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Knowledge Broker Bots in Enterprise Social Media: An Exploratory Study

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ABSTRACT

Enterprise social media (ESM) platforms are a central hub for team collaboration. While they can effectively facilitate communication among distributed individuals and teams, promoting knowledge sharing remains a major challenge. ESM users are often unaware of others' knowledge and therefore are unable to seek experts or share knowledge with those who need it. A potential solution could be the use of *knowledge broker bots* that automatically connect knowledge seekers with knowledge providers to facilitate knowledge sharing. However, given the focus of existing literature on the human element of knowledge brokering, our understanding of the use and impact of such bots on knowledge sharing in ESM is limited. Therefore, we conducted a two-month, exploratory study with five student teams on Slack. Our findings provide initial insights into how users interact with a knowledge broker bot and how the bot establishes connections between users as a critical conduit to successful knowledge brokering.

Keywords

Bots, enterprise social media, knowledge brokering, team collaboration, exploratory study, Slack.

INTRODUCTION

Enterprise social media (ESM) platforms, such as Slack or Microsoft Teams, have become a central hub for virtual team collaboration in both organizational and educational settings. While such platforms have been found to facilitate day-to-day communication among distributed individuals and teams, promoting other important collaboration activities, such as knowledge sharing, remains a major challenge. A key barrier to knowledge sharing is that people often do not know what others know and therefore are unable to seek experts or share knowledge with those who need it (Leonardi, 2014). Although ESM platforms provide users with some visibility into others' skills and areas of expertise (e.g., based on their profiles as well as messages in public channels), manually searching for, identifying, and contacting potential experts who might share their knowledge is tedious (Leonardi, 2014).

Since bots (short for software robots) have become an integral part of many ESM platforms in recent years, it may be possible to address this challenge by using bots to automatically connect ESM users who seek knowledge with other users who possess the requisite knowledge. These bots, hereafter referred to as *knowledge broker bots*, are designed to establish connections between knowledge seekers and knowledge providers with the aim of facilitating knowledge sharing. In contrast to knowledge distributors and knowledge integrators, the role of a knowledge broker is not to create, modify, or disseminate knowledge (Drew et al., 2014). Therefore, unlike other bots in social networks or online communities, knowledge broker bots do not directly engage in conversations or transfer information between users, but rather establish a connection between those who seek and those who possess the requisite knowledge.

Although several knowledge broker bots were developed for major ESM platforms in recent years (e.g., Slack's "Whocan" or "WhoQui", Microsoft Teams' "Who"), our understanding of their use and impact is limited. While there is a growing body of research on bots in social networks (e.g., Salge et al., 2022), online communities (e.g., Safadi et al., 2021), and open source software projects (e.g., Hukal et al., 2019), little attention has been paid to bots designed to support team collaboration in ESM (Seering et al., 2019).

At the same time, the ESM literature has explored the topic of boundary spanning (i.e., establishing and maintaining communication links to external resources) and knowledge brokering (Van Osch & Steinfield, 2018). However, the focus has been on the role of inherent affordances of ESM—such as visibility—on boundary spanning, where boundary spanning is viewed as an intrinsic human activity. The focus on knowledge broker bots shifts the perspective on boundary spanning from a human process facilitated by technology to a process that is inherently sociotechnical.

Against this backdrop, the objective of this exploratory research is to investigate the use and impact of knowledge broker bots in ESM and expand our understanding of knowledge brokering as a sociotechnical process. More specifically, we address the following research questions: (1) How do users interact with a knowledge broker bot when they seek knowledge or when they are contacted by the bot to provide knowledge to others? (2) How can a knowledge broker bot establish new connections between knowledge seekers and providers to facilitate knowledge sharing?

To address these questions, we conducted an exploratory study in the context of a two-month student team project with 21 users on Slack. Based on the analysis of digital traces of user interactions with the bot, communication behaviors on Slack, and a posteriori qualitative feedback, we provide initial insights into how users interact with a knowledge broker bot and how the bot establishes connections between users as a critical conduit to successful knowledge brokering. While our preliminary findings suggest that the bot was successful in connecting knowledge seekers with knowledge providers, we also identified several challenges and opportunities related to the use and the design of knowledge broker bots in ESM. With our exploratory findings, we aim to contribute to IS research on human-bot interaction by generating a deeper understanding of the use and impact of knowledge broker bots. Furthermore, disentangling the role of knowledge broker bots helps to extend the ESM literature on knowledge brokering and boundary spanning by adding a fundamental sociotechnical perspective. For practitioners, our study highlights opportunities and challenges of using bots to facilitate knowledge sharing among distributed individuals and teams.

RELATED WORK AND THEORETICAL FOUNDATION

Bots

Software robots, or bots for short, are fully automated software programs that perform a variety of tasks on behalf of their developers and users (Safadi et al., 2021). They are omnipresent in social networks (e.g., Twitter), online communities (e.g., Reddit), customer service, and open source software projects (e.g., on GitHub) (Gnewuch et al., 2022; Hukal et al., 2019; Salge et al., 2022). Bots can be viewed as a class of agentic IS artifacts as they can react to certain stimuli or action triggers (e.g., a new tweet or an update in a GitHub repository) and carry out actions autonomously (Baird & Maruping, 2021; Salge et al., 2022).

In recent years, bots have also become an integral part of ESM platforms such as Slack or Microsoft Teams. Existing bots are primarily designed to automate repetitive tasks (e.g., meeting organization), provide real-time information (e.g., notifications about GitHub activities), and facilitate communication and collaboration among individuals and teams (e.g., onboarding, project management). In contrast to bots for dyadic, one-on-one interactions or broadcasting bots in social networks, these bots are primarily designed to act as non-human community members that support collaboration between the other (human) members of a community or team (Seering et al., 2019).

Enterprise Social Media

Enterprise social media (ESM) are web-based platforms that enable users to effectively communicate with each other, network, organize, leverage information available on the platform, and collaborate (Leonardi et al., 2013). Most organizations use some form of ESM and the number of ESM users has drastically increased during the COVID-19 pandemic as employees were forced to work from home, a work practice that is forecasted to continue to a large extent even after the pandemic. Further, ESM platforms are increasingly used in educational settings to facilitate communication and collaboration among students.

Users of ESM platforms are able to communicate with other users through text-based synchronous and asynchronous communication. The communication can take place in private chat rooms or in public spaces, often called channels. Users can create and join channels as well as contribute to and consume content. Channels can be open to the entire organization or closed (i.e., involve only invited participants, such members of a specific unit, team, or project) (Van Osch & Steinfield, 2018).

ESM platforms aim to create an environment where users can effectively share knowledge. By participating in ESM, users can learn at least two kinds of knowledge (Leonardi et al., 2013): *instrumental knowledge* (i.e., knowledge about how to do something) and *metaknowledge* (i.e., knowledge about who knows what and who knows whom). Metaknowledge is crucial because it is an antecedent to the transfer of instrumental knowledge (Leonardi et al., 2013). In other words, before users can acquire instrumental knowledge from others, they need to know where that knowledge can be found (metaknowledge). However, users often do not know what others know and therefore are unable to find experts with the requisite knowledge (Leonardi, 2014). Although ESM helps users acquire metaknowledge (e.g., based on reading what others post or comment), manually searching for, identifying, and contacting potential experts who might share their knowledge is tedious (Leonardi, 2014).

Knowledge Brokering and Boundary Spanning

Knowledge brokering can be understood as the process of connecting knowledge seekers with knowledge providers (Haas, 2015; Hargadon, 2002). In contrast to knowledge distributors and knowledge integrators, knowledge brokers do not create, modify, or disseminate knowledge themselves (Drew et al., 2014). Instead, knowledge brokers establish connections between seekers and providers of knowledge in order to facilitate the flow of information from those who possess knowledge to those who need it (Drew et al., 2014).

The concept of knowledge brokering is closely related to that of boundary spanning, which refers to establishing and maintaining communication links to external resources (Tushman & Scanlan, 1981). Some studies have suggested that the critical difference between knowledge brokers and boundary spanners is the fact that the former focus on knowledge sharing between disconnected individuals, whereas boundary spanners aim to connect individuals or teams to external knowledge (Haas, 2015). Nonetheless, both refer to the fundamental process of connecting to critical resources that exist outside the immediate network (whether this is composed of individuals or teams/groups). Furthermore, similar to boundary spanners, knowledge brokers need to acquire metaknowledge of who knows what before they are able to make meaningful connections.

In the past, knowledge brokering has been a central human activity. Many organizations even have formal knowledge broker roles for people whose job is specifically to know what others know and help make connections (Hargadon, 2002). Similarly, the literature on boundary spanning in ESM has explored various boundary-spanning activities—representation, information search, and coordination—as inherent human processes occurring in the context of ESM. Furthermore, it has explored the role of ESM affordances, such as visibility, in facilitating these human processes of boundary spanning (Van Osch & Steinfield, 2018), but a fundamental sociotechnical understanding is lacking.

Recent developments in artificial intelligence (AI) have enabled technology to take on the role of a knowledge broker, for example, in the form of *knowledge broker bots* in ESM. In the context of this study, we define knowledge broker bots as fully automated software programs that acquire metaknowledge of who knows what and connect knowledge seekers with knowledge providers to facilitate the flow of information from those with knowledge to those who need it for a particular purpose. Figure 1 illustrates the concept of a knowledge broker bot, and this study focuses on exploring its role in transforming knowledge brokering into a fundamental sociotechnical process.

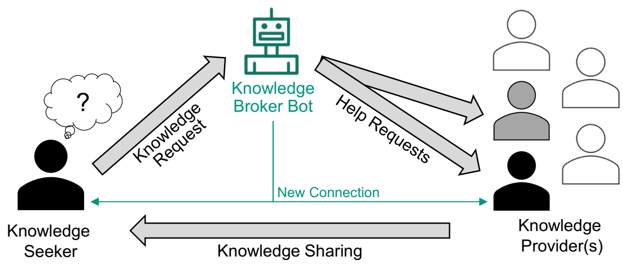

Figure 1. Knowledge Broker Bot

METHOD

Research Context

Our exploratory study was carried out at a large European university in the context of a master's human-computer interaction (HCI) course attended by 21 students with a background in information systems and industrial engineering and management. In the course, students were assigned to one of five teams and completed a two-month design project in partnership with a multinational European energy provider. The overall goal and topic of the project was to create innovative design solutions for supporting the human resources lifecycle of remote employees. Each team worked on a different phase of the lifecycle (e.g., attracting and hiring, onboarding, working remotely, offboarding). Students were assigned to a team based on their individual background, skills, and interests. As two students dropped out in the first week after the project started, one team had three members, while the other teams comprised four to five members. During the project, there were bi-weekly meetings with the instructor team and two employees of the partner company. The teams held three presentations over the course of the project to collect feedback. All official meetings except for the final presentation session took place virtually.

Slack was the primary platform for team communication and collaboration used in the project. The use of Slack was mandatory for students and they were informed that all project-related communication had to take place in Slack and not via email or other platforms. We created public channels for each team (i.e., visible to everyone), a general channel primarily used for messages from the instructor team, and a specific questions channel where students could post and answer questions. We also invited the employees of the partner company to join our Slack workspace so that they could be contacted directly inside the platform. Finally, our Slack workspace included a knowledge broker bot (see below). At the beginning of the project, we explained the bot's features to students and encouraged them to use the bot for seeking help from others for a specific task.

Knowledge Broker Bot "Whocan"

To select a knowledge broker bot for use in our study, we carefully reviewed all existing bots on Slack. We identified only two bots that matched our definition of a knowledge broker bot, namely "Whocan"[1] and "WhoQui"[2]. After testing and analyzing both bots, we decided to use Whocan because it offered a richer set of features related to the role of a knowledge broker. We contacted the developers of Whocan, explained the purpose of our study, and they agreed to share log data of bot interactions with us after the project.

Consistent with our definition of a knowledge broker bot, Whocan is described as a bot that helps users find another user with certain knowledge (called skill) by asking around for them. It also "*keeps track of who is good at what and connects experts to those who need them*". Whocan has two main features. First, for Whocan to be able to identify knowledge providers (called experts), users can use the command "*/skills [skill1, skill2, …]*" to manually set and update their areas of knowledge. Whocan stores this information, which is considered its metaknowledge (i.e., who knows what), in a database. Second, users who need help can make a knowledge request to Whocan using the command "*/whocan [request]*" feature (see Figure 2). In addition, Whocan actively monitors conversations in public Slack channels and reacts to posted questions by offering its help via private chat to the user who posted the question.

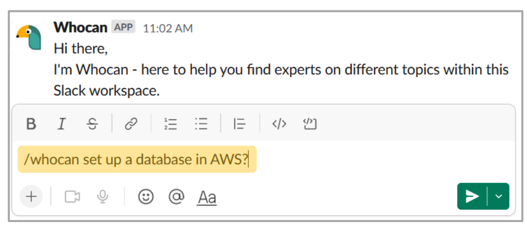

Figure 2. Knowledge Request from a User to Whocan

When Whocan receives or detects a knowledge request, it browses its database (i.e., its metaknowledge) and sends out help requests to five users. To identify potential knowledge providers, Whocan uses a keyword matching algorithm that compares the content of the request with the skills in its database. If no matches are found, Whocan randomly selects five users to contact each day or until the request is cancelled by the user. Potential knowledge providers are contacted via private chat using the message "*On behalf of a team member, I'm looking for someone who can [request]. Can you please help out or know who can?*" (see Figure 3). Contacted users

[1] https://slack.com/apps/A019V8JUJ9X-whocan

[2] https://slack.com/apps/AUBPY2EAC-whoqui

can either agree ("*Yes, I can help*") or disagree to help ("*No, sorry*"), forward the bot to someone else ("*I know who can help*"), or snooze the bot. When a user agrees to help, Whocan connects both users by opening a new group chat with both of them and repeats the knowledge request to start the conversation (see Figure 4).

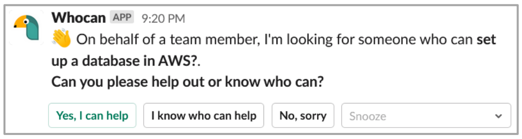

Figure 3. Help Request from Whocan to Potential Experts

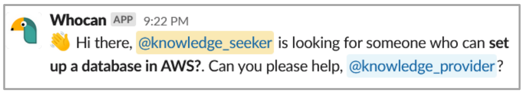

Figure 4. Connecting Users via Opening a new Group Chat

If contacted users forward Whocan to someone else, a window opens where the user can select another user in the Slack workspace who is then contacted by the bot as well. Finally, after two users have been connected in a new group chat, the user who made the knowledge request can rate the expertise of the knowledge provider. This information is used to update Whocan's database and therefore taken into account when selecting potential knowledge providers for similar requests in the future. Over time, Whocan is therefore able to continuously improve its metaknowledge.

Participants

Participants in our study were the 21 students who attended the master's HCI course. Participants were mostly male (85.7%) with a mean age of 23.8 years. Two-thirds studied information systems, while the others studied industrial engineering and management. Most participants were in their second year of study (M = 2.35) and all of them had some experience in the areas of software development, UX design, and user research. We explained the study procedure to all participants and assured them that their data would be anonymized for the analysis, treated confidentially, and not used for grading purposes. All participants provided their informed consent before participating in the study.

Data Collection and Analysis

In our study, we collected, preprocessed, and analyzed different, complementary types of data. First, we collected data on user interactions with the bot (e.g., making knowledge requests, reacting to help requests from the bot) as well as on the bot's activity in the background (e.g., updating skills in the database). After the project, the developers of the bot exported this data for us. The data was in JSON format and included digital traces of all bot-related activities. We preprocessed this dataset in order to build two clean datasets in CSV format, one for skill updates and one for knowledge requests. Second, we collected all messages from both public channels and private conversations on Slack. After the project, we exported this data from our Slack workspace. The export came in the form of a zip file containing many directories (channels and conversations) and JSON files with the message history broken into dates. We collated the exported message histories for each channel or conversation, extracted the message content and metadata, and converted them into a clean CSV format for further analysis. In the final step, we linked this dataset to the bot dataset and anonymized the users' identity by replacing their original usernames with randomly generated ids. Third, we also collected participants' feedback on the bot and their interaction with it in a short survey with open-ended questions at the end of the project.

Given the exploratory nature of our study, our analysis focused on providing initial insights into the use and impact of the knowledge broker bot in the ESM platform Slack. Based on the data of user interactions with the bot, communication behavior on Slack, and qualitative feedback from users, we performed the following analyses. First, we explored if and how users contributed information about their own knowledge areas to the bot's metaknowledge (who knows what) and rated the expertise of others after they were connected through the bot. Second, we analyzed how users interacted with the bot when seeking knowledge or when contacted by the bot to help out others. Third, we examined if the bot was able to establish new connections between users, as a potential indicator of its ability to facilitate knowledge sharing. In each step of the analysis, we complemented our results with qualitative insights from a content analysis of users' feedback in the survey.

PRELIMINARY FINDINGS

Throughout the project, all teams used our ESM platform Slack to communicate and collaborate. In total, 1,491 messages were sent over the two-month period, suggesting that a great deal of project-related communication (e.g., about developing prototypes, preparing presentations, organizing meetings) took place inside the platform. Most messages were sent in the five team channels. Although everyone, including members from other teams, could see these messages, we observed that users rarely interacted with others outside their own team in public. For example, the "questions" channel was never used, suggesting that users preferred private or intra-team communication when asking questions. While all teams regularly posted their presentations in the general channel (as we had asked them to do), we did not observe users or teams who actively shared their knowledge with others (e.g., by posting the results of their interviews with employees of the partner company). However, our analysis indicated that many users interacted with the knowledge broker bot during the two months. These user interactions include 207 manual updates of knowledge areas ("skills"), 83 knowledge requests to the bot, and 40 successful connections between knowledge seekers and providers. In the following, we present the results of our analysis of these interactions and the bot's overall impact.

Contributing and Acquiring Metaknowledge

To be able to connect knowledge seekers and knowledge providers in ESM, a knowledge broker bot needs to acquire metaknowledge of who knows what. Ideally, the bot would automatically extract users' areas of knowledge from existing conversations, profile pages, or other organizational databases. However, since our project started from scratch, there was no existing data to feed the bot and therefore we asked all users at the beginning of the project to use the "/skill"-command to manually provide information about their knowledge areas to the bot.

Our first analysis shows that all 21 users manually entered information about their knowledge areas to help the bot acquire metaknowledge. Their input ranged from single words (e.g., "R", "excel", "surveys") to full sentences (e.g., "i can develop your backend structure"). Frequently mentioned knowledge areas were programming languages (e.g., Python, JavaScript), tools (PowerPoint, Figma), methods (e.g., Scrum, project management), and topics (e.g., entrepreneurship, security). In total, users manually provided information about 207 knowledge areas to the bot (M = 9.86 per user). Most knowledge areas (71%) were entered in the first two weeks of the project (i.e., during the initial 25% of the project timeline); only a few users manually updated them later during the project. The number of unique knowledge areas entered was 112 and on average, a particular area was entered by 1.84 users showing the relative uniqueness and complementarity of knowledge areas. Thirty-seven knowledge areas were entered more than once, with some popular ones entered more than ten times (e.g., Python). In general, these results suggest that users were willing to adopt the knowledge broker bot and help it learn about them in order to build up its metaknowledge. However, the results also indicate some overlap of knowledge areas between users, at least initially, which could be a result of the relative homogeneity of our student participants.

In addition to the knowledge areas manually provided by users, the bot also updated its metaknowledge automatically when a knowledge seeker positively evaluated a knowledge provider after they had been connected by the bot. In total, there were 210 automatic updates of knowledge areas for 17 users, including 84 unique areas. Out of these 84 knowledge areas, 48 areas were new because they had not been entered manually before. This result suggests that the bot was able to increase its metaknowledge 'volume' (by 101%; based on 210 updates to the existing 207) and 'breadth' (by 43%; based on 48 new additions to the 112 unique areas) over time by learning from successful connections.

Knowledge Requests to the Bot

In our second analysis, we examined how users interacted with the bot when they sought knowledge. During the two-month period, users made a total of 83 knowledge requests to the bot, corresponding to ~4 requests per user and 1 request per user per fortnight. These requests were usually short sentences or questions with an average of 13.22 words. As the following examples show, users' knowledge requests varied in their level of detail and degree of specificity:

- *Who can set up a database in AWS?*
- *Who can set up Prometheus and Grafana or similar services to monitor our deployed Kubernetes service?*
- *I need someone who can analyze surveys*

The feedback provided by users indicated that they liked the simplicity of making knowledge requests. They generally found it "*very easy to post Whocan requests*" and mentioned that "*requests can be created quickly and easily*". However, some users made multiple requests in a short time span and were subsequently blocked by the bot's spam protection: "*I asked several questions but was blocked after the first one for half an hour*". Taken together, these results suggest that the bot was easy to use, but sometimes wrongly interpreted messages as spam resulting in user frustration and lost time. While mechanisms need to be in place to prevent spam, classifying whether or not a request is spam is not a trivial task and false positives can lead to frustration among users.

Bot Help Requests to Potential Knowledge Providers

In our third analysis, we examined how users interacted with the bot when they were identified as a potential knowledge provider and contacted by the bot to help out another user. To recap, after receiving a knowledge request, the bot asked around on the ESM platform by sending out help requests to potential knowledge providers (see Figure 3). Based on the 83 knowledge requests made by users in the two-month period, the bot sent out a total of 994 help requests (M = 11.97 per knowledge request). As explained earlier, the bot used a keyword matching algorithm to identify potential knowledge providers by comparing the content of the knowledge request with the list of knowledge areas stored in its database. If no matches were found, the bot randomly selected five users to contact each day or until the request was cancelled by the user. In total, 40 requests (48.19%) were successful in that a potential knowledge provider who was contacted by the bot agreed to help the knowledge seeker with her or his request. The remaining requests were unsuccessful either because no one agreed to help (22.89%), they were cancelled by the knowledge seeker before someone was found (13.25%), or blocked as spam (15.66%). On average, it took 11.37 bot requests and approximately two days for a successful request to be answered. Further, we found that seven requests were forwarded by a user to someone else. Four of these requests were then answered by the referred user (57.14%).

In general, the majority of user feedback about the bot's ability to connect knowledge seekers and providers was positive. Most users felt that the "*bot was quite fast in connecting [them] with experts*". Some only needed "*4-5 hours to find the first expert who [they were] looking for*". However, consistent with our quantitative results above, some users complained that their knowledge requests had not been successful. One user stated that "*half of [his] searches were never answered by any of the other students*" and suggested that "*the bot should give more incentive to answer other people's searches*". These results suggest that the bot was able to connect knowledge seekers and providers for many, but not all, knowledge requests. There are several possible explanations of why some knowledge requests were unsuccessful. One explanation could be that those who were contacted did not possess the requisite knowledge or did not want to help, perhaps due to a request's (poor) timing, a recipient's lack of time or, ultimately, motivation. As the examples above show, some requests were quite unspecific and may have inhibited others from agreeing to help. Finally, it could be that the bot did not contact a user with the requisite knowledge before the request was cancelled.

Users also commented on the volume of the bot's help requests. One user wondered why he was never contacted by the bot: "*There were no suggestions for me, whom I could help.[…] What for did I enter my skills in the beginning?*". However, other users complained about being spammed by the bot: "*I got too many notifications from the bot, which is annoying*". These results highlight the importance of the bot's ability to identify and select potential knowledge providers. Ideally, only those users who possess the requisite knowledge would be contacted. However, randomly contacting users is not an entirely bad idea because users might have acquired new knowledge recently or will forward the bot to someone else who might be able to help. It all depends on the volume of the bot's help requests because users will become annoyed at some point when they are constantly contacted by the bot with requests that may not be relevant to their expertise. Given that we only had 21 users on our platform, many were contacted multiple times. However, nobody blocked or "snoozed" the bot, even though this was possible. Again, an improved identification of users' knowledge areas based on inferences from existing knowledge areas or monitoring public conversations, as well as an intended 'load management' of requests across available users, might help to reduce the number of unrelated requests and keep users motivated to interact with the bot.

Establishing Connections between Knowledge Seekers and Knowledge Providers

In our final analysis, we specifically examined the set of successful knowledge requests where the bot was able to establish a connection between a knowledge seeker and provider. We initially planned to focus our analysis on the conversations between knowledge seekers and providers in the group chat opened by the bot, but we realized that most conversations were rather short as users often set up a video call or exchanged phone numbers to discuss the problem at hand using a different communication channel. Therefore, we could not assess whether and how much knowledge was actually shared between the two users. However, as a potential indicator for the value of the connections made by the bot, we analyzed how knowledge seekers rated knowledge providers. These ratings were requested by the bot two days after it established the connection. Our analysis shows that in 32 of the 40 successful requests, the knowledge seeker confirmed the knowledge provider's expertise in at least one knowledge area. This result suggests that most users (i.e., 80%) were able to get help through the connections established by the bot and that the bot was able to facilitate knowledge sharing among users.

In addition, we analyzed the bot's impact on connections between users on the ESM platform. Specifically, we examined whether the bot was able to establish connections between users who had not been in contact before (e.g., because they were members of different teams), as a potential indicator of its ability to facilitate knowledge sharing outside users' existing network of peers. To do so, we visualized our data in a simple graph, in which nodes represent users and edges represent connections between them. The left graph in Figure 6 displays intra-team connections between members of the same team (black) and cross-team connections between users who had a private conversation or participated in the same group chat (gray). The graph shows that while two teams appear well-connected (team 1 and 3) and one member of team 4 engaged with several other teams, there was not much contact across teams in general, with only 15 cross-team connections in total. In comparison, the right graph in Figure 6 displays intra-team connections (black) and new cross-team connections made by the bot through a successful knowledge request (red). This graph shows that the bot generated 38 new cross-team connections as opposed to the only 15 cross-team connections that already existed (i.e., an increase by 253%), suggesting that the bot was able to facilitate exchanges—i.e., through brokerage—between members of different teams. In summary, these results suggest that the connections through the bot were quite helpful because they connected otherwise unconnected members from different teams who might have never interacted with one another if not for the bot.

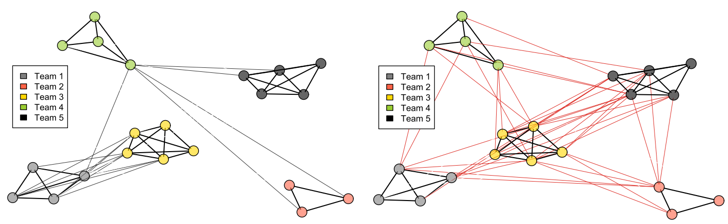

Figure 6. Network of Existing Connections between Users (left) and New Connections established by the Bot (right)

DISCUSSION

In this exploratory research, we investigated the use and impact of a knowledge broker bot in ESM. The preliminary findings of our two-month study with five student teams suggest that the bot was successful in connecting knowledge seekers with knowledge providers on Slack. While our data does not allow us to evaluate how much knowledge was shared, there is some indication that the connections established by the bot helped knowledge seekers find someone with the requisite expertise and facilitated collaboration between members of different teams. In addition, our findings provide initial insights into how users interact with a knowledge broker bot when they contribute information about their own knowledge areas to the bot's metaknowledge, when they formulate knowledge requests, and when they are contacted by the bot to help out others.

With our exploratory findings, we add to ESM literature and the emerging stream of IS research on human-bot interaction by revealing opportunities and challenges related to the use of knowledge broker bots in ESM. First, extant research shows that acquiring and updating metaknowledge of who knows what in an organization is a major challenge for humans (Leonardi, 2014). Our findings suggest that knowledge broker bots face a similar challenge, particularly when they are introduced in a new environment without existing data to use for "mining" users' areas of knowledge (e.g., profile pages or existing conversations). Although we find that users are willing to actively contribute to the bot's metaknowledge, this willingness decreases over time and probably some kind of recurring reminder would be necessary (e.g., the bot could ask users from time to time if their knowledge areas have changed). Moreover, ESM literature suggests that proclaimed expertise is a worse indicator of actual expertise than the content of users' messages (Leonardi, 2015). Thus, the bot's ability to learn from existing conversations and the successful connections it made between knowledge seekers and providers is crucial, not only to update its metaknowledge but also to avoid spamming users with knowledge requests that may not actually be adequately fulfilled considering their expertise. This unique ability of the bot has the potential to improve opportunities for successful knowledge brokering by relying on more "objective" indicators of expertise. Another promising opportunity could be to give the bot access to messages in private conversations or channels rather than focusing on public spaces to identify experts. Existing research has shown that knowledge creation and sharing often happens in private spaces (Van Osch & Bulgurcu, 2020). Although ESM are mostly implemented with the purpose of facilitating unlimited knowledge sharing, if knowledge and expertise largely reside in private spaces, it inherently inhibits access from those outside these spaces. Opening them to other users would undermine the inherent benefits of privacy for knowledge sharing. Thus, knowledge broker bots could be an optimal tool for identifying relevant expertise in private spaces without revealing confidential information to outsiders or undermining privacy.

Our study has two main limitations. First, our study was conducted in the context of a student team project. Although students worked together on a real-world, two-month project in collaboration with a company, this environment is not fully representative of the actual working environment in an organization. Another limitation is that our data did not allow us to analyze how much knowledge was shared after the bot had established a connection between a knowledge seeker and provider due to the fact that users typically leveraged other communication modalities for the actual knowledge exchange. Future research could combine the types of data that we used with other data collection approaches (e.g., surveys) to gain a more holistic understanding of the impact of a knowledge broker bot.

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