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CAN CHATBOTS WORK WELL WITH KNOWLEDGE MANAGEMENT SYSTEMS?

Mathew Erickson, Walsh University, mericks01@walsh.edu
Philip Kim, Walsh University, pkim@walsh.edu

ABSTRACT

Knowledge management systems (KMS) and conversational agents, or chatbots, can increasingly be used to help deliver on-time data to a variety of end users. Chatbot front-ends can be used by remote employees, call center representatives, and even library patrons and students to connect to a KMS back-end for real time delivery of information. Earlier iterations of chatbots relied solely upon user requests, but more advanced interactive agents are improving to include learned responses to a set of searches, or even to a range of movements on a computer screen. In this literature review, examples of studies done in libraries, educational settings, and within the workplace are looked at, as well as studies related to natural language processing. We conclude with recommendations for future research topics suggesting the need to integrate chatbots with KMS.

Keywords: knowledge management systems, chatbots, natural language processing

INTRODUCTION

Corporate knowledge management systems have been around since the early 1990's with the purpose of ensuring that the loss of key personnel in an organization didn't mean the loss of the knowledge the individual might have. Knowledge management systems provide a platform for organizations to more easily centralize, disseminate, and maintain institutional knowledge for their employees. This could save time and resources for onboarding, risk management, and standardizing existing processes (Jelenic, 2011). Therefore, the transfer of knowledge from the expert to the organization is immensely important (McInerney, 2002). These systems typically center around three purposes: best practice sharing, a knowledge directory, or a knowledge network (Alavi & Leidner, 2001). All three of these types of systems require not only content creation and storage, but a method of retrieving the content when needed. If the knowledge is not available in near real time, without the need to search and scan databases of information, then it isn't an effective system.

One potentially effective method of getting this corporate knowledge to an end user without the need to search volumes of data is the chatbot. Around the same time that KMS were being introduced to corporations, individuals were being introduced to instant messaging. In 1996, Israeli firm Mirabilis invented ICQ, the first instant messaging system that was later sold to AOL (Ziv, 2015). As of September 2018, over 1.5 billion people use WhatsApp, while 1.3 billion use Facebook Messenger (Kim, 2018). Chatbot technology is no different than an instant messaging system, with the exception that the responder is an automated, intelligent agent. The first chatbot, ELIZA, was introduced in the 1960's (Wu at al., 2019). By using a chatbot front end with a KMS backend, corporate employees can ask a question and get a response in near real time, eliminating the need to search for needed information and waste the time of the employee and the customer. This technology can also be used by schools, libraries, and other organizations to enhance customer satisfaction and system usability (Harman, 2019).

This literature review will look at the timeline of both KMS and chatbot technology, as well as integration points for the two technologies in use today. This review will conclude with potential research studies that could enhance knowledge of how to successfully implement these two technologies.

REVIEW OF THE LITERATURE

Organizational Learning and Organizational Memory

Over two decades ago, Hackbarth (1998) wrote about the impact of organizational memory on IT systems. He described the OADI Learning cycle of Observe, Assess, Design, and Implement as the basis of transferring organizational memory through what was then called Organizational Management Information Systems (OMIS). He stated "[the] crucial difference between information and knowledge is the ability to match information with a particular set of circumstances that actively promotes innovation and responsiveness to customer needs" (Hackbarth, 1998, p.590). It is from this basis that KMS and chatbot technology integration can grow, by allowing employees to receive immediate knowledge based on the circumstances of their interaction with their customer.

At the turn of the millennium around Y2K, McInerney (2002) provides a useful summary of the emerging field of knowledge management. At that time, the field was more of a theoretical then a technical field, but she did recognize the potential of KMS and the IT infrastructure of knowledge management. She summarized her paper by arguing for the need to value active knowledge sharing and for management to recognize the impact of knowledge exchange to in order to have lasting and meaningful ways to work. The management of knowledge will need to be as dynamic and process-oriented as knowledge itself (McInerney, 2002).

Knowledge Management Retrieval

Alavi and Leidner (2002) discuss the issue of knowledge retrieval. They addressed the two methods of information retrieval for KMS: the pull method, where a user searches for information based on specific queries, and the push method, where information can be delivered to a user based on predefined criteria (Alavi & Leidner, 2002). They also point out "[the] challenge in design of organizational knowledge retrieval strategies is providing timely and easy access to knowledge while avoiding a condition of information overload," (Alavi & Leidner, 2002, p.128). Based on their research, they posed several questions for future research. This review is focused on one of those questions: What retrieval mechanisms are most effective in enabling knowledge retrieval? Explain this further by adding some further research on KM retrieval processes.

Natural Language Processing

For a chatbot to be successful, it must possess the ability to recognize and respond to commands, although these commands could be worded in a variety of ways. This ability is the basis of natural language processing, or NLP. In a 2004 presentation to the 9th International Working Conference on the Language-Action Perspective on Communication Modelling (LAP 2004), Twitchell, Adkins, Nunamaker, and Burgoon (2004) presented a method of using speech act theory to create models of business conversations that could later be used to classify other business communications. This method of communication classification helps facilitate the retrieval of information by basing a search not only on what the searcher *says*, but also by what the searcher *means* (Twitchell et al, 2004).

The other benefit of NLP in chatbot technology is the ability to not only ask and receive information, but to have an actual conversation with the technology, resulting in a richer context-based retrieval of information. This would be useful in specifying the information that the user needs, by being able to ask clarifying questions. In this way, the chatbot would be able to narrow the search to more relevant information (Ikemoto, Asawavetvutt, Kuwabara, & Huang, 2019). In order to accomplish this, the speech program needs to be constantly tuned to ensure the relevance of the speech patterns. As defined by Ji, Lu, and Li (2004) one method of doing this tuning is through deep model matching, which generates a score for each set or subset of words based on the matching models and the neural network used to combine those models.

Another method of context-based retrieval was described by Wu et al. (2019), which they called a sequential matching framework. This method allows the chatbot to take pieces from each response and construct a fuller, more useful interpretation of what exactly it is the user wants information on. It is based on a pull method of information retrieval, with the difference being that each response from the user is combined to form a more accurate and robust search criteria (Wu et al., 2019).

Library Usage

DeeAnn Allison (2011) from the University of Nebraska-Lincoln conducted a pilot of the use of chatbot technology in the library. The chatbot was created using PHP and SQL, and was provided information from library websites, as well as results from previous live person chat analyses. The process the chatbot followed was: conversation initiated by a user who asks a question, the input is checked against the database, if a response is not found, a clarifying question is asked, which becomes the new question, if a response is found, it is either sent to the user, or additional questions are asked to narrow the search (Allison, 2011). With a goal of handling 95% of all interactions, the biggest challenge faced by Allison was the impossibility to predict what the user will say, and enticing users to continue using the system, even if their queries aren't answered (Allison, 2011). This "pattern-matching" method of chatbot information retrieval isn't ideal, as we will see later, but it is the primary method of chatbot/KMS integration.

Library use of chatbot can provide useful insights for chatbot usage with a KMS. There needs to be an understanding that not every query will result in "found" information, and therefore there should be regular maintenanceand fine tune adjustments to ensure continued use, because failure to find information could result in mistrust and discontinued use of the system.

Educational Use

Villegas-Ch, Arias-Navarrete, and Palacios-Pacheco (2020) explain the use of chatbots in an educational environment to complement and supplement the professors and administrators, giving students immediate access to information that they would otherwise have to wait for the instructor to share. It allows the student to have real time feedback and lesson assignment from the Learning Management System (LMS).

In this environment, Villega-Ch et al. (2020) detail the IT layers that would make up this structure. The first layer is the input layer, taking data from IoT devices to track where students frequent, how often they are on campus, and what activities the student does when on campus. The second layer is the cloud, where the data collected can be stored. The third layer is the data analysis segment, using Hadoop to process all the information collected, providing the chatbot with all the information it needs to interact with the student. Finally, the fourth layer is the interaction layer, where the student and the chatbot can discuss upcoming events, activities, and academics (Villega-Ch et al., 2020).

The process for use of the chatbot is a different process than the one used for the library. The user logs in to the university LMS, and the chatbot authenticates the user credentials against its database. Once verified, the chatbot presents the student with pending tasks and asking questions based on academic need. The student can ask questions of the chatbot, or the chatbot can make recommendations to the student based on the knowledge it has accumulated. By making this a two-way process, the student has as much ability to learn from the chatbot as the chatbot does to learn from the student. This also enhances the ability of the student to learn new skills when they are ready for them, rather than at a set schedule or even time-based method of teaching.

Another possible use of the chatbot in an educational environment is outlined by Palasundram et al. (2019). They describe a chatbot used as an online tutor by using a recurrent neural network-based sequence to sequence model of artificial intelligence. This would also allow the chatbot to answer what the researchers called "unseen" questions, or questions that are implied by the original question. In their research study, they prove that the configuration of the chatbot is just as important as the underlying information that is being retrieved (Paladundram et al., 2019).

The uses of the chatbot in education highlight some potential uses in a corporate environment awe well. The potential of a chatbot having access to HR, IT, and personnel information for employees gives the chatbot experience a completely personal feel. As shown in the Villega-Ch et al. (2020) study, as well as the work done by Palasundram et al. (2019), this could open the chatbot and KMS interaction into a more effective level of training, personalized content, and ability for the chatbot to deliver on time materials to an employee before they even ask for it.

Ranking Options for Chatbot Usage

In a thesis study done by Angelica Gardner (2019), the use of recommender systems with chatbot technology is explored. In her study, Gardner used a four-stage recommender system to rank and present web page articles to chatbot users that were looking for information. In this way, the chatbot could avoid using "fallback intent" or generic error responses that are generally presented to a user when the chatbot can't find the information that was requested (Gardner, 2019).

In the study, Gardner (2019) uses the recommender system to gather articles from a website, rank them based on topic, and suggest the highest-ranking article to the chatbot user. She accomplishes this by building a recommender system that includes the following: web spider to parse content, a "bag-of-words" model to story key elements of the parsed data, a graph database to store the data, and graph database APIs to query the data and produce the final results (Gardner, 2019).

Another study done by Hardalov, Koychev and Nokov (2019) uses a similar approach called machine reading comprehension to re-rank answer choices based on the context of the question. In their study, a framework is built that analyzes the difference between "good" answers and "bad" answers by transform words into vectors that can then be analyzed by the weight of the responses and selecting the answer that is "most good" (2019). Using this setup, with a variety of embedding options, they found that doing a sentence level embedding produced the highest accuracy of results. As was seen in the Palasundram et al. (2019) study, the sequence to sequence model was also used in this study and produced the best results (Hardalov, Koychev & Nokov, 2019).

These recommender systems would be useful with KMS/chatbot in a couple of different ways. First and foremost, it would be useful for scenarios where an exact answer isn't found in the KMS. The chatbot could use the recommender system to scour and crawl across company intranets, databases, and potentially external data repositories to find answers to a question that the KMS doesn't have in its database. If the question is an FAQ, then that data could then be published to the KMS database so that the answer would exist, and the recommender wouldn't be needed for that question anymore.

These systems could also be useful to rank possible answers from the KMS and determine the best answer according to the ranking scale results. In this scenario, the web spider wouldn't be needed, but the ranking system could be used within the KMS database to determine best answers for questions.

Chatbots and Knowledge Management Systems

In work done by Pilato, Augello, and Gaglio (2012) a proof of concept for the chatbot and KMS integration is explained. Their system uses modules that can be switched on or off depending on the needs of the conversation. The logic behind this switching is the "corpus callosum," named after the part of the brain that connects the two halves. In the chatbot, it acts as a planner that takes the analyzed dialogue and determines how the system should respond (Pilato et al., 2012).

The improvement expectation is because the general method of a typical chatbot response is based on pattern-matching, meaning that when the system responds to a user, it is simply finding a template that fits the user pattern (Pilato et al. 2012). In this model, the system is too rigid, because question A always gets response A, with no real intelligence involved in the process. The recommendations by Pilato et al. (2012) introduces a concept of connotation to the speech act analysis. In this way, the chatbot can recognize positive, negative, or neutral connotations of speech, as well as assertive, expressive, or declarative speech, and assign a module that fits with that analysis. This allows the chatbot to be friendly, empathetic, submissive, or logical based on the input from the user (Pilato et al., 2012).

The implications of this research on chatbot and KMS integration is the ability for employees to not only get the information they are looking for from the KMS, but to feel like the system is interested in helping them. Studies have shown that even when dealing with a chatbot, people feel emotionally satisfied when a chatbot exhibits human emotions (Ho, Hancock, & Miner, 2018; Satu, Parvez, & Al-Mamun, 2015).

CONCLUSION

Reviewing the current literature reveals a lack of research regarding the integration of chatbot technology with Knowledge Management Systems. However, with the amount of research done on chatbot improvements, there are several interesting research streams that could be pursued in regards to chatbot and KMS integration.

The research study that could yield some promising data would be a further exploration of a combination of topics brought forth in this literature review. Some research topics could include:

1. Chatbot integration with Knowledge Management Systems (KMS) in e-commerce
2. Chatbot integration with KMS in customer service applications
3. Chatbot integration with KMS and the impact of situational factors (semantics, technical jargon, colloquialisms, slang, etc.)
4. Chatbot integration with KMS and Human Computer Interaction

In order to collect data to measure the impact of chatbot and KMS integration, pattern-matching as well as module type chatbots could be tested with a standard KMS to determine agent effectiveness. A variety of NLP could be used to determine potential benefits of different types of language processing. The expectation would be that the chatbot with module-based AI would be more effective than the pattern-matching system, and the employee would be more likely to use the module-based system, as it is more emotionally expressive than a pattern-matching system.

Another topic that could be researched would center on the ability of a chatbot to be completely personalized with HR, personnel information, and prior IT requests, and how effective the interaction is between the chatbot and employee in that scenario. The expectation would be that the chatbot would be able to respond more quickly and accurately to the employee, and the employee would be more inclined to use the chatbot on a regular basis. The possible issue with this study would be the potential misuse of employee personal data, so appropriate security measures and privacy rules would need to be ensured to encourage enough participants.

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