

Realizing the Promise of Cognitive Computing in Cancer Care: Ushering in a New Era

Cancer prevalence in the United States is projected to increase by more than 25% by 2020; increasing longevity will contribute to even higher prevalence worldwide.¹ The supply and distribution of health professionals to care for those affected by cancer is not sufficient to meet these needs, given today's treatment modalities.² However, advances in technologies that augment the skill sets of practicing oncologists and other care providers offer measurable ways to improve care in multiple settings. Cognitive computing technologies that peruse and digest massive volumes of health data to generate diagnostic and therapeutic insights are beginning to demonstrate their transformative value.³

Here, we describe emerging and available tools that use cognitive computing systems to generate, extract, and evaluate insights from multidimensional sets of clinical data, interventions, and outcomes, specifically for cancer specialists. We discuss cognitive computing applications now in use—and being continuously refined—to help clinicians personalize cancer care through genomic analysis, quickly match patients to appropriate clinical trials, and generate evidence to support standard standard-of-care treatment recommendations in the service of practicing oncologists and their patients. We describe challenges and recent advancements in these three promising areas of cognitive computing—assisted cancer care.

A word of background on cognitive computing: it is a holistic approach to designing platforms that leverage the tools of artificial intelligence, including machine learning and natural language processing, to complement and augment human expertise. The field of artificial intelligence covers a broad spectrum of approaches to simulating human intelligence.⁴ Cognitive computing, an artificial intelligence technology, refers to those systems that can learn, understand, reason, and interact (Fig 1).

Cognitive systems serve as data analysts that can intelligently sift through available patient medical records and emerging practice innovations to extract and generate potential treatment options. They can extract and build knowledge from structured and unstructured data at a massive scale; identify patterns and relationships in data that were not otherwise readily visible through manual or traditional analytics approaches; reason by making connections between data elements and prior knowledge; learn from experience so that outputs improve over time; and interact naturally with clinicians, empowering them with useful, timely, data-driven decision support.

Today, the explosion of health-related data from diverse clinical and personal health monitoring sources, combined with advances in medical knowledge, creates unprecedented opportunities to address evidence-based cancer diagnosis and treatment. At the same time, the volume and fragmented, nonstandardized nature of these data present complex challenges for storage, extraction, and analysis. New discoveries in the molecular biology of cancer, targeted drugs, immunotherapies, and cell-based therapies are emerging rapidly, challenging even the most fastidious clinician. (Estimates from a decade ago suggest clinicians would need to read approximately 29 hours each work day to stay abreast of new professional insights in the field of medicine.⁵) Data collected in clinical encounters remain dispersed, stored in varied structured and unstructured noninteroperable fields and networks that, until recently, could not be analyzed in a systematic, large-scale or meaningful manner.

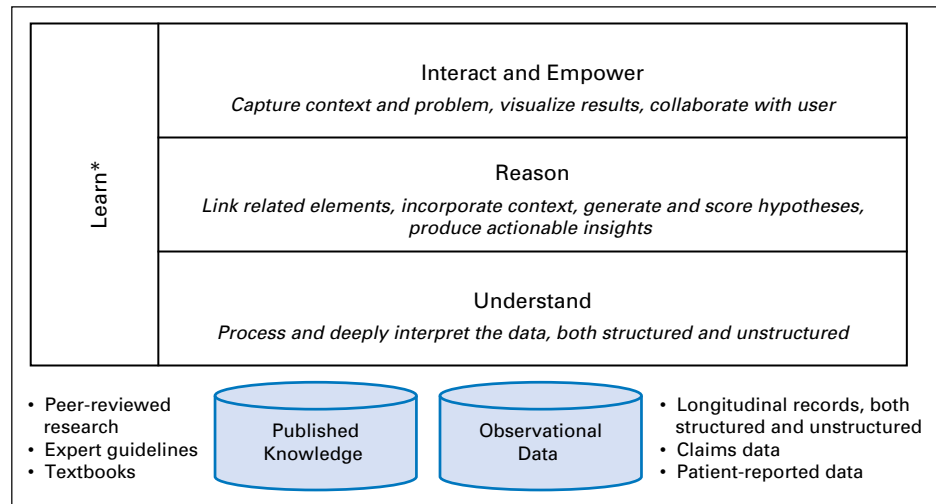
Despite the availability of treatment guidelines, guideline compliance is low.⁶ In community practice in the United States, for example, guideline-concordant prescribing of chemotherapy for patients with non–small-cell lung cancer ranges from 60% to 80%.⁷ Patients with rare cancers face greater challenges, as was recently demonstrated with inflammatory breast cancer. Cognitive computing

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Fig 1. Elements and capabilities of an oncology cognitive computing system. (*)Collect feedback and learn from outcomes at all levels and granularities.



solutions can help expand the capabilities of local care facilities and individual clinicians by making the specialized expertise of high-volume care centers available to a community-based clinician.

Cognitive computing is also poised to possibly help improve clinicians' diagnostic accuracy and refine their prognostic prediction. For example, there is potential to help physicians in image-based fields such as radiology and pathology.^{3,10} In the imaging field, Merge, an IBM company, is developing an emerging technology process called "Markation," the goal of which is to annotate images and create summary reports at the same time to help radiologists evaluate images with more accuracy. This innovation, once complete, is to use image analytics to describe the minute changes observed in serial images of suspicious anatomic lesions, for example, breast lesions identified in mammography. The intent of Markation is to allow the reviewing radiologist to note the location of lesions in serial images and to simultaneously generate the report that documents these observations. Using standardized language and on-screen tools, the radiologist can accurately note and capture observations in one action, eliminating the multiple steps typically associated with radiologic report generation. The goal is to reduce both the time required to evaluate radiologic images and the administrative recording burden.

Although hurdles to achieving fully realized cognitive computing systems remain, the field is advancing rapidly.^{11,12} Several groups are actively engaged in developing and testing such systems in multiple domains.^{13,14} The authors are most familiar with the cognitive tools developed by IBM Watson Health. For example, Watson for Oncology is a cognitive clinical decision support (CCDS)

tool that was trained by experts at Memorial Sloan Kettering Cancer Center. This tool is achieving high levels of concordance in providing clinicians with possible recommendations; for example, Manipal Hospitals, a hospital system in Bangalore, India, uses Watson for Oncology to assist in developing appropriate treatment regimens for many of their patients with cancer. As part of its continuing validation, this cognitive clinical decision support tool was evaluated for its effectiveness relative to tumor board recommendations. It achieved 90% concordance with the treatment recommendations of the multidisciplinary tumor board at Manipal for over 600 patients with breast cancer. The hospital initially conducted a retrospective analysis in which the cognitive clinical decision support tool was used to analyze cases from the prior 2 years. Recommendations generated by Watson for Oncology matched the recommendations the tumor board had made at the initial time of treatment in 73% of the cases.¹³ When the tumor board rereviewed those cases at the later date, concordance rose to 90%, reflecting that the CCDS tool had correctly applied contemporary scientific guidance during its analysis. The designers of the tool interpreted this to mean that the CCDS provided state-of-the-art recommendations, even as science evolved (C. Douglass, personal communication, June 2017). Data are not available on the relationship between the treatment recommendations and treatment outcomes, but efforts to track and measure health outcomes are being developed by Watson Health for the next phase of data and evidence generation in Watson for Oncology.

Another area in which cognitive tools demonstrate unique value is in identifying and matching patients to clinical trials. Clinical trials are an essential resource to build the body of evidence for

treatment and care, in addition to helping patients access new treatments that can potentially help them. However, with clinical trial accrual rates hovering below 5%, most patients seeking cancer care are left out of clinical trials, and the extensive generalizable and unique data on their cancer diagnosis, treatment, and outcomes are not captured by researchers.¹⁵ Although many factors contribute to clinical trial enrollment, a common hurdle is identifying the appropriate trial for which a patient may be eligible. (ClinicalTrials.gov listed over 43,000 trials currently recruiting in June 2017.¹⁶) This is an activity that is well suited to cognitive and noncognitive decision support systems.

The Mayo Clinic recognized the potential of cognitive computing to address the challenge of matching patients with diverse characteristics and comorbidities to clinical trials for various treatment regimens. The Mayo Clinic, which runs thousands of trials, partnered with IBM Watson Health to use the cognitive clinical trials selection decision tool, Watson Clinical Trials Matching. This tool rapidly reviews the complete individual patient record and identifies specific clinical trials for which the patient is both eligible and a potential research participant. Large-scale studies are not yet available to document improvements in clinical care or speed, but an oncologist who works at Mayo reports anecdotally that this tool has accelerated their ability to enroll patients in their clinical trials.¹⁷

Cognitive computing can be a valuable partner for oncologists in helping to develop personalized cancer therapies. Consider that in the past decade, the US Food and Drug Administration has approved or added indications for nearly 200 new drugs for treating cancer.¹⁸ Not only are there many drugs for physicians to learn about, but many of them fall into entirely new mechanistic classes that physicians likely did not learn about during their formal training. For example, the era of targeted molecular therapy that began with the 2001 US Food and Drug Administration approval of imatinib now includes tyrosine kinase inhibitors, antiangiogenic agents, and immunotherapy in clinical practice. In addition to rapid growth of the anticancer drug arsenal, genomic tumor profiling is an increasingly critical contributor to treatment decision making for chronic and acute leukemias, non-small-cell lung cancer, melanoma, and breast and colon cancers. Most clinical trials in oncology now require some degree of genomic tumor profiling as part of eligibility criteria, and some predict that tumor genomic profiling will become the standard of

care in the near future.¹⁹ The optimal approach will move quickly from today's next-generation sequencing panels of several tens or hundreds of genes to a much more comprehensive analysis of the whole exome and then the genome, the transcriptome, and the epigenome.²⁰ The challenge of storing, analyzing, and mining the resulting data for meaningful insights is enormous, requiring classification based on molecular consequences, clinical relevance, and level of evidence.^{21,22}

Many of these highly specialized tasks are ideally suited for cognitive computing.²³ Watson for Genomics is one example of a cognitive computing tool that can automate many of these functions on a large scale. At the University of North Carolina Lineberger Comprehensive Cancer Center, clinicians and researchers partnered with Watson Health to apply Watson for Genomics to help clinicians match treatment protocols to individual patients on the basis of the genomic profiles of their tumors.²⁴ Early in the partnership, clinicians at the University of North Carolina successfully used the tool to identify clinically actionable mutations that were not identified by the molecular tumor board of oncology experts during their review. At this stage, only anecdotal evidence about the effectiveness of the tool is available from Lineberger and the other cancer research institutions that are collaborating with Watson Health to deploy and further train this cognitive computing tool. However, early feedback indicates that Watson for Genomics performs data analysis and generates correct tumor identification and treatment options, tasks that normally require several weeks of research and now can be completed within minutes.²⁵ In an initial trial at Lineberger, Watson for Genomics analyzed 1,022 genomic profiles and achieved 99% concurrence with the molecular tumor board in identifying possible therapeutic options that were also proposed by the molecular tumor board. In addition, in 335 of these cases (33%), the tool identified and suggested additional actionable options that the tumor board had not considered (manuscript in preparation).

The trend in the United States toward provider consolidation means that more clinicians are working in hospital-based or large-group practices. However, most cancer care is still provided in community practice settings where local resources and subspecialty expertise may be limited.²⁶ The burden of cancer care can place considerable strain on small practices, especially when paired with a limited supply of medical and radiation oncologists.²⁷ Payment systems that measure and reward value of service over volume

present additional challenges for providers. To thrive in this environment, a community practice must ensure that cancer care is carefully coordinated to optimize efficacy, limit toxicities, and manage costs. CCDS tools that can aid clinicians in quickly reviewing patient records and that can recommend possibly effective and appropriate treatments can contribute to successful case management and patient care.²⁸

Despite considerable progress in integrating cognitive computing tools into the clinical setting, challenges remain. Clinicians seek rapid and seamless access to effective tools, so further work is needed to fully integrate these tools into the clinical setting. The challenge of integrating multiple IT systems to achieve interoperability remains an obstacle to wider implementation in some settings.²⁹ For example, clinicians using Watson for Clinical Trials Matching can access the cognitive tool by clicking on a link while in a patient's electronic medical record, rather than having to launch it separately. However, some clinicians still do not like the work flow of having to open a new program to use this tool. Not all clinicians readily embrace new technologies, and not all care requires cognitive solutions. It is important to recognize that cognitive computing tools are trained on very large data sets, and they continue to learn. Ongoing validation studies are used to demonstrate and confirm this learning. These activities require partnerships with large cancer care providers and researchers.

The distinguishing features of fully functioning cognitive computing systems include transparency about the sources of training and insight generation and the ability to interact using natural language with the care team. To have confidence in the insights and recommendations supplied by a cognitive computing tool, clinicians need to know how a cognitive computing system developed specific recommendations and the source of this information. Developers must be transparent about how these systems are trained and validated to assure the professional community about the sources and limitations of data, training, and expertise that inform the insights from cognitive solutions.³² Ongoing work to further refine natural language processing capabilities will accelerate adoption in additional clinical settings.³⁰

Cognitive computing tools are becoming more widely available to oncology practitioners and are often supplied as Software as a Service model applications. Watson for Oncology, for example, is in use in at least one medical center in Florida and in several smaller hospitals in Korea and India.³¹ Leaders in cognitive computing anticipate wider adoption of cognitive computing tools at the health system and community provider levels as evidence of their value continues to be demonstrated by the early adopters.

The transition to the era of cognitive computing is ongoing and accelerating.³³ As clinicians use these new tools in their practices, cancer care may be the first health care field to exploit the benefits of cognitive computing. Data harmonization, systems interoperability, standardization of terminology, and data digitization continue to challenge broad implementation, but CCDS tools and approaches are available to address these challenges.

Questions remain that will require time, research, and open discussion to answer. Cognitive systems must be designed with the goal of augmenting human intelligence and complementing the provider-patient relationship. Human qualities such as moral reasoning, compassion, and empathy remain fundamental to the practice of medicine. As such, the optimal use of cognitive computing is in collaboration with health professionals at the point of care.

Workforce development and training for current and future professionals and others in "new-collar" jobs are needed to maximize the effective use of decision support. Properly designed and integrated into the clinical workflow, cognitive computing applications can augment and accelerate discovery, help professionals address ways to improve care delivery and outcomes for patients, and increase satisfaction for physicians and others on the oncology care team. After many years of promise, the benefits of cognitive technology to empower providers to accurately estimate prognosis, tailor therapy, and actively engage patients in their journey are now being realized.

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REFERENCES

1. National Cancer Institute: Cancer prevalence. <https://costprojections.cancer.gov/cancer.prevalance.html>
2. Stitzenberg KB: Oncology workforce studies: Moving beyond the head count. *J Oncol Pract* 11:38-39, 2015
3. Castaneda C, Nalley K, Mannion C, et al: Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *J Clin Bioinforma* 5:4, 2015
4. Alper BS, Hand JA, Elliott SG, et al: How much effort is needed to keep up with the literature relevant for primary care? *J Med Libr Assoc* 92:429-437, 2004
5. McGlynn EA, Asch SM, Adams J, et al: The quality of health care delivered to adults in the United States. *N Engl J Med* 348:2635-2645, 2003
6. Wang Z, Askamit I, Tuscher L, et al: Rates of guideline adherence among US community oncologists treating NSCLC. *Am J Manag Care* 19:185-192, 2013
7. Wang Z, Askamit I, Tuscher L, et al: Rates of guideline adherence among US community oncologists treating NSCLC. *Am J Managed Care* 19:185-192, 2013
8. Ferrucci D, Levas A, Bagchi S, et al: Watson: Beyond Jeopardy! *Artif Intell* 199:93-105, 2013
9. Castaneda C, Nalley K, Mannion C, et al: Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *J Clin Bioinforma* 5:4, 2015
10. Esteva A, Kuprel B, Novoa RA, et al: Dermatologist-level classification of skin cancer with deep neural networks. *Nature* 542:115-118, 2017
11. Janakiram MS V: How IBM and Microsoft are disrupting the healthcare industry with cognitive computing. <https://www.forbes.com/sites/janakirammsv/2017/01/03/how-ibm-and-microsoft-are-disrupting-the-healthcare-industry-with-cognitive-computing/#1bd572e21a92>:
12. Obermeyer Z, Emanuel EJ: Predicting the future - big data, machine learning, and clinical medicine. *N Engl J Med* 375:1216-1219, 2016
13. Somashekhar S, Kumarc R, Rauthan A, et al: Double blinded validation study to assess performance of IBM artificial intelligence platform, Watson for oncology in comparison with Manipal multidisciplinary tumour board-First study of 638 breast cancer cases. Presented at the San Antonio Breast Cancer Symposium, San Antonio, TX, December 6-10, 2016
14. Healthcare Cognitive Computing Market Analysis by Technology (Natural Language Processing, Machine Learning, Automated Reasoning, Data Extraction, Interpretation, Language Processing And Language Training, Automated Planning, Computer Vision, Handwriting Recognition/Optical Character Recognition, Speech Recognition), by End-Use (Hospitals, Pharmaceuticals, Medical Devices, Insurance), and Segment Forecasts To 2022. Market Research Report ID: 978-1-68038-719-3. San Francisco, CA, Grand View Research, 2016
15. Mendelsohn J, Moses HL, Nass SJ. A National Cancer Clinical Trials System for the 21st Century: Reinvigorating the NCI Cooperative Group Program. Washington, DC, National Academies Press; 2010.
16. National Institutes of Health: ClinicalTrials.gov. <https://clinicaltrials.gov/>
17. Parmar A: Mayo Clinic CIO on AI: This stuff is really real. <http://medcitynews.com/2017/02/mayo-clinic-cio-ai-stuff-really-real/>

18. US Food and Drug Administration: Hematology/oncology (cancer) approvals & safety notifications. <https://www.fda.gov/drugs/informationondrugs/approveddrugs/ucm279174.htm>
19. Garraway LA, Lander ES: Lessons from the cancer genome. *Cell* 153:17-37, 2013
20. Iorio F, Knijnenburg TA, Vis DJ, et al: A landscape of pharmacogenomic interactions in cancer. *Cell* 166:740-754, 2016
21. Li MM, Datto M, Duncavage EJ, et al: Standards and guidelines for the interpretation and reporting of sequence variants in cancer. *J Mol Diagn* 19:4-23, 2017
22. Roychowdhury S, Chinnaiyan AM: Translating cancer genomes and transcriptomes for precision oncology. *CA: Cancer J Clin* 66:75-88, 2016
23. Kantarjian H, Yu PP: Artificial intelligence, big data, and cancer. *JAMA Oncol* 1:573-574, 2015
24. UNC Lineberger: Partnering with IBM and Watson to accelerate DNA analysis and inform personalized treatment. <https://unclineberger.org/news/partnering-with-ibm-and-watson-to-accelerate-dna-analysis-and-inform-personalized-treatment>
25. CBS News: How Watson went from winning "Jeopardy" to fighting cancer. <http://www.cbsnews.com/videos/how-watson-went-from-winning-jeopardy-to-fighting-cancer/>
26. ASCO: The state of cancer care in America, 2016: A report by the American Society of Clinical Oncology. *J Oncol Pract* 12:339-383, 2016
27. Yang W, Williams JH, Hogan PF, et al: Projected supply of and demand for oncologists and radiation oncologists through 2025: An aging, better-insured population will result in shortage. *J Oncol Pract* 10:39-45, 2014
28. Neubauer MA, Hoverman JR, Kolodziej M, et al: Cost effectiveness of evidence-based treatment guidelines for the treatment of non-small-cell lung cancer in the community setting. *J Oncol Pract* 6:12-18, 2010
29. Herper M: MD Anderson benches IBM Watson in setback for artificial intelligence in medicine. <https://www.forbes.com/sites/matthewherper/2017/02/19/md-anderson-benches-ibm-watson-in-setback-for-artificial-intelligence-in-medicine/#6714bb8b3774>
30. Zeng J, Wu Y, Bailey A, et al: Adapting a natural language processing tool to facilitate clinical trial curation for personalized cancer therapy. *AMIA Jt Summits Transl Sci Proc* 2014:126-131, 2014
31. IBM: Jupiter Medical Center adopts Watson for Oncology. <https://www.ibm.com/blogs/watson-health/jupiter-wfo/>
32. IBM: Transparency and trust in the cognitive era. <https://www.ibm.com/blogs/think/2017/01/ibm-cognitive-principles/>
33. Musib M, Wang F, Tarselli MA, et al: Artificial intelligence in research. *Science* 357:28-30, 2017