The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0090-7324.htm

Uncoding library chatbots: deploying a new virtual reference tool at the San Jose State University library

Sharesly Rodriguez and Christina Mune
University Library, San Jose State University, San Jose, California, USA

Received 20 May 2022
Revised 18 June 2022
31 July 2022
9 August 2022
28 August 2022
Accepted 30 August 2022

Abstract

Purpose – This paper aims to detail how a university library developed an AI chatbot to meet a growing need for virtual reference services. This chatbot was developed using Google's free Dialogflow bot platform and embedded in the library's website. With the onset of COVID-19 and a greater reliance on virtual services, chatbots have become of increasing interest to libraries as a tool to provide enhanced services during non-staffed hours and to perform basic information triage when virtual chat transactions reach an overwhelming number of available staff.

Design/methodology/approach – Using in-depth research into current practices and readily available tools, a small non-technical team at a university library designed and piloted an AI chatbot that employs natural language processing and AI training. This article describes the chatbot development and implementation process. Results of chatbot interactions after one academic year of usage are also reviewed.

Findings – This study reveals that a university library chatbot may be developed and deployed with minimal coding knowledge using existing tools. Chatbot content can be populated through current library information sources and trained to address typical information inquiries. However, additional development and testing is needed to increase user engagement.

Originality/value – This study indicates that libraries can develop and deploy chatbots to meet user information inquiries without onerous technical training or IT resources. It describes best practices for chatbots and the steps necessary to deploy a chatbot on a library website.

Keywords Chatbots, AI, Virtual reference, Chat reference, Library technology, Academic libraries, Emerging technologies, Online services, User experience

Paper type Case study

Introduction

In the last few years, especially during the COVID-19 outbreak in 2019 and resulting increase in virtual interaction across sectors, a growing adoption of conversational agents that utilize artificial intelligence, machine learning and natural language processing, largely known as "chatbots," has emerged. We are currently in what has been described as a "chatbot tsunami" (Grudin and Jacques, 2019). Adoption of chatbots has been accelerated by tools that promote interoperability and integration of these into all communication platforms, from Facebook Messenger to your organization's website.

The growing interest and adoption of chatbots and other artificial intelligence and machine learning tools can also be seen in libraries (Bilal and Chu, 2021). Through chatbots, libraries may increase engagement with patrons, provide enhanced information services and better understand patron information-seeking behaviors (McNeal and Newyear, 2013; Vincze, 2017; Shi *et al.*, 2021). In addition to the stated benefits, San Jose State University's (SJSU) Dr. Martin Luther King, Jr. Library desired a solution to increase interaction with students seeking help during overnight and weekend hours when no reference librarians or circulation staff were available.

While there are many full-service chatbot options available for purchase or subscription, these services can run well into the tens of thousands a year depending on the number of users and transactions. These costs may not be sustainable at public or non-profit

Reference Services Review
Vol. 50 No. 3/4, 2022
pp. 392-405

0090-7324
DOI 10.1108/RSR-05-2022-0020

organizations such as libraries; lack of means and resources are often cited for the slow adoption of AI and chatbots in libraries (Bilal and Chu, 2021; Ehrenpreis and DeLooper, 2022). Additionally, many libraries are discouraged by the perceived technical requirements of chatbot implementation and upkeep.

To investigate the possibility of building a chatbot with minimal cost and coding, SJSU King Library sought two virtual interns from SJSU's iSchool to perform in-depth research into current chatbot practices, explore readily available chatbot tools, and attempt a chatbot pilot. Dialogflow was selected for the pilot chatbot based on a variety of factors, including cost, ease of use and ability to train the chatbot (Rodriguez and Mune, 2021). This article builds on the authors' previous work by providing in-depth instructions into creating chatbot content, training chatbot responses and embedding chatbots using SpringShare chat widgets. It also presents the first year of user–chatbot interactions, offering insight into possible challenges and ways to address them.

Background

Brief history of chatbots

Chatbots can be defined as, "intelligent conversational computer systems designed to mimic human conversation to enable automated online guidance and support" (Caldarini *et al.*, 2022). The first recognized chatbot, ELIZA, was created by Joseph Weizenbaum in 1966. Weizenbaum used pattern matching and pre-written scripts to deliver responses to user inquiries based on keywords (Weizenbaum, 1966). ELIZA was used as an early test case for the Turing Test, computer scientist Alan Turing's proposed method for determining if an artificial intelligence could exhibit behavior identical to a human (Haenlein and Kaplan, 2019). Creating chatbots indistinguishable from humans was a primary objective for many early chatbot developers.

In 1995, chatbots were developed further with the creation of the XML schema AIML, Artificial Intelligence Markup Language, by Richard Wallace. Wallace's chatbot, A.L.I.C.E., or Artificial Linguistic Internet Computer Entity, used AIML to perform natural language processing (NLP). NLP is considered the manipulation of normal human language, as text or speech, by a computer or software program for computational purposes. AIML created more human-like conversational programs through conversational rules, heuristic pattern matching and an expandable database of topics and categories, allowing AIML bots to be more dynamic in their response (Wallace, 2009). AIML continues to be used in some chatbot platforms today.

One AIML-based chatbot Mitsuku, now Kuki, has won the Turing Test-based Loebner Prize multiple times in recognition of its human-like qualities. Abdul-Kader and Woods (2015) describe how Mitsuku represents a growing interest in chatbots designed specifically for social interaction rather than information retrieval and provision. Over five billion unique users have interacted with Mitsuku online, some on a daily basis (Lewis, 2020). Like Microsoft's popular XiaoIce chatbot, launched in 2014, these chatbots are built to recognize users' emotions and provide encouraging, friendly interpersonal communication that promotes a sense of well-being (Shum *et al.*, 2018).

Increasingly prevalent in our daily lives, Intelligent Personal Assistants (IPAs) including Apple's Siri (2010), Google Assistant (2012), Microsoft Cortana (2013) and Amazon's Alexa (2014) represent an intensive investment into AI bots with NLP skills (Suta *et al.*, 2020). IPAs use big data, web resources and machine learning to answer natural language inquiries from users on a wide range of topics (de Barcelos Silva *et al.*, 2020). Machine learning is the use of algorithms and statistical analysis to draw inferences from patterns found in large data sets. IPAs train on huge data sets to understand contextual clues in spoken or written inquiries and to respond accordingly. Chatbots that use machine learning are able to improve their responses through experience, adapting to various contexts the more they are used (Nath and Sagnika, 2020; Suta *et al.*, 2020).

Adoption in libraries and higher education

Libraries have been experimenting with chatbots for over a decade. In 2009 "Emma the MPL Catbot" chatbot premiered at the Mentor Public Library in Ohio in response to budget cuts requiring staffing reduction (Vincze, 2017). Using the AIML markup language, developers at Mentor Public Library designed Emma with over 30,000 possible responses around operational and catalog questions, in addition to conversational "chat" responses. Within two years Emma had a reported 90% success rate at answering questions, at a cost of only $0.14 per question.

Subsequently, University of Nebraska–Lincoln built a library chatbot called Pixel in 2010 and UC Irvine built its bot, ANTswers, in 2013. These two AIML-based chatbots were designed to briefly answer basic reference questions and refer users to librarians for more complex issues (Allison, 2012; Kane, 2016). They also sought to "flatten" library websites – to essentially remove the need for users to interpret complex, multi-level library sites by providing the same information via chatbot (Allison, 2012). An analysis of five years of ANTswers chat transcripts found its answer success rate improved from 39 to 76% between 2014 and 2018 (Kane, 2019). According to Kane (2019), this is entirely contributed to the improvement of code on the backend by its developers. This analysis also found that users often engaged with the bot regarding non-library topics. UC Irvine librarians initially considered removing the conversational responses to discourage non-library centered interactions but ultimately left those responses intact as some users preferred to, "follow the normal steps of conducting a conversation" with ANTswers, providing an opening greeting, asking how it was, etc. (Kane, 2019, p. 491).

More recently, libraries have purposefully built conversational bots focused on user-centric design to address patron needs and preferences in addition to their information needs. Mckie and Narayan (2019) provide a case study from the University of Technology, Sydney, where library developers are working on a chatbot designed to ease the entry of undergraduate students into the research process while minimizing library anxiety. "Lib-bot" is specifically gender-neutral and programmed with a relaxed, conversational style to elicit comfort in the user and to be available for assistance 24/7. This bot seeks to establish and enhance a user's relationship to the library rather than simply deliver information efficiently.

Institutions of higher education have been adopting chatbots to answer rote student questions and deliver standard information over the last decade, as well. A recent systematic review by Okonkwo and Ade-Ibijola (2021), found higher education adapting chatbots to answer student questions, provide course content, assess student abilities and perform administrative tasks. During COVID-19, universities transitioned to largely online learning and virtual services, a modality that left many students feeling isolated and some unable to reliably connect to campus resources (Shi *et al.*, 2021; Ehrenpreis and DeLooper, 2022). In response, the California State University system evolved chatbots, along the lines of the Mitsuku bot, to provide emotional support to freshman and transfer students struggling during the pandemic. These bots, often branded with local school mascots such as "Cougarbot," create rapport with students by answering their questions about financial aid, immunization and registration while communicating in "the casual tone of texting with friends — lots of endearing emojis, GIFs and memes" (Agrawal, 2021). CSUSM's Cougarbot and Cal State Pomona's Billy Chat are text messaging chatbots. These bots encourage students to interact with them by sending a welcoming text to each student, along with reminders, important dates and surveys (California State Polytechnic University, n.d.; California State University San Marcos, n.d.). Student reception has been overwhelmingly positive to these new bots, with students expressing thanks, love and trust in these chatbots (Agrawal, 2021).

Potential benefits and challenges

Discussion of the potential benefits of chatbots in libraries, for both patrons and library organizations, are found throughout the literature. Patrons may benefit from the ability of chatbots to cut through the information overload experienced on library websites, providing short, direct answers to patrons 24/7 (Allison, 2012; Mckie and Narayan, 2019). Chatbots can also ease library anxiety by offering neutral, conversational help options without fear of asking authority figures "stupid" questions (Mellon, 2015; Mckie and Narayan, 2019). Additionally, a chatbot's usage of approachable non-professional, non-jargon language may be more comfortable for a younger population or those less familiar with library resources (Nawaz and Saldeen, 2020).

For libraries, a significant benefit is the ability to provide 24-h non-staffed service options. Even during live chat hours, deploying a chatbot allows the library to serve multiple patrons at one time with no lag (Nawaz and Saldeen, 2020). Chatbots can also relieve library staff from frequently answering basic, rote questions that require no human interpretation or input, such as hours or directions (McNeal and Newyear, 2013; Kane, 2019).

Ehrenpreis and DeLooper (2022) describe challenges they encountered in their case study from CUNY's Lehman College. These include students' possibly failing to understand they are utilizing a chatbot and rather than speaking directly with a librarian. Some users also lacked an understanding of the purpose of the chatbot and did not realize it was a separate entity from the library's live chat service.

Kingbot, the San Jose State University library chatbot

SJSU is a public masters-granting institution with a typical annual enrollment of 30,000 students. The Dr. Martin Luther King, Jr. Library serves the entire university, supporting over 143 degree programs. Pre-COVID, SJSU King Library provided both in-person and virtual reference services. Virtual reference services are provided using SpringShare's LibChat and LibAnswers. SJSU King Library participated in the Qwidget consortial reference program until 2017, when it dropped the service due to consistently low satisfaction ratings among users and librarians.

In fall 2018, SJSU King Library sought two iSchool graduate student interns for an emerging technology internship to explore the possibility of a library chatbot. The goal of the pilot was to provide a more interactive experience for students seeking help during overnight and weekend hours, which remained unstaffed after discontinuing the consortial Qwidget reference service. Sharesly Rodriguez and Danica Ronquillo were selected for the project based on their desire to learn more about chatbot technologies. Neither intern had notable coding or programming experience.

The first six weeks of the internship were dedicated to reviewing and synthesizing relevant literature and information on chatbots. This resulted in a comprehensive LibGuide presenting an overview of chatbots in libraries, highlighting the benefits of and best practices for AI chatbots (Rodriguez and Ronquillo, 2021). After careful consideration of multiple platforms, it was decided to develop an AI chatbot that NLP and AI training with Google's Dialogflow (Rodriguez and Mune, 2021). This chatbot would eventually become Kingbot, named after the university library's namesake, Dr. Martin Luther King, Jr.

Kingbot is an interactive chatbot utilizing NLP to answer basic circulation and introductory reference questions. Kingbot was originally intended to answer basic reference questions after librarian reference hours were over. However, in 2020, Kingbot was further developed by SJSU King Library's User Experience Librarian in response to the COVID-19 crisis. Beginning in March 2020, patrons could not enter the library due to COVID-19 restrictions, requiring that library services move online to accommodate the university's emergency transition to fully online learning. As a result, online queries, in the form of live chat reference and circulation interactions with librarians and library staff, increased dramatically. Due to the pandemic, there was also an increased need for the library to update users about the availability of resources and provide additional opportunities for students and faculty to receive help and engage with the library website.

Kingbot is currently available from SJSU King Library's chat widget located throughout the library website and on the library's discovery system homepage during all non-staffed hours. In addition to basic circulation and reference information it provides helpful links to LibGuides or resources where patrons may start their research or access specific databases. Kingbot creates an opportunity for patrons to engage with the library in a comfortable, anonymous fashion. They receive help 24 h a day in a virtual environment optimized for mobile devices, especially important during this period when students cannot visit the library and may have limited access to technology.

Methodology

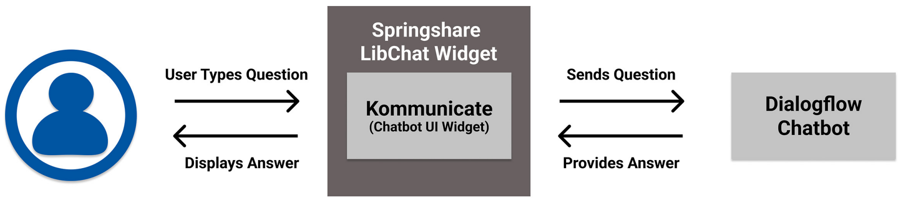
Design and development

Kingbot was developed with Google's Dialogflow, a piece of chatbot development software that allows users to build chatbots with minimal coding skills. In Dialogflow, chatbot "developers" define user inquiries and specify how the chatbot responds to each inquiry based on keywords and concepts. To include interactive elements and embed the chatbot interface within an existing SpringShare chat widget on the library's website, an intermediary software support service was required. (Since the development of Kingbot, Dialogflow has expanded its ability to support interactive chat elements without additional platform support.) Kommunicate is a bot support platform offering embeddable chat widgets that include link, image and video content. Kommunicate's chat widget interacts with the responses already defined in Dialogflow to provide users with a more interactive, dynamic experience. Kommunicate was chosen because of its initial low cost and modern, customizable user interface. Dialogflow is the tool used to create and host chatbot content while Kommunicate provides the interface needed to run and embed an interactive chatbot on a website or other delivery platform with enhanced visual elements.

Dialogflow communicates with Kommunicate to display all elements of the chatbot as shown in Figure 1.

For the after-hours chatbot to display to users Kommunicate's chat widget script was pasted into the existing SpringShare Chat widget using the "Set the Offline text" section. This section allows for the addition of customizable text displayed during chat's offline hours. This section also allows for scripts to be inserted from other applications, making the insertion of a 3rd party chatbot widget possible. Screenshots of the settings used for Kingbot are shown in Figure 2.

Figure 1.
The user types a question inside Kommunicate's chatbot widget located inside SpringShare's chat widget



User inquiries and chatbot responses are defined in Dialogflow. Dialogflow has an online editor used to add or remove information. Some chatbots use "actions" or "parameters" to execute tasks or perform ordering services, i.e. the bot might log a reservation request or place a pizza order based on a certain customer response. For a library chatbot capable of handling average library patron inquiries, these options are not necessary. For the Dialogflow Kingbot, only three elements were needed to build the bot: training phrases, responses, and intents. The interaction of these elements is captured in Figure 3.

(1) *Training phrases* are the questions, phrases and words that users enter into the text field of the chatbot during their inquiries.

(2) *Responses* signify the text the chatbot uses to respond to those training phrases.

(3) *Intents* are the mappings between a user's queries and actions fulfilled by the chatbot. When a user asks the chatbot a question, it triggers the intent, which then produces the chatbot response to the user.

During back-end content creation and editing, Dialogflow opens to a list of intents based on potential inquiries. For each intent, training phrases and the correct responses for those phrases are added as shown in Figure 4.

As responses are written, links and interactive messages may be added. Interactive responses are called "rich messages." The publishing platforms, such as Facebook, Slack or Google (Dialogflow labels publishing platforms as "integrations") need to be specified when

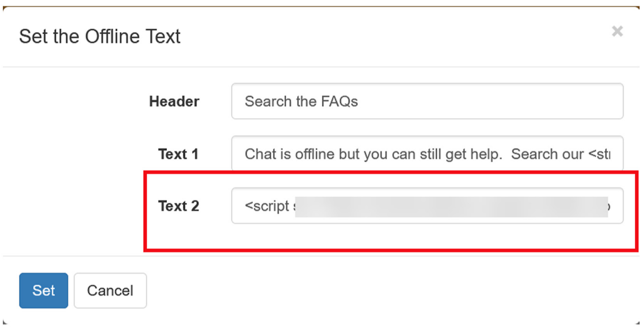


Figure 2.
The script code from the Kommunicate widget was embedded inside SpringShare's chat widget's setting under the "Set the Offline text" section in the "Text 2" field

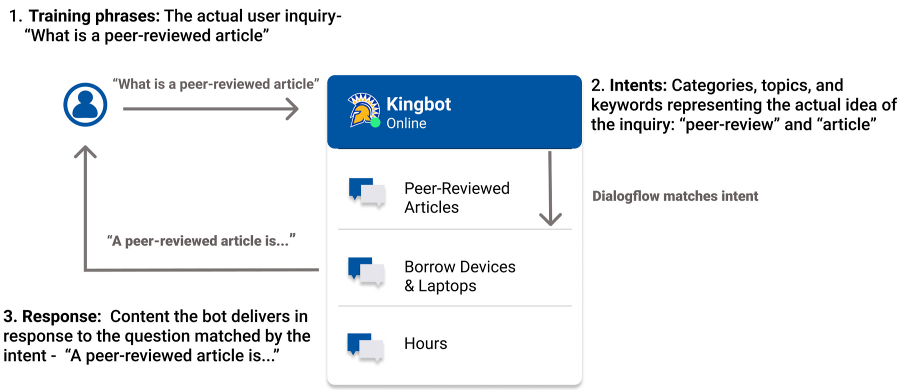


Figure 3.
Dialogflow parses the training phrases to find a matching intent to respond to a user, "A peer-reviewed article is . . ."

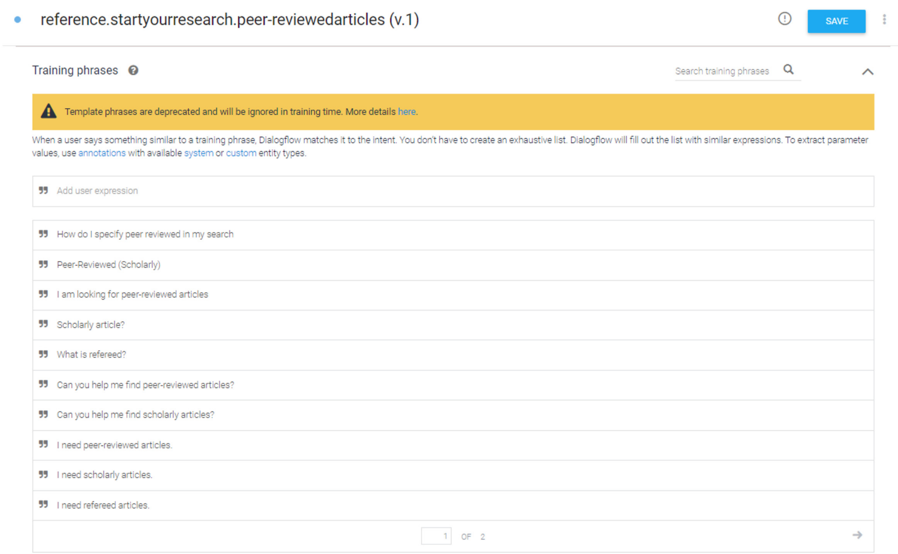


Figure 4.
The intent's name goes at the top and user questions, expressions, and text go under "Training phrases"

adding rich messages. Figure 5 illustrates how chatbot responses are entered under the appropriate tab in the "Text or SSML Response" area of Dialogflow's "Responses" section.

For publishing platforms outside of those specified in Dialogflow the DEFAULT tab is used to specify the type of platform and add interactive messages in JSON format. JSON is a lightweight data interchange format that is human-readable. Most publishing platforms,

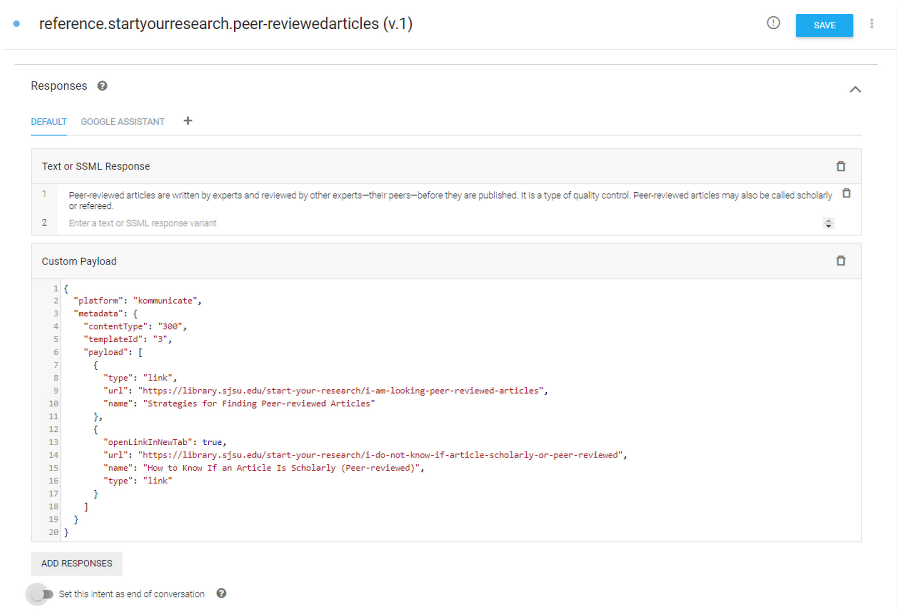


Figure 5.
On Dialogflow, chatbot responses and rich messages are added to the appropriate tab of the "Text or SSML Response" or "Custom Payload" areas under the "Responses" section

including Kommunicate, offer documentation on building rich messages in Dialogflow, including the needed JSON strings. Rich message content is added to “Custom Payload” in the Responses section of Dialogflow (Figure 5). This allows for the links defined in Dialogflow to be clickable in the chat widget. Kommunicate offers other types of rich message options such as forms, card or image carousels and calendar date pickers, if desired.

Content creation

To populate chatbot training phrase and response content, the User Experience Librarian reviewed the library’s LibAnswer frequently asked questions (FAQ) pages, reference email interactions, chat reference and circulation desk transcripts, as well as website and LibGuides analytics for frequently accessed pages and search terms. Once initial content was written, feedback surveys from both staff and student assistants were gathered to further refine training phrases and responses. When developing content and a conversational style for Kingbot, some established best practices were adopted. These practices were derived from chatbots used in both academic and private sectors and adapted to meet the needs of an academic library.

Ferman-Guerra (2018) recommends that chatbots have a singular, well-established purpose to provide users a clear understanding of why the chatbot was designed and what its capabilities and limitations are. This sets user expectations, allowing users a more satisfying experience with what information is available from the bot. Giving the bot a single purpose also makes it easier for content developers to focus on what content should and should not be included. Kingbot specifically provides technical and directional information, as well as basic reference, and links to supportive research resources from SJSU King Library’s website and LibGuides. Campus services and local community resources are intentionally not included in the bot responses due to currency and maintenance issues. Both developers and users should be aware of what information inquiries the bot is expected to fulfill.

One benefit of chatbots in libraries is the potential anonymity bots offer for users hesitant to either share personal information regarding their research or assignment topic with librarians or for those unfamiliar with libraries that sometimes experience “library anxiety” (Mellon, 2015). By not requiring authentication or login to use chatbots, libraries can ease possible anxiety and ensure users have a space to ask questions anonymously. Kingbot does not require authentication and does not collect any personal information about the user.

When writing chatbot responses, the adoption of a pleasant, entertaining and engaging personality has been shown to promote user satisfaction and sustained engagement. Jain *et al.* (2018) studied user interviews around bot–human interaction and found that users enjoyed interacting with bots displaying unique personalities. Users preferred the bot to present a human-like demeanor, using greetings, engaging in small talk and utilizing informal language. These researchers also found that users were more satisfied with chatbot experiences that included interactive elements within the chat interface including option buttons, media content, image carousels and live links. Users seem to desire an interactive, conversational experience with chatbots like that of live human-to-human chat. These elements were adopted in the writing of responses for Kingbot.

Offering users an immediate escalation alternative if the bot does not have the information needed or if the bot goes off track regarding the inquiry is reported to improve the user experience (Ferman-Guerra, 2018). Offering users a “Did I help you find what you were looking for?” option with an accompanying “Yes” or “No” response selection is a simple escalation method. Users that select “No” should be provided with staff contact and hours information. In Kingbot this is done through what’s called a “suggestion chip” in Dialogflow, which prompts users to choose predefined answers during chatbot conversations thus reducing the need for user typing and triggering specific chatbot responses.

Training and usage

A benefit to using an AI bot is that it can "learn," improving its ability to answer inquiries. This is done through training the bot's algorithm. Dialogflow offers the ability to train the bot for future responses by adding the actual user inquiries to the intent's file in the database thereby improving the algorithm. Kingbot was trained using Dialogflow's "Training" feature, which allows back-end users to review past chatbot interactions and map them to better intents and responses. These mappings then inform future responses based on known user inquiries. It is recommended to review chatbot transactions frequently to improve content and add missing information based on user questions and interactions. Many chatbot platforms, including Dialogflow, offer analytics, history and transcripts of chat interactions with users.

To review chatbot transactions and "train" the bot, Dialogflow users select the "Training" option from the main menu. The training page shows a list of conversations between the user and the chatbot. When a conversation is selected, a pop-up window appears with the date of the conversation, the user's inquiry and the chatbot's intent response to the user.

As shown by Figure 6, a user asked, "How to tell if an article is peer reviewed?" (USER SAYS) and the chatbot responded with reference.startyourresearch.isthisscholarly.article (v.1) (INTENT), which is the intent that tells users how they can tell if an article is scholarly. In this case, Kingbot answered the question successfully. As indicated by the arrow in the image, the intent response is clickable and can be changed to an existing or new intent.

Dialogflow uses machine learning based on past inquiries received from users to better answer future inquiries. Thus, the intent should be changed if it did not answer the user's question. The checkmark shown in the figure should be selected when Dialogflow correctly handles the user's request. This will help Dialogflow determine that similar user inquiries in the future can be handled by the same intent. The stop icon should be selected when Dialogflow did not handle the user request correctly. When the stop icon is selected, Dialogflow adds the user request to the Fallback Default Intent. The Fallback Default Intent is used when Dialogflow cannot handle the user's request. As depicted in Figure 7, on Kingbot, the Default Fallback Intent tells users "I'm sorry. I'm having trouble understanding the question," and provides a link to our "Ask a Librarian" form.

Dialogflow also offers history and analytics options. History identifies inquiries with no matched intents but is not as robust a tool as training. The dialog analytics tool can be used to view chatbot data in a variety of visualization methods. However, it will only display a 30-day range of data. Kommunicate offers better analytic analysis as it shows data across the lifetime of the chatbot. It is recommended to use Kommunicate's premium analytical features to see data across different date ranges most clearly.

Figure 6.
The intent response is clickable and can be changed to an existing or new intent

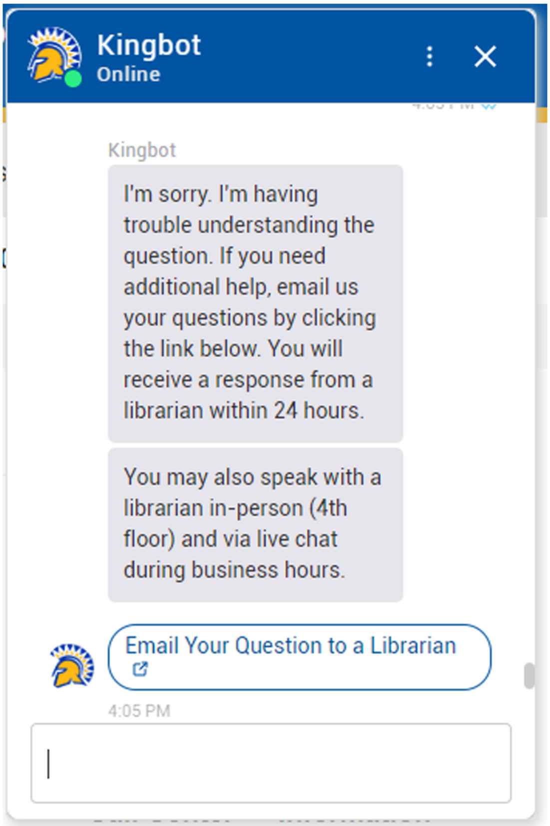


Figure 7.
The Default Fallback Intent tells users "I'm sorry. I'm having trouble understanding the question," and provides a link to our "Ask a Librarian" form

Results

18 months of chatbot interactions

The chatbot was first launched and added to pages of the library website and on the library's OneSearch discovery system in September 2020. As mentioned, the chatbot was enabled after live-chat reference hours were over. Therefore, Kingbot's after-hours schedule consisted of being active on the library website from 7 p.m.–9 a.m. on most weekdays and 5 p.m.–1 p.m. on weekends, depending on the semester.

Kingbot has shown a gradual increase in interaction since its launch in September 2020. Kingbot logged a total of 219 interactions, or approximately 44 interactions monthly, in its first full term, spring 2021. In fall 2021, Kingbot engaged in a total of 487 user interactions, approximately 97 monthly interactions. By spring 2022, Kingbot fielded 687 user interactions, and approximately 137 monthly interactions – a 214% increase over the initial term in production. This increase is in line with the overall increase in virtual chat usage during this period, likely a result of both the increased number of pages the widget was available on within the library's website and a growing comfort with virtual services as students adjusted to online learning.

Kingbot has logged a total of 1,682 chatbot interactions with users since its first release, beginning with its first full month of production, October 2020. Figure 8 shows the distribution of the interactions, which peak during spring 2022 finals.

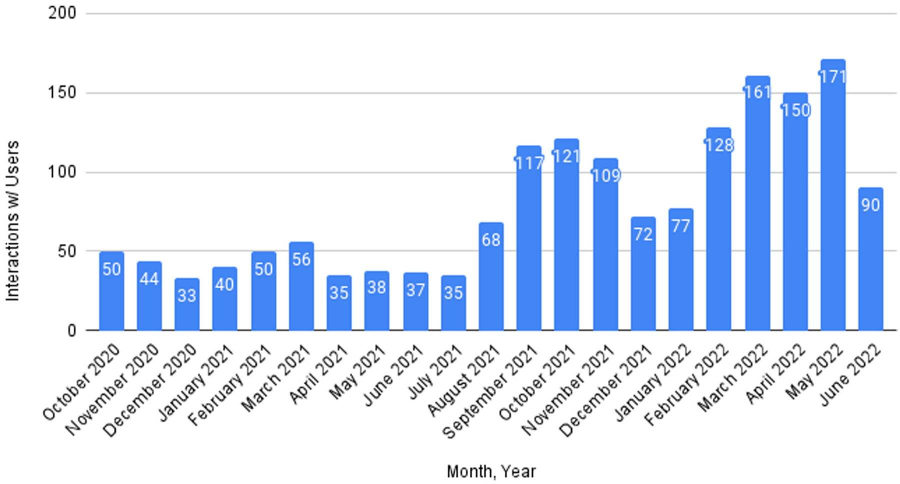


Figure 8.
Kingbot logged 1,682 interactions with users from October 1, 2020 to June 30, 2022

Using analytics from Kommunicate and Dialogflow, we can see the most commonly triggered chatbot intents, based on the bot's interpretation of users' natural language inquiries. Between October 2020 and June 2022 these were:

(1) Building and live reference hours (451)

(2) Finding peer-reviewed articles (290)

(3) Borrowing devices or laptops (120)

(4) Research help or asking to speak with a librarian (84)

(5) Help searching for articles and books (80)

(6) Finding databases or research guides (76)

(7) Borrowing, requesting, and loan periods for books (68)

(8) Reporting a problem with library resources (73)

Challenges

One significant challenge to understanding user interaction within the chatbot is a lack of ability to track the webpage links that users access from the chatbot. While Kommunicate and Dialogflow provide transcripts of chatbot user interactions, their analytical features do not include the tracking of clicks, scroll maps or heat maps inside the chatbot. It was discovered after Kingbots' launch that Google Analytics nor Crazy Egg, both tools used by the SJSU King Library for web usage analysis, could provide this type of in-widget insight. Initiatives to relook at Google Analytics and other web usage software for feedback are planned.

One way to collect feedback on users' perceptions of chatbot usefulness and satisfaction are "suggestion chips," or predefined buttons the users may select through an automated prompt. Suggestion chips might display a question such as: "Did I help you find what you were looking for?" followed by a "Yes" or "No" response selection. Transcripts will indicate the users' selection, allowing for more in-depth data about user satisfaction with the chatbot and the chatbot's effectiveness in answering questions. Suggestion chips not only provide a way for users to engage with predefined responses and interactive buttons but can also be modified to collect custom feedback.

Kingbot currently utilizes suggestion chips to collect feedback in order to assess chatbot user interactions. Analysis of the "Yes" and "No" buttons can reveal what chatbot responses need to be improved. This feedback can indicate ways to better map out conversation flows, links and responses to relevant library resources in order to meet users' information needs and improve the chatbot user experience. Suggestion chip data also provide a method for assessing the types of user questions that may be better suited for referral to a staff member or librarian.

Discussion and future implications

Various tools and development options allow librarians or library staff to develop a chatbot from scratch with little coding or chatbot expertise. The LIS graduate student interns that first developed Kingbot did not have a technical background. The User Experience Librarian responsible for continued development and maintenance does so through self-directed learning, mostly using tutorials available from the chatbot software vendors.

As with any website, app or digital product, there are user experience principles to consider when designing the chatbot conversation and visual experience. Like mobile devices, chatbots have a smaller visible window to work with and should only have the most vital information and links to answer specific questions. Typical library FAQs need to be significantly edited for brevity to fit within the chatbot window in a way that does not overwhelm users with information or require scrolling. The accessibility of chatbot text and interactive elements must also be carefully tested using existing accessibility standards such as W3C.

Another consideration is the time required to maintain chatbot content. Libraries frequently change personnel and policies, add or change services or alter hours. Each of these changes requires updates to chatbot content. As such, library chatbots need to be updated as often as the library website or LibGuides, creating additional work for those responsible for upkeep. During COVID-19 these frequent updates became a significant workload. Having an organized spreadsheet of the chatbot's metadata allows content developers, usually librarians or library staff, to find the intents quickly for editing. Keeping such a spreadsheet also allows for version control. Utilizing APIs to directly call content from LibGuide, or website content into chatbot responses is on the development plan for Kingbot to relieve this burden.

Lastly, more research and user testing on facilitating engagement are needed. Only 10% of current Kingbot users go beyond the chatbot's initial welcome prompt. Understanding how to better encourage interaction with Kingbot and to assure users they can fulfill their information needs using the bot are critical to increasing both usage and satisfaction. However, the ability to deliver targeted content to users based on inquiry using natural language is an important addition in a library's virtual reference toolkit. The ability to do so with readily available tools and minimal coding opens up a depth of service possibilities meriting continued exploration.

Conclusion

The benefits of chatbots are increasingly well documented and the technology is quickly being adapted to improve the user experience in information seeking. It seems natural that libraries would adopt such a technology designed to help users find information more quickly and effectively while providing a conversational interaction. The opportunity to expand information and reference services beyond normal staffing hours without paying for consortia membership is also compelling. While further refinement based on user experience testing is planned, the Kingbot example indicates that libraries can successfully develop, customize and train chatbots regardless of existing technical knowledge and with limited resources.

References

Abdul-Kader, S.A. and Woods, J. (2015), "Survey on chatbot design techniques in speech conversation systems", *International Journal of Advanced Computer Science and Applications*, Vol. 6 No. 7, doi: 10.14569/IJACSA.2015.060712.

Agrawal, N. (2021), "Artificial intelligence meets real friendship: college students are bonding with robots", *Los Angeles Times*, Vol. 7 June, p. 2021.

Allison, D. (2012), "Chatbots in the library: is it time?", *Library Hi Tech*, Vol. 30 No. 1, pp. 95-107, doi: 10.1108/07378831211213238.

Bilal, D. and Chu, C., M. (2021), "Artificial intelligence (AI) in libraries: training for innovation", *webinar slides presented at IDEA Institute on Artificial Intelligence*, available at: https://www.slideshare.net/NaseejAcademy/artificial-intelligence-ai-in-libraries-training-for-innovation-webinar-250810941 (accessed 28 July 2022).

Caldarini, G., Jaf, S. and McGarry, K. (2022), "A literature survey of recent advances in chatbots", *Information (Basel)*, Vol. 13 No. 41, doi: 10.3390/info13010041.

California State Polytechnic University (n.d.), "Introducing bill chat, cal poly pomona's text messaging robot", available at: https://www.cpp.edu/studentsuccess/billy-chat/index.shtml (accessed 31 July 2022).

California State University, San Marcos (n.d.), "CougarBot, CSUSM's chatbot", available at: https://www.csusm.edu/iits/iitsforyou/chatbot/index.html (accessed 31 July 2022).

de Barcelos Silva, A., Miguel Gomes, M., Andre da Costa, C., da Rosa Righi, R., Victoria Barbosa, J.L., Pessin, G., De Doncker, G. and Federizzi, G. (2020), "Intelligent personal assistants: a systematic literature review", *Expert Systems with Applications*, Vol. 147, pp. 113-193, doi: 10.1016/j.eswa.2020.113193.

Ehrenpreis, M. and DeLooper, J. (2022), "Implementing a chatbot on a library website", *Journal of Web Librarianship*, Vol. 16 No. 2, pp. 120-142, doi: 10.1080/19322909.2022.2060893.

Ferman-Guerra, M. (2018), "Towards best practices for chatbots", thesis, University of Victoria, available at: https://dspace.library.uvic.ca//handle/1828/9453 (accessed 9 June 2021).

Grudin, J. and Jacques, R. (2019), "Chatbots, humbots, and the quest for artificial general intelligence", *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1-11.

Haenlein, M. and Kaplan, A. (2019), "A brief history of artificial intelligence: on the past, present, and future of artificial intelligence", *California Management Review*, Vol. 61 No. 4, pp. 5-14.

Jain, *et al.* (2018), "Evaluating and informing the design of chatbots", *Proceedings of the 2018 Designing Interactive Systems Conference*, pp. 895-906.

Kane, D.A. (2016), "The role of chatbots in teaching and learning", Gregor, S. and Rice, M. (Eds), *E-learning and the Academic Library: Essays on Innovative Initiatives*, McFarland and Company, NC, pp. 131-147.

Kane, D.A. (2019), "Analyzing an interactive chatbot and its impact on academic reference services", *Recasting the Narrative: The Proceedings of the Association of College and Research Libraries 2019 Conference*, pp. 481-492.

Lewis, N. (2020), "Robot friends: why people talk to chatbots in times of trouble", CNN Tech for Good, 19 August 2020, available at: www.cnn.com/2020/08/19/world/chatbot-social-anxiety-spc-intl/index.html

Mckie, I.A.S. and Narayan, B. (2019), "Enhancing the academic library experience with chatbots: an exploration of research and implications for practice", *Journal of the Australian Library and Information Association*, Vol. 68 No. 3, pp. 268-277.

McNeal, M.L. and Newyear, D. (2013), "Introducing chatbots in libraries", *Library Technology Reports*, Vol. 49 No. 8, pp. 5-10.

Mellon, C.A. (2015), "Library anxiety: a grounded theory and its development", *College and Research Libraries*, Vol. 76 No. 3, pp. 276-282, doi: 10.5860/crl.76.3.276.

Nath, M.P. and Sagnika, S. (2020), "Capabilities of chatbots and its performance enhancements in machine learning", in *Machine Learning and Information Processing*, Springer, Singapore, pp. 183-192.

Nawaz, N. and Saldeen, M.A. (2020), "Artificial intelligence chatbots for library reference services", *Journal of Management Information and Decision Sciences*, Vol. 23 S1, pp. 442-449.

Okonkwo, C.W. and Ade-Ibijola, A. (2021), "Chatbots applications in education: a systematic review", *Computers and Education. Artificial Intelligence*, Vol. 2, doi: 10.1016/j.caeai.2021.100033.

Rodriguez, S. and Mune, C. (2021), "Library chatbots: easier than you think", *Computers in Libraries*, Vol. 41 No. 8, pp. 29-32.

Rodriguez, S. and Ronquillo, D. (2021), "Chatbots", SJSU Research Guides, available at: https://libguides.sjsu.edu/librarychatbot

Shi, Y., Chundong, L. and Luo, L. (2021), "Impact of the COVID-19 pandemic on Chinese college students' information behavior and library needs: a qualitative study", *The Library Quarterly*, Vol. 91 No. 2, pp. 150-171.

Shum, H., He, X. and Li, D. (2018), "From Eliza to XiaoIce: challenges and opportunities with social chatbots", *Frontiers of Information Technology and Electronic Engineering*, Vol. 19 No. 1, pp. 10-26.

Suta, P., Lan, X., Biting, W., Mongkolnam, P. and Chan, J.H. (2020), "An overview of machine learning in chatbots", *International Journal of Mechanical Engineering and Robotics Research*, Vol. 9 No. 4, pp. 502-510.

Vincze, J. (2017), "Virtual reference librarians (chatbots)", *Library Hi Tech News*, Vol. 34 No. 4, pp. 5-8, doi: 10.1108/LHTN-03-2017-0016.

Wallace, R.S. (2009), "The anatomy of A.L.I.C.E", in Epstein *et al.* (Ed.), *Parsing the Turing Test*, Springer, Dordrecht, pp. 181-210.

Weizenbaum, J. (1966), "ELIZA—a computer program for the study of natural language communication between man and machine", *Communications of the ACM*, Vol. 9 No. 1, pp. 36-45.

Further reading

Mittal, A., Agrawal, A., Chouksey, A., Shriwas, R. and Agrawal, S. (2016), "A comparative study of chatbots and humans", *International Journal of Advanced Research in Computer and Communication Engineering*, Vol. 5 No. 3, pp. 1055-1057.

Rapp, A., Curti, L. and Boldi, A. (2021), "The human side of human-chatbot interaction: a systematic literature review of ten years of research on text-based chatbots", *International Journal of Human-Computer Studies*, Vol. 151, 102630, doi: 10.1016/j.ijhcs.2021.102630.

Reshmi, S. and Balakrishnan, K. (2016), "Implementation of an inquisitive chatbot for database supported knowledge bases", *Sādhanā*, Vol. 41 No. 10, pp. 1173-1178.

Corresponding author

Sharesly Rodriguez can be contacted at: sharesly.rodriguez@sjsu.edu