Understanding student help-seeking for contextualizing chemistry through curated chatbot data analysis

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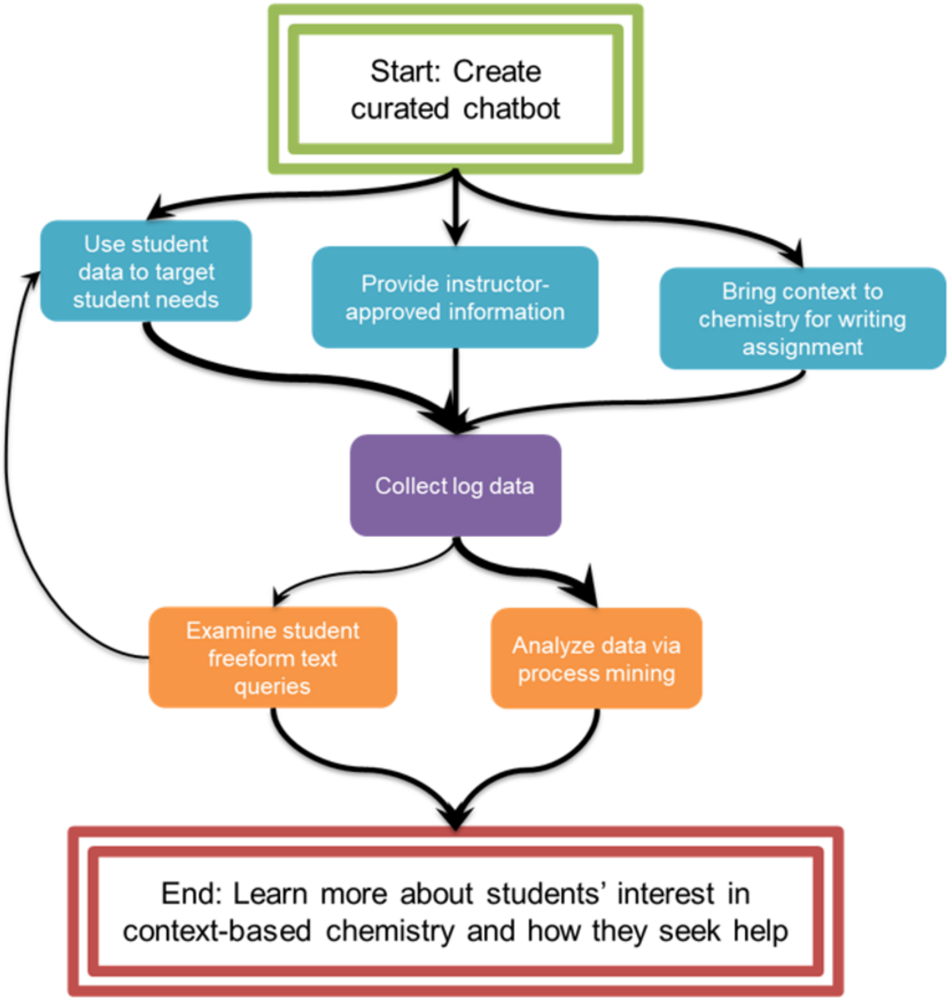
ABSTRACT

Technological tools, like virtual assistants (aka chatbots), have been ubiquitous in people's day to day. The challenge becomes how educators leverage digital omnipresence to benefit the learning environment. Using a curated chatbot allows educators to reach more students with instructor-approved information, particularly in large classrooms. Students can receive direct responses and guidance towards course materials, and educators may have less to manage by automating routine queries to a chatbot. Data from the 293 collected logs from 232 unique student users provide insight into the information students are interested in when tasked to complete an essay assignment contextualizing chemistry through a sustainability lens. Using process mining to show how students seek information, the extracted 5185 events from the logs created 204 unique pathways from students' actions in the curated chatbot. Additional text mining was done on the 116 freeform queries students typed into the curated chatbot. Results from both analyses showed that students were primarily sought information on the sustainability context of the writing assignment in their queries and that the curated chatbot can provide personalized assistance, responding to students' unique pathways of seeking help. A selection of subsets of student users' chatbot interactions, limitations of the study, and extension of the curated chatbot use in other classroom tasks and settings were discussed.

GRAPHICAL ABSTRACT



KEYWORDS

First-Year Undergraduate, Communication, Web-Based Learning, Student-Centered Learning, Interdisciplinary, Student Writing, Digital Assistant, Applications of Chemistry

INTRODUCTION

Help-seeking behavior has been identified as a key trait for many successful students. Research has found that students who seek help are likely to engage in self-regulated learning to monitor how they are learning and identify and modify behaviors to adapt to their learning needs. [1–3] However, help-seeking can be difficult for students to employ, primarily from the perceived lack of resources, such as time and available help.[1,4,5] Concerns about being regarded as less capable may also hinder some students from accessing available resources provided by instructional teams.[6,7] Online environments may exacerbate a sense of distance between students and instructors, but help-seeking remains important, perhaps even more so with online learning modalities. Educators can use the online environment to their advantage to create spaces explicitly geared towards help-seeking, such as forums or discussion boards.[4,8–10] For example, Williams-Dobosz et al.[4] leveraged online discussion forums to determine how chemistry students build connections among peers, particularly those traditionally underrepresented in chemistry, such as students who are non-male, or first-generation college students, or racially and/or ethnically underrepresented,. To gain this advantage all queries are responded to equally regardless of how explicit the request for help was.[4] Additional studies in chemistry found students who sought help outperformed in an organic chemistry course.[11] With the advancement of artificial intelligence, machine learning, and natural language processing, personalized learning in online environments has never been closer for students and educators to leverage.

Virtual assistants in web-based environments

Virtual assistants, or chatbots, are prevalent tools that can answer quick queries and task-oriented questions. Chatbots are increasingly ubiquitous in their presence, from auditory assistants built into smart technology to text-based conversational windows that pop up within a webpage to generative artificial intelligence (GAI) applications within large language model chatbots. The evolution of artificial intelligence improves tools like chatbots so that people find ways to use such technologies to enhance user perceptions of more personalized responses and to automate routine tasks.[12–17] Computer algorithms for chatbots can leverage natural language and artificial intelligence capabilities that underlie the chatbot interactions and can make use of them seamlessly straightforward. In fact, chatbots have become a digital tool that is easy to build and launch for any industry, including education.[18–26] However, examining how educational chatbot interactions with students work and understanding how students seek out information from this tool is still an open area of exploration.

Chatbot use in chemistry and chemical education has been varied. They have been implemented to promote self-regulated learning in online learning environments,[27] assist in database trawls,[28] and provide exam preparation.[29] How chatbots with GAI capabilities may be used, for better or worse, in the classroom has generated significant interest.[30–34] Similar software tools have been used to provide feedback to chemistry students, targeting both writing tasks[35] and large classrooms.[36] Curation in this instance represents a means of providing selected information and resources that can be useful for specific educational purposes or assignments. Instructor-approved resources can be a stepping stone for students to implicitly learn what are adequate scientific spaces online. A curated chatbot in chemistry can also provide an automated, responsive tool that can scale for large lecture courses.[37] This report focuses on the use of such a curated chatbot, using IBM watsonx Assistant[38] (formerly IBM Watson Assistant) as the engine, as an aid for student writing of an essay assignment aimed at contextualizing chemistry through sustainability. Because curated chatbots produce logs of student actions, user interactions with the tool can be broken down to examine the patterns of what information students sought using process mining[39,40]. [39,40] This work details the incorporation of a curated chatbot as a student writing aid, and the collection and analysis of interactive log files. The ways students used the chatbot to seek information are explored through their log data and students' freeform queries are analyzed through process and text mining techniques, respectively. The curated chatbot interactions reached a large majority of students in a large lecture introductory chemistry course, and analysis reveals that the implementation could be improved upon and used for other classroom purposes.

METHODS

Setting

The curated chatbot was launched in an introductory college chemistry course at a research-intensive university in the United States. The semester-long course had an enrollment of 347 students and all students completed a writing assignment that connected a specific general chemistry theme with the concept of sustainability. The curated chatbot was designed to help students address several aspects of the writing assignment and was available for three weeks prior to the written assignment's deadline. The chatbot landing page included an IRB approved opt-in consent dialogue to determine if student explorations that are routinely captured by the chatbot software could be analyzed for the purpose of understanding and optimizing the utility of the technology. Students could use the tool regardless of whether or not they consented to the use of their interaction data for the study.

Context of the writing assignment, participants and data source

The use of a 500-word writing assignment connecting chemistry and sustainability concepts is a routine component of the large-lecture general chemistry course in which the chatbot described here was implemented. The core concepts were that students could choose one of three concepts related to first semester general chemistry content and consider the connections to sustainability as outlined by the United Nations Sustainable Development Goals (UNSDGs). Thus, the chatbot included information about (a) carbon footprints; (b) water footprints; (c) embodied carbon as well as the UNSDGs. In addition, logistical information about the assignment could also be queried by students in the course. In prior implementations, aids to student activities related to writing were generally confined to relatively brief question and answer sessions with the course instructor held at the start of a few lectures prior to the writing assignment due date. As a communication tool, the curated chatbot was meant to provide more broadly available aid to students for this writing assignment (see pages S5-6). The curated information aligned with four broad categories, as displayed in Table 1. These categories were often mentioned by students in previous courses during facilitated one-on-one sessions as described previously.[37]

Table 1: *Top-level areas of information showing the curated chatbot's overall organization that users experience and can explore.*

Category	Description
Top Help	A centralized module for general information to guide users to the rest of the curated chatbot
Science	For queries regarding how much science to include and the level/depth of science necessary for the assignment
Sustainability	Exploration of the 17 UN Sustainable Development Goals, definition of sustainability, and a module to check for a student's understanding about incorporating sustainability within the assignment
Topic	Information regarding the definition, impact, and ties to sustainability regarding the focal topic for the writing assignment. In this version, there are three main choices: water footprint, carbon footprint, embodied carbon.
Writing	Two components: 1) Frequently asked logistical questions about the writing assignment, i.e., parameters or format. 2) An interactive section dependent on whether a student has an idea to check or needs inspiration.

Analyzable user logs were collected in near-real time by being extracted from the IBM watsonx Assistant interface and adapted in a log file format. A brief representative example is shown in Box 1. The log files were anonymized prior to analysis, according to IRB-approved protocols, assigned participant IDs and interaction IDs, which accounted for repeat visitors. Although 78% of the whole class interacted with the chatbot, only 85% of chatbot users (232) consented to the log extraction for research analysis. In total, there were 293 logs of chatbot interactions. Although there are numerous possible routes for analysis of user log data, process mining was used. Particularly in business.[40–42] the data management technique uses event data to discover, observe, and improve information systems. Thus, user log information can be analyzed using process mining methodologies. [39–41] The chatbot logs from consenting participants allowed extraction of 5185 lines of individual processes and the assignment of additional variables to conduct process mining, as shown in Table 2. Additional details regarding the steps taken during log file processing and the fully anonymized data files are available in the in page S6.

Box 1: *A mock-up of a converted chatbot log prepared for process mining. Each individual line delineates either a student's choice or what the chatbot has chosen to do. Bolded commands indicate the chatbot's response in activating a new module within the decision tree built within the tool, else the student choices are displayed. The levels (1, a, i, I, A, etc.) indicate how "deep" within the chatbot a student went.*

1. Yes, would like to see ways can help
2. ***Go*** → Top help
    a. Technical requirements
        i. Paper length
            I. No, don't want to explore more FAQs
            II. "How much chemistry do I need to put in?"
        ii. ***Route*** → How much science
            I. Yes, that helps!

II. I'm done

III. End interaction

Table 2 shows key aspects of the data preparation component of the study. As an exemplar, actions of the first use of the chatbot by "Participant 21" show several types of interaction. The "Level" indicates the location where the idea is incorporated in the curated chatbot organization (called the decision tree). A brief "Text" helps identify the location within the decision tree for further textual analysis. The "Activity Type" describes the way the chatbot presents information to the user. Finally, the "Status" designation indicates the types of actions taken by the chatbot resulting from the information exchange. Possible values for each of these information types are tabulated and described in the Table S2.

Table 2: *An example of how a chatbot log example from Box 1 is transformed for process mining analysis.*

Participant ID	Interaction ID	Level	Text	User or Bot	Activity Type	Status
21	1	1	Yes … ways to help	User	Prompt	Start
		1	Go → Top help	Bot	Prompt	Assign
		2	Technical requirements	User	Prompt	Assign
		3	No explore other FAQs	User	Prompt	Assign
		1	"How much chemistry do I need to put in?"	User	Query	Abort Activity
		3	Route "How much science"	Bot	Bot Match	Assign
		4	That helps!	User	Prompt	Assign

		4	I’m done	User	Prompt	Assign
		4	End	Bot	Prompt	End

Log Data Analysis Preparation

General usage patterns that can be gleaned from user logs can incorporate route tracing, of the type of interactions depicted in Table 2, and they can leverage metadata such as the date and time when components are visited in the chatbot. Such captured log data can be used with analysis tools such as process mining. The process mining methods for analyzing log activity have been previously described, both in general[39,40,42] and for this specific chatbot[43] These process mining analyses have leveraged the method to mine the text conversations people have with the virtual assistant.[16,43,44] The current application of this technique to the logs of student interactions with the chatbot provided insight into the sort of pathways students use to seek information within the curated chatbot. The curated chatbot data was analyzed and visualized through R[45] version 4.3.1 using RStudio’s IDE with the following libraries: bupaR[46], processanimateR[47], tidytext[48,49], tidyverse[50], treemap[51].

ANALYSIS AND DISCUSSION

Chatbot usage

The 293 chatbot interactions came from 232 unique student users. Using the metadata of the log files to observe the use of the chatbot over time, Figure 1 depicts the students’ usage of the curated chatbot leading up to the assignment deadline. Notably, students sought out information from the chatbot at times beyond when in-person interactions are uncommon, such as weekends (depicted with triangles) and non-traditional working hours. As can be inferred from the number and sizes of the data points shown, the chatbot enjoyed widespread usage, both during hours when instructional staff might be available (light blue and green datapoints), and during evening and night hours (yellow and dark blue datapoints) when in-person interactions with instructional personnel would be limited if available at all. Note also by considering the size of the data points, which correspond to the time of interaction, that the earliest access to the chatbot tended to be quite brief. This may be attributable to students checking the availability of and connectivity to the chatbot, while (longer interaction) larger data points become prominent as the writing assignment due date grew closer. This change in the interaction behavior likely indicates more functional usage of the resource. For the duration of the availability of the chatbot, the average time spent using it was 4.1 minutes with a range of 0.0 to 25.0 minutes, with an average of 1.7 modules opened per minute.

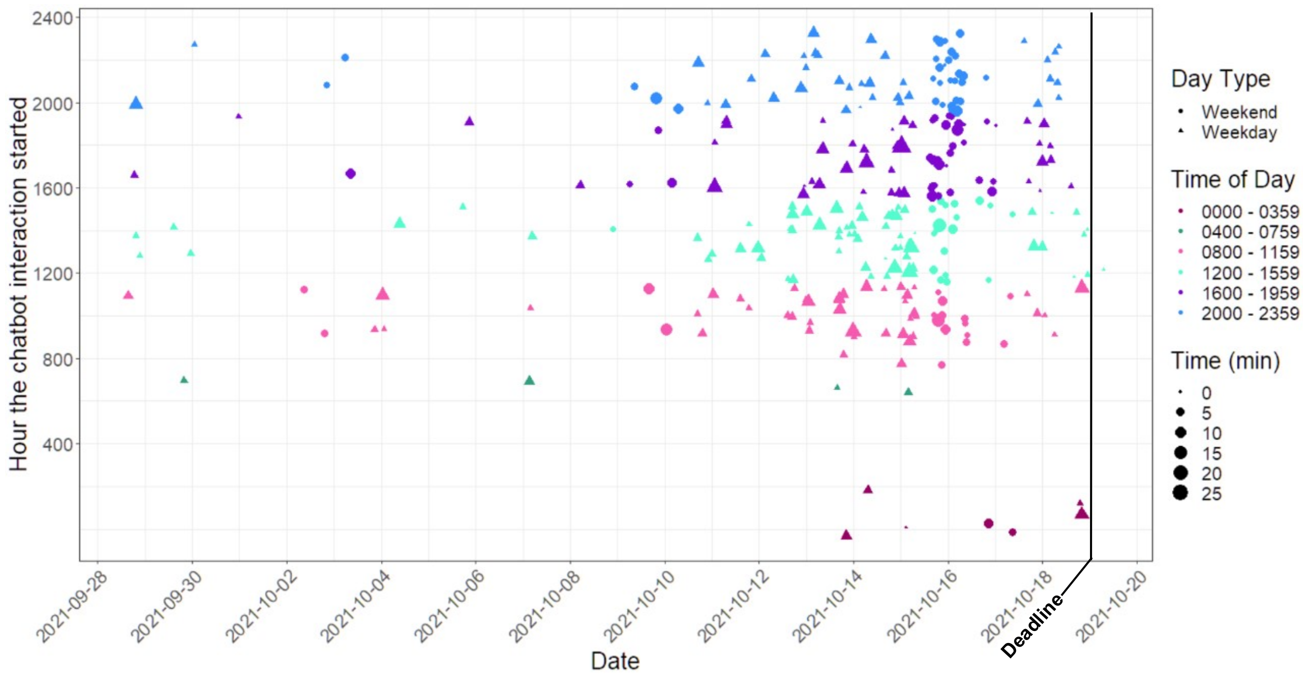


Figure 1: *A scatterplot of students' use of the curated chatbot over the course of its availability by day and what hour of the day they accessed the tool. The point size indicates how long students spent in the chatbot (minutes).*

In addition to the time of day usage depicted in Figure 1, student interest in various components of the curated chatbot were broken down to discrete categories connected to the types of content students could explore. A comparison is shown in Figure 2 of what the chatbot incorporated into its decision tree for the content (Fig. 2A) versus where participants were visiting (Fig. 2B) using treemaps as the visualization tool.

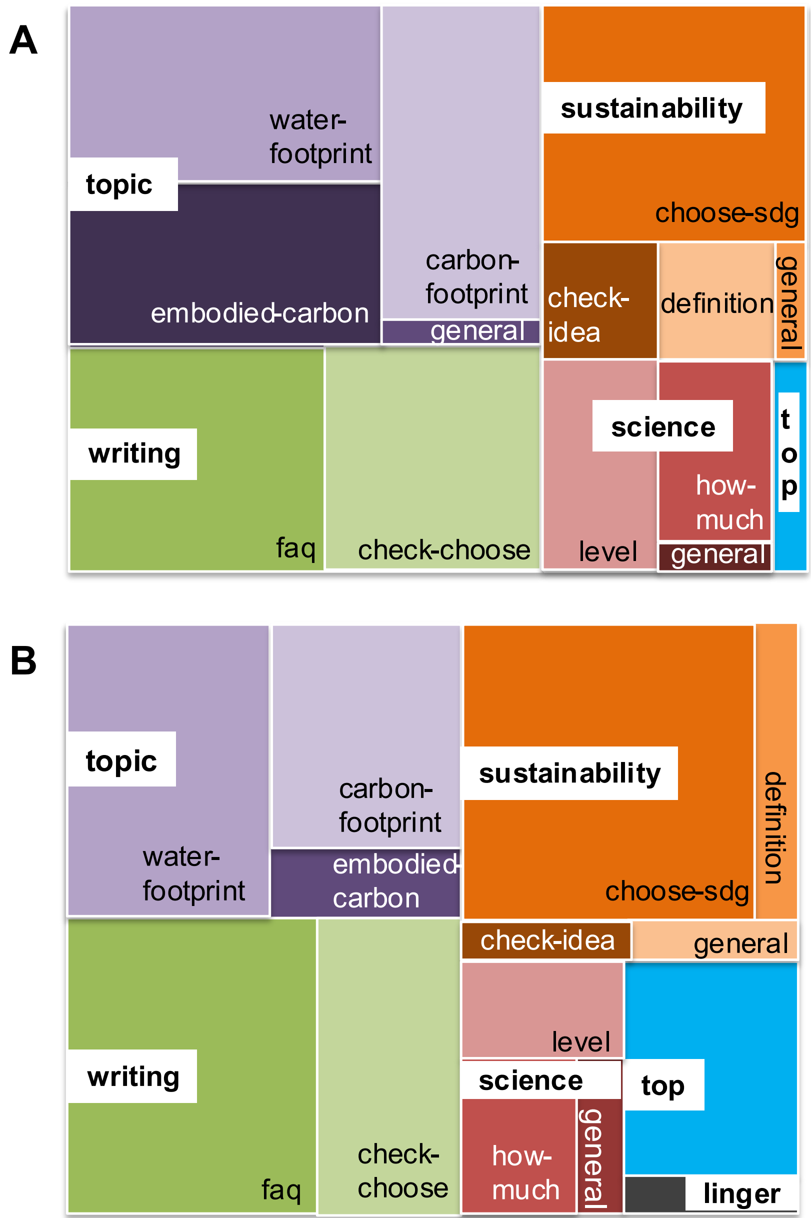


Figure 2: *Comparison treemaps of (A) the component breakdown of the curated chatbot's possible actions versus (B) the areas where students explored within the chatbot. The user logs include a "linger" component that accounts for situations where a student navigates to a new region of the decision tree via free text entry and their previous location is "left to linger" in the chatbot log file.*

Even qualitatively, there are key takeaways from the comparison. For example, embodied carbon was substantially covered by the chatbot, but was not the choice of topic for the focus of many students. Additionally, the exploration of the 17 U.N. Sustainable Development Goals, designated “choose sdg” was the bulk of students’ exploration about sustainability. In the chatbot use treemap (B), there is a ”linger” category in the bottom right of the treemap. This designation reflects student exploratory actions that left one section of the chatbot for another. When the new exploration was completed, the chatbot would return to an incomplete action that the student intentionally left which was categorized with the “linger” description. Additionally, the “top” module, where students were provided all the options the curated chatbot had available to explore was used quite often as all actions were programmed to have a “return to the top” option that could be clicked by the user. The logistical aspects, depicted by the FAQs in the treemaps’ lower left quadrant, were also another pull for students. This may be due to the students wanting more confirmatory information about details such as citation formats and line spacing.

55 users elected to come back to the chatbot more than once. In total, repeat users’ interactions accounted for 41.3% (121) of the data. The highest total number of visits by an individual was six interactions. Although there is no direct measure of motivation for repeat visits, it seems plausible that such use is an indication that the chatbot experience was found useful, particularly in the multiple use case. The average time spent in the chatbot for repeat users was 4.1 minutes, with a range of 0.5 to 13.0 minutes; however, the general trend for most of the users’ subsequent visits was a shorter interaction.

This data represents the first large-class implementation of the curated chatbot tool and routine checks of student usage suggested changes that would improve student interactions. The first nine users, for example, had to provide their own query to start the chatbot, which proved to be a challenge when students were unclear about what information they were looking for.[36] This implementation study did not attempt to quantify the training process for the machine learning algorithm in watsonx, but it is clear that it requires interactions to be trained. Interactions were initially done as part of the development of the curated content and continued with the student users of the tool. As such, earlier uses created instances where information available in the chatbot was not yet identified by the machine learning algorithm and therefore not shown to the students interacting with the chatbot. The observation of this type of challenge led to building introductory scripted interactions at the top level of the chatbot to better guide students about what options were present from the onset of their interaction with it.

Student queries

Student's freeform text queries created several chatbot responses that were used for further analysis. These queries were text typed by the student that ranged from greeting interactions, treating the chatbot as another human individual, to direct questions regarding the assignment, for example, "What do I have to write my paper about?" There were four ways the chatbot could have reacted, based on whether the chatbot had information pertaining to a student query, as described in Table 3. "Bot Match" arose when there was one specific action in the chatbot curated decision tree that had an exact match. In such cases the interaction would proceed seamlessly from query to the prompted action, e.g., "how should I cite my sources" going directly to the module "References." When the information was not found at all within the curated chatbot's decision tree, a "Bot No Match" yielded a chatbot response asking for further clarification or to continue on the current path the student was using. This can be seen when a student queried, "what is LD50," the chatbot would mention that there is nothing found in its system and ask if the student would like to rephrase. If the query was matched to multiple actions in the chatbot, the options would be displayed with radial buttons for the student to pick, constituting a "User Choice" interaction. For example, a student query of "Tell me about water footprint" matches to three actions regarding water footprint's definition, impact and connections to sustainability. The last reaction, dubbed "User No Choice", occurred when multiple matched actions are displayed, but the student decided to not click on any option presented. This observed interaction in the free form data may mean that there was a subsequent query text, often conversational texts, such as "done :)" or "thank you", or that the student abandoned the chatbot, which is discussed further below.

Table 3 *The four responses that may occur after a student types a free-form query into the curated chatbot.*

Response to Query	Description
Bot Match	The chatbot switches over to the single action that corresponds to the student's query automatically.
Bot No Match	The chatbot does not find a match within its curated information data and asks the student to either rephrase or continue on the current action.
User Choice	Multiple actions match the student's query. They are displayed as options and the student will select what is best.
User No Choice	The query matches to multiple actions but the student chooses not to select any; this generally occurs when a student will leave the chatbot after a query.

This free-form style of interaction occurred often with the curated chatbot. Of the 232 users, 64 (27.6%) participants typed 116 free-form queries into the chatbot. The resulting chatbot responses to these 116 queries were broken down into four categories, as described in Table 3. Of the 116 queries, 33 were categorized as Bot Match; 51 were Bot No Match; 30 User Choice, and two were User No Choice. This indicates that 54% of the queries were able to be matched or found within the curated chatbot. Within the 116 queries, the top 5 queries centered around the three broad topics the students could explore (carbon footprint, embodied carbon, and water footprint), sustainability around water, and carbon emissions. Further textual analyses of student free-form queries can be found in the Supporting Information.

Process patterns

A process map presents an opportunity to better understand how students tend to progress through a chatbot interaction using their log data. When applied across the full sample of student interactions, insights into how students are approaching their investigations of chemistry content and contexts as required by the writing assignment were gained. There are two key components to a process map: (1) the activity ID, which provides a marker for what is being observed, and (2) the status, which provides a path that can be drawn between activity IDs. For the chatbot interactions, the activity ID describes what the chatbot is doing. So, in the example depicted in Box 1 and Table 2, Participant 21 follows along the prompts that the chatbot gave. Then there is an instance where the participant types their query and gets a match in the chatbot (a bot match). Additional types of activity

IDs are described in Table 3, such as Bot Move, when a prompt calls component of the curated chatbot from a different branch of the underlying decision tree. For example, a student that is interacting with the chatbot under the "Water Footprint Sustainability" action in the "Context" category of the decision tree may learn more about UN SDG 6 (Clean Water and Sanitation), which is under the "Sustainability" category in the decision tree. A breakdown of the status's different descriptions is defined in Table S2.

Using the activity ID without markers of where specifically in the chatbot the students were visiting, Figure 3 depicts a process map for all the chatbot interactions, summing to a total of 5682 individual processes logged from the 293 interactions from 232 unique users. The average number of events that occurred in a single interaction, is 22.3. The figure depicts general trends of how students moved through the curated chatbot. Common actions have thicker lines, indicating high use, such as student tendencies to use the prompts to move between modules within the chatbot (prompt-prompt). Of the 293 recorded interactions, 204 were identified as unique pathways of seeking help and navigating the chatbot. A sample of the different traces can be found in Figure S5.

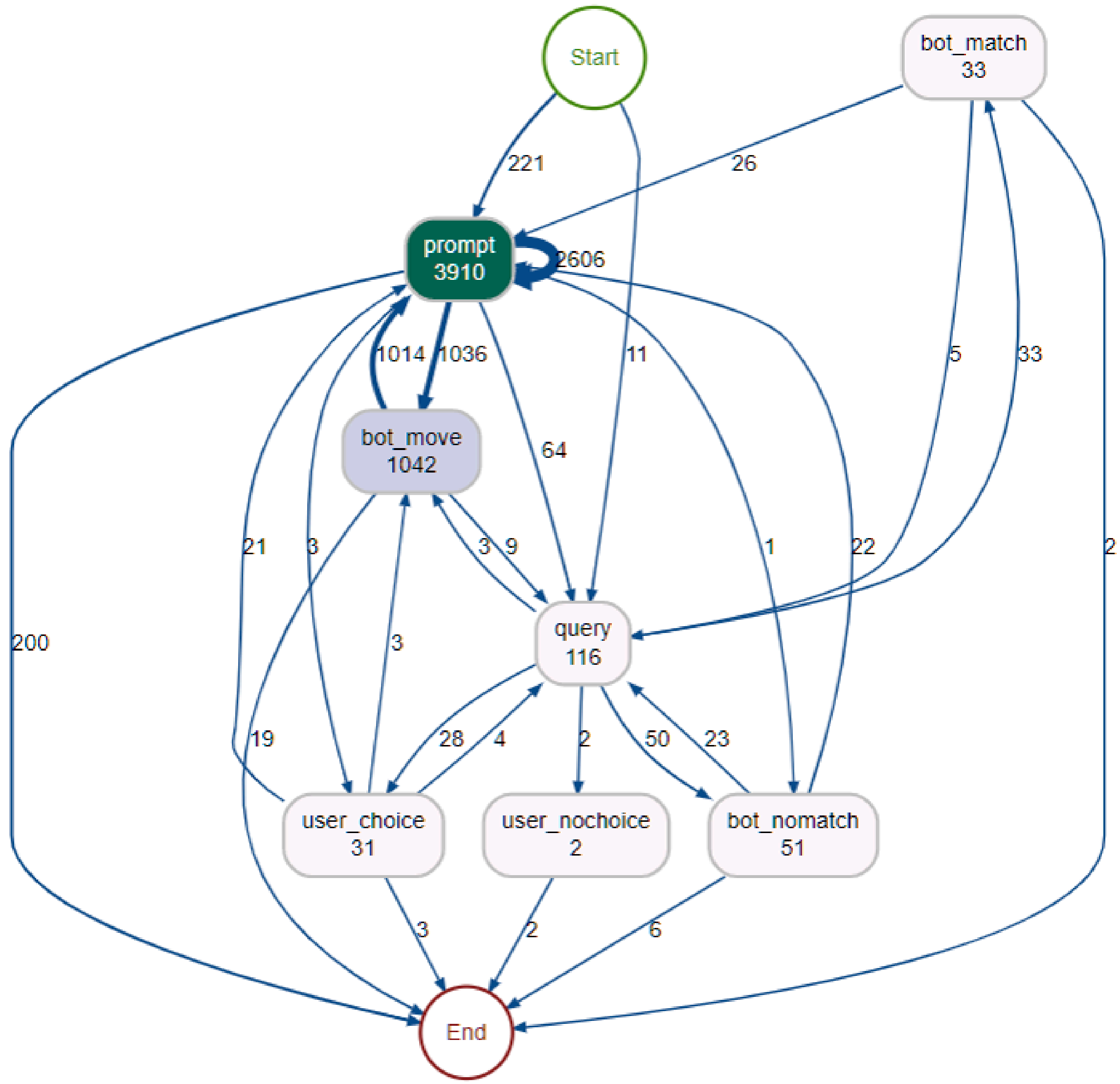


Figure 3: *A process map based on the students' chatbot activities (n = 5,682), shown with absolute frequency values. The darker the process arrow, the more common of an action it was among students' chatbot use.*

The complexity of the process map escalates dramatically when tracking where in the chatbot students were spending time, as shown in Figure 4. Although it is not intended to provide individually created paths, the presentation of a collection of such paths quickly leads to wide ranging paths through the chatbot. However, an interactive version of this process map capable of displaying all the connections can be reached through links in the Supporting Information, page S4.This map incorporates an additional layer in the activity ID by adding the category within the chatbot where the student was located in addition to the activity type. For the purpose of considering common student behaviors, the darker color nodes are areas of high interest and traffic for students. The three darkest activities seen prominently in Figure 4 are, from left to right, sustainability (1035 processes), the main topics (1017 processes), and writing (1005 processes). The chatbot highlighted the content interests of users, showing the power of having a curated chatbot that learns what users tend to seek. This visualization shows that a large fraction of student queries can be answered in an automated or semi-automated manner, as students sought out information built into the curated chatbot's prompts (3910 activities, 68.8%) or were able to be routed to that information (bot match, 33 of 116 queries [28%]).

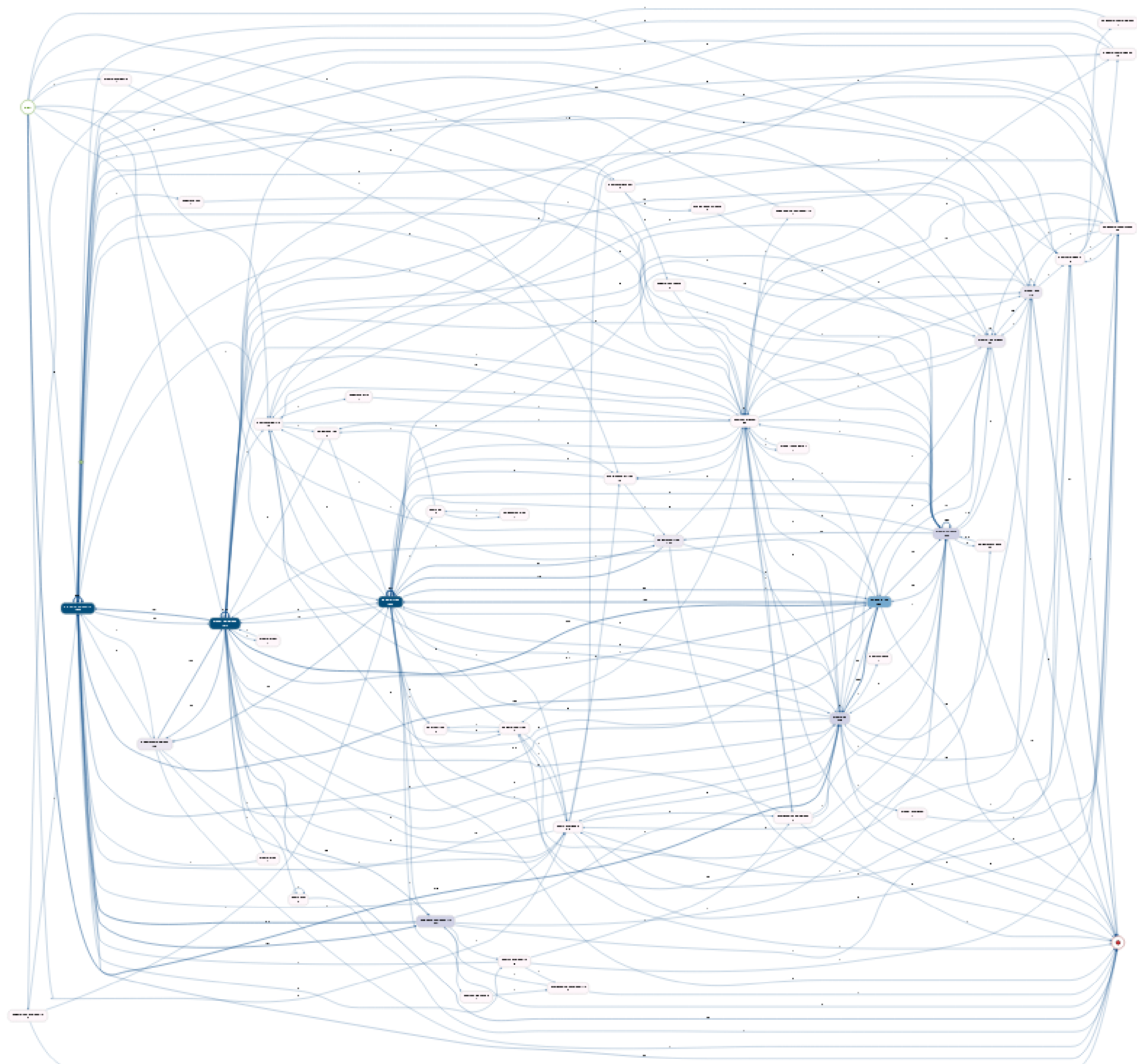


Figure 4: *The process map of the chatbot logs with an added complexity of what categories the activities fall under in the chatbot. The darker nodes on the left-hand side are the most commonly visited categories from left to right: sustainability, main topic, and writing. All of the top three activities were*
295 *prompted by the curated chatbot.*

The design of the curated chatbot tool acknowledges that it will not be the sole resource used by the students to research information regarding the assignment and contextual information. There is little question that the students accessed information using other methods in addition to using the curated chatbot, and the analysis presented here does not indicate at what stage in their research
300 efforts they accessed this tool. Additionally, the design of the information acquired by the curated

chatbot does not determine the extent to which students relied on the tool for information. Students had other means to source information, from their own internet research to other classroom activities. For one such activity, some students accessed one-on-one facilitated soundboard sessions which were launched in parallel to the curated chatbot. Of the chatbot users, 28 (12.1%) were identified in using the soundboard as another resource to provide aid for their writing assignment.

In summary, examining the combination of usage data, textual analysis of student queries, and process patterns can provide a more nuanced picture of when and how students seek help and how effective a curated chatbot tool can be. The usage data showed students accessed the chatbot when it was convenient for them and found what areas of the chatbot were more popular, as illustrated in Figure 2. The areas can indicate content where students may need more clarification, i.e., exploring more of the logistical information around the assignment parameters, or were more engaging, e.g., what U.N. Sustainability Development Goals may resonate with students. This could be particularly of interest for instructors interested in finding relatable contexts that resonate with students. In the same vein, the student queries provided more granular understanding of what sorts of connections and contexts students tend to be interested in, such as water footprints and carbon footprints as components of the writing assignment. An even finer look into students' navigation of the curated chatbot through the process patterns presented the unique ways students seek information. Combined with the usage data on how much time users engage with the chatbot might also give some insight into the nature of student's primary use of the chatbot, where some student access more logistical aspects of the available information while others tend to explore chemistry topics or the contexts where those chemical ideas are connected to sustainability.

Limitations

While chatbot use was studied, the extent of data capture allowed in the IRB for this project was not sufficient to define correlations of how the chatbots have impacted the final essay students submitted. Anecdotally, several students cited the chatbot as a resource of information in their submitted essays.

A small portion (4.3%) of the Bot No Match categorized student queries were not necessarily queries related to the content or a question posed to the chatbot, e.g., "how do I pick a topic that is specific enough for the paper?" or "what are some examples of connecting water footprints to chemistry?". Some instances were of students that treated the chatbot as a conversational partner, i.e., thanking the chatbot for its time or saying they found what they needed.

Methodologically, the capture of chatbot logs for the semester studied here required explicit copy and paste activities on a regular basis to construct the database of actions used in the analysis reported. This manual process introduces possible impacts on the metadata and may lead to some inaccuracies to items such as time spent in the chatbot. Another common limitation for studies reliant on technology user log data arises from not knowing if any user is actively engaged with content on the screen from the log data alone. Ultimately, the time spent with the chatbot on screen may not actually indicate the time students spent perusing the curated information provided. For many of the chatbot actions possible, the curated information from the decision tree is summarized for quick consumption with hyperlinks to instructor-approved resources that the user can review and learn from. Thus, it is unknown if students clicked away from the chatbot interface to read up on the curated resources or abandoned the help-seeking interaction entirely.

CONCLUSION

With the rapid popularization of generative AI tools, such as OpenAI's ChatGPT, significant attention has turned to how big of a role should such interactive technologies play in education.[34,52,53] The curated chatbot takes a different approach from the newly emerging generative AI implementation by incorporating the expertise of the instructional staff to create a tool capable of providing known, high quality resources. Even in this large-scale implementation, the tool met many of the students' requests for information and was readily available and accessible to help students when it was convenient for them. The queries that were not covered by the chatbot provide formative assessment information to the course instructors and chatbot administrators that can be used to improve the curation process for future implementation of the technology. Because the chatbot content has been instructor constructed and approved the information present is effectively assured to be relevant for students who are reviewing content for the writing assignment. Providing a form of engagement between students and instructors in large lecture settings also represents an important asset of such a curated chatbot.

The logs generated by student use of the curated chatbot provided an opportunity to examine how students may seek help with an accessible online tool hosting instructor-approved information. Using process mining, the complexity and uniqueness of students' requests, via their own queries and using the chatbot's decision tree, were highlighted. The simple interface reached a majority of students within a large classroom setting (in total, 262 unique student users were collected, or over 75% of the class) and has since been iterated on in subsequent semesters, improving the connectivity to students' queries.

The experience gained from this work with a curated chatbot's for a writing assignment that connects chemistry and sustainability has provided information that allows development of similar cases in other course settings. In a laboratory setting, a curated chatbot used as a pre-laboratory activity can provide interactive responses to students' queries of how to design their experiment for laboratory activities that include this component. Another use case that is more discipline-agnostic focused on complementing a course syllabus to provide quick, bite-sized responses that allow students to find information of particular interest more rapidly than would be possible via reading the extensive document that syllabi often become. Analysis efforts for these chatbot implementations are underway.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available on the ACS Publications website at DOI: 10.1021/acs.jchemed.XXXXXXX. [ACS will fill this in.] Example brief descriptions with file formats indicated are shown below; customize for your material.

Writing assignment prompt (PDF)

Additional coding results and links to interactive material (PDF)

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ACKNOWLEDGMENTS

The authors would like to extend their appreciation to all the students who interacted with the curated chatbot. Additionally, the authors thank the Parks Library Catalyst staff for their expertise in tidy data that aided in the process mining analysis. This work is funded by the National Science Foundation (NSF) Division of Undergraduate Education (Grant # DUE-2235600).

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