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Computable Knowledge: An Imperative for Learning Health Systems

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Through the actions of multi-stakeholder communities, Learning Health Systems (LHSs) undertake cyclical activities that generate new knowledge and, as seamlessly as possible, apply that new knowledge in direct pursuit of health improvement [1]. Therefore, knowledge links the discovery and intervention components of LHS activity, and metaphorically, as shown in Figure 1, can be seen as the "keystone" supporting the learning cycle.

→ Insert Figure 1 About Here

In this context, health-related knowledge is the result of an analytic and/or deliberative process that holds significance for an identified community. Additionally, health knowledge is actionable when it can motivate and shape an intervention. For example, a community seeking to reduce mortality and morbidity from preventable diseases may learn, from data about many persons, a mathematical model that determines an individual's risk of developing a specific disease in the future [2]. In this case, the predictive model embodies the newly learned knowledge. In an LHS, after local qualification [3], the model would then be applied in practice

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/lrh2.10203

to combine an instance of data from one person to compute a prediction for him/her. If that person is found to be at risk for the disease, this will trigger appropriate preventive measures by their care provider(s). While this familiar pattern of training, testing, and using models describes methods employed in machine learning, here this process is viewed more generally to include any systematic method resulting in and applying new knowledge, including knowledge derived from purely deliberative processes. Moreover, health knowledge spans the domains of health care, public health, biomedical research across the translational spectrum, and health professions education.

New knowledge is fundamental to the LHS concept and its operation. Knowledge embodies what the system "learns". It follows that knowledge has a central, but often underappreciated, role in successful LHS operation. In particular, many descriptions of LHSs are explicit about the key role of "big data" in these systems, while leaving implicit the role of knowledge [4,5]. Inattention to knowledge creates a learning cycle without a keystone, leaving a dysfunctional gap (see Figure 1) between discovery and intervention [6]. It follows that infrastructure supporting the operation of LHSs must address the management and implementation of knowledge as much as the generation of it.

Complementing the conceptual importance of knowledge to LHSs is the more concrete importance of supplementing human-readable knowledge with representations of that same knowledge in machine-executable forms, what may be called "computable knowledge" [7-9]. Human-readable knowledge is expressed in words, pictures, and mathematical symbols--and persistently stored in journals and books. Any action triggered by human-readable knowledge requires an individual to read and comprehend the article or book before deciding what action might be taken in response. This is a slow, serial process. Creating a digital representation of human-readable knowledge, using pdf or similar file formats, changes the way this knowledge is accessed but does not alter how the knowledge is used in the world.

By contrast, computable knowledge is expressed in code, fundamentally machine-executable instructions that are inaccessible to direct human comprehension. When fed instances of data, computable knowledge can generate useful advice [10]. Applying this idea to the earlier example of disease risk prediction, a machine-executable version of the predictive model can be encoded in any appropriate computer language. When given an instance of data about an individual, this encoded model can quickly and accurately generate a risk prediction for that individual, and with equal ease, multiple models in computable form can generate a panel of predictions for that same individual. When, sequentially but extremely rapidly, one or more computable models are given instances of data about multiple individuals, they can generate predictions for these many individuals. For all practical purposes, these predictions are generated simultaneously[*].

Whereas the 15th Century printing press revolutionized the world by enabling *mass-access* to human-readable knowledge, 21st Century information technology enables *mass-action* application of computable knowledge. (See Figure 2.) This has enormous implications for Learning Health Systems because, on the implementation ("knowledge to performance") side of their cyclic operation, LHSs must operate with economies of both scale and scope. Achieving scale economy requires that generating advice for thousands of instances should require little more time and energy than generating advice for one. Achieving scope economy requires that

[*] IBM Watson [12], which uses automated methods to "read" human-readable knowledge and provide advice, is not, in this view, an example of persistent computable knowledge. Watson does not convert what it has learned into computable models for consistent mass action. Instead, Watson learns an extensive but ever-changing knowledge base and uses it to address each case as, effectively, a new problem.

advice generation for multiple domains can be achieved, as easily as advice generation for one, without fundamentally altering the infrastructure supporting the system. Both criteria require computable knowledge to drive mass action.

Equally important, LHSs must accommodate learning across a range of tempos [11]. As noted previously, the "keystone" of the LHS is the representation of the knowledge the system has adopted for implementation. Because the system will continue to learn over successive cycles of operation, these representations must be readily modifiable. In domains where learning will occur very rapidly, the concomitant changes in the represented knowledge can be achieved only through updating encoded representations of that knowledge.

→ Insert Figure 2 (Mass Action in a Learning Health System)

Interest in this topic has given rise to a nascent movement to "Mobilize Computable Biomedical Knowledge" (MCBK) [13]. Two meetings jointly sponsored by the University of Michigan and the National Library of Medicine, held on the NIH campus in July of 2018 and 2019, have demonstrated the importance of machine-executable knowledge as a key strategy to improve health. [14,15]

For these reasons, it is both appropriate and necessary for *Learning Health Systems* to publish peer-reviewed machine-executable knowledge. Accordingly, the Journal has established "Computable Knowledge" as a new publication type and welcome submissions, initially under a pilot set of policies and procedures. Instructions for authors may be found at: https://onlinelibrary.wiley.com/page/journal/23796146/homepage/forauthors.html. Complete publications will include computable versions of the knowledge that can be downloaded for general use, through an appropriate open source license. We will publish papers of two types:

Full-length *Computable Knowledge Enhanced Publication*s will describe a previously unpublished scientific effort resulting in one or more computable artifacts that will be an integral component of the publication.

Shorter *Computable Knowledge Implementation Publication*s will serve as a "bridge to implementation" of a knowledge model that has been previously published. These articles will describe technical deployment and implementation details, and include the computable artifacts.

We are proud that our Journal, in taking this step, will be one of the first biomedical journals to publish peer-reviewed software in pursuit of scalable and sustainable Learning Health Systems.

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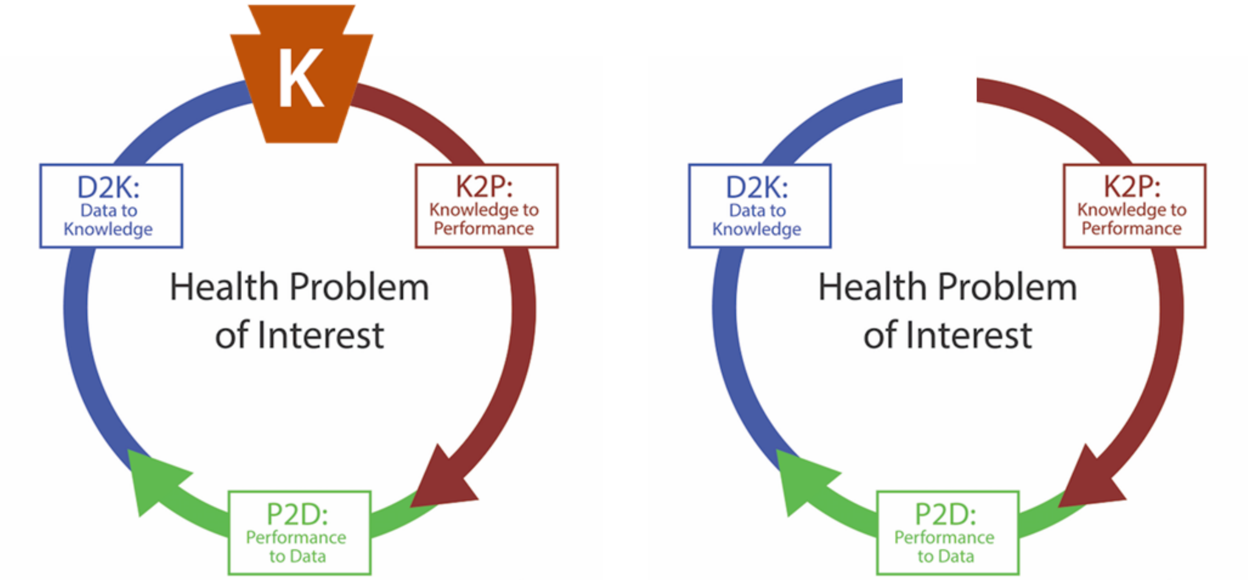

Figure 1: Knowledge as the "keystone" of the learning cycle (left). Absence of persistent knowledge creates a gap in the cycle (right).

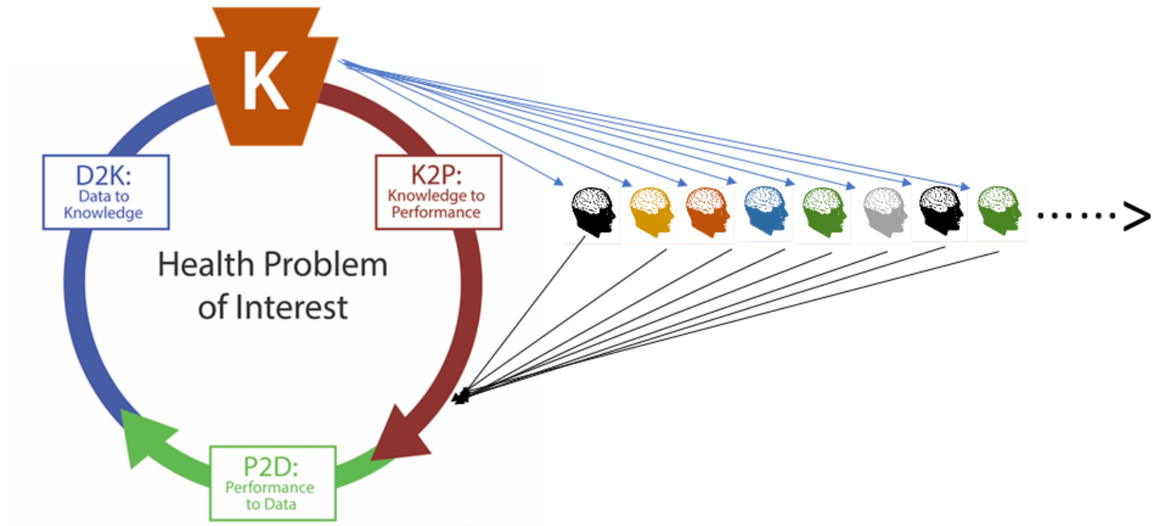

Figure 2: Scalable mass action in a learning cycle enabled by computable knowledge.