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An exploration of Cognitive Computing in Healthcare

by

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DEDICATION

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ABSTRACT

Cognitive Computing is emerging as a powerful technology across disciplines, including healthcare. Given the novelty of this field, little is known about it within a real life context, outside of academia and the organizations developing the technology. IBM's Watson for Oncology, a Cognitive Computing application in healthcare is on the cusp of going live internationally. The purpose of this inquiry is to explore Cognitive Computing and what Watson for Oncology means to the future of healthcare provision in lay terms. Data was collected from the Watson for Oncology team and from extant documents, and analyzed using qualitative content analysis. The results outline where Watson for Oncology stands within the gamut of Artificial Intelligence applications including expert systems and decision support systems. Benefits and risks of Cognitive Computing in healthcare are explored, and some areas for future research are identified.

Key words: Cognitive Computing, Healthcare, Oncology, Cancer treatment options, Machine Learning, Natural Language Processing, IBM Watson, Big Data, Artificial Intelligence, Singularity

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Introduction and Background

Cognitive computing is a term that is gaining popularity, even though the concept itself has been around for a long time. In the simplest of terms, cognitive computing signifies the ability of machines (i.e. computers) to learn based on prior training and experience, and then apply the learning to new situations and contexts without being coded specifically to handle these new scenarios. In the world of Artificial Intelligence, these learning machines are the new wave of superior expert systems. Machine learning (what allows the system to learn without having been explicitly coded for every single scenario it will encounter) and natural language processing techniques (where computers can derive meaning from human language in its natural state) form the underlying basis of cognitive computing. Due to the ubiquity of big data, which is a key input into cognitive systems, the time is ripe for cognitive computing to flourish. As with any emerging technological trend, there is an abundance of debate on risks surrounding the (mis)use of big data. However, it can be argued that if big data is used correctly and ethically, it has the potential to have major benefits to society.

Introducing Watson

'Watson' is a cognitive computing application developed by IBM, named after its first CEO Thomas J. Watson, which "processes information similarly to a human by understanding natural language and analyzing unstructured data" (Doyle-Lindrud, 2015, p. 31). Watson made its public debut on the trivia television game show *Jeopardy!* in 2011 as one of the three contestants on the show. In preparation for participating on *Jeopardy!,* Watson underwent intense training spanning several years, using IBM's DeepQA software. Amongst other sources of data, Watson had been fed entire dictionaries, thesauri, and all the content of Wikipedia. Additionally, it was fed hundreds of thousands of past *Jeopardy!* clue-and-response pairs (Strickland, & Guy, 2013), in order for it to determine the relationships between various attributes and apply similar logic for new trivia items.

Watson went on to defeat its human counterparts on *Jeopardy!* to showcase the possibilities of 'learning' machines and their abilities to understand context (much like humans), but with the added benefit of being able to traverse millions of lines of data to look for clues in a matter of seconds.

Watson is built on the human cognition framework of Observe, Interpret, Evaluate and Decide, to emulate the learning process that humans follow (IBM Watson, 2015):

Figure 1: Human learning process

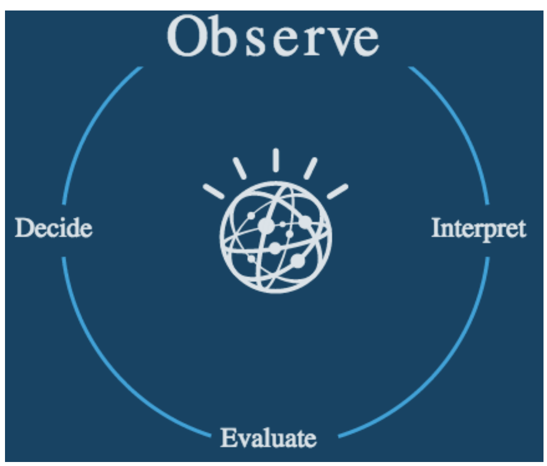


Figure 1: Illustrates the human learning process that IBM's Watson emulates.

While Watson's cognitive abilities do not make it 'human', they do give it the ability, given the requisite training, to become a powerful tool for humans to work with to complement their own abilities such as intuition, experience, and subject matter expertise.

Since Watson's win on *Jeopardy!*, IBM has been developing cognitive solutions to real-life problems in industries such as intelligence, public safety, banking, retail, and healthcare, to name a few. Of particular interest is the Watson for Oncology product, which is a result of collaboration between Memorial Sloan Kettering Cancer Center and IBM. It is one of the first Watson applications to have been developed since its debut on *Jeopardy!*.

Watson for Oncology is the first cognitive clinical decision support tool of its kind to use deep machine learning and natural language processing to assist oncologists in deciding on the best treatments for their patients. This is a significant milestone in the field of healthcare technologies. It has the potential to bring leading cancer expertise to millions of cancer patients, including those who may be living in remote locations with limited access to big city specialists.

At the time of the *Jeopardy!* show, Watson was housed on 90 IBM Power 750 servers, which gave it enough memory to comfortably host the equivalent of all known encyclopedias in the world, and didn't require the Internet to access all the information it needed (Wagle, 2011). 'Watson for Oncology', an application which is distinct from 'Watson' that appeared on *Jeopardy!*, is an iPad compatible cloud-based solution that can be accessed by hospitals and oncologists across the globe for a fee. IBM has since donated one of the original servers from Watson's cognitive computing system to the

Computer History Museum in Mountain View, California (Sweet, 2014). For the remainder of this paper, ‘Watson’ will imply ‘Watson for Oncology’, unless specifically addressing the *Jeopardy! show*.

Watson for Oncology was developed based on training provided by Memorial Sloan Kettering (MSK) oncologists (Doyle-Lindrud, 2015, p. 31), and uses machine learning and natural language processing technologies to traverse millions of textbooks, journals, structured and unstructured patient data and, in addition to the training provided by MSK, to come up with its top recommendations for treatment plans for cancer patients. The training by MSK consists of hundreds of thousands of past cancer cases of patients treated at MSK including the patient histories, comorbidities, treatment plans and outcomes. The MSK data fed into Watson is void of personally indefinable information, in accordance with U.S. laws. Watson gives each recommendation a certain confidence level, based on the richness of the underlying logic used in determining the recommendations. Watson for Oncology can also show its work by referencing and displaying the individual sources of data that it uses for each case to come up with the specific recommendations.

Doyle-Lindrud (2015) provides the following comprehensive commentary of Watson’s functioning (p. 32):

> *“When a healthcare provider inputs a clinical question into the system, Watson generates a list of hypotheses in response to the question. The program then assigns a ranking to the answers based on analyses of the data. It then generates a confidence level for each of the likely answers. Watson will notify the healthcare*

> *provider if additional information is needed and will revise recommendations based on additional data received. The healthcare provider has the option of asking Watson to supply all of the literature citations that support the computer recommendations. Although the tool had originally been programed to focus on breast and lung cancers, it has since been expanded"*.

Through its capability of answering complex questions with speed, accuracy, and increasing confidence, Watson has the ability to change how cancer care is managed. Near-term benefits of Watson may include a faster, easier treatment authorization process. Future benefits may include the possibility of matching patients to clinical trials (where patients are matched to drug trials being conducted based on their specific characteristics best fitting the purpose of the trials), and overall increasing the number of patients receiving evidence-based treatment, which will minimize the variability of treatment decisions that exist today (Doyle-Lindrud, 2015, p. 32).

Like all technologies, cognitive computing has its proponents as well as its fair share of opponents. There is ample ongoing debate on what the role of such technologies should be in society, and whether they will put the livelihood of thousands of people in "jeopardy" if machines can easily replace them.

The purpose of this inquiry is to empirically add to the field of cognitive computing by placing Watson for Oncology within the present context of big data, expert systems, and cognitive computing and outlining the current concerns and future possibilities of it within the health care field in lay terms.

Method

This inquiry was guided by the Qualitative Description method and relied heavily on document review as well as some key informant interviews. Qualitative Description (Sandelowski, 2000) provides a comprehensive summary of an event in everyday language, and draws from naturalistic inquiry, which implies studying something in its natural state, to the extent possible. There is no pre-selection or manipulation of variables to study, and no one theoretical view of the target phenomenon. In qualitative description, there is no mandate to produce anything more than a descriptive summary of an event, organized in a way that best contains the data collected and that will be most relevant to the audience (p. 339).

I am employed by IBM Canada in the Oracle PeopleSoft practice, which does not intersect with the IBM Research line of business. However, given the exposure to IBM-wide communication on ongoing initiatives and developments within the company, I have inside knowledge about Watson. In order to better understand what Watson for Oncology (in its infancy) means to the future of healthcare provision, I purposefully sampled and interviewed five members of IBM's Watson for Oncology team. The interviews were semi-structured and were conducted via Skype calls. The data collected were analyzed using qualitative content analysis, in which transcripts were coded and codes were compared with what is already known about cognitive computing and Watson. Participant quotes are used to illustrate the participants' views as it relates to the literature and documents reviewed. Ethics approval was received from the University of Alberta Research Ethics Board to conduct this inquiry.

Theoretical Context

There are a number of theories and theoretical constructs that can be adapted to help us understand Watson for Oncology's cognitive computing abilities including the Socio-psychological tradition of communication, the Social Cognitive theory, Mathematical theory of Communication and Technological Determinism.

Socio-Psychological Tradition of Communication

Within the Socio-Psychological tradition of communication, of particular interest for this inquiry is the 'uncertainty reduction principle' presented by Berger & Calabrese (1965), in which the communication environment and several non-verbal cues impact uncertainty levels in an interaction – the higher the level and clarity of cues, the lower the uncertainty. This inversely reciprocal trend can be extrapolated to Watson for Oncology. While it doesn't have the ability to pick up patients' non-verbal facial or physical cues, Watson's confidence level in various recommendations is directly related to the clarity of patterns it is able to uncover from the vast volume of training data and patient specific structured and unstructured data. The greater the quality of training and data pattern matches, the higher the confidence in Watson's recommendations – i.e. the lower the uncertainty in Watson's analysis.

Social Cognitive Theory

Bandura's Social Cognitive Theory (SCT) teachings of triadic reciprocity depict a person's ongoing functioning as a product of continuous interaction between cognitive, behavioral and contextual factors. SCT makes the assumption that people have the ability to influence their own behavior and the environment in a purposeful, goal-oriented fashion (Denler, Wolters, &Benzon, 2014). If SCT is extrapolated to Watson for Oncology, we might say that it has the ability to influence its reasoning and hypothesis/recommendation formation based on its machine learning and natural language processing, and adjusts these based on the specific context (i.e. specific patient's cancer and treatment under analysis).

Mathematical Theory of Communication

While the mathematical modeling of communication is outside the scope of this inquiry, the fundamentals of Claude Shannon's theory as it relates to human communication can help put into perspective the orders of magnitude of difference between the information processing powers of a human versus Watson for Oncology. Shannon's original theory states that "the fundamental problem of communication is reproducing at one point either exactly or approximately a message selected at another point" (Shannon & Weaver, 1949, p. 3). From further studies that were inspired by Shannon's theorems, there are estimates that human reading comprehension cannot exceed 16 bits/sec, where a bit = $1/8^{th}$ of a byte in computer terms (Krippendorff, 2009, p. 6). In contrast, Watson for Oncology traverses *millions* of lines of text in seconds, placing its 'reading comprehension' at hundreds of gigabytes per second.

Also of interest in this inquiry is Shannon's theorems around quantification of uncertainty, which illustrates a mathematical model for working out how much is already known in a particular situation, and therefore how much can be learned from new data (Thornton, 2011). This is a key factor in machine learning, which is a fundamental component of Watson for Oncology.

Technological determinism, Social Shaping & Social Construction of Technology

Any new technology or media follows a general life cycle, as is outlined by Nancy Baym in her book, 'Personal Connections in the Digital Age' (2010). Baym states that consequences of a new medium can be explained in terms of technological or social forces, or some combination of these forces. The three main frameworks described by Baym are - *technological determinism* (in which the technologies are 'causal agents and humans have little power to resist them'), *social construction of technology* (in which 'people are the primary source of change in both technology and society'), and *social shaping*, in which social and technological influences flow in both directions (Baym, 2010). Ultimately, the new medium becomes a part of daily life, which is a stage Baym calls '*domestication*' (Baym, 2010, pg. 24). For the purpose for this paper, I illustrate how I visualize Baym's theory in the Visio flowchart below:

Figure 2: Visual interpretation of Baym's theories

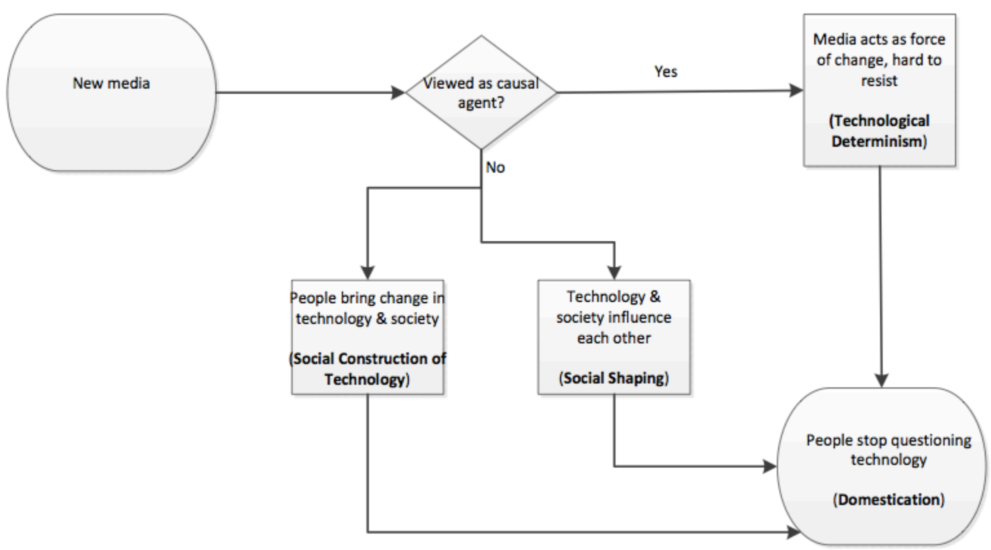


Figure 2: Illustrating Baym's theories using a flowchart

In the case of the Watson for Oncology, social shaping can be extrapolated to oncologists and Watson whereby they influence each other in the sense that MSK oncologists developed the medical content of Watson, and subsequently Watson is expected to influence other oncologists across the globe. Also, as part of Watson for Oncology's training, recommendations output by Watson are regularly vetted by MSK oncologists, and any necessary corrective reasoning is coded, thereby continuing the cycle of social (oncologists) and technology (Watson) influencing each other.

Additionally, given that cognitive computing technologies are very much in their nascence, domestication is a long way out, but if or when it does occur, opponents of the technology will likely have stopped questioning whether it will replace human specialists.

Descriptive Inquiry

In order to gain an understanding of cognitive computing applications, and to understand where Watson for Oncology stands within the gamut of Artificial Intelligence applications, the literature search and document review (information from newspapers and online media) for this inquiry includes the areas of big data, expert systems, cognitive computing, Watson, as well as the benefits and risks associated with these applications. Where the interview data collected in this inquiry relate to the literature and document review, participant quotes are provided.

What is Cognitive Computing?

Basics of Cognitive Computing. Cognitive Computing has its roots in a multi-disciplinary branch of science called Cognitive Informatics (CI), which has surfaced in the last decade. CI draws from computer science, information sciences, cognitive science and intelligence science that has led to the development of cognitive computers that perceive, infer and learn (Wang, et al., 2011, p. 1). Essentially, Cognitive Computing is the development of computer systems modeled on the human brain. It is emerging as a paradigm of intelligent computing methodologies by integrating past experiences into itself (Li, Mei, Xu, & Qian, 2015, p. 447), mimicking human ways of knowing, thinking and processing (ElBedwehy, Ghoneim, Hassanien, & Azar, 2014).

Reynolds & Feldman (2014) depict the three waves of computing. The first wave made numbers computable; the second wave made text and rich media computable and accessible digitally; and the third wave is expected to be cognitive computing, which will make 'context' computable (p. 22). Reynolds & Feldman (2014) indicate that cognitive systems take in information from multiple sources and then filter it using the lens of the specific context (p. 22). Such a profound shift in computing is also observed by Mounier (2010), whereby programmatic computing is giving way to 'cognitive' computing (p. 1).

Cognitive computing differs from conventional computing in that conventional computing follows the von Neumann architecture consisting of 5 basic components: the arithmetic logic unit, the control unit, a memory, a set of input/output devices and a bus that provides the data path between these components (ElBedwehy, et al., 2014, p. 1519). A cognitive computer, on the other hand, can be said to follow a Wang architecture, where parallel mechanisms exist for the inference engine (knowledge, behavior, experience and skills manipulation units), and perception engine (behavior and experience perception units) (p. 1519).

According to Wang et al. (2011), studies in cognitive computing reveal that "computing power in computational intelligence can be classified at four levels: *data, information, knowledge*, and *intelligence* from the bottom up" (p. 4). While traditional von Neumann computers are designed to process data and information, cognitive computers have the capability of processing knowledge to produce intelligence, mimicking the natural intelligence of the brain (p. 4). Given the abundance of data today, making sense of it all to produce business and other intelligence is coming increasingly critical.

Cognitive computing systems "make context computable" (Feldman, & Reynolds, 2014, p. 1) – "they identify and extract context features…to present information in a specific process at a specific time & place" (p. 20), and they often weigh conflicting evidence and suggest an answer that is "best" rather than simply "right" (p. 20). Feldman and Reynolds go on to say that cognitive computing systems provide "machine-aided serendipity" (p. 20), by wading through massive amounts of diverse information to find patterns and apply those patterns to respond to specific needs. By doing so, they may play the role of an assistant or coach of the user, or they may act more or less autonomously in many problem-solving situations (p. 20). Feldman and Reynolds identify a number of characteristics that define cognitive systems – these are quoted below (p.

1. *"Adaptive:*
   a. *must learn as information changes, and as goals or requirements adapt*
   b. *must resolve ambiguity and tolerate unpredictability*
   c. *must be engineered to feed on dynamic data in (near) real time*

2. *Interactive*
    a. *must interact easily with users, so that users can define needs comfortably*
    b. *may also interact with other processors, devices and cloud services, as well as people*
3. *Iterative & Stateful*
    a. *must aid in defining a problem by asking questions of finding additional source input if a problem statement is ambiguous or incomplete*
    b. *must 'remember' previous interactions in a process and return information that is suitable for the specific application at that point in time*
4. *Contextual*
    a. *must understand, identify and extract contextual elements such as meaning, syntax, time, location, appropriate domain, regulations, user's profile, process, task and goal*
    b. *may draw on multiple sources of information, as well as sensory inputs (visual, gestural, auditory or sensor-provided)".*

By meeting the above criteria, Feldman and Reynolds posit that cognitive systems leave the model of "computer-as-an-appliance" behind and seek to bring computing into a closer, fundamental partnership in human endeavors (p. 20).

Modha, et al. (2011) suggest that intelligent machines require various disciplines including philosophy, neuroanatomy, neurophysiology, computational neuroscience, supercomputing and computer architecture to unite in a coherent manner (p. 70). They capture the current state of cognitive computing in Winstonian terms by quoting “Now is not the end. It is not even the beginning of the end. But it is, perhaps, the end of the beginning” (p. 7). They break down what they perceive as the good, bad and ugly news on the cognitive computing front – “the good news is that human-scale cortical simulations are not only within reach, but appear inevitable within a decade” (p.70); “the bad news is that power and space requirements of such simulations may be many orders of magnitude greater than those of the biological brain” (p.70); “… the ugly news is that the core set of algorithms implemented within the brain are as yet undiscovered, making our task as replete with uncertainty as it is rich with opportunity” (p.71).

Watson is intended to provide recommendations for a patient’s treatment options to the oncologist using the system, similar to how a physician may seek a second opinion from a fellow physician. The key here is that these are Watson’s recommendations *to* the physician, not decisions Watson has made *for* the physician. The physician is fully expected to make the final decision on the best treatment option for the patient in front of him or her. The Watson user interface provides a validation step for the physician to indicate whether or not they agree with Watson’s recommendations, and if they do not, they can provide feedback on why/where they disagree. Participant 2 indicates the following:

> *“... so there's a validate step where they have to check this box to say yes I agree with all the things that we've extracted... if you disagree... we allow them to override it and enter the value that is actually accurate... because as anybody who*

> *works in this field would tell you... the NLP stacks are never going to be 100% accurate... due to language inconsistencies and typos... abbreviations and all that sort of stuff... so nobody will ever claim that we can have sort of a 100% fidelity on NLP... so we always will give the oncologist the opportunity to review what was extracted and approve and validate what we found".*

Often, teaching hospitals in larger urban cities will have specialists for various cancers within their own institutions. Smaller or more remote community hospitals may have fewer oncologists on staff. Such cases may provide the grounds for deriving maximum benefit out of Watson for Oncology, by leveraging the expertise of MSK oncologists via their training of Watson. The potential benefit to the community hospitals and the patients residing in remote geographies is enormous, as they would not have to physically travel to MSK in order to get a 'second opinion' from an MSK oncologist. Participant 1 explains this as:

> *"Essentially selling it as an expert system, designed to be kind of a learned colleague, or allow a physician to get a second opinion from MSK without having to go to MSK. Kind of share that knowledge and expertise".*

Participant 4 indicates:

> *"... out in the community, community hospitals, where you have a general oncologist, who knows a little about quite a few cancers, but not, no in depth knowledge about any one of the cancers, they have said they would find that useful. They would, given it's trained by MSK, find it useful. They would trust it to give them, say, dosing information that might go beyond what they would typically do, because they want to play it safe... but if MSK says it's ok... then,*

and it gives better results for the patient, then they may try that. That's where there's a fair bit of value... it's more in the community setting, than in the academic and large hospitals".

Another overarching benefit to using Watson for Oncology is that Watson is likely much more up-to-date than any one physician can be at a point in time, given the enormous amount of information Watson houses from a content provider perspective, and of course the fact that it takes Watson a few mere seconds to traverse it all, as is seen from Participant 1's quote below.

"So everything from curated information and rationale from MSK's experts, Watson Oncology has a corpus of almost 15 million pages of text so it's over 300 medical journals and 200 medical textbooks… so all of that evidence... Watson is breezing through and pulling out those that would be relevant to a patient and the particular treatment option that that physician might be looking at".

Participant 1 indicates that the time saved thanks to Watson's cognitive powers is expected to free up the physician to spend more quality time with the patient:

"Physicians will have more time... you know they'll spend less time trying to read through a record ... and trying to cross all information and trying to put everything together... and spend more time with their patient and quality care... and help to align around the best standards of care".

Watson for oncology uses a browser based user interface, designed by IBM. At this time it is a text-based interface and can be used on an iPad. The interface was built based on the requirements of and feedback from MSK. The user interface is intuitive and since it can be used on iPads, it gives the physicians the ability to move as needed within the hospital while continuing to work with Watson for Oncology, and also provide feedback using the feedback feature. Below are some screen captures of the user interface, showing a page of sample patient cases in the evaluation (beta) version of Watson for Oncology, followed by a sample patient summary and sample treatment plan.

Figure 3: Example of IBM Watson for Oncology user interface screen for sample patient cases

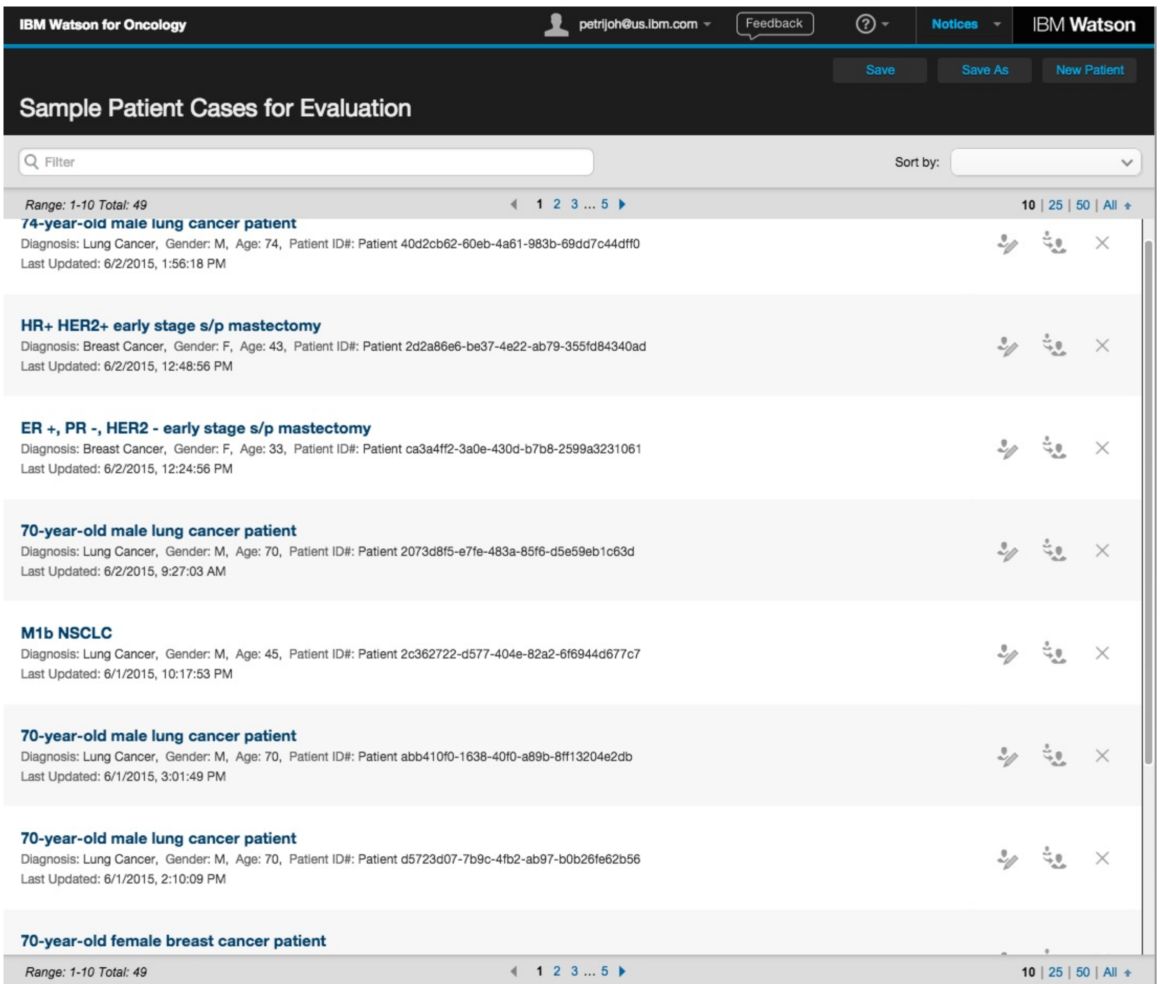


Figure 3. Shows how a list of sample patient cases from a test (beta) system are displayed on the user interface.

Figure 4: Example of IBM Watson for Oncology user interface screen for patient details

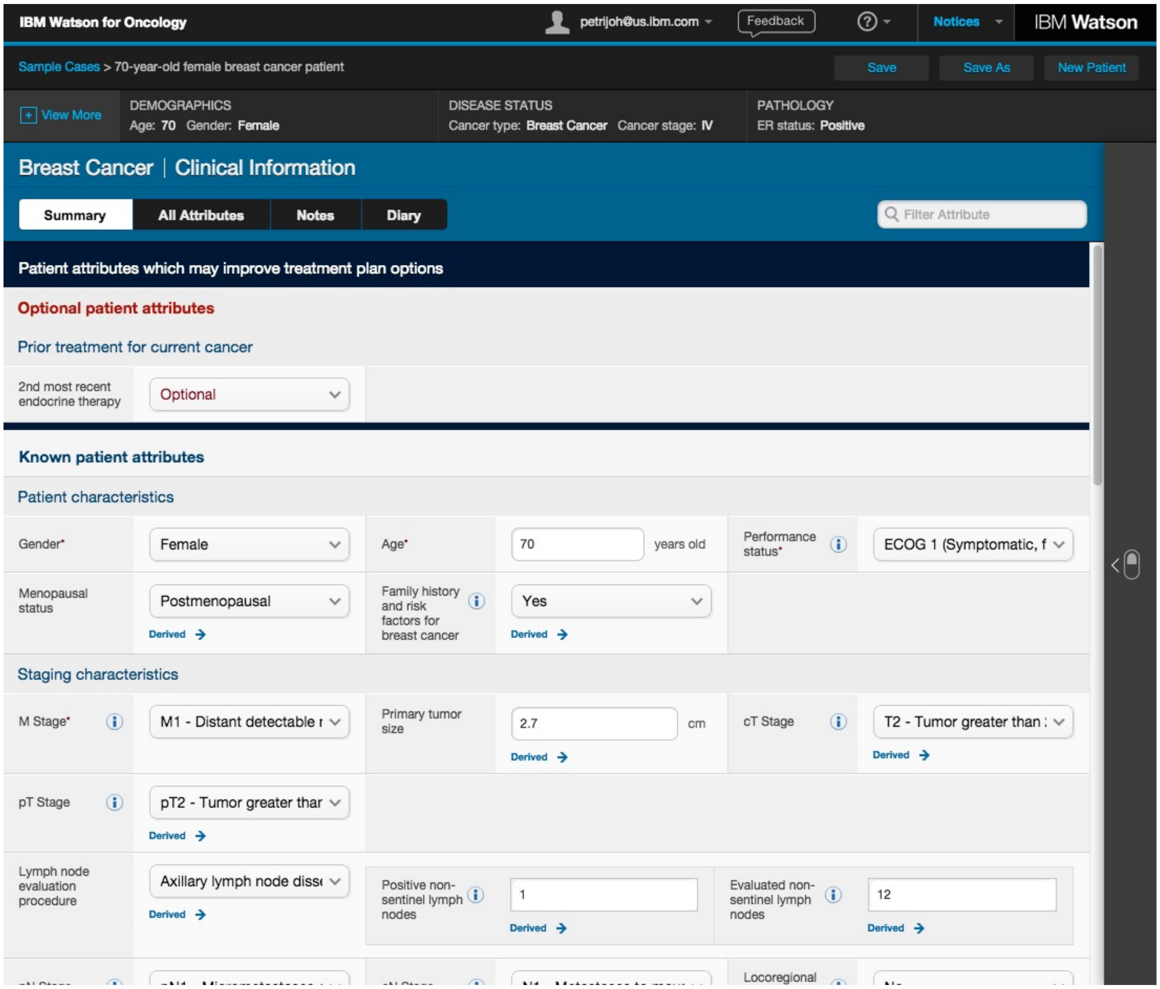


Figure 4: This example shows how patient details are displayed on the IBM Watson for Oncology user interface from a test (beta) system, including patient characteristics and cancer specific characteristics.

Figure 5: Treatment Options image from IBM Watson for Oncology test (beta) system

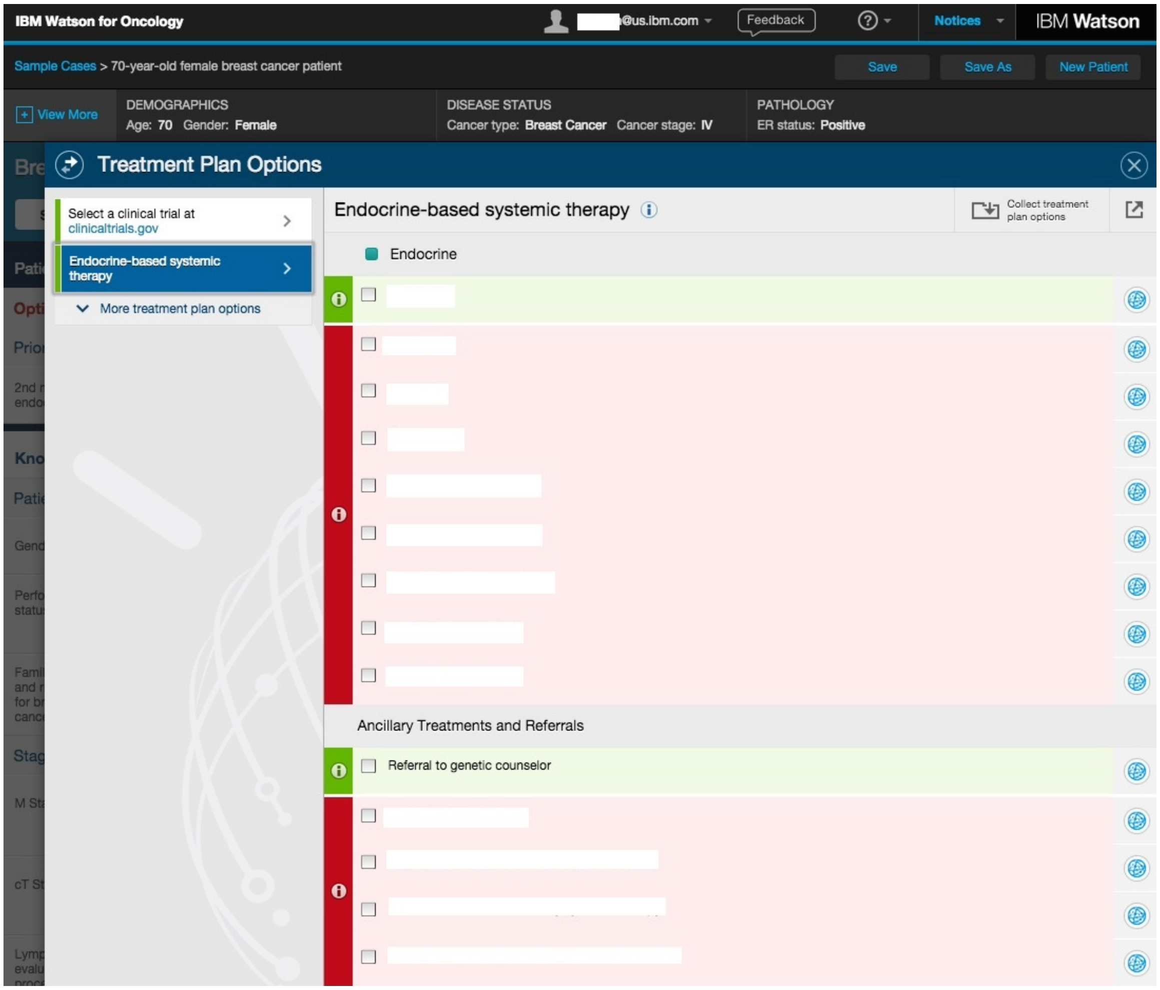


Figure 5. Illustrates how IBM Watson for Oncology would list the various treatment plan options for a specific case.

Watson processes both structured and unstructured data, and has been programmed to distinguish between the two, so it knows when to run its NLP stack to process unstructured data such as patient notes, versus when to run its Application Programming Interface (API) to export structured data from electronic medical records - these two can also work together. The patient Summary tab on the user interface demonstrates this feature where it provides information on where certain values were derived from, as seen the Summary screen capture above. Participant 2 says:

> *"…. so you can say, we got patient age and gender from the structured, and some lab values from the structured… but then we've combined that with some other family history and other factors from the unstructured. We've combined those two to come up with a full patient summary".*

The Watson for Oncology user interface also has a Rationale tab (screen capture shown below), which provides details of where it got the information for a particular recommendation, which is extremely valuable information for the physician.

Figure 6: Rationale screen from IBM Watson for Oncology test system

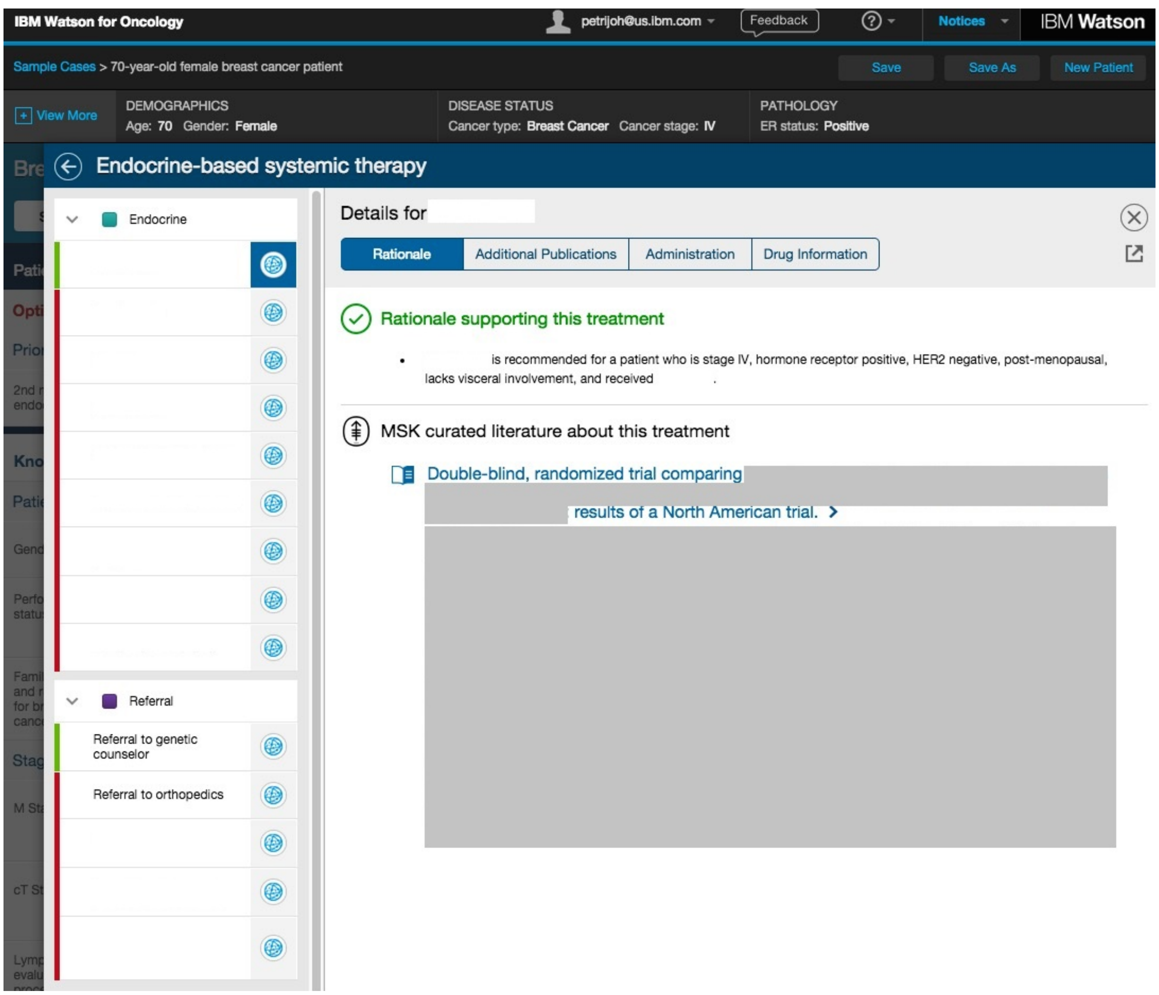


Figure 6. Illustrates how Watson would display its rationale behind a specific treatment plan.

On the user interface feedback so far on Watson for Oncology, Participant 4 indicates:

> "*When we get feedback from the hospitals, their comments about sort of the ease of use, ease of learning, how intuitive the interface is… all were quite positive*."

Other cognitive computing applications. While artificially intelligent machines such as smart phones, personalized advertisements/marketing and self-driving cars are becoming ubiquitous elements today, applications that meet the defining characteristics of cognitive computing systems discussed above are fewer and farther apart. In addition to Watson for Oncology, IBM is developing a suite of Watson products for different industries – including Watson Discovery Advisor, which is a heavy duty research tool with potential applications in intelligence, oil & gas, life sciences and pharmaceuticals, finance and banking, as well as more fun undertakings such as experimenting with recipes as 'Chef Watson' does. Also along the cognitive trajectory, IBM has offerings such as Watson Policy Advisor used in clinical trial matching, and Watson Genomics Advisor.

In the literature search and document review for this inquiry, no other cognitive computing applications specific to oncology were found. Three other non-oncology cognitive applications that were found in the literature and are discussed next.

Google's "*conversational search*" allows the user to build on their previous questions without having to reiterate parts of the first question (Mims, 2014). It will understand the context of a question such as *how about the following day?,* when the preceded by a question like *what is the weather like today in Timbuktu?*

Amelia, is a cognitive computing application developed by IPSoft, that learns from textbooks, conversation transcripts, email chains amongst other text to search for answers to IT infrastructure questions that exist within the texts. Unlike Watson for Oncology which functions as an advisor to humans, the goal for Amelia is to replace humans especially in customer support type of situations (Mims, 2014), where answers to questions may be repetitive and readily appear in texts.

A joint initiative by Cognitive Scale and Deloitte Consulting aims to catalyze the shift in the U.S. healthcare system from ‘volume based’ to ‘value based’, thereby playing a role in transforming to a consumer-centric healthcare system. They plan to leverage Cognitive Scale’s open standard cognitive cloud (hosting healthcare models, graphs and data sets for diseases, symptoms, medicines, side effects, doctors, reviews, pharmacies, medical images, physicians notes from electronic medical records, as well as social and device data) to provide healthcare organizations greater data security, sovereignty and transparency while maintaining maximum flexibility and control over how and where data are stored and accessed (Cognitive Scale and Deloitte Join Forces to Drive Consumer Centric Healthcare Through Cognitive Computing, 2015).

Cognitive computing markets are growing rapidly. The North American region currently has the largest market share and highest growth rate, followed by Europe and the Asia-Pacific region, while the Middle East, Africa and Latin American markets are still in the introductory stage. The forecast is for the cognitive computing market to grow from $2,510.4 Million in 2014 to $12,550.2 Million by 2019, representing a compound annual growth rate of 38.0% from 2014 to 2019 (Cognitive computing market worth $12,550.2 million by 2019, 2015).

Watson for Oncology is closely aligned to the guidelines published by local authorities such as the National Comprehensive Cancer Network (NCCN) in the United Sates or Canadian Cancer Care of Ontario in Canada, as well as any other legal requirements that are in place in various international geographies.

Guidelines and rules are built into Watson, however the product also has a heavy machine learning and natural language processing component as seen above.

Other clinical decision support systems within the realm of healthcare are primarily guidelines oriented, such as those built by insurance companies (payers) in the U.S. partnered with software development companies. These are popular in the U.S. largely due to the fact that reimbursement of treatments are directly linked to whether or not they are from the payer's approved list of treatments. Participant 1 indicates:

> *"So some of the clinical decision support system tools are partnered with these payers... so essentially a payer would say you know, for disease X, you can give that patient treatment A, B or C. And if you give them A, B or C, then we are going to approve it. So what they actually do is they partner with software developers to make tools available that they give to physicians to kind of help guide them a little bit. So it is pretty pathway based. So a physician will know what the treatment options may be or they might get funding for, for most of their patients based on those guidelines".*

In addition, Participant 1 indicates that are also third party applications such as in-house platforms built by hospitals that are not directly linked to the payers.

> *"So there are some third party software development companies, some EMR companies that may build some applications, and then maybe even hospitals who are large providers. So if you think of a really large hospital in the U.S. or Canada, who might build an application. Most of those tend of be fairly small, in the sense that if a provider is building an application, usually they are doing it in-house... they may have a few other people... mostly in their network of providers who may use it. But for the most part, they don't have a lot of market penetration. So again, those ones are similar and truly just about trying to align their hospitals or doctors around some sort of standards or what they see as a practice for care".*

Other non-cognitive platforms also exist such as NCCN's trees or pathways on treatments for specific sets of characteristics such as stage of cancer, and treatment option information from content developers.

Cancer care products by Flatiron in the U.S. include data-driven technologies, and joint initiatives with NCCN to bring workflow and analytics based products. These might be the closest competitors to Watson for Oncology, however at least for the time being, they don't appear to be a true competitor yet on the cognitive learning level. Participant 5 says:

> *"… there are competitors... Flatiron participates here ... there are a number of others... Due to the approach we've taken that's unique, in employing Watson's Cognitive capabilities to identify best set of treatments for a given patient, based*

> *on training with MSK, and capitalize their clinical expertise and patient cases to inform the training of Watson. So I think the approach is unique and that the result is a better experience for both physician and patient as part of the recommendations process. There are other players in this space, which is a good sign… you want to have competition… so you know the market has an opportunity".*

Given that cognitive computing is so new in the healthcare field, competition will likely increase in the years to come.

Artificial Intelligence, Expert systems, Decision Support Systems

The concept of Cognitive Computing has been around for a long time, and can be traced back to efforts within Artificial Intelligence in the 1950s where intelligent systems began to be developed as systems that could be taught a set of parameters, but could not make decisions or come up with solutions that were not pre-programmed (ElBedwehy, et al., 2014, p. 1519). The term "Artificial Intelligence" itself originates from a 1956 Dartmouth summer research project (Armstrong, Sotala, Ó hÉigeartaigh, & Seán, 2014, p. 327). Development of 'neural networks' aided the advances within Artificial Intelligence that led to the advent of Cognitive Computing, allowing computers to organize information to make decisions based on series of events and experiences (p. 1519.)

The key difference between cognitive systems of today and earlier machines designed to think like humans, is that today's cognitive systems are not being programmed to perform specific tasks alone. They are being built to learn autonomously by interacting with data and humans to perform new tasks; they are intelligent, personalized and constantly learning about the environment, the users and their preferences and expectations (Basson, 2014, p.8).

Cristianini (2014) discusses ‘paradigm shifts’ in the world of Artificial Intelligence based on Thomas Kuhn’s definition of the term. Kuhn coined the term ‘paradigm shift’ in 1962, and defined it as occurring “when a scientific community changes its values, goals, and methods, and this is reflected by the replacement of the success stories that are used to define the field” (p. 37). Where Cristianini defines Artificial Intelligence (AI) as the “quest for automation of intelligent behavior” (p.37), he indicates that in AI, we are now in a ‘data-driven’ or ‘statistical AI’ paradigm, exemplified by a range of success stories from statistical machine translation, information retrieval to computer vision (p. 38). In this current paradigm of AI, it is possible to transcribe speech, translate text and recognize faces in real applications, made possible by the deployment of data intensive methods (p. 38). These methods include machine learning and natural language processing (discussed below). Cristianini contrasts the current paradigm to previous ones in AI, calling them “knowledge-driven”. These saw intelligent behavior as the result of “symbolic reasoning, where reasoning was in turn framed as a search problem” (p. 39). In this paradigm, early examples of ‘expert systems’ can be found which needed large amounts of “symbolic knowledge about the world” (p. 40). This led to “an explosion in the need for increasing amounts of symbolic knowledge to be encoded to make these systems relevant” (p.40). Here, the power of the AI algorithms was not in the reasoning methods they used, rather the knowledge base they had. An example of this was the expert system called Mycin, which recommended specific antibiotics to give a patient based on their systems (p.40). The problem quickly became the lack of ability to assemble vast knowledge bases (p.40), thus limited the use of such expert systems. The important takeaway from Cristianini (2014) is that the emphasis moved from 'knowledge' to 'data' when shifting to the current AI paradigm, where data became central in the new narrative (p.40). Cristianini provides a powerful visualization (p. 40) of the paradigm shift in the following word cloud images -from article titles in the proceedings of the International Joint Conferences on Artificial Intelligence in 1981 and then in 2011:

Figure 7: Article titles in the proceedings of the International Joint Conferences on Artificial Intelligence in 1981. Cristianini (2014, p. 40)

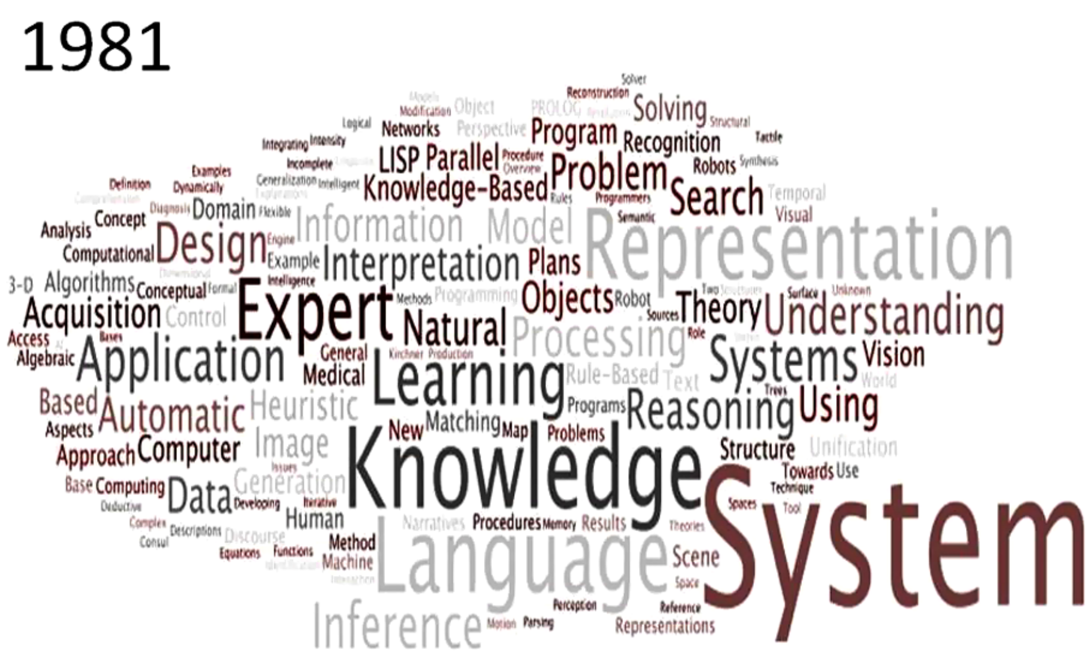


Figure 7. Illustrates the titles that appeared most commonly in the proceedings of the 1981 International Joint Conferences on Artificial Intelligence. The more the titles appeared, the bigger the font in the figure. "System" appears to have been the most used

title in 1981.

Figure 8: Article titles in the proceedings of the International Joint Conferences on Artificial Intelligence in 2011. Cristianini (2014, p. 40)

Figure 8. Illustrates the titles that appeared most commonly in the proceedings of the 1981 International Joint Conferences on Artificial Intelligence. The more the titles appeared, the bigger the font in the figure. The most common title shifted to “Learning” in 2011.

***E*xpert Systems versus Decision Support Systems.** Traditional expert systems function based on the computer programming logic of ‘If-Then’ statement pairs, where the system finds a match, executes a rule, and then starts looking for next executable rule

(Borthick, & West, 1987, p.11). For each pair, the systems looks for –'If <condition exists> Then <specific conclusion/execute certain action>'. Expert systems typically consist of rule sets, a fact database, and a control structure for directing the operation of rules on facts (p.11). Borthick, & West posit that the appeal of expert systems stems from the opportunity they present for capturing and disseminating scarce and costly expertise in organizations, where experts themselves can also benefit from the consistency and completeness provided by these systems (p.11). Because the rules in an expert system are pieces of a human expert's knowledge that have been codified, every time a new rule has to be added, the code itself needs to be changed, which risks introducing errors (p.12). Borthick, &West see the following as limitations of expert systems (p.12):

1. Narrow range of expertise
2. Fragile behavior – knowledge base is finite, there maybe problems the system cannot solve
3. Difficulty in representing knowledge
4. Disagreement amongst experts
5. Restricted input/output formats
6. Possible lack of user acceptance

The benefits to expert systems identified by Borthick, &West are as follows (p.13):

1. Preserve, replicate and distribute expertise
2. Gain new insights into the decision process – by deconstructing the expert system's decision making process
3. Support performance in complex domains

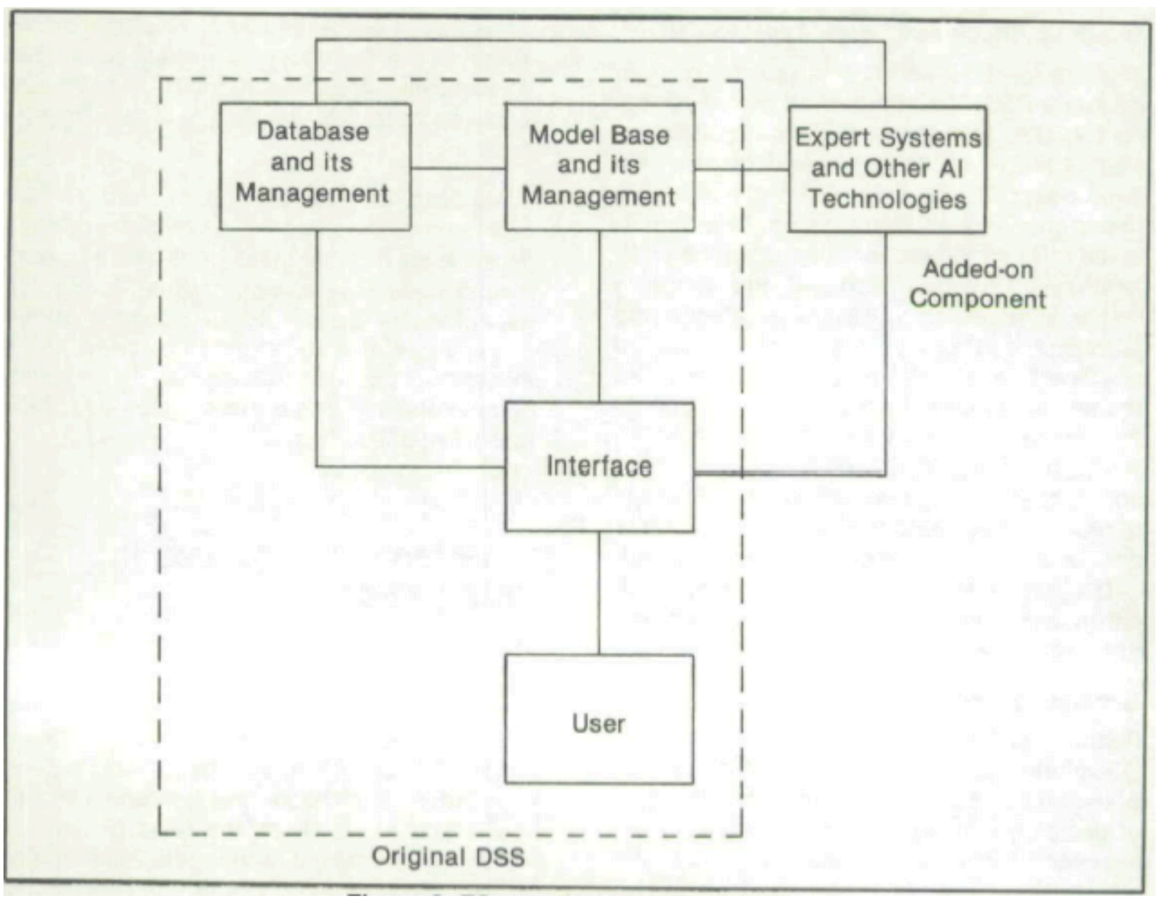
4. Maintain consistency of performance
5. Increase productivity
6. Achieve training efficiencies

Overall, expert systems can reduce costs and improve decision-making depending on the choice of applications and the effectiveness of their implementations (p.16).

Decision Support Systems are "interactive, computer-based information systems that utilize decision rules and models, coupled with comprehensive databases" (Turban, & Watkins, 1986, p.122). Within the spectrum of AI systems, Decision Support Systems are a distant cousin of Expert Systems. The differences between Decision Support Systems (DSSs) and Expert Systems (ESs), as summarized by Turban & Watkins as shown in their table below (p.123):

Attributes	DSS	ES
Objectives	Assist human decision maker	Replicate a human advisor and replace him/her
Who makes the recommendations (decisions)?	The human and/or the system	The system
Major orientation	Decision making	Transfer of expertise (human-machine-human) and rendering of advice
Major query direction	Human queries the machine	Machine queries the human
Nature of support	Personal, groups, and institutional	Personal and groups
Data manipulation method	Numerical	Symbolic
Characteristics of problem area	Complex, broad	Narrow domain
Type of problems treated	Ad-hoc, unique	Repetitive
Content of Database	Factual knowledge	Procedural and factual knowledge
Reasoning capability	No	Yes, limited
Explanation capability	Limited	Yes

As such, the key difference between the two types of systems is that a DSS is meant to assist human decision-making, while an expert system is meant to replicate the human expert (p.123). While the systems are often distinct, the two can be integrated to reap benefits of each system's contributions. In order to maximize integration benefits, an expert system can be added on as a component of a DSS to result in a structure depicted by Turban & Watkins as follows (p.129):



This allows the DSS to reference the ES as necessary.

Watson for Oncology falls under the general umbrella of Clinical Decision Support Systems, however, is set apart from a typical decision support systems by its massive and constantly growing machine learning model as well as its deep natural language processing (NLP) capabilities. Watson shares the three broad components of an expert system – knowledge base, inference engine and user interface, however, the middle layer is a hybrid of rules-based reasoning, as well as Watson's defining feature, which is the machine learning component. Participant 2 says:

> *"And that to me is the biggest difference between a cognitive learning system and just a preprogrammed decision support system. In that it's learning as it goes, it's using machine learning techniques to determine what types of answers are appropriate in a certain setting based on the training it's been given... and that can evolve over time as it gets more training"*.

Watson learns by examples, and these examples come in the form of training datasets from the foremost cancer specialists in the world, oncologists from Memorial Sloan Kettering Cancer Center in New York City. The datasets contain hundreds of thousands of cancer cases including defining characteristics such as patient age, gender, cancer stage, tumor size, lab results, family history, comorbidities, drug history, drug sensitivities to name just a few of the dozens of attributes Watson ingests; along with the treatment plan that an MSK oncologist would provide in that particular setting.

Machine Learning

Mounier (2014) points out that smart systems and data mining have been around for a while, but what is different now is the new engineering approaches, not so much new algorithms (p. 1). In this section on machine learning and the next on natural language processing, new approaches are outlined in lay terms.

The idea in machine learning is for the machine to learn from experience, and apply the learning in future situations. The term ‘machine learning’ refers to a family of mathematical and statistical methods including “classification trees, random forests, neural networks, support vector machines, and lasso and ridge regression to name a few”, that have historically been focused on predictions (Crown, 2015, p.137). Crown explains the basic approach with all machine learning is to (pp. 137-138):

> *“… segment the data into learning and validation data sets to develop highly accurate classification algorithms. Once the algorithms have been developed, they are applied to the full data set to do the prediction. The idea is that one should be able to perform these classifications without human intervention, and the methods should also be able to operate on very large data sets and be very fast… this process of using learning and training data sets is used to develop prediction algorithms”.*

The actual logic followed subsequently is explained by Crown as follows (p. 138):

> *“The idea is to take the initial dataset and randomly split it into several (typically 5 or 10) subsamples. For each subsample that is held aside, the classification algorithms are built on each of the other remaining subsamples. Once the algorithms have been built, each is used to predict the membership prediction error that is associated with each one of the subsamples. Finally, a sum of prediction errors is calculated over all subsamples. Using this approach, one can evaluate different machine-learning methods simultaneously and then compare the average errors associated with each model to determine which method performs the best. The process is completely automated. The best algorithm is*

applied to the entire dataset —typically to do a prediction".

Given the above, machine learning appears to pass Descartes' test for 'real intelligence' as described by Bringsjord & Govindarajulu (2012) - "to follow Descartes in testing for real intelligence we must present you with a problem that you have never seen before, and wait to see whether you can provide a solution by means that you invent on the spot" (p. 466).

Machine learning typically is only as good as the data it is given for the training. Simply having a lot of data does not protect against bias; however, linking the various data sets in a situation should mitigate the concern (Crown, 2015, p.140). Contact with "real problems, real data, real experts, and real users can generate the creative friction that leads to new directions in machine learning" (Brodley, Rebbapragada, Small, & Wallace, 2012, p.22).

The training of Watson is an ongoing joint initiative between Memorial Sloan Kettering & IBM. The MSK treatment plans in the datasets essentially form what Watson learns to be the 'right answers' or decision points for the given scenarios, and machine learning helps Watson determine the right weight to put on the various factors. Watson uncovers and learns patterns from these training cases, and when a new scenario is fed into Watson, it then runs it against its training to come up with recommendations for the patient's treatment plans. The idea is for Watson's recommendations to match what an MSK oncologist would recommend in the same setting. Because Watson's learning is an ever growing process, deviations in Watson's recommendations are taken to MSK as part of the regular meetings with IBM to help understand why Watson got the answer wrong, and the oncologist's feedback is then built as a new feature back into Watson, or a bug in the natural language processing is fixed. This error analysis process followed by feature engineering continually refines Watson's machine learning model. Constant flow of feedback between MSK and IBM also ensures medical knowledge is not lost in translation when IBM codes Watson with the expertise from MSK's oncologists. Participant 3 explains:

> *"… machine learning is basically learning by example. So just like a child learns what's right and what's wrong... they have to do the right thing and do the wrong thing and then be corrected or praised appropriately… The idea behind machine learning is that there are too many variables to take into account in a rules engine… so you use machine learning to let it learn by example... and on hundreds of thousands of cases that have happened before that it learns from. And then in the end you get a model that has those weights... set appropriately… and then you run test cases through it... and then it uses those weights to look at each of those features and then comes up with a recommendation… and then it either gets it right or wrong… and if it gets it wrong... then we go through and figure out why it got it wrong… and maybe have to adjust the training data… or add new features that it takes into account."*

In the initial training phases, Watson was at a 70% accuracy, and has since worked its way up to about 90% accuracy at present.

Watson is kept up-to-date on current medical literature via quarterly updates from publishers, data providers and partners. This is part of Watson's evidence ingestion process. Data ingested by Watson can then be used to build knowledge graphs, or database tables as required. Indexes are built, so that users can search on Watson's corpus of data. Articles returned in searches can then produce feature scores contributing to the learning model.

Natural Language Processing

Traditional information retrieval or search systems do not understand context or metaphors (Barnden, 2008, p. 121). They return documents based on keywords alone. They generally do not directly provide answers to questions posed by users; therefore, the users are then left to extract the answers they are looking for from the documents themselves. Natural language search or processing was developed in response to this type of problem (Hariri, 2013, p. 287).

Natural Language Processing (NLP) began in the 1950's as the intersection of AI and linguistics, and has undergone transformations most notably in the 1970s and 1980's to bring us to the current state of machine learning and data-driven approach to NLP (Nadkarni, Ohno-Machado, & Chapman, 2011, pp. 544 -546). Tasks performed by NLP are portrayed as low-level and high-level by Nadkarni et al. summarized below (p. 545):

Low-level NLP tasks include:

1. Sentence boundary detection
2. Tokenization – identification of individual tokens i.e. words, punctuations in a sentence
3. Parts-of-speech assignment to individual words
4. Morphological decomposition of compound words – especially important in medical terms which often need to be decomposed for comprehension

5. Shallow parsing (chunking) – identifying phrases from constituent part-of-speech tagged tokens
6. Problem-specific segmentation – segmenting text into meaningful groups, such as sections including Chief Complaint, Past Medical History etc.

Higher-level tasks built on low-level tasks are problem-specific and include:

1. Spelling/grammatical error identification and recovery
2. Named entity recognition – identifying specific words or phrases and categorizing them e.g. locations, diseases, genes, medications, etc.
3. Word sense disambiguation – determining correct meanings
4. Negation and uncertainty identification – identifying whether a named entity is present or absent.
5. Relationship extraction – determining relationships between entities or events such as 'causes', 'treats', 'occurs with', etc.
6. Temporal inferences/relationship extraction – e.g. inferring that something has occurred in the past or may occur in the future
7. Information extraction – identifying problem-specific information and transforming into structured form.

The low-level tasks typically execute sequentially before the higher-level tasks can commence (p. 548).

Two popular data-driven NLP models discussed by Nadkarni et al. are the Hidden Markov model (HMM) and N-grams model, where the HMM is based on inferences, pattern matching and training (p. 547) and N-grams are essentially a kind of multi-order

Markov model (p. 548). N-grams have several uses including suggested auto-completion of words or phrases using searches, as seen on Google's search interface; spelling correction, speech recognition and word disambiguation (p. 548).

No NLP method is perfectly accurate, and errors in one step propagate to the next (p. 548). "One way to address this problem is to use alternative algorithms and contrast the final results obtained" (p. 549).

In the field of healthcare, Electronic Medical Records (EMRs) hold immense amounts of data in both structured/standardized and (majority in) unstructured formats such as physicians' notes in natural language, indicating how crucial NLP is for cognitive computing in healthcare (Wu et al., 2013). Wu et al.'s illustration of NLP (p.11) shown below nicely builds on Nadkarni et al's data extraction logic described above – it shows where in the text information such as the symptoms and temporal context is derived from in this example:

Figure 9: Wu et al.'s illustration of NLP (p.11)

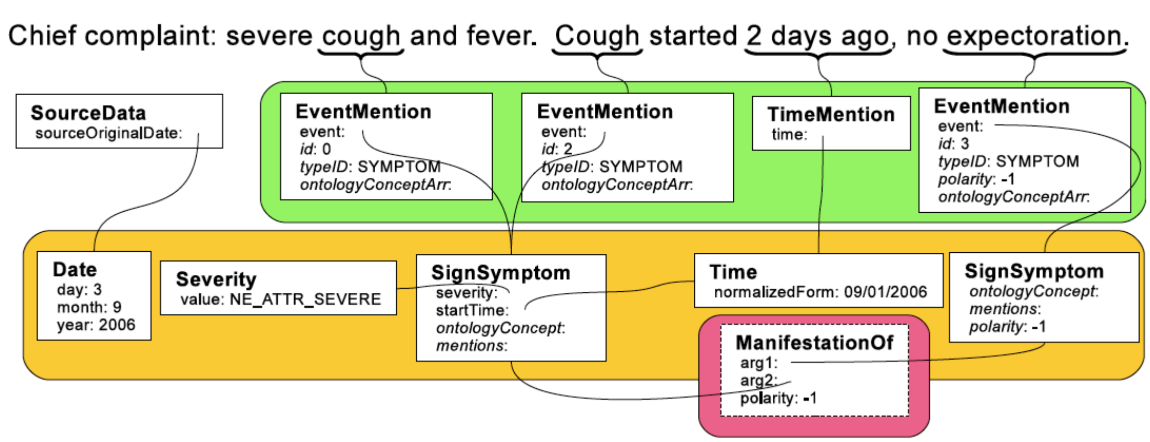


Figure 9. Illustrates an example of where in the source text, information such as the

symptoms and temporal context are derived from.

NLP enables generation of patient-specific assessments or recommendations in clinical DSSs, by matching individual patient characteristics to the DSS's knowledge base, which ultimately aids physicians in decision-making (Demner-Fushman, Chapman, & McDonald, 2009, p. 760).

Big Data and Analytics

In a world where every interaction is tracked digitally, there are both tremendous opportunities and pressures on speed and innovation (Mounier, 2014, p. 14). The advances in data generation have led to the term "Big Data" being coined by the Gartner Group (Kuiler, 2014) and is defined by them as "high-volume, high velocity, and/or high-variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization" (Shah, Rabhi, & Ray, 2015, p. 352).

The volume, velocity and variety (3 V's of Big Data) require special techniques and technologies for analysis and inference; and if exploited effectively, can bring much value in the form of cost savings, improved decision-making and better productivity in fields such as healthcare, finance, education, national security, emergency management, weather forecasting, etc. (Shah et al., 2015, p. 351). Shah et al. elaborate the significance of Big Data in healthcare by saying:

> *"This … is especially pronounced in healthcare where the use of electronic health records can generate huge volumes of high velocity data that must often be analyzed in real time to make patient-related decisions such as diagnosis,*

> *treatment plans, medication prescription, etc. Moreover, with an increasing focus on holistic care approach, healthcare practitioners require patient data from across different health domains to make informed decisions"* (p. 351).

In healthcare, the last decade has witnessed an extraordinary growth in data-driven medicine resulting from structured and unstructured data in Electronic Health Records (EHRs), digital imaging and procedures, lab results, real-time availability of sensor data, and the introduction of genomics-related projects (Kuiler, 2014, p. 311). Kuiler depicts the continuum of data→information→knowledge by defining data as "a fact or individual piece of information", information as "creation of meaning" and knowledge as "the understanding gained from analyzing information" (p. 312). This highlights the importance and critical need of technologies such as cognitive computing to aid physicians in making sense of all the data around them to make informed decisions for their patients. Sometimes, the information presented to physicians as a result of cognitive technologies can be surprising - "Meaningful things can pop out that you hadn't expected… Hiding within those mounds of data is knowledge that could change the life of a patient, or change the world" (Bottles, Begoli, & Worley, 2014, p. 6). As indicated by Goth (2012), "Real patients have more than one disease, and the patient records give us an opportunity to discover comorbidities and disease correlations - not only those that co-occur but also disease trajectories, that is, those that come before others. The message should be that we can start disease profiles of real patients instead of doing what medicine has done for hundreds of years, studying people disease by disease" (p. 15).

Big data is marked by ambiguity, conflict and inconsistency (Kohn et al., 2014), and as much as 80% of the world's healthcare data is dubbed as unstructured (p. 154). As such, Kohn et al, go on to say "Big Data required cognitive computing, using data-centric, probabilistic approaches to data, where, after a fashion, the computer "thinks" based on human reasoning, cognitive computing identifies complex associations, draws inferences, and learns from experience. It is designed to navigate complex, dynamic, uncertain environments" (p. 154). In other words, cognitive computing is likely the solution to our big data infested world.

Kohn et al, do caution on the limitations of such tools and Big Data in general. These and other critiques of big data, AI and cognitive computing follow in the next section.

Big Data, AI, Cognitive Computing – Some Caveats and Concerns

Caveats. Kohn et al. caution that "analytic tools are not the panacea for problems in healthcare. They offer nothing in isolation… An additional limitation to the role of analytics is the availability and quality of information… The variability or uncertainty that is inherent in big data represents another limitation. Published articles can be contradictory or flawed. Data in EHRs can be inconsistent or erroneous." (p. 161). Additional quotes from Kohn et al. highlight issues surrounding big data analytics (p. 161):

> *"Big data has inherent limitations. The process of looking for patterns in big data will yield a large number of statistical associations. However, many of them will be inconsequential with no discernible causal relationship to the outcome being studied. The number of meaningful relationships may be orders of magnitude smaller. Evaluation and feedback from domain experts can help address this problem by helping identifying the meaningful relationships. The hype surrounding big data, creating unachievable expectations, is a problem in itself."*

There are instances where physicians disregard or do not use clinical DSSs, which hinders the progress of such systems, as they are only valuable if used, and get better with increased use and training (p. 161). Expert systems have less breadth of scope and flexibility than human experts, which is a common criticism of such systems, as they may create unrealistic expectations (Bobrow, Mittal, Stefik, 1986, p.880).

Cristianini (2014) cautions about not turning our eyes away from aspects that cannot be conquered by the sheer power of 'big data' by focusing on only the tasks that can be done with this paradigm and "ignoring those that defy its power as these will just wait for the next paradigm shift" (p. 43). Kohn et al. make the argument that "The need to compensate for data limitations is one of the reasons that all these tools thrive on more data. More data gives them more opportunity to identify and compensate for the flaws. The necessity of managing such conflicted and inconsistent data is what mandates cognitive computing" (p. 161).

Based on both pros and cons of big data that exist, Bottles, Begoli, & Worley (2014) provide the following wise concluding remarks (p. 12):

> *"Big data is a disruptive technology that will transform health care, and physician leaders would be wise to use data analytics to decrease per capita cost and increase the quality of the care they deliver to their patients. They also need to recognize the pitfalls and complexity of this new approach. One cannot simply combine multiple databases, crunch the numbers, and magically uncover actionable correlations that can automatically and unthinkingly be implemented. Human beings with domain expertise and knowledge of the problem being investigated have to oversee the collection of the data, the asking of the right*

questions, and the interpretation of the results in order to make the best use of this disruptive technology tool."

Concerns. Safe de-identification of Big Data is a concern that is critical in healthcare, as is discussed by Warner (2013) – "Health care organizations and patients continue to have concerns with patient data collection and de-identification for subsequent use. Therefore, the ability to support the de-identification of patient data for subsequent uses such as research, population management, and disease control while maintaining patient privacy must be strong to ensure all safeguards are in place and that HIPAA is met" (p. 63), where HIPAA is the Health Insurance Portability and Accountability Act in the U.S.

In building the knowledge base of expert systems, the risk of losing important subject mater expertise may present itself when translating medical jargon into machine language, as an example; or if more than one knowledge engineer is working on similar parts of the knowledge base, there may exist gaps in the knowledge validation process (Mykytyn et al. 1990). Even though these expert, or decision support systems are not meant to decide for the specialists using them, it is important for the makers of such systems to establish where their legal liabilities start and finish (p. 30).

A risk to using technologies such as Watson for Oncology that was identified in the interviews is the potential for overreliance on the technology. Since Watson for Oncology is only meant as a reference tool much like a learned colleague, caution must be taken to not value Watson's recommendations more than the physician's own intuition or experience. Participant 3 indicates:

> *"We're always careful to say we don't want you to view what Watson is putting out as a decision… or an edict or anything like that… we're constantly trying to make known that what we're providing is a recommendation... we're doing analysis... much like a colleague… so you should treat Watson as a colleague… that you're asking questions… bouncing things off of, getting opinions from. But in the end, it's your decision and you have to live with that decision. We're always afraid that people might get complacent... and if Watson always seems to come up with the right answer… that they'll automatically do it... and won't check themselves as things like that. And in the end, Watson is still only as good as the data you feed it, the training that it has... and things like that. It, like a human, can make mistakes… so don't view its recommendations with a higher esteem than you would a colleague's. The only thing is … this is a colleague that has a huge memory, and is able to retain lots of information… but it doesn't have the experience that you or your colleagues have".*

Singularity. 'Singularity' is a term coined by mathematician, computer scientist and science-fiction writer Vernor Vinge, which he describes as the "theoretical future point that takes place during a period of accelerating change sometime after the creation of a super intelligence", which would bring about "drastic change in society" following an "intelligence explosion" (Cordeiro, 2010, p. 27).

This concept has been fueled by a handful of academic and public figures – Raymond Kurzweil's best-seller from 2005 "The Singularity is Near: When Humans Transcend Biology" was reviewed by Bill Gates as "Ray Kurzweil is the best person I know at predicting the future of artificial intelligence. His intriguing new book envisions a future in which information technologies have advanced so far and fast that they enable humanity to transcend its biological limitations–transforming our lives in ways we can't yet imagine." (p. 27). It appears Kurzweil has predicted that such a technological singularity 'should' occur by 2045, following unprecedented advancements in technologies such as biotechnology, nanotechnology, AI, robotics and genetics (pp. 27-28). Physicist Stephen Hawking has also recently vocalized in public statements his fears about the dangers of singularity, further sensationalizing the term. These propagate Hollywood-blockbuster-style mental images where "humans can no longer control their hyper intelligent, technological superiors" (Papallo, 2014), i.e. machines that humans have created will reprogram themselves to act independently and possibly turn against their creators.

It remains to be seen if such a technological singularity occurs in the near or not so near future. However, the notion that at some point soon, technologies such as Watson for Oncology will replace human specialization, was unanimously dispelled by the participants. Quote from Participant 2:

> *"… having gone through the actual process of teaching it and all that... and I would say that there are always going to be uniquely human aspects of decision making. They're always going to be there. I happen to be working the healthcare space, where that is even more true. Where you just can't possibly codify every piece of information every kind of subtle intuition that a doctor has of years of training…. I would think that Watson, at its best is helping them, making them more productive, and eliminating errors. That's when it's at it's best. And it's freeing them up from that, so that they can really sit there and talk to the patient*

you know, we hear examples all the time, record comes in that says, patient's performance status is good, no apparent comorbidities, otherwise health patient, and then the patient walks in, and they're barely able to lift their feet, and they're shuffling, and they have osteoporosis, and they're you know, barely able to get out of bed or whatever, and that wasn't in the record, because you know that's a subtle human thing, you're sitting across from the patient and you go, oh I'm going to give them this incredibly aggressive form of chemotherapy that's maybe going to be worse for them than then it is going to be in terms of treating their cancer, that's a very nuanced sort of decision that a doctor has to make, and to think that Watson is going got evaluate just how frail or how susceptible this patient would be to sort of saying, you may cured my cancer, but the toxicities, or whatever were so bad that you ended up killing the patient, that happens, So I'm just going to go on record and say we're never going to completely replace human intuition and patient to doctor interactions and those subtle aspects of care that come from human experience and expertise".

Looking ahead

The current offering of Watson for Oncology is English-only, and text-based. It is training on four types of cancer, and two lines of treatment – chemotherapy and endocrine-based systemic therapy. Watson for Oncology is not being used on live patients yet, although the first deployment is expected in the second half of 2015 at the Bumrungrad International Hospital in Bangkok, Thailand. A hospital in Peru is also expected to deploy Watson for Oncology in the coming months. Within Canada, The Ottawa Hospital completed an evaluation (beta trial) of Watson for Oncology in 2014.

At present, there are number of sales engagements across the globe. Watson for Oncology provides the option of localization of the hospital's data and treatments within Watson, although this data specific to another hospital will not update the training of Watson by MSK, nor will it be linked to the evidence provided by Watson for various recommendations.

Watson for Oncology commitments without any localization or integration take approximately 3 months to deploy. With localization and integration, the timeline to implement could take 6 months or longer. The current pricing for the Watson for Oncology offering subscription is based on a per patient model and starts at approximately $1,500/patient and goes down based on the volume of patients, while the evaluation phase costs roughly $500,000.

In the future, the participants expect that Watson for Oncology will cover more types of cancers and types of treatments. Participant 2 would like to see it go to a whole new level and become an actual source of information:

> *"I would like to have it expand to all cancers, all lines of therapy... and really have it become the ... you know if I was really shooting for the moon... I would say that I want this to be a collection point for expertise around the world... and we're not only using information... but we're eventually becoming another source of information. Because as we're getting more cases coming through... and we're collecting what treatments have been chosen and what the outcomes are from those... we can essentially be creating new insights from enough people using this... and enough cases coming through. And that to me would be the ultimate".*

In the near future, Watson for Oncology will also be offered in conjunction with the Watson Clinical Trial Advisor product (each product will be offered on its own as well). A Patient Diary application is expected to be released shortly, which will enable patients to document their progress and tie in that data to their profile into Watson for Oncology for their physician to review at the next appointment.

The participants each identified the impact that Watson for Oncology on people's lives as a highlight of their experience with Watson, and the learning curve and challenges in obtaining data for Watson for Oncology were mentioned as some of the more challenges moments in their journey to date.

Conclusion

This inquiry has shown that Watson for Oncology fits the AI label of clinical decision support the closest, however it has highly advanced and complex machine learning and natural language processing capabilities, which is unparalleled in the healthcare industry at this time. Extensive design considerations have gone into designing the user's experience of interacting with Watson for Oncology's browser based interface, which has been made compatible with iPads for physicians' convenience to aid mobility while caring for patients.

Watson for Oncology is a cognitive technology expected to aid physicians in their decision making by processing structured and unstructured patient data against Watson's training by Memorial Sloan Kettering oncologists. Watson for Oncology shows its reasoning and confidence levels in the various recommendations put forth; it does not make decisions on behalf of the physicians. The main role of Watson for Oncology is to act a ‘learned colleague’ for the physicians, and in no way is meant to replace them.

The experience of the development team has been a hugely positive one, and the members of the Watson for Oncology team visualize expanding on the types of cancers Watson can process and reaching a maximum number of patients across the globe.

While the overall impacts to society and healthcare are deeply positive, the risk of over-dependence on Watson for Oncology may exist.

The one lacking feature that the researcher feels exists at this time for Watson is a ‘cancer-prevention’ application, which may be a consideration for future enhancements of Watson for Oncology. This would be of paramount value to society.

While I have had the unique opportunity of exploring cognitive computing and Watson for Oncology from within IBM, I feel this is just the tip of the iceberg. Future areas of research can look to incorporate physician and patient feedback, once Watson for Oncology goes live internationally. Do the patients feel any differently about their treatment plans knowing that their specific data has been analyzed and cross referenced in such detail by an AI application? Do the physicians feel comfortable or threatened by such applications? How does the success of cognitive computing applications vary by geography? How can these cognitive computing applications be used in preventative healthcare? These and many more fascinating questions remain to be explored in the near and distant future.

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Appendices

A. Recruitment tool: Information Letter

University of Alberta

INFORMATION SHEET

Title of Research Project: Capstone Project for Communications 900, Masters of Arts in Communications & Technology – Cognitive Computing: Applications in Healthcare

Student Researcher:
SaminaHossain
University of Alberta

Email: samina1@ualberta.ca

Research Supervisor:
Maria Mayan, PhD
University of Alberta
Phone: 780-492-9209
Email: maria.mayan@ualberta.ca

Purpose:
The purpose of this research is to better understand the current status of cognitive computing applications in healthcare.

Methods:
You will be interviewed on Skype or in person for approximately 30 to 60 minutes, with the possibility of a follow up interview of similar duration. The interview will be audio recorded and transcribed by the researcher.

Voluntary Participation
You have the right to refuse this invitation to participate or to refuse to answer any of the questions asked during the interview. You are also free to stop the interview at anytime or request that we withdraw your information (transcripts, audio recording) up to one week from the day of the interview.

Confidentiality
The information gathered during the interviews will be used solely for purposes of this capstone project. No one will see your transcript other than the researcher and possibly the research supervisor. Your name will not be used when the researcher writes and submits her research findings for the capstone project. However, due to the nature of the data collected (which can only be provided by the Watson team), readers of the final report may make guesses about who participated in this research. I will provide you a copy of the final report to ensure you are comfortable with the level of confidentiality.

Analysis
Audio recordings will be typed into transcript format, removing all identifying information. Transcripts and audio recordings will be destroyed by December 31,2020 by the researcher.
Benefits:
This study may or may not have any direct benefits for you.

Risks:
It is not expected that being in this study will harm you. However, if you would like to speak to someone after the interview, you may contact either the researcher or research supervisor identified above.

Withdrawal from the study:
If you choose to withdraw from the study, the audio recording and any transcripts that have been made will be destroyed immediately. You are free to withdraw up to one week from the day of the interview.

Use of your Information:
The interview will be recorded, transcribed and analyzed. The researcher will present research findings in the project write up but your name will not be explicitly used.

Thank you very much for taking part in this study.

The plan for this study has been reviewed for its adherence to ethical guidelines by a Research Ethics Board at the University of Alberta. For questions regarding participant rights and ethical conduct of research, contact the Research Ethics Office at (780) 492-2615.

CONSENT FORM

Title of Research Project: Cognitive Computing: Applications in Healthcare

Student Researcher:
SaminaHossain
University of Alberta

Email: samina1@ualberta.ca

Research Supervisor:
Maria Mayan, PhD
University of Alberta
Phone: 780-492-9209
Email: maria.mayan@ualberta.ca

Please circle your answers:

Do you understand that you have been asked to be in a class project research study?	*Yes*	*No*
Have you read and received the Information Sheet?	Yes	No
Do you understand the benefits and risks involved in taking part in this study?	Yes	No
Have you had an opportunity to ask questions and discuss this study?	Yes	No
Do you understand that you can quit taking part at any point during the interview?	Yes	No
Do you understand that you can withdraw up to one week from the day of the interview, and that any comments that you provided up to that point will not be used?	Yes	No
Has confidentiality been explained to you?	Yes	No
Do you understand who will have access to the data collected?	Yes	No
Do you understand that the results from this study may be presented in a class setting or at a conference?	Yes	No
Do you understand that the interviews will be audio-recorded and transcribed?	Yes	No
Do you understand that you have up to one week from the day of the interview to withdraw what you have shared in the interview?	Yes	No

If you have further questions regarding the research, please contact the student listed above.

This study was explained to me by: ________________________________

I agree to take part in this study.

____________________________ ____________________

Signature of Research Participant Date (dd/mm/yyyy)

____

Printed name

The plan for this study has been reviewed for its adherence to ethical guidelines by a Research Ethics Board at the University of Alberta. For questions regarding participant rights and ethical conduct of research, contact the Research Ethics Office at (780) 492-2615.

B. Data gathering instrument: Interview schedule

1. What is your role in Watson for Oncology?
2. What 'type' of Watson is Watson for Oncology? Watson Explorer, Watson Analytics, etc?
3. Artificial Intelligence & Expert Systems have been around for a long time - what makes Watson, Watson?
4. How is Cognitive Computing different from Predictive Analytics?
5. Would you say Watson is an evolved Expert System? Or more of a Decision Support System?
6. During Jeopardy!, Watson was not connected to the Internet, but now Watson is on the Cloud:

    i. Why the switch?
    ii. Pros & cons of being on the cloud?
    iii. What type of security measures are in place for Watson data on the Cloud?
    iv. What measures are in place to minimize potential cloud downtime/network interruptions?

7. In lay terms, how does Watson 'learn'?

8. How does Watson for Oncology 'work'? Can you explain, in lay terms, the process/steps in which data/journals are 'fed' to Watson? How does Watson keep up with new material?
9. How does Watson differentiate between structured & unstructured data?
10. What are the input & output formats for Watson?
11. Does Watson understand speech?
12. What does the user interface look like for the physicians using Watson for Oncology?
13. What is the ballpark cost to implement Watson for Oncology at a hospital the size of The Ottawa Hospital?
14. Why was The Ottawa Hospital chosen as the pilot for Watson for Oncology in Canada? Are there any other hospitals participating at this time in Canada?
15. What are some other cognitive computing platforms you have come across of know of in the field of healthcare? Do any of them overlap with Watson (i.e. does Watson have any direct competition that you know of)?
16. How many basic components does Watson for Oncology have? (From literature, typical ES in has 3 - Knowledge base, Inference engine, User interface)

17. What are the legal ramifications of using Watson in aiding physician decision making? Can Watson/IBM be held ‘liable’ for decisions made using Watson’s input?
18. How many knowledge engineers and domain experts were involved in ‘teaching’ Watson? Since knowledge engineers are technical experts, but not necessarily oncology experts, what type of measures were in place to ensure minimize risk of misinterpretation of expert knowledge when coding Watson?
19. I understand Watson for Oncology will be used as a sort of ‘colleague’ by physicians - would you say Watson has attributes of ‘intuition’ comparable to experts in the field?
20. What are your thoughts on the concept of ‘singularity’, recently made popular within the context of Artificial Intelligence by Stephen Hawking?
21. Overall, what were the hardest moments in your Watson journey? What were some of the best moments?
22. Where do you see Watson for Oncology going in the future?