SPECIAL COMMUNICATION

What Complexity Science Predicts About the Potential of Artificial Intelligence/Machine Learning to Improve Primary Care

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Primary care physicians are likely both excited and apprehensive at the prospects for artificial intelligence (AI) and machine learning (ML). Complexity science may provide insight into which AI/ML applications will most likely affect primary care in the future. AI/ML has successfully diagnosed some diseases from digital images, helped with administrative tasks such as writing notes in the electronic record by converting voice to text, and organized information from multiple sources within a health care system. AI/ML has less successfully recommended treatments for patients with complicated single diseases such as cancer; or improved diagnosing, patient shared decision making, and treating patients with multiple comorbidities and social determinant challenges. AI/ML has magnified disparities in health equity, and almost nothing is known of the effect of AI/ML on primary care physician-patient relationships. An intervention in Victoria, Australia showed promise where an AI/ML tool was used only as an adjunct to complex medical decision making. Putting these findings in a complex adaptive system framework, AI/ML tools will likely work when its tasks are limited in scope, have clean data that are mostly linear and deterministic, and fit well into existing workflows. AI/ML has rarely improved comprehensive care, especially in primary care settings, where data have a significant number of errors and inconsistencies. Primary care should be intimately involved in AI/ML development, and its tools carefully tested before implementation; and unlike electronic health records, not just assumed that AI/ML tools will improve primary care work life, quality, safety, and person-centered clinical decision making. (J Am Board Fam Med 2024;37:332–345.)

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Background

Artificial intelligence (AI), and its branch machine learning (ML), have been touted as among the "10 big advances that will improve life, transform computing and maybe even save the planet."[1] (Table 1) Other less dramatic AI/ML supporters say that it

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Table 1. Overview of Artificial Intelligence and Deep Learning

What is Artificial Intelligence and Machine Learning?
• *Artificial Intelligence* (AI) is a discipline that studies systems that exhibit behaviors associated with human intelligence, whether embodied solely in computer software, or as embedded software in a physical structure like a robot. • *Machine Learning* (ML) is an automated approach to learning patterns from empirical data using training examples, usually large databases, with the development of an ML algorithm that when applied to new examples improve prediction. ML is concerned with identification of patterns in a wide range of data include quantitative databases such as diagnostic images or textual corpora such as in medical records, and personal reporting or personal health records. The challenge that ML addresses is to identify patterns of interest in data sets that encode extremely large numbers of factors and with vast numbers of cases from which generalizations are to be formed. Conversely, it is problematic to generalize from relatively small numbers of known cases to recognized patterns for new possibilities. • *Supervised* versus *Unsupervised Learning* – It is common to distinguish supervised and unsupervised methods, even though the label "unsupervised" is slightly misleading in that for any method to work, a machine-readable data set must be developed and encoded by a human. However, where methods are explicitly supervised, this tends to mean that there is a designated target feature and values within that feature such that training can be tuned to identify with greater levels of supervision. Error analysis from initial training is fed back into the training process and the models can be progressively refined. • *Deep Learning* – Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain—albeit far from matching its ability—allowing it to "learn" from large amounts of data. Although a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy. Deep learning drives many AI applications and services that improve automation, performing analytical and physical tasks without human intervention.

will facilitate new opportunities for doctor-patient connection,[2] and if implemented wisely, AI can free up physicians' cognitive and emotional space for their patients, even helping them to become better at being human."[3] Some primary care clinicians are excited at the possibility of AI/ML and envision many potential uses,[3–5] whereas others are more apprehensive, believing that the doctor-patient relationship is founded on communication and empathy,[6] and that AI/ML cannot duplicate this.[7]

The recent hype over nonhealthcare AI/ML applications demonstrates that the potential benefits and harms of AI/ML are on many peoples' minds. Autonomous vehicles have had some successes, but also failures leading to fatal accidents that have prompted regulatory scrutiny.[8] The large language model ChatGPT demonstrated success at passing standardized legal exams, but when tasked to write legal briefs, it wrote about nonexisting case law precedents.[9] In health care, ChatGPT has successfully answered medical license test questions,[10] but ChatGPT has been found to produce errors in both stating facts and synthesizing data from the medical literature,[11] and there is now evidence emerging that the mass use of ChatGPT actually worsens its accuracy and reliability.[12]

Complexity science may provide some insight into which predictions about the future of AI/ML in primary care are full of reason or full of hype (Table 2). Briefly, complexity arises from the interconnectedness and interdependence of multiple agents in a particular context (a hospital setting vs a clinic vs the community, eg,).[13] The dynamics between these agents results in feedback loops that alter the nature and behavior of its agents, that is, they adapt to changing circumstances resulting in emergent behaviors, which can be expected, but not predicted.[14,15] Complex systems consist of a large number of elements that in themselves can be simple. Even if specific elements only interact with a few others, the effects of these interactions are propagated throughout the system, and these interactions are nonlinear. An everyday example could be a shortage of toilet article "caused" by the COVID-19 virus. Other aspects of complex adaptive systems (CAS) are further explained in the Appendix.

Primary care must manage many interconnected and interdependent issues, and thus by definition is complex. Unlike specialty care, there is a breadth of undifferentiated patient presentations and irregular timing of presentations to primary care and acute services.[16,17] Their clinic visits are more complex than specialists' visits.[18] Primary care providers

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Table 2. Salient Features of Complex Adaptive Systems

Complexity Science
• Complex systems have hierarchies of power and control. • They contain independent agents that interact with other agents are often resistant to top-down control. • Agents interact with other agents that are above, equal to, or below their position in the hierarchy. • Knowing the parts of a complex system does not equal understanding the system. • There are non-linear relationships between efforts to change systems (usually from higher levels in the hierarchy) and the amount of change that actually occurs in the lower levels. o A complexity science concept that has moved into popular thought is the tipping point, or the notion that a small change can spread from its own momentum across agents in a system without much external energy spent to drive the change. • In more resilient complex adaptive systems, the top hierarchies provide information and resources to the lower levels. The agents in the lower levels use these resources that make the most sense in their local environment. • This top-down/bottom-up information and resource cycle results in emergent properties through a complex system that is unpredictable. • Complexity principles even apply to an individual human. The human "system" contains many hierarchies that interact from the top-down and bottom-up at the same time. The impact of the external environment on health comes from stress activation, etc., at the lowest level. In clinic, we see the effects of heterogeneity of dynamic interactions within body systems at lower level, and environment elements at the whole person higher levels.

have to navigate the greatest volume of patient care information across all other health care entities such as hospitals, nursing homes, lab and imaging facilities, specialists, insurance companies, government agencies, pharmacies, home health agencies, and so on. AI/ML could help or harm managing this information.

Supporters believe that AI/ML will revolutionize primary care—improving risk prediction and intervention, dispensing medical advice and triage, improving clinic workflow, broadening diagnostic capabilities, assisting in clinical decision making, assisting in clerical work, and aiding population or panel management including risk assessments, and remote patient monitoring.[3] However, primary care AI/ML implementation research remains at a very early stage of maturity,[19] and as with many technological advances before, there is no guarantee that AI/ML will successfully transform care delivery and/or care outcomes.

The purpose of this article is to discuss the opportunities and challenges of AI/ML in primary care, seen through the lens of CAS.

The Opportunities and Challenges of AI/ML for Primary Care

Detection/Diagnosis of Single Diseases

Early examples of successful implementation of AI/ML include analyzing data from images to diagnose specific conditions. Examples include retinal scans to diagnose diabetic retinopathy,[20] data from mammogram imaging to identify radiographic images suggestive of breast cancer,[21] using wearables to detect atrial fibrillation,[22] and using tele-dermatology with AI/ML assistance to improve diagnostic accuracy for skin lesions.[23] AI/ML successes have been described as less that of a certain diagnosis and more like a good guess at what the answer might be,[21] which helps explain why the impact of AI/ML even in a digital field such as diagnostic radiology has been only modest so far.[24] For primary care, AI/ML might augment a physician's knowledge and confidence to diagnose rare diseases.[25]

However, even apparent successes of AI/ML for diagnostic outcomes have been found to be nonsensical when deeply explored post hoc. For example, an AI tool for detecting melanomas in photographs of skin lesions did so by recognizing that photographs with cancer were more likely to have small rulers in the image.[27] Judging AI/ML accuracy in clinical diagnosis is particularly challenging outside of well-structured case vignettes.[28] Although AI/ML-trained systems may aid the diagnostic process, it cannot determine the final diagnosis, which involves human interactions, judgments, and social systems understandings that are beyond what computers can model.[29]

Treat Specific Diseases

AI/ML also has the potential to inform decision making by quickly synthesizing a wide variety of information from the medical literature or electronic health record (EHR). It could also incorporate patient pathways including hospital discharge summaries, drug databases, drug-drug and drug-disease interactions with the ability to analyze large amounts of data and discover correlations that may

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have been missed by researchers and health care providers, enhancing patient-centered care.[30] For example, a hospital bedside AI/ML-based consultation service had only a limited effect on treatment decisions in 10 out of 100 queries, mostly involving unusual understudied patient presentations or rare diseases.[31]

AI/ML was not successful at improving cancer treatment, which may more closely reflect the complexity of primary care. Studies concluded that IBM Watson did not improve on the decisions of oncologists, and the project was abandoned.[32,33] Attempts involving diagnoses that require integrating clinical findings, a crucial task in primary care, have not achieved the same success as single disease efforts.[34]

AI/ML models based purely on historic data would only learn the prescribing habits of physicians in retrospect that may not represent an ideal state in emerging practices.[35] For example, computerized decision support systems (CDSS) designed with a high tolerance for risk favored algorithm performance over patient safety, potentially exposing patients to inappropriate medications.[36] Determining if AI/ML improves patient outcomes remains the most important test, and currently there is scant evidence of downstream benefit. AI/ML optimists consider real world data such as pharmaceutical postmarketing surveillance as a valid source of evidence to connect treatments with outcomes.[37] Skeptics believe AI/ML is no substitute for more rigorous methodologies, which may include randomized controlled trials or learning health system approaches.[38]

Predict Future Health Events

AI/ML may provide new opportunities to construct more acute predictions of disease risk, which could inform smarter decision making algorithms.[39] Oak Street Health implemented an ML approach that increased the number of patients identified at high risk for hospitalization compared with retrospective models, but not improve mortality.[40] ML may be particularly useful when dealing with "wide data," where the number of subjects is greater than that of input variables. Other observers believe most studies on ML-based prediction models show poor methodological quality and are at high risk for bias.[41] Existing prediction models that use large data sets and AI/ML can give similar population level estimates of cardiovascular disease, while giving vastly different answers for individual patients.[42]

An explanation for this discrepancy is that ML focuses on the strength of the correlation between variables rather than the direction of causality,[26] and ML may add little value to predictions of future events compared with traditional methods. And even if one assumes that AI/ML applications might increase the predictive accuracy for future events, it does not mean that there is an action available to decrease the risk, which in turn raises important ethical concerns.

Decrease Administrative Burden

AI/ML using voice recognition has been implemented to listen to a physician-patient encounter and document a preliminary note, or autocharting.[43] A tool called Suki was found in a demonstration project to reduce documentation time with this technology by 72%,[44] critical in an age where such administrative burden has been clearly linked to growing rates of reported US clinician burnout.[45] An assessment of the performance of ChatGPT to generate histories of present illness documentation in medical notes found that it sometimes reported information that was not present in the source dialog, an error called "hallucinating."[46] Other possible uses include optimizing coding for value-based payments and automating aspects of previsit planning.[3] However, a substantial proportion of patient symptoms in primary care are vague, such that even human scribes present in the room do not agree how to document them.[43] A possible distinction between these disparate findings may be recording and categorizing information (converting spoken history and physical examination elements to a dictated note) versus improving understanding. AI/ML used to automate prior authorizations has also been proposed.[47]

Expand Primary Care Capacity

Some AI/ML innovations aimed to extend the work of the primary care team beyond the office visit, the home visit, and even beyond telehealth. Conversational agents using AI/ML improved depression scores in small 2-week trial, a time frame that is likely clinically irrelevant.[48] A recent randomized comparative effectiveness trial indicated that AI/ML could allow many more patients to be served effectively by CBT-CP programs using the same number of therapists.[49] Other

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examples of AI/ML used for single-issue primary care tasks include mental health assessments during telehealth calls,[50] mental health support,[51] and weight management.[52]

AI/ML may help with remote monitoring, for example, alerting patients and doctors when a continuous glucose monitor stops functioning, or decreasing false alarms in telemetry units.[53] However, algorithms that are applied repeatedly to track a patient's condition likely will trigger repeated false alarms or information the clinician is already aware of, which contributes to alarm fatigue.[54]

Data Issues—Signal, Noise, and Action

Data Accuracy

Some of the successes of AI/ML outside of health care have been noteworthy, for example, the progression of AI to defeat humans in the games of checkers, chess, then Go.[55] These programs were trained on tens of millions of previous games, where the input data were essentially perfect. In contrast, "noisy" data decreases classification accuracy and prediction results in ML.[56] In fact, the information that should be classified as signal versus noise is difficult to determine even for highly focused questions in medicine, for example, determining if heart rate variability derives more from normal physiologic events (stress), normal "abnormal" states (sinus bradycardia in a young athlete), or disease (paroxysmal tachycardias).[57]

Noisy data are a challenge in all potential uses of AI/ML, but will likely be an especially significant barrier to the utility of ML in primary care, where inaccurate data are already abundant, which erodes accuracy of ML predictive models.[58] In a detailed investigation of EHR data fidelity, diagnostic codes for hypoglycemia were found to have moderate positive predictive value (69.2%) and moderate sensitivity (83.9%).[59] Accuracy rates of medical registry data ranged from 67% to 100% and completeness ranged from 30.7% to 100% in another study.[60] Important drivers of EHR inaccuracies are copied and pasted notes, a work pattern that is not likely to change going forward.[61] In addition, the timeliness and accessibility of EHR data are challenging. Raw data from an EHR must be cleaned and formatted before use, but if this process is delayed, the models cannot be applied in real time for patient care.[62] Whether ML approaches can sort out which data inconsistencies are errors, and which add useful information, remains unknown.

Actionable Data

AI/ML has been shown to predict risks of future events in some cases. But merely providing the probability of a particular outcome, such as readmission or mortality risk, is unlikely to change physician or patient behavior in most primary care settings, as physicians incorporate their patient's unique context and preferences into their decision making.[63] Poor calibration might often be expected with application of a model from one population to another, which can lead to harmful decisions.[63,64] Although modern imputation methods can mitigate some bias due to missing information, these methods are less useful in EHR settings where it is not possible to distinguish the true absence of a relevant characteristic (such as a particular comorbidity) from data incompleteness. Even if efforts are undertaken to maximize calibration, patterns seen in existing data sets should be considered as no more than hypothesis generating, and will still require classic hypothesis testing.[65]

A summary of the potential uses and features of AI/ML applications for which primary care physicians could be excited or apprehensive is provided in Table 3.

New Approaches May Emerge Using AI/ML in Complex Adaptive Systems

Complexity principles have been used to improve health system outcomes with AI/ML at the macro-level. Using hospital admissions and emergency data, Monash Health in Victoria, Australia developed an algorithm to predict patients who were at high risk of readmissions within the next 12 months. The algorithm had a positive predictive value of 33%.[66,67] Monash Health leveraged the primary care teams' preexisting relationships with patients and initiated an outreach team of medical, allied health and community health workers (CHWs) to augment the care by primary care physicians using an online system to predict deteriorating patient journeys. Nonclinicians made regular monitoring phone calls (≥ weekly) prompted by a clinical algorithm that continually predicted unmet needs and risk of deterioration or admission based on the most recent phone calls. The intense outreach effort using conversations aimed to address unintended repeat investigations, loneliness, hospital infection, and posthospital syndrome, aligned with the goals of patients.[68] Interventions the clinical teams developed were not defined a priori,

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Table 3. Excited or Apprehensive—Likely Uses of Artificial Intelligence/Machine Learning from a Complexity Perspective

Primary Care Function	Excited/Less Complex Care	Apprehensive/More Complex Care
	AI/ML more likely to help	Factors making AI/ML less likely to help
Diagnose	• Improve physician confidence to diagnose a patient concern likely explained by one diagnosis. • Possibly improve diagnosis of rare diseases. • More quickly sifting through and sizing up evidence. ◦ Possibly better than doing your own Google or literature search. ◦ More quickly and more focused searches with less time taken from actual patient care.	• Complex interaction of multiple symptoms and possible diseases including psychosocial and social determinant effects that is too much for the computer to manage. • Actual diagnostic computer "nuts and bolts" can be nonsensical. • Diagnoses more accurate in AI/ML demonstrations with well-structured vignettes. • AI/ML diagnoses not likely to include contextual and relational factors.
Treat specific diseases	• Better at judging the chances of what treatment will work best for what patient. ◦ Helping the physician become a better "odds-maker." ◦ Greater objectivity—more evidentiary basis and less sense of exposure ◦ Readiness to take on complex work that might otherwise have seemed "beyond my bandwidth" when not assisted by AI tools, especially for rarer diseases.	• Noisy and inaccurate data in EHRs. • May only add real value for rarer diseases. • AI not successful at improving cancer treatment. • Using historical treatment data may not reflect newer approaches. • Many treatment decisions are based on a negotiation with the patient using patient-shared decision making. • Relationships of data elements in existing databases (EHRs, billing data, and so on) often non-linear with Pareto distributions, which makes mathematical predictions challenging.
Predict future health events	• Identify patients at increased risk for hospitalization.	• Predictions may not be actionable. • Existing models may give similar population estimates, but vary widely for individuals. • AI/ML predictions may not improve upon existing tools.
Decrease administrative burden	• Getting through all those letters and forms with less burden. • For U.S. physicians mostly, decrease documentation time and burden.	• Patient symptoms in primary care are often vague, and even human scribes do not agree how to document them. • Distinction between typing spoken words onto a clinic note versus increasing understanding.

Abbreviations: AI, artificial intelligence; ML, machine learning; EHR, electronic health record.

but emerged through dynamic feedback loops between the interacting agents.

They reduced readmissions by 1.1 bed-day per person per month, with a > 60% participation rate in eligible patients.[68] The physicians, wider teams, and CHWs could continually update their interventions, which is a feature of a well-functioning CAS. Clinical teams learned from their ongoing interactions with patients and adjusted their recommendations based on each patient's personal journey. The AI/ML software looked at individual call data, records of all the calls and outcomes, and all patients in the database. It improved CHWs' prediction of an event, that is, the likelihood that something would happen before the next weekly call, by 80%.[69]

In this example, the primary care teams used AI/ML to manage a large volume of data that would be difficult and expensive for humans, but relied on existing relationships and clinician judgment to determine the best actions. The researchers concluded that the algorithm determined only 10% to 20% of the success; the primary care team workflow determined 80% to 90%.

Other Concerns with AI/ML

Health Equity

The US Food and Drug Administration and others realize AI/ML has inclusiveness problems and may exacerbate outcome differences in vulnerable populations.

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There are many types of biases in machine learning.[70] Many data sets lack diversity and completeness of data by gender, race, ethnicity, geographic location, and socioeconomic status.[71,72] For example, AI/ML was used to identify cancerous moles in whites, but not blacks.[73] In contrast, AI/ML has been shown to positively impact implicit racial bias in the prevention of deep vein thrombosis.[74] Human health care workers certainly have biases too.

Datasets that reflect historic disparities in care related to racism and privilege have been shown to produce AI/ML results that retain these biases and thereby perpetuate the structural disadvantages and disparities.[75] Users of AI/ML may not even recognize the biases. Clinicians with a propensity to trust suggestions from AI/ML support systems may discount other relevant information, leading to so-called automation complacency.[76] To combat this, fairness audits were used to reflect on AI/ML performance in prompts for end-of-life care planning, and found application performance differences by race/ethnicity, for example, in Hispanic/Latino males whose race was recorded as "other."[77] This particular audit required 115 person-hours and did not add clinically meaningful information due to poor demographic data quality and lack of data access. AI/ML was also largely unsuccessful at incorporating social determinants of health indicators into prospective risk adjustment for private insurance payments in the U.S improving the predictive ratio by only 3%,[78] though this performance may worsen over time as so-called latent biases emerge with subsequent use of an AI/ML tool.[79]

It is beyond the scope of this commentary to review other concerns about AI/ML such as privacy, data ownership and transferability, intellectual property, cybersecurity, and medical liability for the creators and owners of AI/ML tools.[80] AI/ML was recently challenged to "not just replicate human thinking processes, but should aim to exceed them," a bar that is likely insurmountable for many aspects of complex primary care.[65]

Discussion

Despite the emergence of intriguing Al/ML tools such as ChatGPT, successful transformation of primary care using AI/ML is far from guaranteed. Primary care should play a critical role in developing, introducing, implementing, and monitoring AI/ML tools, especially regarding common symptoms, acute diseases, chronic diseases, and preventive services.[81] To avoid making the same mistakes with AI/ML implementation as happened with the forced EHR implementation onto primary care without adequate vetting, US policy makers should assume that AI/ML products will only improve primary care if its stakeholders are heavily involved in its development, piloting, vetting, and wider implementation.

No tool can account for the inherent complexity of primary care. It is not the existence of AI/ML tools that are the potential problem, but the way the tools are used that matters–are they ultimately able to integrate the tacit domains required for participatory, effective, and ethical decision making? Do the potential cognitive and data-management improvements of AI/ML add any value to patient outcomes beyond the pre-existing deep relationships between primary care clinicians and their patients?

Complexity science recognizes that primary care decision making emerges from not only the doctor-patient relationships and knowledge of confounding factors for treating an individual patient such as comorbidities, social determinant challenges, and unique patient attitudes and beliefs, but also the interrelated hierarchical layers and feedback loops of health care systems.[13] AI/ML approaches may harm primary care by acting to minimize an understanding of these complexities, often by limiting the number of features that it uses to develop its algorithms.[57] In fact, many potential AI/ML tools are described as synthesizing information (EHR data and billing data) from the front lines of the health care system hierarchy and sending conclusions to the macro administrative layers (analysts and administrators), which is opposite that of a natural and sustainable CAS.[82] The series of interventions in Victoria, Australia demonstrate a CAS-consistent flow of information. AI/ML was used to collate a large amount of data to identify patients who were potentially about to "tip" into worse health states, but the synthesized information was not sent to the top levels of the system hierarchy, but rather to the front-line clinicians. In addition, AI/ML was not used to make medical decisions of how to respond to the patients flagged as being at increased risk for hospitalization. What made this AI/ML application successful was not only the model itself (which actually played a relatively small role), but more importantly the way the model augmented

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existing relationships and human-driven processes of care.

A key limitation of AI/ML lies in the fact that its predictions arise from existing data. It cannot, at least at this point in time, synthesize the multiple perspectives of a health professional in the context of the patient in front of them. Creating new data upfront for unmet clinical needs and specific purposes is time and resource expensive, but gives the best chance of being useful in practice.

A deliberative patient-physician relationship is important for healing, particularly for complex conditions and when there is a high risk of adverse effects, because individual patients' preferences differ.[83] There are no algorithms for such situations, which change depending on emotions, nonverbal communication, values, personal preferences, prevailing social circumstances, and many other factors. For example, AI/ML will not likely reduce the uncertainty inherent in making ethical decisions about care at the end of life. AI/ML sceptics point out that algorithms and prediction instruments, ironically, exercise tyranny over the true freedom of moral agency that we claim to be respecting in our patients.[84]

Policy makers (and investors) should not just assume that AI/ML tools can significantly improve the complex person-centered work of primary care physicians and their teams. Useful applications of AI/ML in primary care will undoubtedly emerge. Complexity science suggests that it is much more likely that these tools may assist primary care with discrete functions with highly focused outcomes, but it is very unlikely that AI/ML tools will replace complex relationship-centered decision making by physicians and their teams (though the team composition may evolve if administrative burden can truly be reduced).

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Appendix.

Complex Adaptive Systems Further Explained

Complex systems contain many direct and indirect feedback loops. Complex systems are open systems —they exchange energy or information with their environment (their context) — and operate dynamically. Any complex system thus has a history, and the history is of cardinal importance to the behavior of the system influenced by its previous path. Because the interactions are rich, dynamic, fed back, and, above all, nonlinear, the behavior of the system as a whole cannot be predicted from an inspection of its components. The notion of "emergence" is used to describe this aspect. The presence of emergent properties does not provide an argument against causality, only against deterministic forms of prediction. Complex systems are adaptive. They can (re)organize their internal structure without the intervention of an external agent.[1]

Practice Domains

Knowledge itself is complex and thus not all knowledge contributes equally to what we know.[2] The Cynefin framework (Figure 1a) is 1 approach to understand decision making in complex systems, and it helps visualize the medical knowledge domains (Figure 1b) that facilitate clinical decision making in a primary care context.[3] In the obvious quadrant, direct cause and effect relies on explicit knowledge trials such as randomized controlled trials (RCTs) and meta-analyses of RCTs. This is the domain most conducive to monitoring by simple single disease guidelines. Perhaps the recent success of large language models such as ChatGPT to answer medical license test questions fit in this domain.[4] On the other hand, ChatGPT has been found to produce errors in stating facts and synthesizing data from the medical literature.[5]

In the complicated quadrant, cause and effect are discernable through multilayered interacting parts that also rely on explicit knowledge trials. In these clinical scenarios, complicating factors such as comorbidities may influence patient care recommendations, but the relationships of inputs and outputs are linear and follow parametric patterns. An example is balancing the negative impacts of comorbidities on a decision of whether a major surgical procedure is more likely to benefit or harm a patient.

In the complex quadrant, there are so many interacting parts whose relationships are perceivable, but not fully predictable in real time, and thus it is difficult to predict the behaviors and outcomes based on the knowledge of its component parts. Multiple layers of system hierarchies interact through nonlinear feedback loops with nonlinear relationships between inputs and outputs, making outcomes unpredictable and sometimes surprising. Relationships between inputs and outputs often follow log-linear, or Pareto distributions. An example is caring for a dying patient and her family, balancing all the often competing organic medical, psychological, legal, and familial needs. It is often tacit knowledge rather than explicit data that direct care for these complex needs.

In the chaotic quadrant, the various components have no apparent relationship to each other, leading to a crisis with an emergent new order and/or a breakdown of the existing order, for example, the early days of the COVID-19 pandemic.

The ability of AI/ML to add value to care delivery likely diminishes as 1 moves from the simple to the chaotic domains. A further examination of complex system understandings and the role of AI/ML is shown in Table A1.

Figure A1. The Cynefin domains and its application to knowledge in medicine.[6]

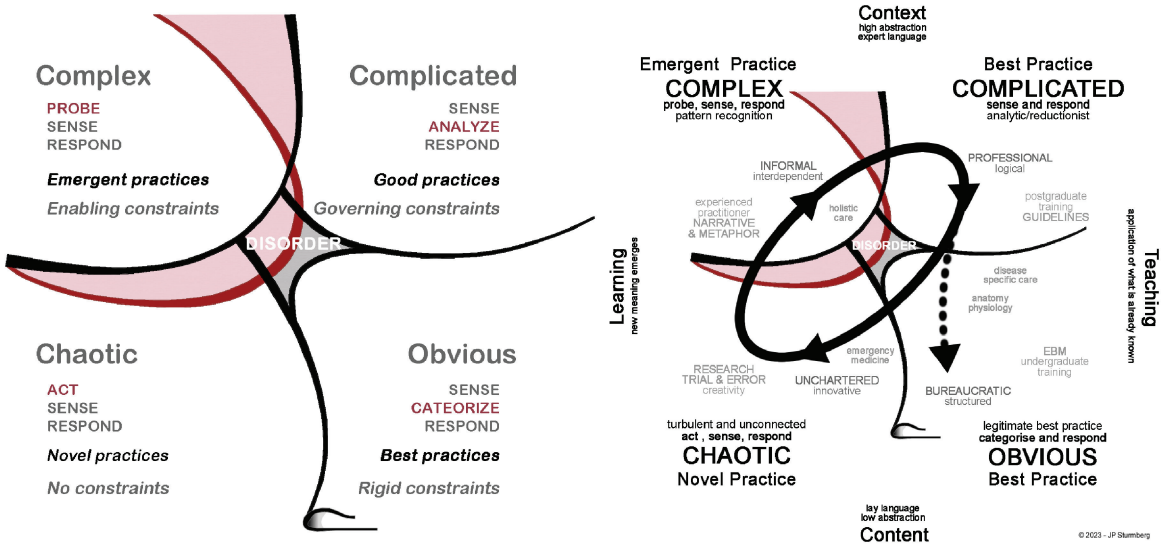

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Table A1. AI/ML Features and Their Relationship to Complex Adaptive Systems and Primary Care

	Complexity in Primary Care	AI/ML/Big Data
Philosophy	A complex system is one **in which there are so many interacting parts that it is difficult** to predict the behavior of the system based on knowledge of its component parts. People are the glue that binds and maintains the system.[7] Complex systems have chaotic and non-linear complex parts as well as linear and complicated features.	**Artificial intelligence** (**AI**) is intelligence—perceiving, synthesizing, and inferring information—demonstrated by machines, as opposed to intelligence displayed by non-human animals and humans. No established unifying theory or paradigm has guided AI research for most of its history.
The Challenge	The General Systems Theory (GST)[8] is studying the whole system, to clarify the principles that can be applied to all types of systems at all levels of their nesting in the other systems in terms of their viability in all subject areas of research, given their interaction with each other in real-time and in fuzzy environment, surrounding them.[9] How to inform the human in the loop with intelligent reliable information that is relevant?	Develop intelligent systems thinking in an autonomous fuzzy control, operate in fuzzy environments under uncertainty, and communicate with humans and other systems in different languages, in the dissimilar domains, where processes, situations and factors of influence on the control object and back; a) cannot be determinate and structured in advance, and b) may be understood relevantly and unambiguously.[9–11]
Responding to the dynamical systems that vary over time.	The human brain can be understood as a complex adaptive system itself that have evolved to enable humans to navigate complex environments[12] and dynamical systems. Exploration is ongoing in attempts to understand, emotion, context and human reasoning.[13,14]	Dynamical systems obey differential equations involving time derivatives. Analytical resolution of such equations or their integration over time through computer simulation may facilitate the prediction of the future behavior of the system.
Intelligence	Human Intelligence aims to adapt to new environments by utilizing a combination of different cognitive processes. The human brain is analogous and uses its computing power to recognize multiple patterns, diverse memories, interoception[14,15] and ability to think to make sense[16] of their environment and make decisions.	Artificial Intelligence aims to build machines that can mimic human behavior and perform human-like actions. AI-powered machines rely on data and specific instructions fed into the system. They have perfect memory but the memory is constrained by their capacity to analyze and infer from human and other inputs.
Environmental and sensory Inputs - theory	Human consciousness in an adaptation to a new environmental disturbance. Through the conversion of neural cognitive activity - thoughts - about the state of the outside world into the way that world is experienced through the senses, the thoughts gain the reality that sensory images have.[17]	Human intelligence (explicit) is the main contributing factor that has given definition to the simulations that are created in machine intelligence. Artificial intelligence depends on the best current theoretical models, input data, and the constraints of the AI machine problem-solving skills.
Strengths	Human cognition has evolved to adapt to our changing world and navigate our environments.[18] Garnering both explicit and implicit knowledge, exhibits the highest degree of evolutionary cortical expansion, supported by receptor diversity and human-accelerated genes underpinning synaptic function.	Artificial machine learning is a development from human cognition to address weakness in human cognition – access to information, memory, processing time, etc. Machines are better than humans at processing large amounts of data. This will be most useful in the simple and complicated domains of health care knowledge.
Weaknesses	Humans have limited explicit memory (e.g., cannot easily use the whole of PubMed on a topic) compared with machine intelligence; Humans have as a group a wide spectrum of intellectual capabilities; however these are influenced by stress, unsupportive environments, distractions, lack of access to a vast body of knowledge that is exponentially growing every day.	AI is still in its early stages of development. Training AI systems is a time-consuming process. AI will have all the biases and limitations of those who wish to ensure top-down control via protocol vs guidance.

Continued

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Table A1. Continued

	Complexity in Primary Care	AI/ML/Big Data
Challenges	Many tasks are time consuming. Workforce and remuneration challenges undermine personal communication, interoception, and person-centered care. How to self-organize bottom-up care when practice is driven by top-down constraints and funding formulae?	Top-down medical industrial for-profit drivers of the artificial data and information systems may come to dominate the primary care space without truly understanding the human and environmental dynamics.
	How to self-organize and adapt in the complex and even chaotic domains of practice?	The information system should serve rather than dominate clinical care.

Most existing successes in AI/ML represent small and constrained components of the complex health care system such as measuring pixels on an image to help make a diagnosis, or using voice recognition to monitor and treat a single mental health concern. The data used are relatively confined and have linear deterministic relationships with outcomes (a direct predictable link from input to output). AI/ML has generally failed when more complexities are considered across different informational silos, agents, and hierarchies; and when the relationship between data input and desired outcomes are nonlinear with power law distributions of inputs and outputs, include feedback loops, and are nondeterministic.

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