cappellaro, G. (2024). Implementation of machine learning applications in health care organizations: Systematic review of empirical studies. Journal of Medical Internet Research, 26, e55897.