Towards a Systemic Approach to Knowledge Integration in Learning Health Ecosystems: AI and DLT Perspectives

Nabil Georges Badr[a]
Higher Institute of Public Health, Faculty of Medicine, Saint Joseph University of Beirut, Beirut, Lebanon

Keywords: Learning Healthcare Systems, Distributed Ledger Technology, Artificial Intelligence.

Abstract: A Learning Health System (LHS) is an essential paradigm for addressing the evolving complexities of healthcare systems, fostering continuous improvement, adaptability, and stakeholder collaboration. By integrating knowledge management with technological advancements, LHS enhances data-driven decision-making and the responsiveness of healthcare interventions. Artificial Intelligence (AI) has emerged as a powerful tool within Learning Health Systems, yet its evolving nature presents challenges related to ethical, traceable, and trustworthy data management. Distributed Ledger Technology (DLT) offers immutable and transparent data governance, yet its full potential remains unrealized due to the absence of integrated frameworks that could reinforce accountability and reliability in AI-driven processes. Addressing this gap is critical for developing robust, ethical, and efficient healthcare solutions. This paper examines the synergistic potential of AI and DLT within LHS, proposing a framework that leverages systematic knowledge integration, predictive analytics, and proactive interventions. By harnessing AI-driven automation, IoT-enabled data collection, and the secure, decentralized architecture of DLT, LHS can advance evidence-based healthcare, mitigate disparities, and promote equitable access to high-quality care.

1 INTRODUCTION

A Learning Health System (LHS) is a vital approach for addressing the evolving complexities of contemporary healthcare systems. It emphasizes continuous enhancement, adaptability, and cooperation among stakeholders, including healthcare providers, policymakers, researchers, and community members. The effectiveness of an LHS relies on the integration and management of knowledge. By systematically generating, sharing, and applying insights, the LHS supports evidence-based practices, advances predictive analytics, and drives proactive interventions. Utilizing data-driven insights and fostering innovation, an LHS strives to improve health outcomes, reduce disparities, and ensure equitable access to quality care. Technological advancements, like Internet of Things (IoT) and Artificial Intelligence (AI), play a crucial role in this integration. Using technology and automation artifacts, data elements are organized, then transformed into information. Closing the cycle, newly acquired explicit knowledge converts to tacit, restarting the cycle of renewable knowledge, thus growing the skills and capabilities of the stakeholder actors through knowledge integration. For instance, integrated knowledge can inform predictive models for disease outbreaks or environmental hazards, empowering smart cities to proactively address public health challenges while promoting equity, sustainability, and improved health outcomes. Smart sensors can monitor environmental conditions, detect emergencies, and provide real-time data to both public health and safety agencies. Predictive analytics can identify trends and potential risks, enabling coordinated responses. This interconnected approach not only improves individual and community safety but also fosters resilience and sustainability (Badr et al., 2023).

We investigate the possible value creation of joining AI to Distributed Ledger Technology (DLT) as applied to the complex health service ecosystem. DLT might track an immutable attribute for preserving identity of sources of truth, without maintaining an inherent level or trust in the information collected and managed by AI (Pandl et

[a] https://orcid.org/0000-0001-7110-3718

Badr, N. G.
Towards a Systemic Approach to Knowledge Integration in Learning Health Ecosystems: AI and DLT Perspectives.
DOI: 10.5220/0013657100004000

In *Proceedings of the 17th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2025) - Volume 2: KEOD and KMIS*, pages 332-339
ISBN: 978-989-758-769-6; ISSN: 2184-3228

al., 2020). Through this synthesis, we aim to advance the discourse on intelligent health systems capable of co-creating value, fostering systemic learning, and responding effectively to present and future public health challenges. We treat our concept of LHS as an ecosystem with interconnected and adaptive elements, decentralized and diverse components that evolve based on interaction and feedback.

2 BACKGROUND

2.1 Visions of a Learning Health System

Public health relies on service intelligence to transform data into knowledge integration to power learning healthcare systems. In general, knowledge management focuses on the collection, storage, dissemination, and utilization of knowledge within an organization or system, enabling informed decision-making and continuous learning. For instance, in a public health ecosystem, knowledge management facilitates the integration of patient data, research findings, and operational insights across healthcare networks. This allows service providers to tailor interventions, improve service delivery, and address population-specific needs effectively.

A Learning Health System integrates diverse data sources to drive knowledge creation, inform policy decisions, and enhance operational processes (Easterling et al., 2022). The concept of a Learning Health System revolves around creating a continuous cycle of learning and improvement in healthcare (Figure 1).

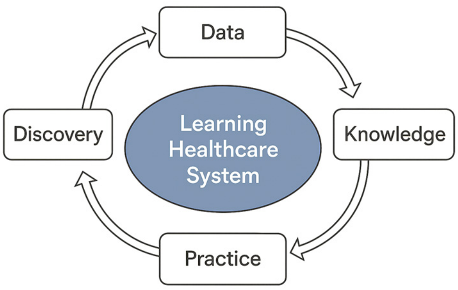

Figure 1: Conceptual Representation of Knowledge Cycles Learning Health System.

It integrates data collection, analysis, and application to enhance patient outcomes and system efficiency (Yano et al., 2021). The LHS operates through iterative cycles, often described as "*Practice to Data*," "*Data to Knowledge,*" and "*Knowledge to Practice*." This means that real-world healthcare practices generate data, which is analysed to produce actionable knowledge, and this knowledge is then applied back into practice.

The implementation of an LHS offers significant benefits, including strengthened disease prevention efforts, evidence-based policy formulation, and improved health outcomes for populations. Introducing an LHS has the potential to revolutionize public health practices. To unlock this potential, stakeholders across the public health ecosystem must take coordinated action. Essential steps include investing in advanced informatics infrastructure, prioritizing the development of a skilled workforce, establishing comprehensive data governance frameworks, and creating incentives to support LHS implementation and growth. By addressing these critical areas, public health systems can evolve to become more adaptive, efficient, and impactful in achieving better health outcomes for all (Tenenbaum, 2024). Therefore, the production of useful, renewable knowledge (Badr et al., 2020) that is required for timely and effective decision-making. In context, knowledge management in the healthcare sector exhibits the full lifecycle of knowledge production from knowledge creation, acquisition and storage (Florio, 2019) for sharing, decision-making and application of ethically sound knowledge translation (Mutashar, 2024). The latter must be manifested through measures of knowledge protection that drive equity (Badr et al., 2023) and intellectual property safeguards (Zhang et al., 2024).

To accelerate learning within a Healthcare system, envisioning a closed-loop process is key. This approach ensures the integration of truthful information to enable timely decision-making, enhance stakeholder collaboration, and foster interoperability. Crucially, it also maintains transparency and trust in the shared knowledge. Potential elements of acceleration include integrated data systems, creating platforms where diverse data sources—like patient records, environmental health data, and research findings—are unified and accessible for analysis. Advanced analytics leverage

2.2 Potential of DLT in Healthcare KM

Distributed Ledger Technology (DLT) refers to a decentralized system of electronic records that enables independent entities to reach consensus on a shared ledger without relying on a central authority (Rauchs et al., 2018). Unlike traditional databases, DLT systems maintains data across multiple nodes. These systems typically employ cryptographic techniques, consensus algorithms, and immutable data structures to validate and secure transactions

(Zheng et al., 2017). DLT systems serve as "consensus machines" that facilitate secure, transparent, and tamper-resistant data exchange across distributed environments (König & Neumaier, 2023). Key functionalities include decentralized data validation, whereby, transactions are verified through consensus mechanisms eliminating the need for centralized oversight. Once recorded, data entries are cryptographically linked and cannot be altered retroactively, ensuring auditability and trust (Immutable Recordkeeping). Programmable logic (Smart Contracts) is embedded in the ledger to automate processes such as access control, asset transfers, and compliance enforcement (Christidis & Devetsikiotis, 2016).

Despite its challenges in scalability, interoperability, and regulatory uncertainty ongoing research and hybrid architectures—such as combining DLT with federated learning or semantic ontologies are improving the potential in enhancing data integrity, provenance, and accessibility across sectors such as healthcare, finance, and supply chain management (Antal et al., 2021; König & Neumaier, 2023). Its effectiveness in knowledge management is particularly evident by maintaining a tamper-proof history of transactions, DLT ensures that knowledge assets remain authentic and verifiable (Ferraiolo et al., 2021). Attribute-based access models integrated with DLT allow for granular, policy-driven sharing of sensitive data across organizational boundaries (DeFranco et al., 2024). Emerging frameworks leverage DLT to construct distributed knowledge graphs, enabling consistent and trustworthy knowledge sharing in decentralized systems (Zaarour et al., 2024).

2.3 AI in Healthcare KM

Artificial Intelligence (AI) refers to the design and development of computational systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, perception, and decision-making (Russell & Norvig, 2021). AI systems operate through algorithms that enable machines to analyze data, recognize patterns, and adapt to new information.

AI significantly enhances both data management and knowledge management (KM) by automating processes, improving accuracy, and enabling intelligent decision support. AI systems naturally excel in processing structured and unstructured data, extracting relevant insights from diverse sources such as documents, images, and speech (Sterne & Davenport, 2024). Natural language processing (NLP) and machine learning (ML) algorithms play a critical role in generating metadata and organizing data assets to improve discoverability (Taherdoost & Madanchian, 2023). Despite its transformative impact on knowledge management (KM), AI faces persistent challenges, including issues with data quality, integration, user trust, and ethical concerns such as algorithmic bias and privacy. These barriers can hinder adoption and system reliability. Nevertheless, AI continues to advance as a core component of KM systems, offering scalable, intelligent, and adaptive solutions tailored to the demands of complex, data-driven environments.

Empirical studies and industry applications demonstrate that AI is highly effective in transforming knowledge management (KM) practices. AI was reported to enhance the speed and precision of knowledge discovery, substantially reducing time spent searching for information and enabling more informed decision-making (Davenport & Kirby, 2016). By automating routine KM tasks, AI liberates human resources to focus on strategic and creative work (Vadari & Desik, 2021).

The advancement of AI and its integration within Learning Health Systems (LHS) present significant opportunities for rapid learning cycles and value creation. However, the inherently probabilistic and evolving nature of AI poses challenges to ensuring ethical, traceable, and trustworthy information handling. AI and machine learning to process information rapidly, uncover patterns, and predict outcomes. Collaborative networks encourage partnerships across disciplines and institutions to share knowledge and resources effectively.

3 TOWARDS ACCELERATING LEARNING HEALTH SYSTEMS

In a learning healthcare system, there must be a clear cycle of information exchange between practice and research. The system capitalizes on advancements in health information technology and the expanding health data infrastructure to access and utilize evidence in real time. Simultaneously, it extracts insights from real-world care delivery processes, fostering innovation in care practices and driving health system transformation through rigorous research.

3.1 Adaptability and Scalability

Artificial Intelligence (AI) empowers data-driven decision-making in healthcare by transforming vast, complex datasets into actionable insights that enhance clinical, operational, and strategic outcomes.

Integrating consolidated and amalgamated information from different sources in a decentralized infrastructure may introduce ambiguity and lack the transparency necessary to instil trust in the decisions.

Through advanced machine learning algorithms, AI systems analyse structured and unstructured data—from electronic health records and sensor inputs to genomic sequences and social determinants—to uncover patterns, predict trends, and recommend interventions with speed and precision. This analytical capability supports real-time decision support, personalized treatment plans, and resource optimization, facilitating a shift from reactive care to anticipatory and adaptive health management.

AI continuously learns from emerging data, it strengthens feedback loops and enhances the agility of decision-making across the Learning Health System, paving the way for more responsive, equitable, and evidence-informed healthcare delivery. Such LHS must be designed to operate at various levels, from individual organizations to national healthcare systems, ensuring adaptability and scalability.

3.2 Collaboration and Interoperability

We expect AI to enhance systems interoperability by enabling communication and data exchange across diverse platforms and applications. Advanced techniques like data mapping and transformation allow AI algorithms to convert information into formats compatible with different systems, addressing challenges like data silos and inconsistent standards (Nilsson et al., 2024). Natural Language Processing (NLP) further supports interoperability by extracting structured data from unstructured sources, such as clinical notes, making integration across systems more efficient (Dennehy et al., 2023). Additionally, AI facilitates predictive analytics, identifying patterns and trends that improve coordination and decision-making across interconnected systems. By leveraging these capabilities, AI drives more cohesive interoperability, ultimately enhancing outcomes in industries like healthcare.

3.3 Transparency and Trust

Illustrative to the complexity of knowledge production and management, numerous attributes of trustworthy AI, including privacy, interpretability, bias, and fairness, are closely linked. Explainable AI has the potential to overcome this issue and can be a step towards trustworthy AI (Markus et al., 2021). Building trustworthy and explainable AI (XAI) in healthcare systems is still in its early stages (Albahri et al., 2023). Where explainability is the process by which the AI model derives its output can be presented so that users can understand it (Samek et al., 2017). Explainable AI (XAI) for example is a set of tools and frameworks to help the user understand and interpret predictions made by machine learning models. Explainable AI (XAI) is a growing field that aims to make AI models more understandable. In Healthcare, XAI aims to make AI system decision-making processes more transparent, allowing users to trust, understand, and manage AI. AI-driven models used in diagnosing diseases or suggesting treatment options often leverage XAI to help physicians understand the basis of their recommendations. Hospitals can use explainable AI for cancer detection and treatment, where algorithms show the reasoning. This is done by providing clear explanations of how AI models make decisions or predictions.

3.4 Automation and Efficiency

Healthcare providers may now increase operational efficiency, precision, and the fundamental building blocks of decision-making processes thanks to the combination of AI algorithms, machine learning paradigms, and deep learning methodologies. AI is assisting medical professionals and life sciences organizations in improving early illness detection and intervention. AI technology (with machine learning capabilities) can identify disparities (e.g., housing conditions, food insecurity, transportation issues) that negatively impact the ability to find the right patients for the right trials and assist them in participating successfully by sifting through unstructured data and narrative notes. On the other hand, DLT significantly enhances automation and efficiency within a learning Healthcare system (Badr, 2019).

3.5 Ethical and Secure Learning

Ethical manipulation of data components would involve user engagement, full disclosure and feedback on justifiable use of information (Badr et al., 2021). By using AI technologies, healthcare professionals and academics may more effectively assess unfair inequities and assist communities and providers in creating solutions that improve health equality by connecting them to community resources, treatment alternatives, and access to care. When maintained, the trustworthy nature of AI systems is complemented by their responsible use and application. AI systems are not intrinsically dangerous or harmful; rather, their potential for harm depends largely on the context in which they are used.

In simpler terms, we must be able to trust the accuracy, veracity and accuracy of the data feeding the knowledge production cycle, entering the cycle at any point.

3.6 Continuous Feedback for Improvement

Closing the cycle, newly acquired explicit knowledge converts to tacit, restarting the cycle of renewable knowledge, thus growing the skills and capabilities of the stakeholder actors through knowledge integration (Badr et al., 2020). Parenthetically, the evolution of knowledge in public health is a model where two principles collide: the need to have integral information for decision-making and the necessity to maintain ethical boundaries of privacy (Badr et al., 2021). Aside from the noble goal of public safety, these tools must be ethically compliant to ensure that no "harm is done" to fundamental ethical principles that must protect individuals' autonomy, privacy, and non-discrimination today (Badr et al., 2021).

3.7 AI – DLT Synergistic Advantage

The lack of a robust framework for maintaining transparency, accountability, and immutability in AI-driven data processes creates risks of compromised data integrity and trust. DLT offers deterministic and immutable capabilities that could address these challenges, there is a need for effective integration of DLT into AI-driven systems.

However, the absence of standardized pathways for utilizing smart contracts and leveraging DLT's capabilities to track sources of truth and ensure data security further complicates the creation of ethical and reliable Learning Health Systems. This gap highlights the need for a framework that synergizes DLT's transparency and AI's analytical power to support ethical, efficient, and trustworthy healthcare solutions.

Recent studies highlight the transformative potential of DLT, particularly blockchain, in healthcare and AI applications. For instance, blockchain is being explored for enhancing data security, interoperability, and patient privacy (Bundi et al., 2023). It offers decentralized and immutable data management, which is crucial for handling sensitive health records and AI-driven analytics (Drosatos & Kaldoudi, 2019). Key applications include Secure Data Sharing, where Blockchain facilitates secure and interoperable health data exchange, enabling AI models to access reliable datasets for training and predictions. On the other hand, the regulatory requirements of Patient Consent Management can be addressed through DLT's Smart contracts ensure transparent and automated consent processes (Plenk et al., 2019).

By ensuring secure, decentralized, and tamper-proof data management, DLT minimizes the need for manual interventions, streamlining processes like patient record updates and medical supply tracking. Smart contracts, a feature of DLT, automate complex workflows such as insurance claims processing, reducing administrative burdens and accelerating operations. Its interoperability enables data sharing across healthcare providers, researchers, and patients, eliminating redundancies and fostering collaboration. Furthermore, DLT offers transparent traceability for clinical trials and treatments, ensuring accountability and improving trust. With reduced operational costs and enhanced data handling efficiency, DLT plays a pivotal role in enabling real-time analytics and personalized care, driving better patient outcomes and operational excellence.

Continuous feedback and improvement in a learning healthcare system can be revolutionized by the synergy of DLT and AI. DLT ensures that healthcare data is securely stored and transparently shared, enabling stakeholders to access immutable records for analysis and collaboration. This decentralized data structure allows real-time feedback loops between researchers, providers, and patients, ensuring that insights are consistently integrated into practice. AI enhances this process by analysing large datasets, identifying patterns, and generating actionable recommendations for care improvement. Together, DLT and AI enable dynamic updates to protocols, personalized treatment plans, and efficient resource allocation, fostering an ecosystem that adapts and evolves in response to new evidence, ultimately driving better health outcomes and operational efficiency.

4 PUTTING IT ALL TOGETHER

A learning health system is designed to detect, validate, and respond to public health threats while continuously improving through feedback and analytics. This enables proactive responses to health emergencies, such as outbreaks or contamination events. A LHS is structured to detect, validate, and respond to health threats such as outbreaks or contamination, while continuously refining its processes through feedback and analytics. This proactive approach integrates systematic workflows centred on monitoring, validation, decision-making, and adaptive learning (Gheibi et al., 2021).

In the healthcare system, the integration of these workflows enables rapid advancements in clinical outcomes and operational efficiency. For example, the use of AI and big data in disease outbreak monitoring can expand into broader applications like personalized medicine, predictive diagnostics, and real-time hospital resource management. The continuous feedback loops and analytics-driven adjustments ensure that the system learns from every case, refining its processes to deliver better care over time. By integrating AI and DLT, healthcare systems can accelerate learning, enhance efficiency, and improve patient outcomes. Therefore, accelerating learning within a healthcare system involves applying principles that enhance the speed and effectiveness of knowledge acquisition, decision-making, and system improvement.

DLT and AI are transformative forces in accelerating Learning Healthcare Systems (LHS). DLT, such as blockchain, ensures secure, transparent, and decentralized data sharing across healthcare networks. This technology addresses critical challenges like data integrity, privacy, and interoperability, enabling collaboration among stakeholders, including healthcare providers, researchers, and patients. By creating immutable records, DLT fosters trust and accountability, which are essential for advancing LHS. AI complements DLT by analysing vast datasets to uncover patterns, predict outcomes, and optimize decision-making processes. In LHS, AI-powered tools enhance diagnostics, personalize treatments, and streamline administrative tasks. For example, machine learning algorithms can identify trends in patient data, enabling proactive interventions and improving population health management. AI also supports real-time monitoring through wearable devices and telemedicine platforms, enhancing patient engagement and accessibility. The integration of DLT and AI creates a synergistic ecosystem where data-driven insights and secure information exchange drive continuous learning and improvement. DLT ensures that data shared across the system remains tamper-proof and accessible, while AI transforms this data into actionable knowledge. Together, they enable LHS to adapt to emerging challenges, innovate care delivery, and reduce inefficiencies.

We can therefore exemplify our model in a simple, practical, and comprehensive knowledge management life cycle model (KMC). Building on the harmonization concept from Heisig, P. (2009) and following the example of Evans and Ali's (2013), we suggest a model for *Conceptual KMC Integration in Learning Health Systems*. Each stage is powered by technologies such AI and DLT. We further explain essential principles for accelerating learning healthcare systems (Figure 2).

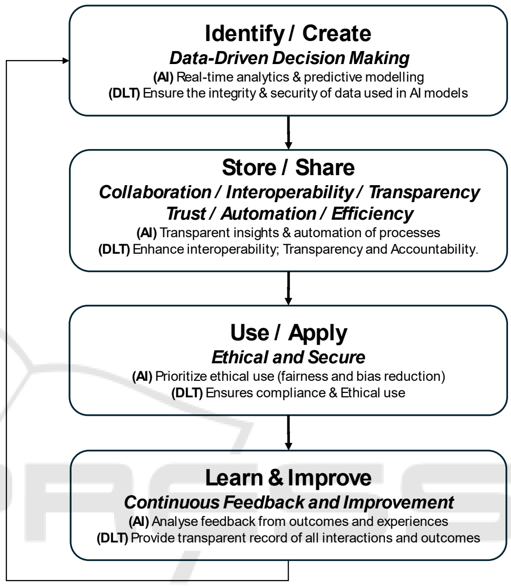

Figure 2: Conceptual KMC Integration in Learning Health Systems (By author inspired by Evans and Ali's (2013).

We envision the following: In the Identify/Create phase, AI facilitates real-time analytics and predictive modeling, enabling timely insights, while DLT ensures data integrity and origin traceability, reinforcing trust in the foundational data layer. The Store & Share stage emphasizes interoperability and collaboration; AI offers transparent insights and process automation, whereas DLT provides decentralized data governance and transparency, securing seamless and accountable data exchange. As knowledge is Used/Applied, ethical considerations come to the forefront—AI systems are designed to minimize bias and enhance fairness, and DLT ensures compliance and auditability, safeguarding ethical data use across stakeholders. Before the cyclical iteration, in the phase Learn & Improve, AI analyzes outcomes and feedback to refine predictions and actions, while DLT maintains a transparent history of interactions, enabling robust traceability and systemic evaluation. Together, these stages exemplify a dynamic learning cycle, where AI and DLT operate in synergy to support adaptive decision-making, ethical data stewardship, and sustainable innovation in healthcare systems.

5 CONTRIBUTION AND FUTURE RESEARCH

This paper advances the discourse on systemic knowledge integration in Learning Health Systems by proposing a novel framework that synergizes Artificial Intelligence (AI) and Distributed Ledger Technology (DLT). It contributes to the field by conceptualizing an approach that addresses the dual challenges of data governance and dynamic knowledge generation within healthcare environments. Specifically, the integration of immutable DLT architectures with predictive and adaptive AI workflows offers a blueprint for designing transparent, interoperable, and responsive health systems. The framework operationalizes foundational principles of trust, collaboration, and continual learning—core tenets of sustainable LHSs—while aligning with broader goals of equitable care and system resilience.

DLT and AI are pivotal in fostering collaboration within a Learning Healthcare system (LHS). Several applications of AI in healthcare are focused on enabling caregivers to better care for patients in order to improve the quality of care (Badr, 2022). DLT provides secure, transparent, and decentralized data-sharing capabilities, which create a trusted environment for stakeholders such as healthcare providers, researchers, and patients to exchange information without compromising data privacy or integrity. This secure framework is complemented by AI, which processes vast amounts of data to uncover patterns, predict outcomes, and personalize interventions, thereby enhancing decision-making (Badr, 2022). Together, DLT and AI promote continuous learning through knowledge integration and feedback loops, enabling dynamic responses to emerging health challenges. Their synergy fuels co-creation and innovation in healthcare delivery, ultimately building a more resilient and patient-centred ecosystem (Badr et al., 2021).

Future research ought to focus on operationalizing this conceptual model within real-world healthcare settings and diverse sociotechnical ecosystems. Exploratory studies are needed to evaluate the model's scalability, performance, and regulatory compliance across heterogeneous infrastructures and stakeholder groups. Empirical investigations into the implementation of AI-DLT synergy in patient consent management, adaptive diagnostics, and inter-organizational knowledge exchange will help validate its practical utility. Additionally, interdisciplinary inquiry into behavioral, organizational, and systemic barriers to adoption can inform strategies for stakeholder engagement, trust-building, and ethical design. Expanding this model to encompass Smart Cities and global health networks may further uncover its potential for promoting equity, sustainability, and personalized "care at scale".

Disclosure of Interests. Author has no competing interests to declare that are relevant to the content of this article.

REFERENCES

Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., Albahri, O. S., Alamoodi, A. H., Bai, J., Salhi, A., & others. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information Fusion*, *96*, 156–191.

Antal, C., Cioara, T., Anghel, I., Antal, M., & Salomie, I. (2021). Distributed Ledger Technology Review and Decentralized Applications Development Guidelines. *Future Internet*, *13*(3), 62. https://doi.org/10.3390/fi13030062

Badr, G. N., Carrubbo, L., Baldi, G., & others. (2023). Engaging our Digital Technology Actors in Learning HealthCare Ecosystems for Sustainability and Equity. In *Managing Knowledge for Sustainability* (pp. 2141–2162). Institute of Knowledge Asset Management (IKAM).

Badr, N., Drăgoicea, M., Walletzkỳ, L., Carrubbo, L., & Toli, A. M. (2021). Modelling for ethical concerns for traceability in time of pandemic "do no harm" or "better safe than sorry!" *Proceedings of the 54th Hawaii International Conference on System Sciences*, 1779.

Badr, N. G. (2019). Blockchain or distributed ledger technology what is in it for the healthcare industry? *KMIS*, 277–284.

Badr, N. G. (2022). Learning Healthcare Ecosystems for Equity in Health Service Provisioning and Delivery: Smart Cities and the Quintuple Aim. *The Proceedings of the International Conference on Smart City Applications*, 237–251.

Badr, N. G., Carrubbo, L., Ruberto, M., & others. (2021). Responding to COVID-19: Potential Hospital-at-Home Solutions to Re-configure the Healthcare Service Ecosystem. *HEALTHINF*, 344–351.

Badr, N. G., Dragoicea, M., & Crihana, I. (2020). What do we know about renewable knowledge and sustainable societal growth? A scoping review. *17th Conference of* *the Italian Chapter of AIS (Association for Information Systems)*.

Bundi, D. G., Mutua, S., & Karume, S. (2023). A review of distributed ledger technologies application in medical systems interoperability. *African Journal of Science, Technology and Social Sciences*, *2*(2), 1–11.

Christidis, K., & Devetsikiotis, M. (2016). Blockchains and Smart Contracts for the Internet of Things. *IEEE Access*, *4*, 2292–2303. https://doi.org/10.1109/access.2016.2566339

Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines* (Vol. 1). Harper Business New York.

DeFranco, J. F., Roberts, J., Ferraiolo, D., & Compton, D. C. (2024). An infrastructure for secure data sharing: A clinical data implementation. *JAMIA Open*, *7*(2), ooae040.

Dennehy, D., Griva, A., Pouloudi, N., Dwivedi, Y. K., Mäntymäki, M., & Pappas, I. O. (2023). Artificial intelligence (AI) and information systems: Perspectives to responsible AI. *Information Systems Frontiers*, *25*(1), 1–7.

Drosatos, G., & Kaldoudi, E. (2019). Blockchain applications in the biomedical domain: A scoping review. *Computational and Structural Biotechnology Journal*, *17*, 229–240.

Easterling, D., Perry, A. C., Woodside, R., Patel, T., & Gesell, S. B. (2022). Clarifying the concept of a learning health system for healthcare delivery organizations: Implications from a qualitative analysis of the scientific literature. *Learning Health Systems*, *6*(2), e10287.

Ferraiolo, D. F., Defranco, J. F., Kuhn, D. R., & Roberts, J. (2021). A New Approach to Data Sharing and Distributed Ledger Technology: A Clinical Trial Use Case. *IEEE Netw.*, *35*(1), 4–5.

Florio, M. (2019). *Investing in science: Social cost-benefit analysis of research infrastructures*. Mit Press.

Gheibi, O., Weyns, D., & Quin, F. (2021). Applying machine learning in self-adaptive systems: A systematic literature review. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, *15*(3), 1–37.

König, L., & Neumaier, S. (2023). Building a Knowledge Graph of Distributed Ledger Technologies. *arXiv Preprint arXiv:2303.16528*.

Markus, A. F., Kors, J. A., & Rijnbeek, P. R. (2021). The role of explainability in creating trustworthy artificial intelligence for health care: A comprehensive survey of the terminology, design choices, and evaluation strategies. *Journal of Biomedical Informatics*, *113*, 103655.

Mutashar, M. K. (2024). Navigating ethics in AI-driven translation for a human-centric future. *Academia Open*, *9*(2), 10–21070.

Nilsson, J., Javed, S., Albertsson, K., Delsing, J., Liwicki, M., & Sandin, F. (2024). Ai concepts for system of systems dynamic interoperability. *Sensors*, *24*(9), 2921.

Pandl, K. D., Thiebes, S., Schmidt-Kraepelin, M., & Sunyaev, A. (2020). *On the Convergence of Artificial Intelligence and Distributed Ledger Technology: A Scoping Review and Future Research Agenda* (No. arXiv:2001.11017). arXiv. https://doi.org/10.48550/arXiv.2001.11017

Plenk, M., Levant, I., & Bellon, N. (2019). How technology (or distributed ledger technology and algorithms like deep learning and machine learning) can help to comply with regulatory requirements. In *The impact of digital transformation and FinTech on the finance professional* (pp. 241–258). Springer.

Rauchs, M., Glidden, A., Gordon, B., Pieters, G. C., Recanatini, M., Rostand, F., Vagneur, K., & Zhang, B. Z. (2018). Distributed ledger technology systems: A conceptual framework. *Available at SSRN 3230013*.

Russell, S. J., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach, Global Edition 4e*.

Samek, W., Wiegand, T., & Müller, K.-R. (2017). Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *arXiv Preprint arXiv:1708.08296*.

Sterne, J., & Davenport, T. H. (2024). A brief history and the future of customer data. *Applied Marketing Analytics*, *10*(3), 194–204.

Taherdoost, H., & Madanchian, M. (2023). Artificial intelligence and knowledge management: Impacts, benefits, and implementation. *Computers*, *12*(4), 72.

Tenenbaum, J. D. (2024). Accelerating a learning public health system: Opportunities, obstacles, and a call to action. *Learning Health Systems*, *8*(4), e10449.

Vadari, S., & Desik, P. A. (2021). The role of AI/ML in enhancing knowledge management systems. *IUP Journal of Knowledge Management*, *19*(2), 7–31.

Yano, E. M., Resnick, A., Gluck, M., Kwon, H., & Mistry, K. B. (2021). Accelerating learning healthcare system development through embedded research: Career trajectories, training needs, and strategies for managing and supporting embedded researchers. *Healthcare*, *8*, 100479.

Zaarour, T., Khalid, A., Pradeep, P., & Zahran, A. (2024). Using Distributed Ledgers To Build Knowledge Graphs For Decentralized Computing Ecosystems. *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, 3083–3092.

Zhang, D., Xia, B., Liu, Y., Xu, X., Hoang, T., Xing, Z., Staples, M., Lu, Q., & Zhu, L. (2024). Privacy and copyright protection in generative AI: A lifecycle perspective. *Proceedings of the IEEE/ACM 3rd International Conference on AI Engineering-Software Engineering for AI*, 92–97.

Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2017). An overview of blockchain technology: Architecture, consensus, and future trends. *2017 IEEE International Congress on Big Data (BigData Congress)*, 557–564.