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Do Healthcare Workers Need Cognitive Computing Technologies? A Qualitative Study Involving IBM Watson and Dutch Professionals

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Abstract

The healthcare ecosystem continually produces huge volumes of structured and unstructured data. Cognitive computing, a new computing paradigm, promises to effectively help healthcare researchers and practitioners to derive precious information from data. Arguably, the most famous cognitive computing system is called IBM Watson, which has been adapted to different domains, including healthcare. In this paper, we investigate whether there is a natural demand for cognitive computing systems coming from healthcare workers. Specifically, using the technology acceptance model to guide our efforts, we study different perceptions from healthcare professionals from the Netherlands regarding IBM Watson. The results from our interviews show that virtually all the perceptions are very negative. We list several reasons underlying these perceptions alongside potential ways of changing them. We believe our results are of great value to health information technology professionals trying to introduce a potentially groundbreaking product and to organizations that are contemplating investing in those technologies.

Keywords: Cognitive Computing; Decision Support Systems; IBM Watson; Health Information Technology.

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1. Introduction

Recent years have seen a tremendous increase in the amount of data generated from a variety of sources, a phenomenon now referred to as big data (Watson, 2014). The creative analysis of these data, aided by modern analytics technologies, creates huge opportunities for businesses. For example, e-commerce companies can continuously collect information about the products consumers buy. These data can be combined with personal data gathered from public records and social media. The final merged data can then be put into refined algorithms that are able to predict, for example, how a person will respond to a specific marketing offer.

Personal data are also very valuable in the healthcare industry. They allow, for example, tailored treatments and insurance plans. Unfortunately, most of healthcare-related data are unstructured in nature, meaning that they do not follow a standardized, predefined format. One can see that characteristic when considering the heterogeneity of traditional healthcare data sources, e.g., medical records, handwritten notes, medical imaging, sensor data, audio notes, etc. The huge volume of heterogeneous data from various sources means that useful knowledge discovery is incredibly challenging when performing healthcare data analytics (Yang & Veltri, 2015).

Cognitive computing, an arising computing paradigm, promises to address similar data-analytics challenges in an effective manner. It is expected that cognitive computing systems "... will be able to learn from both structured and unstructured data, discover important correlations, create hypotheses for those correlations, and suggest actions that produce better outcomes" (Kelly III & Hamm, 2013, p. 25). In other words, cognitive computing systems employ sophisticated machine learning techniques to understand and organize contextual data to provide a series of alternative answers alongside explanations to patterns found in the data. Instead of replacing a subject-matter expert, cognitive computing systems behave as decision support systems that can collaborate with humans by gathering huge amounts of structured and unstructured data related to a specific topic and, eventually, to provide new insights on that topic.

Naturally, healthcare is one of the most promising domains one can apply cognitive computing systems to. For example, consider electronic medical records (EMRs). Although individual EMRs are not always accurate in their own recollections, a cognitive computing system can collect and aggregate data from several patients' EMRs alongside individual case files to discover relationships between combinations of symptoms and disorders/diseases. Discovering these relationships would likely be infeasible if a researcher only had access to limited information, such as the data from the researcher's own practice/institution. Moreover, the cognitive computing system can examine the existence of several relationships between symptoms and disorders/diseases and suggest the most promising ones to be further investigated by the researcher, thus working in close collaboration with and improving the productivity of the latter.

As we explain in the following subsections, when we further elaborate on cognitive computing systems, IBM has been at the forefront of the development of cognitive computing with its system called IBM Watson. After beating former winners of the Jeopardy! competition, Watson has been tailored to work in several domains, ranging from music composition to dish creation. Since IBM Watson is a relatively new technology, it is important to understand whether there exists a natural acceptance/demand for its services. Focusing on the healthcare domain, we seek to understand the type of professionals and organizations that can benefit most from using IBM Watson. To do so, we use the Technology Acceptance Model (Davis 1989; Davis et al., 1989) to guide our efforts and investigate the perceived usefulness, ease of use, and other variables regarding IBM Watson. Our analysis and conclusion are based on qualitative data collected from interviews with Dutch healthcare workers.

1.1 Research Background

Our primary goal in this paper is to understand different healthcare workers' perceptions regarding different aspects of the cognitive computing system IBM Watson. That said, we provide in this subsection a more comprehensive definition of cognitive computing and IBM Watson, and review relevant work related to the application of cognitive computing systems in the healthcare domain.

The ultimate goal of cognitive systems is often associated with (big) data understanding and analysis. For example, in his cognitive computing book, John E. Kelly III - the director of IBM Research at the time of writing, stated that with cognitive computing "... we will be able to apply new kinds of computing power to huge amounts of data and achieve deeper insight into how things really work" (Kelly III & Hamm, 2013, p. 4). Nonetheless, there is virtually no consensus on what a cognitive technology is or what it is truly capable of. According to Hurwitz et al. (2015), cognitive computing systems are defined by three fundamental principles:

1. Base Corpus: cognitive systems are first trained using a base corpus;
2. Continuous Learning: cognitive systems can extend their knowledge bases by continuously and autonomously learning from new, previously unobserved data, and
3. Generate/Evaluate Hypotheses: cognitive systems can generate and evaluate hypotheses that explain some of the patterns present in the data.

The major step in the design of cognitive computing systems is the creation of a corpus representing a particular domain or topic. This corpus is used to define the initial knowledge base of the system, which in turn is used when answering domain-related questions, discovering new patterns in the data, and to deliver new insights. When first created, the content of the corpus constrains the types of problems that can be solved by the cognitive system. Therefore, the system designer needs a good understanding of the domain area to plan and build a corpus. For example, if one wants to develop a cognitive system able to create new dishes or suggest different combinations of ingredients to chefs, then the system designer should have knowledgeable chefs helping with the creation of the corpus. Clearly, the choice of data sources and data types to include in the initial corpus is crucial. Potential data types include textual data (e.g., from encyclopedias), images, ontologies, and taxonomies. Some of these unstructured data types highlight the importance of techniques such as deep learning and from the natural language processing field to transform the raw data into representations that capture the essential properties of the domain, which is what is stored in the corpus. Finally, a corpus is not static, in a sense that the base corpus will be updated with more data from different sources while the cognitive computing system is in operation.

After building a corpus of relevant data for a certain domain, cognitive computing systems can generate and score hypotheses in response to a user's question. For example, in the healthcare domain, the user might ask the question: "which diseases might be associated with the symptoms X, Y, and Z?" The system could then present several hypotheses that answer the asked question, where each hypothesis is a candidate disease that might cause the underlying symptoms. Each hypothesis is evaluated (scored) based on the existing evidence (supporting) data in the knowledge base. If none of the hypotheses score above a certain predefined threshold, the system might ask for more evidence (e.g., a diagnostic blood test) if that information can change the confidence in any hypothesis. After scoring the hypotheses, the system presents the most relevant results back to the user, who could further evaluate (provide feedback on) the hypotheses. Currently, IBM Watson is the most prominent implementation of a cognitive computing system. In what follows, we briefly describe the architecture and major components of IBM Watson.

1.2 IBM Watson

Originally, IBM Watson was designed as a question-answering system whose purpose was to compete at the human-champion level in the Jeopardy! competition. Its *DeepQA* architecture, whose main components are displayed at a very high level in Figure 1, was developed based on four major principles (Ferrucci et al., 2010): 1) massive parallelism is the ability to consider multiple interpretations and hypotheses of a question at the same time; 2) many experts, meaning that the architecture easily allows for the integration, application, and contextual evaluation of a wide range of probabilistic questions and content analytics; 3) pervasive confidence estimation means that different framework components produce features and associated confidence scores by scoring different questions and content interpretations; and 4) integrating shallow and deep knowledge means balancing the use of strict and shallow semantics, leveraging many loosely formed ontologies.

The base corpus of Watson was derived from a range of structured and unstructured data, including encyclopedias, dictionaries, thesauri, literary works, databases, taxonomies, and ontologies such as WordNet (Miller, 1995). Being a cognitive computing system, Watson is able to automatically expand its knowledge base by following four high-level processes: 1) identify seed documents in its corpus and retrieve related documents from sources such as the web; 2) extract self-contained text nuggets from the previously found related documents; 3) score the nuggets from the related documents based on whether they are informative with respect to the original seed document, and 4) merge the most informative, high scored nuggets into the initial corpus.

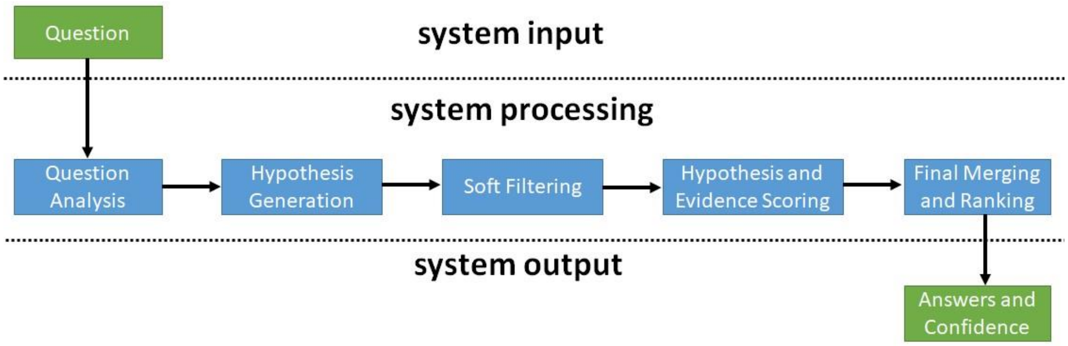

Figure 1. High Level Description of IBM Watson's DeepQA Architecture

When a user sends a question in natural language to Watson, the system then tries to understand what the question is asking by performing an initial analysis that might include finding the question type (e.g., puzzle question, math question, etc.) and/or decomposing the question into sub-questions, which will then be analyzed individually by the rest of the system. Thereafter, the system generates answers (hypotheses) to the question by searching its knowledge base. To obtain several, potentially different hypotheses, Watson employs a variety of search techniques, ranging from passage search to single-entity search. The focus of this phase is to recover any plausible, even if unlikely, hypothesis. The expectation is that the following steps will be able to tease out the most likely answers. Next, during the soft-filtering phase, fast machine-learning algorithms score the initial candidate hypotheses to prune them down to a smaller set of candidates before the application of a more intensive and comprehensive scoring process. Candidate hypotheses that score above a predetermined threshold undergo a rigorous evaluation process that involves a secondary knowledge base search, where the system obtains additional supporting evidence for each candidate hypothesis. Different types of scoring algorithms, ranging from probabilistic techniques to frequency-based approaches, consider different dimensions when determining the degree of certainty that the retrieved evidence supports the candidate answers. The scores produced by different methods are combined to produce a single final score per answer. Finally, Watson ranks the hypotheses based on such combined scores and reports back to the user the most plausible answers alongside confidence values representing the likelihood that each answer is correct.

The above system was able to beat up two previous winners of the Jeopardy! competition. This led IBM to heavily invest in the Watson technology and to showcase its capabilities in different domains. As previously mentioned, healthcare is a natural domain to apply a cognitive computing technology to. In the following subsection, we explain how IBM Watson has been applied in different healthcare settings.

1.3 IBM Watson and Applications in the Healthcare Domain

After the success of Watson in the Jeopardy! competition, it was just natural that IBM would try to leverage this powerful technology in different domains. The underlying framework, DeepQA, was proven to be a powerful architecture for reasoning over unstructured data, which is precisely the type of data commonly found in the healthcare domain. For example, one can use Watson in clinical settings to reason over a patient's medical condition by searching and analyzing large volumes of medical data and eventually generating a ranked list of diagnoses with the associated evidence and confidence scores. In such scenarios, Watson effectively becomes an evidence-based clinical decision support system (Ferrucci et al., 2013).

Given that the diagnostic error rate in clinical settings is estimated to be between 10% (Kirch & Schafii, 1996) and 23.5% (Shojania et al., 2003), and that about 75% of these errors are estimated to be linked to cognitive-related issues (Graber et al., 2005), such as failing to consider alternatives after an initial diagnosis is reached, it should then come as no surprise that several decision support systems have been previously proposed to support healthcare professionals. According to Ferrucci et al. (2013), these previous systems can be roughly classified as systems that rely on structured knowledge (Hance & Buchanan, 1984; Barnett et al., 1987, Warner et al., 1988), systems that rely on unstructured knowledge (Ramnarayan et al., 2003), and systems that are based on predetermined clinical decision formulas, rules, and/or algorithms (Cannon & Allen, 2000).

It has been suggested that some decision support systems can indeed improve healthcare professionals' diagnostic reasoning and accuracy (Friedman et al., 1999). Nonetheless, these systems are still underused due to, among other reasons, outdated knowledge base and the reasoning behind diagnostic suggestions not being always transparent (Sim et al., 2001; Berner, 2006). The ability to suggest and explore alternative hypotheses (diagnoses) and to report confidence scores alongside associated supporting evidence are key differentiating features of DeepQA/Watson when compared to previous systems. Besides showing the evidence behind its conclusions, Watson can also expand its knowledge base and keep itself updated, as we previously discussed, which means that its users continuously have the most up-to-date evidence-based information to make accurate healthcare decisions (Dilsizian & Siegel, 2014). Kelly III & Hamm (2013) and Hurwitz et al. (2015) report many pilots and projects involving healthcare organizations using/testing IBM Watson. We briefly summarize some of them next:

- WellPoint, one of the largest health insurance companies in the United States, is using IBM Watson to improve the efficiency and effectiveness of treatment pre-approval management. Healthcare professionals, such as nurses and physicians, helped training Watson to understand the American medical treatment code system as well as WellPoint's medical policies, clinical guidelines, and processes for reviewing treatment-authorization requests. Healthcare providers and payers, such as WellPoint's subsidiaries, can now quickly query the system to retrieve information about pre-approval processes;
- The American company Welltok designed an app called CaféWell Concierge to help individuals manage and optimize their health and well-being. The goal of that app is to help individuals understand their health status and to receive personalized guidance to help them achieve desired health goals. Powered by IBM Watson, CaféWell Concierge allows individuals to ask questions about their own health status, specific diseases, search for nutritional information, and to obtain personalized and accurate recommendations regarding health improvements such as food choices and workout plans;
- In a partnership with IBM and WellPoint, Memorial Sloan-Kettering Cancer Center is using IBM Watson to help physicians choose the most effective treatments for helping patients who have cancer. Specifically, researchers from that cancer research center are feeding into Watson vast amounts of data related to diseases, treatments, and outcomes. The corpus of the system includes several academic papers, case histories, clinical guidelines, best practices from top physicians, reports from drug trials, etc. The researchers hope the system will allow physicians to make evidence-based decisions when choosing the best treatment plans to fight cancer;
- The Cleveland Clinic's Lerner College of Medicine is using IBM Watson to train medical students using problem-based learning techniques. Specifically, the students use an adaptation of Watson, called *WatsonPaths*, to visualize and go through the chains of evidence, inference, and beliefs about a patient's condition and potential case conclusions. By keeping track of the evidence used to support its hypotheses and conclusions, IBM Watson can justify the resulting confidence level that a certain diagnosis is accurate;
- Cleveland Clinic is using IBM Watson to improve the quality of individuals' personal data inside electronic medical records (EMRs) in order to help physicians make more informed decisions regarding patient care. To do so, Cleveland Clinic is building a comprehensive knowledge base using IBM Watson that can be used to test for omissions and improve the accuracy of EMRs. Besides providing more accurate EMRs, the system will eventually provide relevant summaries of a patient's medical history, which in turn can improve medical decision making.

1.4 Research Questions

As we previously mentioned, we rely on the Technology Acceptance Model (TAM) to guide our efforts in understanding the type of healthcare organizations and professionals who might accept and benefit most from IBM Watson. TAM asserts that the acceptance of a new technology by an individual is driven by two major variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). That is, an individual is more likely to adopt a technology or innovation when the same is perceived to be useful and easy to use. There is some evidence that TAM can indeed explain technology acceptance in the healthcare domain (Holden & Karsh, 2010). We further elaborate on PU and PEOU in what follows.

PU is defined as "... the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In other words, PU measures whether a certain technology is perceived to make individuals more accurate and/or to decrease the amount of time and effort required to complete an underlying task. Hence, "... a system high in perceived usefulness ... is one for which a user believes in the existence of a positive use performance relationship" (Davis, 1989, p. 320). In every one of the 16 healthcare-related studies reviewed by Holden & Karsh (2010), PU had a significant impact on the intention and/or actual use of a healthcare technology. A similar conclusion was drawn by Yarbrough & Smith (2007) when reviewing applications of TAM in the healthcare domain. Therefore, to better understand the suitability of IBM Watson for different types of healthcare organizations, we investigate in this paper the PU of IBM Watson among different healthcare professionals. Thus, our first research question is:

Research Question #1: is the PU of IBM Watson among healthcare workers positive or negative?

The second variable that drives technology acceptance according to TAM is the perceived ease of use (PEOU), which is commonly described as "... the degree to which a person believes that using a particular system would be free of physical and mental effort" (Davis, 1989, p. 320). Individuals may believe that a certain technology is useful but may also find it difficult to use. In this case, the gains in performance may be outweighed by the effort required to use the technology. Although there are mixed results on whether PEOU can explain technology acceptance in the healthcare domain (Holden & Karsh, 2010; Hu et al., 1999), we nonetheless believe that PEOU might provide precious insights into which healthcare professionals are likely to accept and potentially use IBM Watson. This leads us to our second research question:

Research Question #2: is the PEOU of IBM Watson among healthcare workers positive or negative?

Over the years, TAM researchers realized that other variables are antecedents of PU and PEOU and/or directly affect the intention of use of a certain technology. Some of these variables include relative advantage, compatibility, complexity, observability, and trialability (Moore & Benbasat, 1991; Lee et al., 2003). In this paper, we also investigate healthcare professionals' perceptions of these variables concerning IBM Watson.

Oftentimes, a new technology needs to have some relative advantage over existing technologies to get adopted and to diffuse more rapidly (Premkumar & Potter, 1995; Rogers, 2003). This is also true in the healthcare domain (England et al., 2000), where a new technology needs to have some comparative advantage over traditional ways of getting a task done, e.g., see the survey by Dumont et al. (1998) regarding the acceptance of computer-based patient records among healthcare workers. A crucial component when quantifying the relative advantage of a certain technology over others is to understand the users' perceptions of such a technological advantage. This is true because it is estimated that between 49 and 87 percent of the variance in the rate of spread of a technology is predicted by perceptions of innovation (Berwick 2003). We take the above discussion to IBM Watson in our third research question:

Research Question #3: is the perceived relative advantage of IBM Watson among healthcare workers positive or negative?

Compatibility is another variable that plays a major role in the adoption process of a new technology (Chin & Gopal, 1995; Xia & Lee, 2000). Specifically, compatibility is a measure of how well the technology fits in an organization's culture, practices, past experiences, and investments (England et al., 2000). Technologies that fit well with an organization tend to diffuse more quickly than those that do not fit well (Rogers, 2003). For example, if hypothetically speaking, the physicians at a certain hospital do not care as much whether surgeries start on time or not, then they are unlikely to be interested in new technologies that can help with the surgeries starting on time. The above said, compatibility is clearly task dependent, e.g., some physicians find computers useful for administrative support and self-development, but not so helpful when it comes to clinical work (Institute of Medicine, 1997). We investigate the perceived compatibility of IBM Watson with healthcare organizations through our fourth research question:

Research Question #4: is the perceived compatibility of IBM Watson among healthcare workers positive or negative?

The (perceived) complexity of a technology also impacts its acceptance and diffusion (Igbaria et al., 1996). In particular, complex innovations tend to diffuse slower than simpler innovations (Rogers, 2003). Major information-technology changes might require higher levels of technical skills and, hence, to cause disruptive changes in organizations. Therefore, this can retard the adoption and acceptance of technologies such as IBM Watson, which leads us to our fifth research question:

Research Question #5: is the perceived complexity of IBM Watson among healthcare workers positive or negative?

Observability is the ability of potential adopters to easily watch others trying a certain technology first. It has been shown that positive (perceived) observability increases the acceptance of new technologies (Moore & Benbasat, 1991; Rogers, 2003). The observability of successful information technologies in the healthcare sector is relatively low in comparison to banking and general administration areas (England et al., 2000), which leads to our sixth research question:

Research Question #6: is the perceived observability of IBM Watson among healthcare workers positive or negative?

The last variable we are interested in is trialability, which is the ability to test the impact of a new technology on a small scale, without having to fully deploy the technology (Berwick, 2003). Easily trialed technologies diffuse more rapidly and are more acceptable than those that cannot be trialed (Karahanna et al., 1999; Rogers, 2003). This leads to our final research question:

Research Question #7: is the perceived trialability of IBM Watson among healthcare workers positive or negative?

In what follows, we explain our methodology in section 2, discuss our findings in sections 3 and 4, and finally conclude the paper in section 5.

2. Methodology

The main goal of our study is to investigate healthcare workers' perceptions of IBM Watson to understand whether there exists a natural demand for cognitive computing technologies in the healthcare domain. We believe our results can be of great value to organizations that are contemplating investing in such technologies as well as health information technology professionals trying to introduce a potentially groundbreaking product. We fulfill our primary goal by following a qualitative approach based on semi-structured interviews. It has been suggested that qualitative studies that rely on TAM, the model that inspired the questions we asked during the interviews, are very useful in obtaining relevant information from a small number of subjects (Lee et al., 2003).

The semi-structured, one-to-one interviews were conducted based on a set of key questions (see Appendix A). These questions were chosen to encourage interviewees to freely discuss their own opinions on IBM Watson, cognitive systems and, more broadly, technology adoption in hospitals. Although these key questions were developed a priori, i.e., before conducting the interviews, we note that additional questions were asked when needed. In other words, using a set of predefined, open-ended questions allowed us to adjust follow-up questions depending on the specific answers the healthcare professionals provided.

Each interviewee was approached individually by email where we provided a brief explanation of the purpose of the study. The interviewees (also referred to as respondents) were asked to participate in the research and, if they agreed, the interviews were subsequently planned and scheduled. All the interviews were about 1-hour long and conducted face-to-face, except for one interview that was conducted by phone. The interviews took place in a private room at the location where the interviewee worked. We started the interview by introducing the interviewer, and the content of both the interview and the research to ensure a clear understanding of the research goals, research questions, and to establish a good rapport. Foreseeing the potentially negative nature of their answers, we promised the interviewees that we would preserve their identities. As such, we use letter codes to denote interviewees' names throughout the paper. The interviews were recorded with permission of the interviewees to ensure all data were correctly analyzed a posteriori.

Table 1 provides an overview of the 11 interviewees we interviewed in this study, including their roles, the number of years in this (or related) function, and whether they worked with IBM Watson before. The reason for the last variable is that we wanted to contrast the perceptions of the workers who already used Watson against the perceptions of potential future users. To summarize, we interviewed mostly Dutch physicians from different hospitals to understand their perceptions of the IBM Watson technology. Regarding their backgrounds, the physicians worked in both academic (research oriented) and non-academic hospitals in the Netherlands. All physicians had bachelor and master's degrees at the time of the interview. Moreover, two out of the eight interviewed physicians were enrolled in PhD programs. Physicians B, C, and H had hands-on work experience with IBM Watson before the interviews. Other than physicians, we also interviewed three professionals working directly with innovations in hospitals.

3. Empirical Findings

After conducting the interviews, we perform a thematic content analysis. In particular, we describe each collected answer by creating codes matching each respondent's own words. Thereafter, we interpret the themes emerging from clusters of similar codes. Some themes are not very popular in that they only relate to one response reported by one interviewee. That said, we only report themes associated with more than one response. We introduce in the following subsections the results of our analysis. For the sake of readability, we translate the quotations we use throughout this section from Dutch to English.

3.1 Perceived Usefulness of IBM Watson

Before asking about the perceived usefulness (PU) of IBM Watson, we talked to each respondent about technologies in general and their adoption processes (see Appendix A). This allows us to derive precious information on what makes a technology useful according to the respondents. Generally speaking, the interviewed healthcare professionals perceive a technology as useful when it performs well and satisfies the user's needs. Besides these points, the interviewees also state that the usefulness of a new technology is tied to its relative advantage with respect to the already existing technologies. This relative advantage can exist in various forms. For example: 1) the new technology might have the same application as an existing technology, but it performs faster and/or produces more accurate results; 2) the new technology can be cheaper and/or easier to use than existing ones; and 3) in the healthcare context, the new technology can be more patient friendly and/or improve patient satisfaction. We summarize the above results in Table 2, and we note that some of these themes are in line with the usefulness construct by Davis (1989).

After the initial set of professional and/or technology related questions, we asked the interviewees questions specific to Watson. Table 3 shows the obtained themes related to the question on the usefulness of that technology. Some respondents explain that it is very difficult for an external company to bring an innovative product/technology into a hospital. Alternatively, when innovative ideas come from people within the hospital, support is created from the beginning, and the development is consistent with the needs of the in-house healthcare professionals. On the other hand, when an external company wants to "push" a technology into a hospital, it might become harder to find the appropriate internal support and easier to question whether the technology solves any real problem. As stated by Respondent I: "Most of the time, external companies develop a product without consulting the users. Due to this, many products are developed that are not perceived as useful because they do not solve the "real" (sometimes underlying) problem." As suggested in Table 2, to be perceived as useful, a technology oftentimes needs to solve a real problem and meets the needs of the users. On this point, Respondent A's answer agrees with Respondent I's: "Watson is a nice technology. However, it does not solve the real problem. The real problem is the EHR [Electronic Health Record] and the non-systematic way data is collected. When this problem is solved, Watson might succeed." Besides this, another problem s/he sees which impacts the usefulness of Watson is that it only understands English. This is not a problem in itself, but because the technology needs to be able to collect information from the EHR of a patient (and this is all in Dutch), it will not be perceived as useful as long as it cannot cope with the Dutch language. Regarding language, Respondent J corroborates Respondent A's point by saying: "As long as it does not understand Dutch, it will cost us extra time and, therefore, will not be perceived as useful."

Respondent	Role	Work Experience	Watson Experience
A	Pediatric intensivist and chief medical information officer in a Dutch academic hospital	29 years	NO
B	Associate professor in a Dutch academic hospital	8 years	YES
C	PhD candidate in internal medicine in a Dutch academic hospital	1.5 years	YES
D	Cardiologists in a Dutch non-academic hospital	2.5 years	NO
E	Internist-oncologist in a Dutch nonacademic hospital	11 years	NO
F	PhD candidate in radiation oncology in a Dutch academic hospital	3.5 years	NO
G	Geriatrician in a Dutch non-academic hospital	14 years	NO
H	Internist-oncologist and researcher in a Dutch academic hospital	13.5 years	YES
I	Innovation manager in a Dutch academic hospital	14 years	NO
J	Digital and ICT director in a nonacademic Dutch hospital	5 years	NO
K	Senior director of an oncology consulting firm	21 years	NO

Table 1. Overviews of the Interviews.

Besides the above, other respondents voiced different concerns regarding the usefulness of Watson. Respondent B, who worked with Watson before, is skeptical about the relative advantage of Watson at this point in time: "IBM has shown that they are very good at the bread-and-butter cases. However, this is probably not where the gains lie." Respondent B further argues that those cases are not very time consuming and questions whether Watson will actually save healthcare professionals any time. Respondent G is also very skeptical about the usefulness of Watson. S/he argues that it is not clear what Watson does behind the scenes and how it arrives at a hypothesis. It is important to highlight that not all the answers about the PU of Watson are negative. An interesting observation made by Respondent B is that physicians and IT professionals might have different perceptions regarding Watson: "When IBM introduced and presented Watson to our hospital, there were 5 physicians and 20 IT people in the room. All the IT staff loved it, but they were not saying a thing waiting for the response of the physicians to see what they thought of it." Respondent J disagrees with the fact that a new technology needs to solve a problem. His/her perception is that it would be very useful to have Watson for a "second opinion." Nonetheless, s/he points out that, despite his/her positivity, many oncology specialists do not agree with him/her: "The specialists state that they do not need a second opinion that often. Moreover, when a second opinion is needed, the specialists would rather prefer to talk to their colleagues from a specialized oncology hospital than to a computer."

Themes	Respondent
Very specific application or series of applications	C, I, K
Satisfies the user's needs	C, D, I, K
Solves an existing problem	A, H, I
Faster than other technologies	D, F, K
Cheaper than other technologies	B, E, F, G, H, I
Yields better/higher quality outcomes than other technologies	A, B, D, K
Easier to use than other technologies	C, E, F, H, K
More patient friendly than other technologies	C, E, F, H, K

Table 2: Derived Definition of Usefulness According to the Interviewees.

Themes	Respondent
It does not solve a real problem	A, I
The relative advantage is unclear	A, B, G, I
It does not understand Dutch	A, D, E, J
Useful to small hospitals	B, C

Table 3. Perceived Usefulness of IBM Watson According to the Interviewees.

Besides the above, Respondent B sees the potential of Watson inside small hospitals. S/he indicates that specialists are frequently asked to join multidisciplinary teams in small hospitals to help with some diagnostic and treatment efforts: "These specialists are present during the discussions of all cases. However, they are only needed during a couple of cases. If Watson can show which cases need a specialist, and these patients are discussed first, the specialist can then leave after 10 minutes." Moreover, Respondent B recalls that the business case of IBM is that some physicians cannot keep up with the amount of medical information that is being produced. S/he uses this business proposition to further corroborate the argument that Watson is better positioned to help smaller hospitals: "We [less resource-constrained hospitals] have national experts and I dare to say that we are better than Watson." Respondent C, who too worked with Watson before, also states that Watson is not always useful, but only when specialists are not available at the hospital.

Analyzing Research Question #1 considering the above discussion, we conclude that the overall PU of Watson, as reported by the interviewed healthcare professionals, is negative. It is not entirely clear which problems Watson can solve and, generally speaking, there is the perception that a highly specialized physician is much more reliable and accurate than a machine. Therefore, Watson would be better suited to small, resource-constrained hospitals.

3.2 Perceived Ease of Use of IBM Watson

Similar to what we did with PU, we first gain insights into what influences the easiness of use of a technology according to the interviewees. This is done based on a set of preliminary questions related to technologies and the respondents' professions. Generally speaking, the interviewees have a high ease-of-use perception when the underlying technology flawlessly fits in the current workflow. As Respondent A says: "It [the technology] has to fit in the hectic hospital process, where you have a very limited time per patient (only 10 minutes)." Other than this, the technology itself also needs to be easy to use and to learn. Finally, the technology must be intuitive, meaning that users must be able to recognize the next step in the usage process, instead of having to remember what the next step in the process is. We summarize the above results in Table 4 and note that some of these themes are consistent with the PEOU construct by Davis (1989).

Themes	Respondent
Fit in the workflow	A, B, C, D, F, H, I, J, K
Easily learned	A, B, K
Usage does not consume too much time	all respondents
Intuitive	D, F, G, H, I

Table 4. Derived Definition of Ease of Use According to the Interviewees.

Themes	Respondent
Very easy to use for research purposes	B, C, H
Not user friendly for general physicians	B, C, H
Time consuming	B, E, G, J
Generally, not easy to use	E, G, J

Table 5. Perceived Ease of Use of IBM Watson According to the Interviewees.

Moving to Watson-specific questions, Table 5 shows the obtained themes. It is fair to acknowledge that some interviewees struggled to answer this question due to the lack of hands-on experience with Watson. Those respondents had to resort to what they read about Watson before, previous discussions with their peers, as well as the preliminary discussion about Watson we had with them in the beginning of the interview. Starting with the respondents familiar with Watson, Respondent C states that the technology is very easy to use: "The system works simple and clear. You see easily what you have to fill out and where, and it comes with clear recommendations." Respondent B and H, who also had hands-on work experience with Watson before, state that the technology is useful for researchers, but that it is not user friendly for a general physician. Respondent B states that: "Watson consists of many dropdown menus which you have to fill out. In the beginning, you do not need to fill in that much information, but further down the process Watson needs more information to make a decision. Sometimes, it costs a physician 5 minutes to fill out a form. This is a huge barrier [to adoption] because it costs a lot of time." Besides this, Respondent H also highlights that it is very difficult to quickly add new information to the system.

We focus now on respondents who never experienced the technology before, but who are nonetheless familiar with its capabilities. Respondent A states that Watson "... has to fit in the workflow of a hospital. As far as I have heard, at this moment, Watson is not easily manageable and easily integrated into the workflow." Respondent E's and G's answers are in agreement with Respondent A's in that a technology will be time consuming and not very useful when physicians need to fill out the same information about a patient in two different systems to get treatment advice. On that note, Respondent E states that: "... if you are a physician and you are 90% sure about a certain treatment, it is then too much effort to consult with Watson. This also holds for patients in a polyclinic. When you are a general physician and you want to consult with Watson before talking to a specialist, that might cost you 5 to 10 minutes to fill out all the dropdown menus. The patient might have already left when that is over." Respondent J also believes that it will be a huge barrier to adoption if using Watson costs time: "The gains have to be really big in order to adopt a technology that costs physicians time. We are mostly funded by production (number of people we treat). If production goes down because physicians need more time per patient and the cost stays the same, then we are having a problem."

We conclude this subsection by noting that the responses from the interviewees, no matter whether they used Watson before or not, are most often negative. In particular, the main perception is that using Watson is/will be time-consuming. Thus, analyzing Research Question #2 in light of the above comments, we conclude that Watson's PEOU is currently negative among the interviewed healthcare professionals.

3.3 Other Perceptions Regarding IBM Watson

Besides PU and PEOU, other perceptions can also directly or indirectly influence the adoption of a technology. That said, we asked the interviewees to quickly elaborate on their perceptions of the relative advantage, compatibility, complexity, observability, and trialability regarding IBM Watson. We briefly discuss the obtained results in the following subsections. Not surprisingly, many of the answers below were already discussed before during PU and PEOU analyses.

3.3.1 Perceived Relative Advantage

IBM's selling proposition is that Watson can be used to improve research and to support physicians, in a sense that physicians might struggle keeping up with the growing number of academic papers that are constantly published. Hence, Watson can help physicians by delivering the right information in the context of a patient. We note that almost no respondent acknowledges this problem. As such, although a few respondents are unsure of the relative advantages brought by Watson due to the lack of a hands-on experience with this technology, others emphatically argue that they do not see any relative advantage of using Watson at this moment. To reduce the underlying perceived risk and uncertainty, users need some assurance that a new technology is beneficial. In the healthcare domain, this is usually demonstrated by academic publications that contrast the disadvantages of the new technology in comparison to existing technologies or processes. Many respondents highlight the current lack of such case studies involving Watson (see also subsections 3.3.4 and 3.3.5 below). This leads us to conclude that the perceived relative advantage (Research Question #3) is currently negative.

3.3.2 Perceived Compatibility

Compatibility also plays an important role in the adoption process of a new technology. As mentioned earlier in this section, some interviewees do not have the feeling that Watson fits in the workflow of their organizations. Therefore, the perceived compatibility of this technology is negative (Research Question #4). A crucial problem when using Watson in Dutch hospitals is the language. Respondents B, C, and F noted that they are willing to change their workflow and even report in English when Watson proves itself useful in terms of time and cost savings. However, this change is not a consensus among all the interviewees.

3.3.3 Perceived Complexity

Besides the relative advantage and compatibility, the perceived complexity of a technology can also impacts its adoption rate. It is well-known that more complex innovations spread slower than simpler innovations (Rogers, 2003). This perception is where respondents usually are positive about Watson. For example, Respondents B, C, and H, who are familiar with Watson, state that Watson is easy to use, consisting primarily of filling in text fields and selecting answers via dropdown menus. Some respondents who never used Watson before also agree that the above operations, although costly in terms of time, are not complex. Overall, we conclude that the perceived complexity of IBM Watson is positive (Research Question #5).

3.3.4 Perceived Observability

The next investigated perception is observability (Research Question #6). The collected responses show that the perceived observability regarding Watson is negative. This is understandable because only a handful of hospitals around the world have adopted Watson at this time. Because Watson is still in the training/testing phase and not fully deployed yet, the hospitals and IBM are not necessarily willing to publish preliminary results. Some respondents highlight the fact that the hospitals that work with Watson have put a lot of effort and money into training the technology and might not want other hospitals to observe the outcomes yet in order to preserve their potential competitive advantage.

3.3.5 Perceived Trialability

We note that only a few healthcare professionals in the Netherlands have worked with Watson before (this can also be inferred from Table 1). Citing the lack of hands-on experience and published studies, many respondents' responses imply that the perceived trialability concerning Watson is currently negative (Research Question #7). Some respondents would like to individually try the system to better understand its capabilities. For example, Respondent G mentions the following: "I have no idea what it [Watson] is doing and how it determines its recommendations. Because of this it is very hard to trust this technology. I want to try it myself, insert cases from the past and see if its recommendations correspond to my knowledge and treatment plans."

4. Discussion

In this section, we interpret the above findings considering the seminal ideas on diffusion of innovations by Rogers (2003). Among other things, the theory of the adoption of innovations states that characteristics of potential adopters influence the rate of diffusion of a technology. Specifically, Rogers (2003) states that there are five categories of adopters:

innovators, early adopters, early majority, late majority, and laggards. These categories make up, respectively, 2.5%, 13.5%, 34%, 34%, and 16% of the underlying population. Rogers (2003) further suggests that a significant departure from the status quo can occur when 15 to 20 percent of the underlying population have adopted a new technology. In other words, once innovators and early adopters have embraced a new technology, the early majority may then follow their lead. When the early majority adopts the technology, the late majority will feel comfortable to make a change as well.

Berwick (2003) discussed the ideas by Rogers (2003) in the context of healthcare. For example, the "innovators" can be seen as mavericks, or healthcare professionals who are heavily invested in a specialized topic. The "early adopters" are often elected leaders that are chosen as representatives of a clinical group. As such, these professionals are more likely to be targets of pharmaceutical marketing and IT vendors. The "early majority" in healthcare settings consists of professionals who are ready to try technologies that meet their immediate needs, whereas the professionals in the "late majority" category wait until a technology is the new standard of practice before adopting it. The final group of healthcare professionals, the "laggards", are the traditionalists, i.e., the group who "swear by the tried and true" (Berwick, 2003, p. 1972).

Given the above discussion, it might make sense for IBM to target healthcare professionals who are innovators and early adopters. As such, it makes sense for IBM to focus on academic/research-oriented hospitals since these organizations are more likely to have innovators and early adopters in their staff. Looking at some of the pilot programs we described in Section 1.3, it seems that this is precisely what IBM is doing. This practice is in line with the findings by Yarbrough & Smith (2007), who suggest that smaller (non-academic) hospitals are more technology reluctant than academic hospitals, and therefore innovation must start in academic hospitals.

Some respondents do agree with IBM's focus on academic hospitals. Respondent K, for example, states the following: "The early innovators are often academic hospitals. They want to be the first to try out new technologies because there are many possibilities in the early stage of an innovation to do research and to publish about." According to respondent J, Watson is a typical innovation that needs to start in academic hospitals and with specialists: "They [specialists] have the knowledge to train Watson and the capacities and resources to adopt and implement this innovation ... We, the nonacademic, do not have the budget to adopt and train Watson, even if we wanted to." Besides this, Respondent J also states that academic hospitals and specialists need to disprove the advantages of Watson. When the advantages are proven, adoption will then be quicker.

It is very interesting to note, however, that some respondents do not agree with IBM's strategy. In particular, we observe that the respondents who had no hands-on experience with Watson believe that this technology should be used in research intuitions, whereas those who had a hands-on experience with Watson are more in favor of using Watson in small hospitals. For example, as we discussed in Section 3.1, some specialists who worked with Watson before state that the usefulness and relative advantage of the technology both lie with the general physicians and smaller hospitals.

We take the above discussion as evidence that healthcare professionals unfamiliar with Watson might be biased by IBM's efforts to place Watson in academic institutions. It seems that as soon as the professionals become familiar with the technology (i.e., have a hands-on experience with it), then the perception that Watson is more appropriate to small hospitals become more common. This point shows that IBM's strategy of focusing on large academic hospitals might actually be wrong. Nonetheless, IBM and partners should clearly publish unsuccessful stories of institutions using Watson so as to raise the awareness among healthcare professionals of the capabilities of that technology. We further elaborate on this point in the final section of this paper.

4.1 Comparing IBM Watson with the da Vinci Robot

The previous sections reported negative perceptions regarding a specific health information technology, namely IBM Watson. In this subsection, we contrast our results to results of prior studies. In particular, we focus on another groundbreaking technology, which unlike IBM Watson, was overwhelmingly well received: the da Vinci robot. It is noteworthy that there were many uncertainties regarding the clinical benefits of the da Vinci robot as a new surgical device, and the overall cost of that technology was very high (Abrishami et al., 2014). Moreover, the clinical superiority of the da Vinci robot depended to a large extent on the surgeon's experience, the rate of learning robotic surgery skills, and the patient's risk portfolio (Robertson et al., 2013; Novara et al., 2012). Despite the unclear clinical benefits and high expenses, hospitals adopted the da Vinci robot anyway.

First, compatibility played an important role in the adoption process of the da Vinci robot. Specifically, the concept of minimal-invasive surgery (MIS) was becoming popular among patients and professionals, and the da Vinci robot was conceived as a perfect interface to transition from the old techniques to MIS (Hakimi et al., 2009). MIS was seen as the future status quo and this created a strong incentive for urologists and hospitals to consider switching to robotic surgery (Abrishami et al., 2014). This technology was therefore compatible with the (future) workflow, and this increased its PU. Contrasting the above with IBM Watson, it is still unclear what the latter can and cannot do, and how the same can fit in a healthcare institution's workflow.

The adoption of the da Vinci robot was also boosted by research-related affordances. Unlike IBM Watson, surgeons, hospitals, technical universities, and the manufacturer all had a stake in conducting and publishing research related to the da Vinci robot (Abrishami et al., 2014). For example, urologists wanted to publish about their techno-surgical experiences so as to boost their research profiles, whereas the manufacturer wanted feedback to incrementally develop the technology (Abrishami et al., 2014). Because the stakeholders had their incentives to conduct research and develop knowledge about the robot, its perceived trialability and, consequently, PU were high, thus leading to a quick adoption.

The da Vinci robot also created a perception of relative advantage since its adoption was seen as an opportunity to perform better than the competition (Abrishami et al., 2014). This perception was further boosted by the name of the technology, which induced an image of perfection and advanced care (Paul et al., 2013). In particular, the perceived high-tech precision was taken as a synonym for high-quality care (Abrishami et al., 2014). The perceived relative advantage naturally led to higher PU. In contrast, as we elaborate on in the following section, the name IBM Watson appears in many different contexts, and most of them are not at all associated with healthcare. The ambiguity regarding its name might be partially responsible for the negative perceptions concerning IBM Watson.

5. Conclusion

The healthcare ecosystem continually produces a huge volume of data from sources such as digital images from CT scans and MRIs, reports from medical devices, patient medical records, clinical trial results, and billing records. These data exist in many different formats ranging from structured data stored in spreadsheets to highly unstructured data in paper records. Cognitive computing is a new paradigm that promises helping researchers and practitioners leveraging these data. IBM, a pioneer in the development of cognitive systems, developed the cognitive computing system called Watson to participate in the Jeopardy! competition. After shocking the world by beating previous Jeopardy! winners, IBM started adapting Watson to different domains, including healthcare. This adapted system promises to collect evidence from huge volumes of information to support or refute medical diagnoses and treatments. In our work, we investigated whether there is a natural demand for cognitive systems from healthcare workers.

Grounded in the technology acceptance model, we interviewed 11 healthcare professionals working in the Netherlands. Some of these professionals had previous hands-on experience with Watson, whereas others only read/heard about the technology and its capabilities. This fact allowed us to analyze different perceptions from different potential users. We first found that the perceived usefulness of Watson is rather negative. In particular, the respondents do not see any relative advantage of using Watson over existing technologies and/or which problems can be tackled by that technology. Similarly, the perceived ease of use is negative in that respondents are not convinced that Watson can fit easily in the current workflow of their organizations. An interesting point we found is that respondents who experienced Watson before believe this technology is better suited to help general physicians in small, resource-constrained hospitals, whereas respondents who did not have a previous hands-on experience believe that Watson is more suitable for academic hospitals.

The above results just show how fuzzy different perceptions of Watson are in that, generally speaking, it is not clear what this technology is or can do. We further interpreted the above results in light of the seminal ideas on diffusion of innovations by Rogers (2003). We concluded that IBM's current strategy is to introduce Watson to specialists in academic hospitals who are innovators or early adopters. However, this might be a wrong strategy in that respondents familiar with Watson believe that the same is more suitable for small hospitals and general physicians. This fuzzy environment might help explaining the recent troubles the underlying Watson Health division is facing at IBM, e.g., there is an estimated layoff of 300 employees (Strickland, 2018).

Despite the above conclusion, we argue that IBM's efforts at introducing Watson into academic hospitals might still be fruitful. As both Respondents B and C suggest, although they see the relative advantage of Watson inside small hospitals, specialists from academic hospitals can write case studies and publish about the observed evidence in favor or against Watson. Such case studies can lead to a better understanding of what the technology is capable of. The more knowledge potential users can gain about the expected consequences of an innovation, the more likely they are to adopt it (Rogers 2003). This reduction in uncertainty was one of the reasons the da Vinci robot got easily adopted by some Dutch hospitals according to Abrishami et al. (2014).

Other than perceived usefulness and ease of use, we also investigated five other perceptions of Watson: relative advantage, compatibility, complexity, observability, and trialability. A new technology is likely to get adopted faster when these perceptions are positive. Unfortunately, at this moment, there is still a lot of uncertainty influencing those perceptions. According to the interviewees, except for complexity, the other perceptions are very negative, which creates uncertainty regarding different aspects of Watson and, hence, a barrier to its adoption.

Looking at the obtained results, it is clear that IBM should try to demonstrate the usefulness of Watson before trying to commercialize it on a large scale. One standard way of doing so in the healthcare domain is by publishing case studies, which are currently very scarce. On top of that, we believe that there is unnecessary ambiguity and confusion surrounding the term “Watson,” which might be contributing to the negative perceptions regarding that technology. For example, the term “Watson” was used to represent a family of off-the-shelf artificial intelligence technologies available on the IBM’s cloud platform (e.g., see an application by Jerdack et al., 2018). The same term has also been used to refer to healthcare technologies used in clinical work, oncology research, etc. This gives the impression that IBM is trying too hard to reuse its Jeopardy! technology. As stated by a former IBM employee: “It’s like having great shoes but not knowing how to walk - they have to figure out how to use it” (Strickland, 2018). Even the term “cognitive computing” that is being pushed by IBM is not clearly defined. It simply feels like an attempt to rebrand several well-established technologies and techniques.

We believe that technologies that favor evidence-based decision making, such as IBM Watson, will lead to more consistency in decision making, improved health outcomes, program performance monitoring that allow for comparisons with other programs, and the opportunity to learn from experience. Ultimately, the success of cognitive computing systems and IBM Watson will be based on their ability to integrate effectively into clinical workflow, to improve quality of care, and to reduce costs. As of today, it is not at all proven that cognitive systems can achieve these goals.

It is fair to acknowledge a limitation of this work in that it was performed in the Netherlands. Since IBM Watson is currently used in some healthcare institutions in the United States of America, from Cleveland Clinic (Ohio) to the Memorial Sloan-Kettering Cancer Center (New York), it is then important to investigate how generalizable our results are. In particular, we anticipate that some perceptions, such as perceived compatibility, might not be so negative since, for example, the technology’s language (English) is no longer a barrier. Second, we used the technology acceptance model to guide our efforts and better understand perceptions about Watson. From a more theoretical perspective, it is worthwhile trying to understand what makes cognitive computing technologies unique and, in particular, finding specific constructs that may lead to the extension and/or revision of current information systems theories.

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Appendix A. Interview Questions

- **Basic questions**
  - For how long have you been working on your current position?
  - What is your organizational role?
- **Introduction of the content of the interview and about the researchers**
- **Professional and/or technology related questions (questions directed to physicians)**
  - How much time per week do you spend on reading medical information?
  - If you are unsure about a diagnosis or a treatment, what do you do?
  - What is your opinion on technological innovations in general?
  - What criteria does an innovation have to meet in order for you to adopt it?
  - Where does innovation start in a hospital and with whom?
- **Professional and/or technology related questions (questions directed to innovation professionals)**
  - What kind of innovations are you trying to implement?
  - How do you select these innovations? On what criteria?
  - Where do you start when implementing an innovation? and with whom?
  - What is the role of physicians in innovation?
  - What do you experience as the main barrier(s) when implementing an innovation?
- **Watson related questions**
  - Are you familiar with IBM Watson? If yes, could you please explain what you know about it?
  - What is your perception of IBM Watson when it comes to usefulness and easiness of use?
  - What is your perception of the relative advantages of using IBM Watson?
  - What is your perception of the compatibility of IBM Watson?
  - What is your perception of the complexity of IBM Watson?
  - What is your perception of the observability of IBM Watson?
  - What is your perception of the trialability of IBM Watson?

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