

Chapter 20

Learning Health Systems: The ideal home for AI model development and real-world evaluation

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Abstract

Artificial intelligence (AI) is expected to transform healthcare. Learning Health Systems offer the perfect home for AI creation and evaluation: a multi-disciplinary stakeholder community working on an important healthcare problem; a human and digital infrastructure; capabilities in data science, knowledge engineering and implementation science; an iterative learning culture; understanding of real-world healthcare complexity, workflow, operational environment and the wider ecosystem; and openness to collaborative partnerships. AI will only successfully transform healthcare if it is useful, safe, efficient, interoperable, and implementable. Learning Health Systems can make that happen. To support this argument, we will describe the concept and methods of Learning Health Systems, distinguishing them from other approaches to improving health and care. With this description as a basis, we will describe a synergistic partnership, illustrating how Learning Health Systems, by their very nature, both support and require rigorous evaluation of AI tools

Keywords: Learning Health System, artificial intelligence, evaluation, socio-technical, infrastructure, quality improvement.

Learning objectives

After reading this chapter, you should know the answers to these questions:

- What are the origins and purpose of the Learning Health System concept?
- What are the components and the principal stages of a Learning Health System cycle?
- Identify and explain the characteristics that distinguish a Learning Health System from other approaches to healthcare quality improvement.
- Justify the importance of Learning Health Systems in the development and real-world evaluation of artificial intelligence tools.

20.1 Introduction

Organizations that fail to learn are likely to learn through failure. In healthcare, failure

can cost lives and missed opportunities to deliver better patient outcomes. There is a strong case for building learning into the essence of healthcare organizations, and the best-known model for doing this is the Learning Health System (LHS). The LHS is a continuous cycle based upon implementing evidence into practice, collecting data from operational service delivery to evaluate its impact, and deriving new knowledge from that data [1].

Artificial intelligence (AI) has begun to make impacts in health and care, and it is widely believed that AI tools will enable radical transformation. However, there is substantial financial and research waste currently incurred in building AI models that never progress beyond internal validation [2,3]. This chapter aims to show that there is a natural affinity between an LHS, with its distinctive structure and purpose, with the creation and evaluation of a broad spectrum of AI products. Indeed, we argue that the LHS is the perfect home for AI development and real-world validation and we illustrate this with several examples.

We briefly describe the history of the LHS concept before delving into its essential components and characteristics that argue for it being a holistic and coherent way to unite critical thinking about and management of (1) digital infrastructure, (2) focused health and care improvement goals, and (3) AI model development and evaluation in practice. This third point includes clinical and process outcome evaluation, data drift [4] and concept drift [5]. We illustrate this in Figure 20.1, asserting a three-way connection between the core components of the LHS, AI models, and evaluation. LHS and AI are connected by a shared dependence on a mature socio-technical infrastructure - a set of services that include technologies, policies, processes, and people--capable of supporting health and care improvement at scale. This infrastructure provides essential human skills along with the technical capability to host very large data sets and support high-performance analytical computation to derive new knowledge [6]. By sharing these services across multiple implementations, infrastructure allows AI implementations to achieve necessary economies of scale. Evaluation is connected to LHS by process and outcome assessments of quality improvement activities and of AI impact. Evaluation is connected to AI models by appraisal of their validity, reliability, safety and utility. Importantly, these three components are centered around a common problem scope and a multi-disciplinary stakeholder learning community. It is this diverse learning community and its purposeful focus that can give the AI models both a grounding in significant real-world problems that have an agreed priority, and a rationale that AI could offer an intervention that is implementable (Figure 20.1).

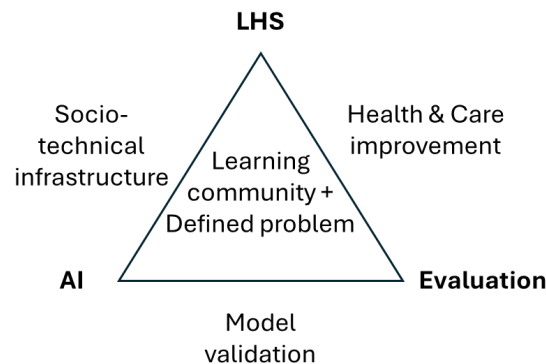


Fig 20.1 LHS unites health and care improvement, socio-technical infrastructure and AI model validation.

The LHS concept draws upon notions from continuous quality improvement (CQI) [7,8], systems thinking [9], data science [10,11] and computerized clinical decision support (CDS) [12,13]. In 2006, in response to the United States' healthcare quality and safety issues identified in the seminal reports *To Err is Human* [14] and *Crossing the Quality Chasm* [15], the Institute of Medicine (now National Academy of Medicine) commissioned a workshop series which became known as the Roundtable on Value & Science-Driven Health Care. The initial report of the Roundtable was entitled *The Learning Healthcare System* [16] and its final report gave the first formal definition of LHS [17] (Box 20.1). There was a conscious shift from LHS being about *healthcare* to being about *health* in its broadest sense [18]. LHS became a recognized term in the NLM Medical Subject Headings (MeSH) in 2019 [19].

A learning health system is one in which science, informatics, incentives, and culture are aligned for continuous improvement, innovation, and equity—with best practices and discovery seamlessly embedded in the delivery process, individuals and families active participants in all elements, and new knowledge generated as an integral by-product of the delivery experience.

Box 20.1: LHS definition [17]

The LHS is visually represented as a cycle, shown in Figure 20.2, comprising three segments: Knowledge to Performance (or Practice) (K2P), Performance to Data (P2D), and Data to Knowledge (D2K). The diagram aims to illustrate the continuous integration of discovery and implementation activities, unlike a traditional linear ‘knowledge pipeline’ view of ‘translating’ research into practice [20].

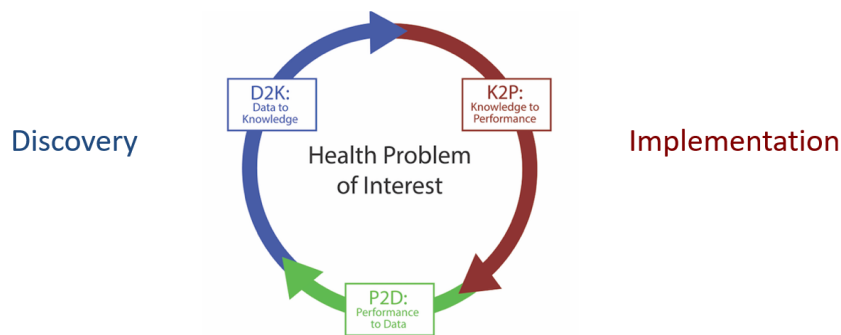


Fig. 20.2 The Learning Health System cycle (Reproduced with permission from [21]).

Optimally, the LHS cycle starts with the formation of a stakeholder learning community around an agreed problem. The Health Foundation depiction of an LHS initiation [22] is reproduced in Fig 20.3.

How to get started in developing a learning health system



Fig. 20.3 Starting a Learning Health System (Reproduced with permission from [22]).

Alternatively, the LHS may begin to form in a reactive mode after unsuccessfully trying to implement some external evidence-based clinical guideline or process improvement. If post-implementation performance data shows that outcomes remain sub-optimal, this can trigger the growth of a broader-based learning community that unites the three segments of the LHS cycle around a common vision of improving their shared problem.

Regardless of its mode of origin, the community will introduce a purposeful collection of data, primarily from routine operational sources (P2D). Then the analytics in the D2K phase aim to produce new knowledge. This new knowledge may identify outliers in performance variance [23], perhaps due to inherent complexity (see section 20.3.3) [20], or implementation issues such as gaps in communication [24], incorrect assumptions about patient or clinician adoption [25], cultural context [26], or algorithm errors [27]. Or work during D2K may find flaws in the external knowledge that the system tried to apply in the preceding K2P stage, for reasons such as multi-morbidity complications [28] or misleading inferences in the evidence base about population sub-groups [29].

Although sharing basic principles, four distinct patterns of LHS have emerged [30], shown with examples in Table 20.1.

Table 20.1 Four models of Learning Health System [30].

Pattern	Home discipline(s)	Change strategy	Morphology	Scale	Urgency	Example
Participative	Behavioral and system science	Iterative cycles by collaborative communities	Co-occurring cycles with shared infrastructure	Meso	Low	[31–33]
Embedded Researcher	Health services research, health economics	Real-world evidence generated by LHS scientist	Embedded in projects	Micro-meso	Moderate	[34]
Pragmatic trial	Informatics, clinical research	Statistical comparison of alternatives	Self-contained studies	Micro-meso	High	[35,36]
Programmatic	Public policy and organizational	Embedded in the aims of funded programs	Funded programs	Macro	Moderate	[37]

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20.2 LHS characteristics

In this section, we expand on identifying characteristics of the LHS as compared to other forms of quality improvement in healthcare, to lay the groundwork for demonstrating its importance to the AI product lifecycle.

20.2.1 Systemic structure and behavior

The LHS pattern is distinct from other cyclical models of quality improvement in that, as the name indicates, it is a *system*. The fundamental concept arising from General System Theory [38] (itself drawing upon biology) is that any system comprises a collection of interacting components that together constitute an organized whole, functioning with a defined boundary in a particular environment. The components can be sub-systems that have their own semi-autonomous structure and behavior. Systems range from the microscopic (atoms, molecules and cells) to the macroscopic, such as interacting physiological sub-systems in autonomous organisms and even large-scale socio-technical networks [39]. As stated in the formal definition, it is the *health system itself* that acquires the distinctive learning properties of an LHS. This can be a “micro” or embryonic LHS in a single sub-system of an organization, or a “macro” or “mega” LHS that scales across regions, whole nations or even work internationally.

An LHS is defined by having a human/organizational learning community and capabilities for data collection/analytics and knowledge generation/application. Therefore, an LHS necessarily has some human, organizational and technical *infrastructure* [21].

20.2.2 LHS components, maturity and competencies

The fundamentally socio-technical nature of the LHS is further demonstrated by its core components, the key competences of its practitioners and the way the maturity of an LHS can be assessed. The literature demonstrates common recurring themes.

Forrest et al. defined the four main components of an LHS as an organizational design that facilitates multi-disciplinary learning communities, availability of large electronic data sets, quality improvement based on integration of research knowledge, and observational research and clinical studies based in routine clinical settings [32].

Essential LHS competencies at individual and system level were proposed by McDonald et al., derived from a scoping review of 89 papers [40]. At the health system worker level they emphasized skills in evidence-based practice, leadership and teamwork, analytical and technical skills including ecosystem navigation, data science and self-reflective capacity, evidence-based practice, and leadership and teamwork. At the system level they highlighted (1) data, infrastructure and standardisation; (2) integration of data and workflow; and (3) culture and climate supporting ongoing learning.

Similarly, Lannon et al. [41] co-developed a learning network maturity grid, working with nine United States learning networks, mostly in children’s health. They identified six domains of assessment for maturity: (1) systems of leadership, (2) governance and management, (3) quality improvement, (4) community building and engagement, (5) data and analytics, and (6) research. These domains all primarily relate to human skills and behaviors, even domain (5) which needs expert analysts. Table 20.2 unpacks some of the

detail of these six assessment domains. Trinkley and colleagues [42] supplemented this model with important maturity factors drawn from dissemination and implementation science, illustrating the use of frameworks such as the Practical, Robust Implementation and Sustainability Model (PRISM) [43], the Reach, Effectiveness, Adoption, Implementation, Maintenance model (RE-AIM) [44] the Quality Enhancement Research Initiative Implementation Roadmap [45] and the Consolidated Framework for Implementation Research (CFIR) [46].

Table 20.2 Learning network maturity domains [41]

Domain	Activities
Systems of leadership	Developing the purpose of the organization, viewing the organization as a system, measuring the system, obtaining information to improve the system, strategic planning, managing improvement and financial performance and sustainability.
Governance and management	Structuring and regulating policies, processes, norms, resources and actions, including interactions with other organizations in a network and inclusion of stakeholders.
Quality improvement	Planning for improvement, developing innovations, executing improvement at specific network centers, development of quality improvement education, scaling-up improvements throughout the network.
Community building and engagement	Establishing a culture of collaboration and partnership in all network activities and increasing engagement in the network, developing capabilities and processes to facilitate co-production of improvement and to grow local improvement leadership, systems to create and share information and knowledge.
Data and analytics	Collect, validate, organize, and standardize data relevant to the network's purpose, including patient-level data, population-level data, and clinical quality measures. Electronic Health Records (EHR) should integrate seamlessly with other network systems and capture data that can be readily extracted for efficient, on-demand analysis.
Research	Using both qualitative and quantitative to generate new knowledge related to the specific health focus and knowledge related to improvement of the network itself.

More recently, attention to LHS maturity has focused specifically on health care delivery organizations. A new organizationally-focused maturity model [47] rests on the four pillars of: (1) governance and leadership, (2) socio-technical infrastructure, (3) improvement execution, and (4) culture and values. In the current version of the model, maturity of an organization as an LHS is assessed through 130 indicators. The number of indicators reflects the complex system nature of the LHS.

20.3 LHS as the optimal environment for AI development and evaluation

This section examines the defining characteristics described in section 20.2 more closely, building the argument that the LHS is the ideal home for real-world, problem-focused AI conception, development and evaluation. We consider the respective roles of data and knowledge in the LHS, lifecycle parallels, and the nature of the real-world healthcare environment in which both LHS and AI deployment exist. Ten aspects of the argument for the transformative potential of LHS have been recently articulated [48]. These include, for example, the broad emphasis of LHS on health rather than just care, purposeful inclusion of all stakeholders in improvement processes, and the capability of LHSs to begin at small scale and grow organically. We believe that these features offer further support to the thesis of this chapter.

20.3.1 Knowledge and data: critical assets in LHS and AI

LHS and AI lifecycles both critically depend on data and knowledge. There are some differences in language: LHS terminology prefers ‘knowledge’ to describe the result of its data analysis, whereas AI developers usually talk about ‘models’. However, an AI model

is attempting to operationalize knowledge of some kind (for example, risk prediction), and LHS knowledge is in effect a model of improved practice, so the two terms are functionally synonymous in this context.

LHS data is predominantly from dynamic operational functions in clinical and administrative systems, often requiring data set linkage, de-identification and aggregation, but there may also be supplemental special purpose data collection. However, in AI design, the data is often from one or more previously collected or specially curated public sources or a static data snapshot. In both cases there may be biases in the data (for example, socioeconomic factors affecting access to services making the data set unrepresentative), but in the LHS these biases will be more immediately detectable and open to exploration by the learning community. Additionally, in a real-world LHS there may be opportunities to ‘shadow test’ prognostic models by estimating their impact based on actual data patterns in the background before attempting any change in point-of-care decision making.

AI models by definition encode their knowledge in a computational form. This can be either symbolic, sub-symbolic or neuro-symbolic. Examples of symbolic AI are knowledge graphs or rules-based expert systems. Sub-symbolic AI is entirely data-driven and includes machine learning methods such as neural networks. Neuro-symbolic AI seeks to combine the two approaches to enhance explainability and performance [49].

The LHS also considers how knowledge is *produced* and how it is *represented*. Some knowledge generated in the D2K phase is a purely technical output (albeit with human analytic design) as opposed to being a direct artefact of human cognition [50]. This can be viewed as a spectrum from primarily deliberative to primarily analytical, as depicted in Figure 20.4 (which is illustrative, not definitive, as it is context-dependent). This concept of a knowledge production spectrum implies that the kind of knowledge produced from a primarily deliberative approach is not computable, whereas the kind of knowledge produced from primarily analytical methods is not human-readable or human-actionable. For the purposes of safety, explainability and trust, some rendering of the knowledge with a minimum level of human readability should usually be required.

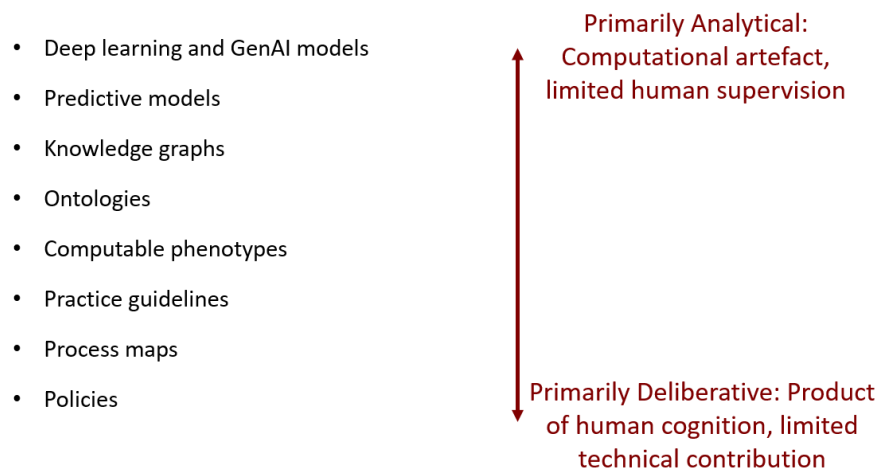


Fig. 20.4 LHS knowledge production and representation.

The related fields of clinical guidelines and decision support offer other rich typologies: (1) detailed layers of *representation*, (2) level of *density*, and (3) level of *evidence*. Layer of representation is in some ways a more explicit version of Figure 20.4, indicating the degree of structure and computability. This framework was specifically developed by

Boxwala for clinical practice guidelines (Figure 20.5, [51]), and has been adopted into the Health Level 7 Fast Healthcare Interoperability Resources (HL7 FHIR) implementation guide for Clinical Practice Guidelines [52].

- **Level 1 - Narrative:** Narrative text, broadly shareable, site independent, authored by guideline developer.
- **Level 2 – Semi-structured:** Organized text, broadly shareable, site independent, authored by clinical domain expert.
- **Level 3 – Structured:** Coded and interpretable by computer, broadly shareable, site independent, precise, authored by knowledge engineer.
- **Level 4 – Executable:** Coded and interpretable by computer, limited sharability, specific to a site, directly actionable, authored by CDS implementer.

Fig. 20.5 Boxwala knowledge layers (Based on [51], reproduced with permission).

The level of density (or abstraction) indicates the relative simplicity or sophistication of a knowledge object. For example, the CREDO knowledge ladder for clinical decision support represents conceptual layers from the lowest level atomic constructs, such as terms from a code system, to the highest level aggregations and orchestrations as found in pathways or agents (Figure 20.6, [53]).



Fig. 20.6 CREDO knowledge ladder (Reproduced with permission from [53]).

Level of evidence describes the degree of certainty that a particular recommendation or explanation is valid and reliable, based on rigorous knowledge synthesis. The global best practice standard is the GRADE approach, used by Cochrane, the National Institute for Health and Care Excellence in England (NICE) and the World Health Organization (WHO) [54]. Clinical guideline developers sometimes reflect the level of evidence implicitly in the choice of verbs in their narrative recommendations [55], but the HL7 FHIR specification contains emerging work to represent this concept explicitly and computably [56].

In summary, the LHS approach to data is typically more dynamic, closer to the problem space and more aware of potential biases than a purely lab-based AI project. The LHS conceptualization of knowledge is broader, deeper and more richly nuanced for clinical decision-making than general AI models. LHS therefore offers the most effective environment for AI model design and evaluation using these two critical assets.

20.3.2 Lifecycle parallels: LHS and AI products

The LHS lifecycle comprises problem identification, community formation, data collection, data analytics, knowledge generation and knowledge application. The AI lifecycle has been variously described, but comprises many similar elements [57,58]. Both, in essence draw upon the Shewhart cycle (popularized by Deming) of learn-do-study-act [59]. Figure 20.7 illustrates some parallels, using selected elements from the three main phases of the CDAC AI lifecycle, broadly similar to Coiera's description [58,60]. ISO has published a detailed standard on the AI lifecycle [61], but this simplified three stage model is sufficient for the purposes of this chapter.

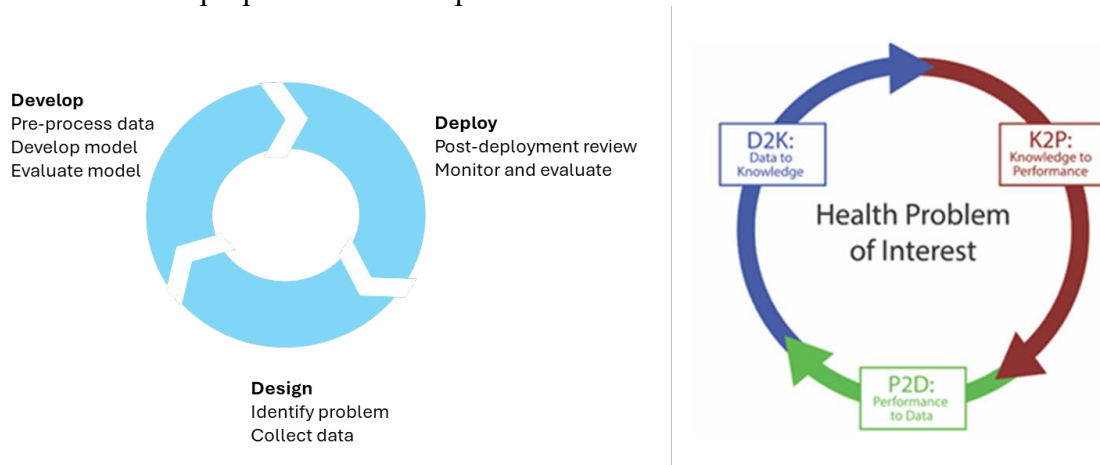


Fig. 20.7 LHS and AI lifecycle parallels.

Both cycles are centered on a defined problem, and there are clear analogies in content and sequence, but there are important differentiators.

- In both the AI design phase and the LHS P2D stage, data relevant to the selected problem is collected, with the differences noted in 20.3.1.
- In both the AI development phase and the LHS D2K stage, data is cleaned, prepared and analysed to produce and internally evaluate some knowledge or model. The internal evaluation in AI development will depend upon which analytical methods were used. For example, if machine learning methods were used the model will be assessed for accuracy, sensitivity and precision. In LHS D2K, there is a broad range of knowledge types (see 20.3.1) and hence considerable variety of internal evaluation methods. The data and analysis might be primarily qualitative, resulting in some form of human-readable narrative knowledge (such as expressed in policy), that in turn could be evaluated by qualitative surveys or stakeholder focus groups. At the other extreme, the knowledge might constitute executable software somewhere on the AI spectrum, so AI evaluation techniques can be applied.

- In both the AI deployment phase and the LHS K2P stage, the knowledge product is implemented. This is of course the most difficult part of the lifecycle. AI products which have been developed to address theoretical concerns, such as very slightly more accurate predictions or earlier diagnosis of particular conditions, face the hard challenge of whether their model is safe, offers any real clinical value or is even practicably implementable in operational workflows and existing ecosystems [60]. Of the tens of thousands of health AI models now being published every year, most fail to be deployed. Even when deployment is attempted, most do not learn from established frameworks and principles of implementation science [2]. This can of course also be true of LHS K2P activities, but in the case of LHS, a complete socio-technical infrastructure will provide services informed by implementation science to increase the likelihood that interventions will receive careful attention to principles known to promote their success [6,62]. Most fundamentally, the LHS approach is driven by the identified problem being agreed by its multi-stakeholder community to be high-value, tractable to analysis and feasible to improve.

Analogies also exist in enterprise governance of LHS and AI ecosystems. Hummer et al. proposed ModelOps as a standardized enterprise-wide framework for AI lifecycle management, observing that in common practice machine learning teams “typically build custom tools and work in ad hoc ways to address requirements in different parts of the AI lifecycle...” [63]. Modern software is often designed for frequent, highly automated deployment of bug fixes and new features through a combined pipeline of Development and Operations known as DevOps. ModelOps extends the principles of DevOps to AI models and provides a coherent and holistic approach that addresses automation (pipeline management from data cleaning to live performance monitoring), quality assurance (data drift detection, bias checking), traceability (provenance and audit), risk management, and a feedback cycle “all the way from the user interface to the model training backend” [63]. ModelOps has widespread adoption in industry, with projected increasing importance for applications such as agentic AI [64]. ModelOps is obviously applicable to LHS work that develops AI models, but arguably its principles can also be extended to curation and lifecycle management of non-computable knowledge artefacts in an LHS environment. The additional benefit of the multi-stakeholder LHS community and its defined problem scope is to have governance that is deeply aligned to operational and strategic business needs and is not merely a technical process.

20.3.3 Complex adaptive systems: the environment for all healthcare

Complexity is an ever-present fact of life in health and healthcare and consequently in health and healthcare quality improvement. There is a significant risk that AI projects which are initiated and developed solely in a lab setting may take an overly simplistic, linear approach that does not address the realities of implementation in a healthcare environment. Therefore, this section aims to unpack the meaning of complexity and show how the LHS helps to navigate it.

Complexity means much more than being complicated. There are numerous and diverse definitions of complex adaptive systems [65–68], but some of the commonly listed differentiating attributes are:

- There is no overall central control of the system.
- The system comprises numerous autonomous components (sub-systems).
- Components are capable of communication and interaction with each other.
- Components and the system adapt: one component's actions changes the context for others.
- System boundaries may be fluid or fuzzy.
- System behavior is *emergent* (unpredictable), but has stable patterns over time and demonstrates characteristic statistical distributions [69,70].
- Reactions are often disproportionate and sensitive to initial conditions.

Complexity theory is sometimes conflated with General System Theory [71], but not all systems are complex: there are numerous relatively simple systems (see section 20.2.1). Complexity also has some similarities with chaos, but it is better understood as ‘on the edge of chaos’ ([72], see Figure 20.8). A chaotic system may appear random but is actually deterministic. In principle a chaotic system is entirely predictable, but in practice only to some level of approximation due to the system’s high sensitivity to initial conditions – which typically are only known very imprecisely, if at all. By contrast, a complex system is *inherently* unpredictable due to the free action of the sub-system components. Whereas weather behavior is ultimately based on physical laws, healthcare institutions and termite mounds operate according to the independent actions of individual or group agents.

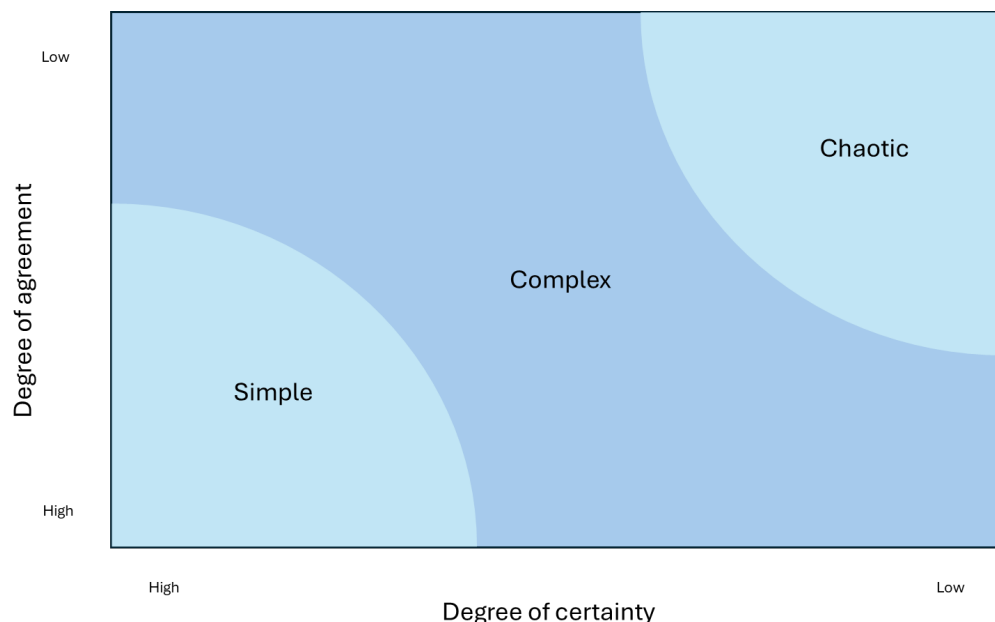


Fig. 20.8 The zone of complexity (Based on [73]).

Healthcare systems nominally have strong central control mechanisms, as manifested by their executive “C-suite”. However, the supposed ‘levers of control’ used by executives frequently have limited effect in normal practice, as commonly seen in operational issues such as emergency department overload. Many such healthcare activity patterns

demonstrate statistical distributions characteristic of complex systems [69,70,74]. Unlike a normal distribution, where data points bunch around the mean and the tails of the curve are thin and short, complex systems often manifest heavy-tailed and ‘bursty’ distributions. Among other factors, this reflects the variations in patient and carer choices, the autonomy of clinical judgement and the functional independence of wards, departments and external services. This is exacerbated by the cultural divides between the executive, clinical, academic and technological ‘tribes’ in healthcare provider organizations [75]. Although, in times of crisis, services can be shut down or totally reconfigured, many process outcomes in routine healthcare match the pattern of complex adaptive systems, not that of simple control systems [76]. For these reasons and others, it is generally recognized that health and care systems are, in and of themselves, complex adaptive systems [73,77,78].

Inherent complexity has been cited as a barrier to LHS progress in some systems [79]. However, while complexity is universal in health and care services, culture is variable. Given that the progress toward achievement of LHS has been slower in some places than in others, it is arguably not the complexity in itself but the underlying culture that creates the more significant barrier. Supportive organizational culture is a well-known prerequisite for successful transformational change [80]. Implementation science describes many other factors hindering change [25,42,62], but an entity with a culture aligned with LHS principles will progress more rapidly, and that progress will in turn engender further cultural changes as the infrastructure matures and the scope of improvement activity broadens.

This raises the question of whether the LHS is, in itself, a complex adaptive system. The question may be answered simply, and perhaps definitely, by recognizing that an LHS is not intended to be a component of a health system, but rather a *state* of it. Over time, through a process of “organic infiltration”, health systems *become* learning health systems [48]. So if any health system is a complex adaptive system, then a health system that has transformed into an LHS must be a complex adaptive system as well.

A counterargument to this assertion would take the position that an LHS is the antithesis of a complex adaptive system because the LHS seeks to introduce order and structure, which in a mature LHS, would tend to move a health system from the complex to the complicated part of Fig 20.8. This counterargument would be valid if LHS methods were top-down and rigid; but in practice LHS methods are characterized by decentralization and diffusion of authority and control. The learning communities that drive improvement cycles are intentionally diverse and work by consensus. The infrastructure supporting multiple improvement cycles is non-rigid and designed to respond and adapt to the changing requirements of the improvement cycles. It follows that the adaptive approaches associated with LHS harmonize with the already adaptive nature of health care organizations rather than seeking to change them.

20.3.4. Summary of LHS advantages for AI projects

Table 20.3 concisely highlights the factors we have discussed to demonstrate that the LHS is a superior environment for AI development and validation, compared to standalone, lab-based work. Some of these factors have been reported in studies addressing AI implementation in itself as the end-goal [81], or as the foundation for a future LHS [82]. Keeping the problem front and center will guide the mental model of participants far more effectively, and make successful implementation much more achievable [83].

Table 20.3 LHS superiority for AI development and validation.

Factor	LHS advantages for AI projects
Scope	Based on an identified and tractable real-world problem endorsed by multiple stakeholders, not a lab-based solution looking for a problem.
Data	Promotes use of existing operational data as opposed to ad hoc collections. Creates opportunity to “shadow test” models by running them in silent mode using live EHR and other needed data sources.
Knowledge	Richer understanding of knowledge types and applications in healthcare. Emphasizes practical utility over technical achievement.
Complexity	Balances consensus-based central coordination with autonomy of improvement cycles. Anticipates emergent change, not linear deployment [84]. Multi-disciplinary learning community embedded in adaptive healthcare environment helps to negotiate the complexity.
Implementation	Implementation science methods are a key part of LHS infrastructure. Designed to fit with healthcare workflow and ecosystems, not left as afterthoughts to the technical solution.
Lifecycle and governance	Led by healthcare and business needs with multi-stakeholder governance, not merely a technology agenda. Cyclical nature of LHS improvement activity addresses the need for algorithm vigilance [85,86].
Sustainability	Attractive to investors, innovators and implementers [87].

20.4 LHS examples

The LHS exists in many places and many forms. In this section we present some examples. Table 20.4 shows a selective list of LHSs from the peer-reviewed literature, covering a range of problem spaces and a variety of knowledge artefact types. Most LHSs are not focused on AI, many are entirely concerned with narrative (e.g. policy) or semi-structured knowledge (e.g. pathways or guidelines) and few have developed the full lifecycle model for AI that we promote here. However, each element of that ideal lifecycle

has been demonstrated somewhere.

Each of the examples in Table 20.4 manifests all five LHS lifecycle attributes: (1) a multi-disciplinary learning community, (2) a defined problem scope, (3) an iterative learning and application cycle comprising operational data collection (P2D), (4) data analytics and knowledge generation (D2K), (5) interventions seeking improvement based on knowledge application (K2P). For each example LHS knowledge artefact in the table, we show its level using a slightly modified form of the Boxwala classification (we have used the word “computable” rather than the word “executable”, to include a broader range of implementation types). This is not a value judgment of maturity or success, as the LHS problem scopes are so varied.

It is important to emphasize that our aim is to demonstrate the *breadth* of the field, not to offer an exhaustive review, so we have only cited one example for each LHS from many problems of interest and knowledge artefacts. We refer the reader to more general reviews for comprehensive LHS analysis [88–90].

20.4.1 Published studies

Given that the LHS concept originated in the USA and has had strong policy support from the federal government and professional bodies there, it is not surprising that it is easier to find peer-reviewed published examples of LHS there than in other countries. All the examples in Table 20.4 are US-based. There is growing clinical, research and policy interest in LHS, notably in Canada [91], Western Europe [92,93] and Asia [94], but few fully operational examples with published reports.

Table 20.4 Learning Health System examples.

Refs	Organization	Example topic	Knowledge artefact	Knowledge level (See Fig 20.5)
[95–97]	Geisinger Health System	Process inefficiency.	Workflow automation, including pre-populated forms and order sets.	L4 computable
[98]	ImproveCareNow (International learning network)	Children and adolescents with inflammatory bowel disease.	Clinical protocols. Key Driver Diagram.	L2 semi-structured
[99,100]	Indiana Learning Health System Initiative (Multi-organizational network)	Chest pain.	Integration of selected data from Health Information Exchange relevant to chief complaint directly with EHR in 15 Emergency Departments.	L4 computable

[101]	Kaiser Permanente Northern California	Sepsis.	Updated sepsis treatment guidelines, phenotype definition and data capture strategy.	L2 semi-structured
[102]	Kaiser Permanente Washington	Reducing COVID-19 hospital admission and mortality.	Real-time risk predictions available in the EHR, to prioritize anti-viral prescribing in outpatient care.	L4 computable
[103]	University of Colorado	Failed requests for add-on laboratory tests.	Change in EHR test ordering logic.	L4 computable
[104]	University of Minnesota Center for Learning Health System Science	Cardiac monitoring overuse.	Clinical decision support and best practice alert (BPA) that encourages adherence to guidelines.	L4 computable
[35]	Vanderbilt University Medical Center	Routine fluid administration.	Best practice alerts in the EHR to advise providers about fluid choice.	L4 computable
[105]	Veterans Administration Health Systems	Opioid use disorder.	Organizational facilitation using monitoring and feedback, process adaptation and normalization.	L2 semi-structured

20.4.2 Views from practitioners

For this section, we conducted informal interviews with three leading LHS practitioners in the USA and one health innovation director in the UK to supplement the published examples in Table 20.4 with brief descriptions of real-world context, current thinking and practical experience. Like the list of published studies, this set of interviews is purely illustrative and does not claim to be an in-depth or comprehensive review. The selection of interviewees was based on personal knowledge of leading LHSs in the USA and emerging LHSs in the UK.

Professor Genevieve Melton-Meaux is Director of the Center for Learning Health System Sciences (CLHSS) at the University of Minnesota, established in 2021 as a collaboration between the Medical School and the Department of Public Health. CLHSS has defined its mission as “To foster fast, continuous learning within Minnesota’s healthcare systems where evidence informs practice and data from practice generates new knowledge” [106]. They have an extensive portfolio of funded research and innovation, a

collaborative data architecture, and a range of industry partnerships. They have a specific program for clinical AI (P4AI), which has had validated models for sepsis, acute clinical deterioration and rib fracture adopted for deployment in clinical decision support systems at their partner M Health Fairview [106,107]. The CLHSS organizational structure comprises a substantial workforce of multi-disciplinary experts who lead and support research, administration and infrastructure.

Professor Melton-Meaux highlights that the entire LHS lifecycle is important for AI, and that health systems are increasingly aware that “linear doesn’t work”. There is particular value from K2P: the “last mile” problem of getting a knowledge-based intervention into practice. Industry partnerships are an important component of the CLHSS portfolio. Both startups and established companies value the partnership opportunity to work in a “living lab” and demonstrate real return on investment. One of the greatest LHS benefits is also one of its greatest challenges: working as an interdisciplinary team. (Personal communication, Genevieve Melton-Meaux, CLHSS, 9 December 2025).

Dr Yates Coley is a biostatistician in the Kaiser Permanente Washington (KPWA) LHS Program, which was established in 2017 and is now part of the KP Accelerating Care Transformation (ACT) Center [108]. The LHS has an interdisciplinary team of clinical, operational and research personnel with expertise in advanced analytics, evidence synthesis, implementation science, quality improvement, and communications. Their strategic priorities include social health, mental health, persistent pain, and opioid use. Based on a review of 17 LHS frameworks, they developed the KPWA LHS Logic Model. This model aims to provide a consistent language for LHS by defining concepts and terminology and describing LHS inputs, activities and outcomes [109].

Dr Coley emphasizes the importance of the LHS multi-disciplinary learning community in the development of diagnostic or predictive models. Operational and clinical leaders know what live data is *actually* available at the point of use, which can be messy and error-prone, unlike a “pure” research data set that has been cleaned and aggregated from various retrospective sources. The learning community can also identify which decision to inform and which intervention will make a difference. The LHS is unique in that it works in its own system; generalisability is secondary – the non-universality of predictive models is explicitly recognized. Data analysis across multiple sites with multiple EHRs has revealed not just data model inconsistencies, but *conceptual* variance. Precisely what is meant, for example, by a term like “diagnosis” in one EHR may convey different semantics elsewhere. However, a common data model does facilitate research across multiple sites within the LHS. The continuous learning cycle enables monitoring that model predictions are still working and credible. (Personal communication, Yates Coley, KPWA, 9 December 2025.)

Dr Katy Trinkley is Director of the Learning Health System Core at the University of Colorado Anschutz, established in 2023, which evolved from an existing LHS team. They have expertise in implementation science, qualitative and mixed methods, biostatistics, analytics, informatics and user-centered design [110,111]. The LHS purpose is to support the development of new projects and grant proposals and offer consultative support and education to investigators and clinicians. The University of Colorado also has the UCHS CARE Innovation Center which partners with investors, entrepreneurs and innovators to develop and spin out new digital technologies [112].

Dr Trinkley stresses that each element of the learning cycle is crucial. Multi-disciplinary working is essential to enable fast and rigorous innovation. The learning can also become

a synergy between disparate operational needs and illuminate previously undetected problems. For example, previous work on blood sample testing [113] revealed an issue with test processing: thousands of requests for extra tests that had been submitted after the blood sample had been collected were failing due to incorrect decision logic in the EHR [103] (cited in Table 20.4). Dr Trinkley observes that for an improvement to succeed, the team must be willing to accept that a minimal viable solution is good enough to start with and to iterate from there. Relationships with commercial providers are variable, but can spark ideas that lead to internal innovation. As well as AI products being outputs of LHS in some cases, they can accelerate the work of LHS – enabling more rapid data science, offering automation and tools like natural language processing to extract the value from unstructured text in EHRs, and perhaps in the future even chatbots for qualitative data capture and analysis. (Personal communication, Katy Trinkley, University of Colorado, 9 December 2025.)

Dr Gareth Thomas is the Digital Innovation Director of Health Innovation Manchester (HInM), formed in 2017 as one of England’s regional networks designed to connect the National Health Service (NHS) to academia, local authorities, the voluntary sector and industry [114]. HInM works in partnership with NHS Greater Manchester Integrated Care Board which hosts the Greater Manchester Analytics and Data Science Platform (ADSP). This provides a shared digital infrastructure to support operational planning and multiple concurrent innovation and improvement programs by modelling population impact of health problems of interest. Although not formally named an LHS, HInM has all the key attributes as noted in Table 20.4, and functions as a partner to the operational healthcare providers in the regional integrated care system. Not all of their programs operate iteratively, but that is an increasing trend especially when proof-of-concept initiatives are scaled up or, over time, when population impacts are re-assessed.

Dr Thomas notes that many of their knowledge outputs are pathways or packages of care, which are typically L1 (narrative) or L2 (semi-structured). HInM identifies benefits arising from cross-fertilization between disparate projects in their portfolio, so their knowledge artefacts also include shared lessons around issues such as re-usable data science skills and methods, information governance, and project transition to business-as-usual. They are applying their data science infrastructure to explore the effectiveness of interventions, economic modelling and exploratory analysis to inform potential future initiatives. (Personal communication, Gareth Thomas, Health Innovation Manchester, 26 November 2025.)

20.5 Discussion

AI is currently a dominant, but poorly understood, topic in public discourse: it is hailed by politicians as an engine for economic growth and by the giant technology companies as the answer to everything. This hype will no doubt subside – at the time of writing, the markets are anticipating an “adjustment” to the overvaluation of some tech firms [3]. Relatively speaking, the LHS is a niche topic for people interested in improving health and care. But we have tried to make the case that AI in health and care *needs* the LHS to be optimally effective.

There are frankly more data and evidence than can be meaningfully consumed, even with the help of AI tools. There are big risks in having big data without a genuine problem focus, clinical context, longitudinal continuity and population representativeness. Massive

retrospective data sets are susceptible to dredging, bias and confounding variables [115]. For example, ready access to large cohort data sets, along with the usual academic publishing expectations, can lead to a surfeit of “unnecessary, irrelevant, and fraudulent studies” [116]. Another aspect of data excess is the volume and velocity of facts and findings available at the point of clinical decision-making, which for some time has exceeded unaided human cognitive capacity for comprehensive retention and reasoning [117]. The same can be said of evidence overload and under-application, arguably two sides of the same problem. In 2011, Densen reported estimates that “the doubling time of medical knowledge in 1950 was 50 years; in 1980, 7 years; and in 2010, 3.5 years”, with a prediction of knowledge doubling every 73 days by 2020 [118], while Morris and colleagues cite a range of estimates for the lag between discovery and implementation – often cited as 17 years or so [119,120]. Both of these factors have long driven the need for evidence summaries and clinical guidelines which can be embedded into decision support, which as a form of AI is best developed and iterated in an LHS. We suggest that research funders give greater weight to the path to implementability in their prioritization decisions, so that important new evidence does not just get ‘thrown over the wall’ (adding to the existing pile of unused findings) but has routes to deployment designed-in from the outset. Again, we suggest that LHS study settings are the obvious way to achieve this.

Of course, not every self-professed LHS actually operates with the full suite of defining attributes. Conversely, the published literature in the field of LHS is not a complete picture of global activity: “much of the recent published work that should fall within the domain of LHS fails to claim or be identified as such” [121], or there may not be a clear-cut moment when an evolving strategic collaboration can truly be said to have become an LHS [122].

How do we evaluate an LHS? An LHS is primarily, but not exclusively, *self-evaluating*. It has inputs, outputs and feedback loops: the learning community is constantly gathering and analyzing data to maintain (or adapt) its problem focus and its ever-growing knowledge about what works and what approaches are ineffective [36]. If an LHS is demonstrating improvement in its defined problems, it is working. A skeptic might argue that this progress might have happened without the work of the community, but the tight coupling of the community to all improvement activity makes this highly unlikely. Beyond that basic metric of improvement against a stated problem, there are numerous methods that have been proposed for external LHS evaluation and reported in scoping reviews and synthesis articles [88,109,123–126].

None of this is to suggest that developing and maintaining an LHS is easy. For example, as noted in the previous section, working as an interdisciplinary team is one of the greatest challenges. Whereas a *multi*-disciplinary team brings distinct independent perspectives to a collaboration, *interdisciplinarity* is “synthesis of two or more disciplines, establishing a new level of discourse and integration of knowledge” and *transdisciplinarity* requires “a shared conceptual framework, drawing together discipline-specific theories, concepts, and approaches to address a common problem” [127]. Whichever label is applied, the problem-focused LHS community needs to develop a shared vision, a common language and an appreciation of multiple worldviews to manage professional culture gaps, power relations and inter-discipline social hierarchies [128,129]. While not straightforward, either to initiate or to sustain over time, interdisciplinary working has led to notable progress in many LHSs and resulted in powerful and effective service improvement. Any AI initiative would be far more likely to succeed with such a diverse learning community.

The opportunity for an LHS to function as a ‘living lab’, collaborating with commercial partners to scope, develop, test and validate AI models in the real world to show clinical utility and practical implementability, is easy to understand in the privately funded market model of healthcare delivery that exists in the USA [87]. However, the US healthcare funding system is not typical; most countries have social insurance based schemes and some are funded directly from general taxation. Is this industry collaboration model transferable from commercial healthcare to healthcare as a public service? We pose this as a question for discussion below, but would point readers to analogous shared benefit models such as national and regional innovation agencies where governments invest in industry to stimulate overall economic growth [130].

20.6 Conclusion

In this chapter, we have aimed to signpost some of the key LHS literature, current experience and principles that make the case for LHS as the ideal home for AI development and evaluation. An LHS is not a simple or easy endeavor, but it offers a strategic focus for improving health and care and a practical testbed for AI. Not every AI idea can work with an LHS community, but the concept should be widely promoted as good for health and care systems, good for industry, and ultimately good for patients and citizens.

The renowned medical statistician Doug Altman, when writing about the scandal of poor medical research, said that we need less research, better research, and research done for the right reasons [131]. Now is the time to call for less AI, better AI, and AI done in a Learning Health System.

Questions for Discussion

- (a) Does your national health policy promote and support Learning Health Systems? If it does, what are the policy goals and are they translated into funded programs? If it does not, would the opportunities for AI development and evaluation persuade policy makers of the socio-economic and health value of Learning Health Systems? Discuss ways to influence policy.
- (b) If you lived in a country with a health and care system funded by general taxation (like the UK or Denmark) or social insurance (like many European countries), how do you think the model of industry partnership for collaborative AI development and validation with a Learning Health System could be made to work, so that there is genuine benefit to both parties and to the population? Explain how the health, financial and social benefits could flow.
- (c) Would you evaluate current AI-enabled changes in health and care as transformative or merely incremental? How would a Learning Health System help to scale up the change? Give examples to justify your assessment.

Suggested Readings

Johnson O. (2019). General System Theory and the Use of Process Mining to Improve Care Pathways. In: Scott P, de Keizer N, Georgiou A, editors. *Applied Interdisciplinary Theory in Health Informatics*. Amsterdam, NL: IOS Press. <https://doi.org/10.3233/SHTI190107>

A helpful introduction to General System Theory and its relevance in health informatics, with application to process mining as a valuable pathway improvement method.

Stacey R. (2003). The foundations of learning organization theory: System dynamics and cognitivism. In: Strategic management and organisational dynamics: the challenge of complexity. 4th ed. London: Prentice Hall/Financial Times.

The textbook addresses complexity in organizational management, so many sections are relevant to Learning Health Systems. This chapter explains some of the theories underlying learning organizations.

Wilson P, Kislov R. (2022). *Implementation Science*. Cambridge University Press, Cambridge, UK. <https://doi.org/10.1017/9781009237055>

An accessible introduction to the field of implementation science, with helpful pointers to the relevant literature.

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Tables

Table 20.1 Four models of Learning Health System [30].

Pattern	Home discipline(s)	Change strategy	Morphology	Scale	Urgency	Example
Participative	Behavioral and system science	Iterative cycles by collaborative communities	Co-occurring cycles with shared infrastructure	Meso	Low	[31–33]
Embedded Researcher	Health services research, health economics	Real-world evidence generated by LHS scientist	Embedded in projects	Micro-meso	Moderate	[34]
Pragmatic trial	Informatics, clinical research	Statistical comparison of alternatives	Self-contained studies	Micro-meso	High	[35,36]
Programmatic	Public policy and organizational science	Embedded in the aims of funded programs	Funded programs	Macro	Moderate	[37]

Table 20.2 Learning network maturity domains [41]

Domain	Activities
Systems of leadership	Developing the purpose of the organization, viewing the organization as a system, measuring the system, obtaining information to improve the system, strategic planning, managing improvement and financial performance and sustainability.
Governance and management	Structuring and regulating policies, processes, norms, resources and actions, including interactions with other organizations in a network and inclusion of stakeholders.
Quality improvement	Planning for improvement, developing innovations, executing improvement at specific network centers, development of quality improvement education, scaling-up improvements throughout the network.
Community building and engagement	Establishing a culture of collaboration and partnership in all network activities and increasing engagement in the network, developing capabilities and processes to facilitate co-production of improvement and to grow local improvement leadership, systems to create and share information and knowledge.
Data and analytics	Collect, validate, organize, and standardize data relevant to the network's purpose, including patient-level data, population-level data, and clinical quality measures. Electronic Health Records (EHR) should integrate seamlessly with other network systems and capture data that can be readily extracted for efficient, on-demand analysis.
Research	Using both qualitative and quantitative to generate new knowledge related to the specific health focus and knowledge related to improvement of the network itself.

Table 20.3 LHS superiority for AI development and validation.

Factor	LHS advantages for AI projects
Scope	Based on an identified and tractable real-world problem endorsed by multiple stakeholders, not a lab-based solution looking for a problem.
Data	Promotes use of existing operational data as opposed to ad hoc collections. Creates opportunity to “shadow test” models by running them in “silent mode” using live EHR and other needed data sources.
Knowledge	Richer understanding of knowledge types and applications in healthcare.

	Emphasizes practical utility over technical achievement.
Complexity	Balances consensus-based central coordination with autonomy of improvement cycles. Anticipates emergent change, not linear deployment [84]. Multi-disciplinary learning community embedded in adaptive healthcare environment helps to negotiate the complexity.
Implementation	Implementation science methods are a key part of LHS infrastructure. Designed to fit with healthcare workflow and ecosystems, not left as afterthoughts to the technical solution.
Lifecycle and governance	Led by healthcare and business needs with multi-stakeholder governance, not merely a technology agenda. Cyclical nature of LHS improvement activity addresses the need for algorithm vigilance [85,86].
Sustainability	Attractive to investors, innovators and implementers [87].

Table 20.4 Learning Health System examples.

Refs	Organization	Example topic	Knowledge artefact	Knowledge level (See Fig 20.5)
[95–97]	Geisinger Health System	Process inefficiency.	Workflow automation, including pre-populated forms and order sets.	L4 computable
[98]	ImproveCareNow (International learning network)	Children and adolescents with inflammatory bowel disease.	Clinical protocols. Key Driver Diagram.	L2 semi-structured
[99,100]	Indiana Learning Health System Initiative (Multi-organizational network)	Chest pain.	Integration of selected data from Health Information Exchange relevant to chief complaint directly with EHR in 15 Emergency Departments.	L4 computable

[101]	Kaiser Permanente Northern California	Sepsis.	Updated sepsis treatment guidelines, phenotype definition and data capture strategy.	L2 semi-structured
[102]	Kaiser Permanente Washington	Reducing COVID-19 hospital admission and mortality.	Real-time risk predictions available in the EHR, to prioritize anti-viral prescribing in outpatient care.	L4 computable
[103]	University of Colorado	Failed requests for add-on laboratory tests.	Change in EHR test ordering logic.	L4 computable
[104]	University of Minnesota Center for Learning Health System Science	Cardiac monitoring overuse.	Clinical decision support and best practice alert (BPA) that encourages adherence to guidelines.	L4 computable
[35]	Vanderbilt University Medical Center	Routine fluid administration.	Best practice alerts in the EHR to advise providers about fluid choice.	L4 computable
[105]	Veterans Administration Health Systems	Opioid use disorder.	Organizational facilitation using monitoring and feedback, process adaptation and normalization.	L2 semi-structured

Figure legends

Fig 20.1 LHS unites health and care improvement, socio-technical infrastructure and AI model validation.

Fig. 20.2 The Learning Health System cycle (Reproduced with permission from [21]).

Fig. 20.3 Starting a Learning Health System (Reproduced with permission from [22]).

Fig. 20.4 LHS knowledge production and representation.

Fig. 20.5 Boxwala knowledge layers (Based on [51], reproduced with permission).

Fig. 20.6 CREDO knowledge ladder (Reproduced with permission from [53]).

Fig. 20.7 LHS and AI lifecycle parallels.

Fig. 20.8 The zone of complexity (Based on [73]).