On Chatbots for Visual Exploratory Data Analysis

Brodrick Stigall*, Ryan Rossi†, Jane Hoffswell†, Xiang Chen†, Shunan Guo†, Fan Du†, Eunyee Koh†, Kelly Caine*
* *Clemson University* † *Adobe Research*

***Abstract*—Analyzing data and creating effective visualizations often requires extensive domain expertise. For users with less experience, it can be difficult to know how to get started with exploratory data analysis (EDA) and how to approach the code. Chatbots can reduce the gap between analysis outcomes and user expectations by leveraging multi-turn conversations to provide a more natural interface between the user and computer-agent. To inform the design of future visual EDA chatbots, we conduct a survey and interview study with ten potential users. Our results suggest that users want a visual EDA chatbot that can make exploratory data analysis easier, while also augmenting their knowledge of visualization and analysis techniques. Between the initial survey and post-interview questionnaire, we saw increased optimism overall for the usefulness and anticipated analytic ease of visual EDA chatbots. Based on these results, we identify four key design guidelines: future visual EDA chatbots should (1) understand the user's data and intent, (2) respond with useful visualizations, (3) leverage the history of the visualizations and data, and (4) produce verifiable and shareable analysis processes.**

***Index Terms*—Chatbots, exploratory data analysis, visualization, visual analytics**

I. INTRODUCTION

Exploratory data analysis and visualization are crucial steps towards better understanding the characteristics and insights from the data. However, the barrier for entry to exploratory data analysis, visualization, and other analytic tasks remains high and often requires extensive training or domain expertise. While systems like Tableau [1] are designed to make visualization creation easier, this approach still requires familiarity with the systems and data to get started. More recent visualization recommendation techniques aim to further ease this burden by automatically presenting interesting visualizations to the user [2]–[10]. Despite this added support, users maintain the core responsibility for steering the analysis process to realize their unique needs.

In this work, we study conversational interfaces for exploratory data analysis (EDA) and find that they can provide several benefits over existing methods of EDA and natural language visualization generation. For example, ease of use for chatbots can lower the barrier of entry for inexperienced users and increase the speed that analytic tasks are completed. A visual EDA chatbot can also act as a collaborative agent in the analysis process to suggest interesting visualizations or analytic directions, which can help users gain a deeper understanding of the data without requiring them to recall or learn the exact programmatic or system steps that would otherwise be required.

Within the realm of visualization and EDA, prior work has mainly focused on expressing visualizations in natural language [11]–[15], so we build on this foundation to focus on the more challenging problem of employing a conversational approach to enable visual EDA and insight discovery.

To better understand the expectations for a visual EDA chatbot, we conducted an interview study with ten potential users to understand their unique visualization and analysis needs. Users wanted a chatbot that could augment their ability to do visual EDA by making suggestions about relevant insights to inspect, analytic directions to explore, or new visualizations to consider. Users also wanted to be able to verify and share the analysis with collaborators or in future analysis sessions.

Based on these interviews, we propose four design guidelines for future chatbots for exploratory data analysis and visualization (see Section V). In particular, chatbots for visual EDA should (1) understand the user's data and intent, and (2) respond with useful and relevant visualizations for the user. To ensure that the chatbot is effective and useful, it should (3) leverage the history of the visualizations and data, to ultimately (4) produce explainable, verifiable, and shareable analysis processes.

II. RELATED WORK

Chatbots work best with tasks where the input and responses are straightforward [16]–[18], [18]–[22].

Chatbots have been developed for a wide variety of applications, including social needs screening [23], customer service [20], healthcare [24], advertising [25], surveys [26], authorship attribution [27], commerce [28], suicide prevention [29], among many others [18]–[21]. For further details on other application-specific chatbots, see [21], [30]. Our goal is a novel type of chatbot for visual EDA.

Prior works have performed interview studies focused on the data exploration and visualization needs of data analysts [31]–[33]. A few works have studied how chatbots can be used to analyze data. Ravi et al. explored using chatbots for communicating business insights from raw web analytic data [34]. The bot responds to single queries in tabular data and does not address visualizations that are fundamental to our problem.

For exploratory data analysis, chatbots are most useful when the user has access to a screen to visually view the results before further exploration via voice or natural language queries. Some recent work proposed a preliminary framework for developing chatbots for general data analysis [35]. However, little work has explored the unique challenges and opportunities for leveraging chatbots in *visual* exploratory data analysis. In this work, we

979-8-3503-2445-7/23/$31.00 ©2023 IEEE

conduct a user study and propose four guidelines for designing chatbots for visual exploratory data analysis.

Natural language has recently been used to specify visualizations, making it easier for users to visualize their data [11]–[15]. DataTone [12] supports user-specifying visualizations using NL. Articulate [36] generates visualizations derived from user queries. FlowSense [37] uses NLIs for exploratory data analysis (one query at a time). NL4DV is a Python toolkit for incorporating NLIs into other visualization systems [38].

Some preliminary work called Eviza [39] focused on preserving the context between two queries (the previous and the subsequent one), while Evizeon [40] extended that work to multiple queries. Both approaches are based on simple predefined pragmatic rules and thus lack any true intelligence and ability to generalize beyond the tiny set of supported queries.

While chatbots designed for visual exploratory data analysis can offer many important advantages, they have yet to be explored. To our knowledge, this paper is the first to introduce design guidelines for developing chatbots for visual EDA.

III. Study Methodology

To inform the design of future visual exploratory data analysis chatbots, we conducted a three-part study consisting of a pre-survey, a semi-structured interview, and a post-survey. We completed six pilot interviews to refine the survey & questions.

Pre-Survey. The pre-survey included 25 questions that served the dual purpose of gathering information about participants' prior experience and perception of exploratory data analysis and chatbots, as well as scheduling for the optional follow-up interview. The first set of questions asked about the participant's experience with chatbots and voice user interfaces (VUIs). The second block of questions asked about the participants' prior visual EDA experience. The third block of questions included six 7-point Likert scale usefulness questions adapted from the Technology Assessment Model (TAM) [41] and four questions about potential features for a visual EDA chatbot.

Interview. Each interview lasted 30 minutes. The interview began with a general explanation of chatbots and a description of chatbots for visual exploratory data analysis. The first set of questions covered the visual EDA experience. The interviews then asked participants our primary research question:

> *"imagine a chatbot for visual exploratory data analysis that has no limitations... what would the top three features be that you would look for in this chatbot?"*

Once the participants enumerated their initial ideas, we introduced a simple paper prototype to prompt further discussion. Participants were then asked to describe any new ideas for features, and whether or not their top three features remained the same. Next, participants were asked to describe the desired behavior for their top feature in detail. Participants were then asked for their preferences regarding the general behavior of the chatbot. Finally, participants were asked to reflect on the anticipated advantages and disadvantages of an ideal chatbot for visual EDA.

Post-Survey. After the interview, participants completed a survey that included the TAM-adapted instrument from the pre-survey, the same four questions about chatbot features, and an open-ended question about the visual EDA process.

Analysis. We exported survey data from Qualtrics and analyzed the results using a combination of Microsoft Excel and RStudio. To analyze the interviews, we used an inductive thematic analysis [42] approach to code the data and identify emerging themes, such as the expected features, benefits, and disadvantages of an EDA chatbot.

Participants. To recruit participants, we distributed a flyer describing the study through email in two large corporations and one university. Twenty-six people responded to the initial survey. Twelve survey participants indicated a desire to participate in the interview, two of whom had scheduling conflicts, leaving us with ten interview participants. In this paper, we focus on the data from the ten participants who completed all three parts of the study.

Participant ages ranged from 23 to 55 (mean 30.6, stdev 9.08). Five women and five men participated. All participants had at least a four-year degree, and six had a graduate degree. Participants were split evenly between industry and academic jobs; 90% worked with data for their jobs.

IV. Study Results

Overall, we found that participants wanted a visual EDA chatbot that would make their jobs easier. Ninety percent of participants had experience creating visualizations using tools such as D3 and Tablaeu, and regularly worked with data for their jobs. However, all ten participants had neutral to negative views of chatbots at the start of the user study (mean 3.1 on a 7-point Likert scale). During the user study, participants shared several crucial features they expected in a visual EDA chatbot and further reflected on their perceptions about the usefulness of such a chatbot.

A. Requested Features for Visual EDA Chatbots

Participants requested features that would make the chatbot easier and more useful to them, such as support for creating and modifying visualizations, quick summarization of the data, explainable analysis processes, and multi-modal interaction.

1) Quick Data Summarization: 50% of the participants mentioned that the chatbot should be able to quickly give an overview of the data (P4, P5, P8, P9, P10). One participant noted that such summarization *"could be statistical measures like mean, standard deviation, etc."* (P4), but further explained that the main reason a quick overview would be useful is that *"I feel like my biggest struggle is trying to figure out where I should start... it would be nice to have a chatbot point out interesting places or even different values for measures that might look different across different groups"* (P4). However, participants noted that this summarization does not only occur at the start of the analysis process; participants wanted the chatbot to present visualizations that could give an understanding of the overall trends in the data and generate summary reports of the analysis process.

2) Visual Design, Customization, and Recommendation: One participant noted that the chatbot could make it easier to create visualizations, thus offloading some of the programming burdens: *"I don't have a lot of experience and I have to actually look up what commands that I need to use to generate this kind of visualization"* (P4). The ability to modify existing visualizations was also important, such as the ability to *"alter colors"* (P9), *"zoom in"* to specific areas (P5), and *"highlight"* important information (P5). Beyond simply creating visualizations, participants saw the chatbot as an assistant to give feedback on existing visualizations and to suggest novel visualizations that could better convey the information of interest. Participants were particularly interested in the chatbot's ability to augment their knowledge (P3, P5, P6, P8) by teaching the principles of visualization design and helping them understand when different visualizations are useful. To this end, 60% of participants mentioned effective visualization recommendations as a crucial feature for a visual EDA chatbot (P3, P5, P6, P8, P9, P10). For example, one participant explained that *" Maybe you rank [the visualizations] and it would be great to see what it feels like for them so that I can have a sense of what it looks like"* (P3).

3) Trust and Explainability: Some participants had differing opinions about the potential for a visual EDA chatbot, primarily revolving around questions of trust and reliability. Notably, 80% of the interview participants listed trust issues as reasons not to use the chatbot. Participants were generally concerned about the accuracy of the visualizations and data assessments that the chatbot would produce. In order to improve transparency for the analysis process, some participants noted that it would be helpful to export the analysis process for manual verification by the user. For example, when reflecting on how a chatbot would perform the analysis, P10 noted that *" I guess [the chatbot] did some fine-tuning or processing to the datasets behind it, so maybe translating those kinds of conversations into a series of query expressions will help us understand [the behavior]."* Other participants wanted to export the analysis process and code used to generate the visualizations to share with colleagues and superiors for verification and replication purposes. One participant explained that *"The conversation I had with the chatbot is some my thought process, so if it can be organized in a nice smart way, then it would be really nice to share the results with other people"* (P5).

Explainability is one way in which the chatbot could support verification and enhance trust; another approach is for the chatbot to explain what it could do and what capabilities it has. For example, one participant noted that *"I should know the system's capability. What all can it understand?"* (P1) and another participant explained that *"I would like to see everything that it's capable of upfront, so I can decide if it's worth using if it'll even answer the question that I have"* (P2). Participants noted that the ability to provide clarity around what interactions are possible is important for those who do not have much experience with exploratory data analysis.

4) Multi-modal Interaction: Though a visual EDA chatbot is inherently multi-modal because the visual channel is a fundamental component of the interaction, participants wanted the chatbot to support other interactions beyond voice and natural language. When asked to reflect on whether the chatbot should be part of a larger suite of applications or a standalone system, participants generally felt that the system needs to exist within a larger suite of applications (Figure 1). Participants also noted the importance for the system to have opportunities to interact with the data visually, through touch or mouse, and via the keyboard to *"combine different modalities to have a more seamless experience"* (P1). This interaction was also important for helping the chatbot better understand the user's intent, because users could express or clarify their intent using different modalities.

B. Perception After User Study & Prototype

Overall, participants had an increased positive perception of a visual EDA chatbot after exposure to the interview and prototype (Fig. 1). To measure this change, participants answered six 7-point Likert scale usefulness questions adapted from TAM and four questions about potential system features.

1) Usefulness: All six usefulness metric scores increased after the interview and exposure to the prototype. The mean score increase was 1.1, meaning participant agreement that the chatbot would be useful generally shifted from "somewhat agree" to "agree" (Figure 1). Participants agreed that the chatbot would help them do EDA and visualizations more quickly, improve performance, increase productivity, enhance effectiveness, and simplify the visual EDA design process. For example, P7 explained that *"this is probably applicable to 80 to 90% of analytical professionals."*

2) Importance of Potential Chatbot Features: There was also an increase in the positive ratings for three of the four potential visual EDA chatbot features asked about in the user study. In particular, participants' desire to ask follow-up questions to the chatbot increased from 5.8 to 6.8. The importance of the chatbot having the ability to reason about prior conversations increased from 5.1 to 6.7; notably, this increase was the highest recorded change in any metric measured during the user study. Finally, the importance of the chatbot to be able to reason about the data and visualizations directly increased from 5.1 to 6.5 (see Figure 1). Similar to the positive increases in the usefulness metrics, these ratings show that participants generally felt more optimistic about the possibilities for a visual EDA chatbot after the interviews. The one exception was participants' interest in the chatbot being included in a larger software environment vs being a standalone application, which decreased slightly from 6.1 to 5.8 (the smallest reported change in the ratings for any metric). As discussed in Section IV-A4, participants saw some value in using the chatbot as a standalone system but felt that the chatbot and surrounding system should support a variety of interaction types to navigate and view the data, visualizations, and analysis procedure.

V. Design Guidelines

The following guidelines emerged from our interviews. For brevity, "chatbot" is used to refer to our *visual EDA chatbot*.

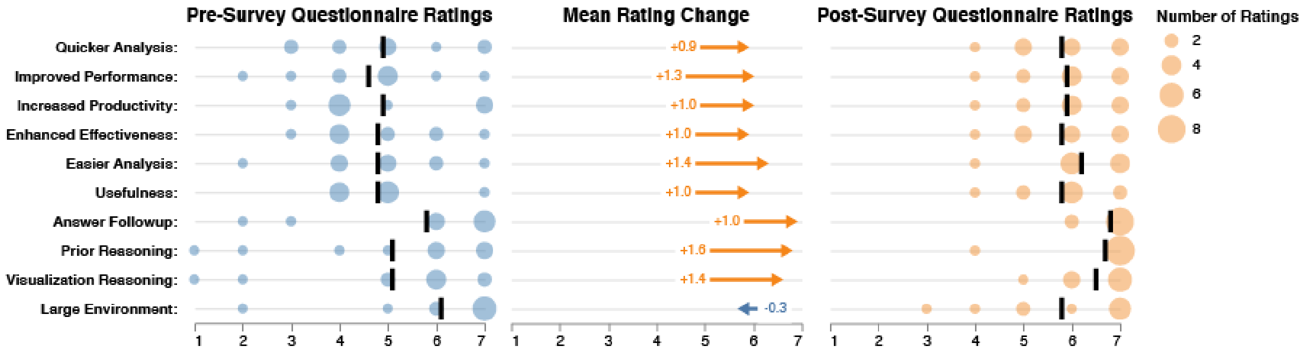

Fig. 1. Pre- and post-survey ratings for six usefulness questions and four questions about the utility of particular visual EDA chatbot features (1: Strongly Disagree to 7: Strongly Agree). The circle size shows the number of ratings, the black line shows the mean score for each question, and the arrows denote the amount and direction of change between pre-and post-survey. Overall, participants generally had an increased positive perception of the utility of the proposed chatbot features.

Chatbots should understand the user's data and intent, and respond with appropriate insights. Users should be able to upload any dataset of their choice and still have the chatbot respond intelligently to their questions. As discussed in Section IV-A1, the chatbot must therefore be able to understand and reason about the user-uploaded data in order to quickly summarize the data characteristics and most important insights. During the user study, some participants expressed concern that the chatbot would misunderstand their intent and therefore slow down the analysis process. This potential for misunderstanding felt particularly frustrating for participants who were not native English speakers, especially in the face of a chatbot with rigid requirements for expressing the intended functionality. To ensure a smooth analysis experience, a visual EDA chatbot should have advanced language processing skills to understand what users mean by their queries quickly. These features would make the chatbot feel more like talking to a human instead of a computer like those in [43]. Furthermore, participants wanted the chatbot to be more than just a basic tool to replace their existing EDA methods. In particular, the chatbot should leverage AI and machine learning to identify and share useful insights about the data. Beyond simply suggesting interesting data attributes or trends, the chatbot should further be able to understand and explain why such trends occur to help users make decisions. For example, P7—who is upper-level management in a large data organization—explained that *"I want to make decisions and I want this analysis to be more credible than my gut. Help my mind make a decision fast"* (P7). Finally, users wanted the chatbot to provide suggestions on how the data could be improved to inform future EDA sessions.

Chatbots should respond with relevant and useful visualizations about the user's dataset. While most chatbots are entirely text-based, for the visual EDA domain it is essential for the chatbot to have a visual component in order to better communicate the insights from the data and make the results more interpretable at a glance. Users, therefore, want the chatbot to help them understand their data with useful visualizations (see Section IV-A2), affirming prior research in this area [11]–[15]. To this end, the chatbot should suggest effective visualizations and explain the utility of different visualizations for different tasks, by leveraging the knowledge of visualization best practices. Furthermore, creating an effective visualization can involve more nuanced characteristics such as annotations and highlighting or further visual reasoning after the fact. The chatbot should therefore understand the intricacies of the data and visualization designs to iteratively update or produce new visualizations optimized for the user's most recent query.

Chatbots should appropriately leverage the history of the visualizations, data, and insights. Chatbots must be able to have a multi-turn conversation taking into account the sequence of visualizations produced, the data insights detected (e.g., correlation, outliers, etc.), and the data attributes and values used. This is in contrast to single query chatbots like those in [34] and supports the work in [39] and [40]. The chatbot should be aware of what topics have been discussed in the conversation previously and be able to make inferences about the user's intent based on that knowledge. The chatbot should be able to learn and adapt to the users' preferences and flow of the analysis process. An important part of this functionality is that the chatbot should understand and reason about the visualizations it creates, in order to discuss the insights with the user. Additionally, some users expect the chatbot to maintain knowledge about all previous conversations and the history of the current analysis process. For example, one participant noted *"If it could remember models I've done in the past and the next time I'm logging on it can be like 'You did this. Do you want to use the same model and for a new type of data?"'* (P6).

Chatbots should produce verifiable and shareable analysis processes. The chatbot should be able to explain to the user how and why it came to its conclusions about the data (see Section IV-A3). This explanation can include descriptions of what data contributed to which parts of a visualization, a discussion of why the particular visualization is useful for the chosen task, or details about the algorithm used to make a particular calculation. To ensure that results are verifiable and shareable, users should be able to export the entire conversation and analysis procedure, which would allow users to investigate and replicate the data analysis manually.

VI. Limitations and Future Work

This work contributes a formative user study with ten participants about perceptions of and expectations for a visual EDA chatbot. Future work should incorporate participants from other backgrounds (outside US and highly educated individuals) as well as increase the number of such participants in additional studies or through user-centered design methodologies when implementing a new visual EDA chatbot. (Section IV-A4), so future work should explore the use of Voice User Interfaces (VUIs) in such an environment. VUIs are the next step in making the analysis process with a chatbot similar to the process with human collaboration, making the proposed visual EDA chatbot even more accessible.

VII. Conclusion

We conducted a survey and interview study with ten participants to understand the features necessary to design an effective visual exploratory data analysis chatbot. Participants generally felt that a visual EDA chatbot should make their data analysis process easier by providing quicker data summarization and teaching fundamentals for effective visualization design via explainable analysis procedures. Based on the results of this user study, we identify four key guidelines for the design of future visual EDA chatbots; in particular, a visual EDA chatbot should (1) understand the user's data and intent and (2) respond appropriately with useful and relevant visualizations by (3) leveraging the history of the visualizations and data, to ultimately (4) produce verifiable and shareable analysis processes. An effective visual EDA chatbot could expand access to data analysis pipelines by providing an intuitive interface in which to discuss and explore data, regardless of the user's particular data or programming expertise.

VIII. Acknowledgments

This material is based upon work supported by the National GEM Consortium: GEM Fellowship (gemfellowship.org). We thank the members of Human and Technology Lab (hatlab.org) at Clemson University for their feedback on this project and the anonymous reviewers for their input that improved the final version of this paper.

References

[1] Tableau Software, "Tableau," 2020. [Online]. Available: https://www.tableau.com/

[2] K. Wongsuphasawat, Z. Qu, D. Moritz, R. Chang, F. Ouk, A. Anand, J. Mackinlay, B. Howe, and J. Heer, "Voyager 2: Augmenting visual analysis with partial view specifications," in *CHI*, 2017, pp. 2648–2659.

[3] D. Moritz, C. Wang, G. L. Nelson, H. Lin, A. M. Smith, B. Howe, and J. Heer, "Formalizing visualization design knowledge as constraints: Actionable and extensible models in draco," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 438–448, 2018.

[4] D. B. Perry, B. Howe, A. M. Key, and C. Aragon, "Vizdeck: Streamlining exploratory visual analytics of scientific data," 2013.

[5] K. Hu, D. Orghian, and C. Hidalgo, "Dive: A mixed-initiative system supporting integrated data exploration workflows," in *Workshop on Human-In-the-Loop Data Anal.*, 2018, pp. 1–7.

[6] C. Harris, R. A. Rossi, S. Malik, J. Hoffswell, F. Du, T. Y. Lee, E. Koh, and H. Zhao, "Insight-centric visualization recommendation," *arXiv:2103.11297*, 2021.

[7] K. Hu, M. A. Bakker, S. Li, T. Kraska, and C. Hidalgo, "Vizml: A machine learning approach to visualization recommendation," in *CHI*, 2019, p. 1–12.

[8] X. Qian, R. A. Rossi, F. Du, S. Kim, E. Koh, S. Malik, T. Y. Lee, and J. Chan, "Learning to recommend visualizations from data," in *KDD*, 2021, pp. 1359–1369.

[9] V. Dibia and Ç. Demiralp, "Data2vis: Automatic generation of data visualizations using sequence-to-sequence recurrent neural networks," *IEEE Computer Graphics and Applications*, vol. 39, no. 5, pp. 33–46, 2019.

[10] A. Wu, Y. Wang, X. Shu, D. Moritz, W. Cui, H. Zhang, D. Zhang, and H. Qu, "Survey on artificial intelligence approaches for visualization data," *arXiv:2102.01330*, 2021.

[11] A. Srinivasan and J. Stasko, "Natural language interfaces for data analysis with visualization: Considering what has and could be asked," in *EuroVis Short Papers*, 2017, pp. 55–59.

[12] T. Gao, M. Dontcheva, E. Adar, Z. Liu, and K. G. Karahalios, "DataTone: Managing ambiguity in natural language interfaces for data visualization," in *UIST*, 2015, pp. 489–500.

[13] K. Cox, R. E. Grinter, S. L. Hibino, L. J. Jagadeesan, and D. Mantilla, "A multi-modal natural language interface to an information visualization environment," *Inter. J. of Speech Technology*, vol. 4, no. 3-4, pp. 297–314, 2001.

[14] P.-M. Law, L. Y.-H. Lo, A. Endert, J. Stasko, and H. Qu, "Causal perception in question-answering systems," in *CHI*, 2021.

[15] A. Srinivasan, N. Nyapathy, B. Lee, S. M. Drucker, and J. Stasko, "Collecting and characterizing natural language utterances for specifying data visualizations," in *CHI*, 2021.

[16] J. Zamora, "I'm Sorry, Dave, i'm afraid i can't do that: Chatbot perception and expectations," *HAI*, pp. 253–260, 2017.

[17] M. Dahiya, "A Tool of Conversation: Chatbot," *JCSE*, vol. 5, p. 2347, 2017.

[18] A. P. Chaves and M. A. Gerosa, "How should my chatbot interact? a survey on social characteristics in human–chatbot interaction design," *International Journal of Human–Computer Interaction*, pp. 1–30, 2020.

[19] D. C. Uthus and D. W. Aha, "Multiparticipant chat analysis: A survey," *Artificial Intelligence*, vol. 199, pp. 106–121, 2013.

[20] M. Nuruzzaman and O. K. Hussain, "A survey on chatbot implementation in customer service industry through deep neural networks," in *ICEBE*, 2018, pp. 54–61.

[21] K. Ramesh, S. Ravishankaran, A. Joshi, and K. Chandrasekaran, "A survey of design techniques for conversational agents," in *ICICCT*, 2017, pp. 336–350.

[22] E. W. Pamungkas, "Emotionally-aware chatbots: A survey," *arXiv:1906.09774*, 2019.

[23] R. Kocielnik, E. Agapie, A. Argyle, D. T. Hsieh, K. Yadav, B. Taira, and G. Hsieh, "Harborbot: A chatbot for social needs screening," in *AMIA Annual Symposium Proceedings*, vol. 2019, 2019, p. 552.

[24] T. Nadarzynski, O. Miles, A. Cowie, and D. Ridge, "Acceptability of artificial intelligence (ai)-led chatbot services in healthcare: A mixed-methods study," *Digital health*, vol. 5, 2019.

[25] E. Van den Broeck, B. Zarouali, and K. Poels, "Chatbot advertising effectiveness: When does the message get through?" *Computers in Human Behavior*, vol. 98, pp. 150–157, 2019.

[26] Z. Xiao, M. X. Zhou, Q. V. Liao, G. Mark, C. Chi, W. Chen, and H. Yang, "Tell me about yourself: Using an ai-powered chatbot to conduct conversational surveys with open-ended questions," *ACM Transactions on Computer-Human Interaction*, vol. 27, no. 3, pp. 1–37, 2020.

[27] N. Ali, M. Hindi, and R. V. Yampolskiy, "Evaluation of authorship attribution software on a chat bot corpus," in *ICAT*, 2011, pp. 1–6.

[28] C. Pricilla, D. P. Lestari, and D. Dharma, "Designing interaction for chatbot-based conversational commerce with user-centered design," in *ICAICTA*. IEEE, 2018, pp. 244–249.

[29] R. Bond, S. O'Neill, E. Ennis, and M. Mulvenna, "Chatbots for mental health and suicide prevention: Is this even ethical?" in *European Conference on Mental Health*, 2019.

[30] E. H. Almansor and F. K. Hussain, "Survey on intelligent chatbots: State-of-the-art and future research directions," in *CISIS*, 2019, pp. 534–543.

[31] K. Wongsuphasawat, Y. Liu, and J. Heer, "Goals, process, and challenges of exploratory data analysis: an interview study," *arXiv:1911.00568*, 2019.

[32] S. Alspaugh, N. Zokaei, A. Liu, C. Jin, and M. A. Hearst, "Futzing and moseying: Interviews with professional data analysts on exploration practices," *IEEE TVCG*, vol. 25, no. 1, pp. 22–31, 2018.

[33] S. Kandel, A. Paepcke, J. M. Hellerstein, and J. Heer, "Enterprise data analysis and visualization: An interview study," *TVCG*, vol. 18, no. 12, pp. 2917–2926, 2012.

[34] R. Ravi, "Intelligent Chatbot for Easy Web-Analytics Insights," *ICACCI*, pp. 2193–2195, 2018.

[35] N. Castaldo, F. Daniel, M. Matera, and V. Zaccaria, *Conversational Data Exploration*. Springer, 2019, vol. 11496 LNCS.

[36] Y. Sun, J. Leigh, A. Johnson, and S. Lee, "*Articulate*: A semi-automated model for translating natural language queries into meaningful visualizations," in *Inter. Symposium on Smart Graphics*, 2010, pp. 184–195.

[37] B. Yu and C. T. Silva, "FlowSense: A natural language interface for visual data exploration within a dataflow system," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 1–11, 2019.

[38] A. Narechania, A. Srinivasan, and J. Stasko, "NL4DV: A toolkit for generating analytic specifications for data visualization from natural language queries," *IEEE TVCG*, 2020.

[39] V. Setlur, S. E. Battersby, M. Tory, R. Gossweiler, and A. X. Chang, "Eviza: A natural language interface for visual analysis," in *UIST*, 2016, pp. 365–377.

[40] E. Hoque, V. Setlur, M. Tory, and I. Dykeman, "Applying pragmatics principles for interaction with visual analytics," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 1, pp. 309–318, 2017.

[41] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly: Management Information Systems*, vol. 13, no. 3, pp. 319–339, 1989.

[42] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, 2006.

[43] J. Aron, "Software tricks people into thinking it is human," 2011. [Online]. Available: https://www.newscientist.com/article/dn20865-software-tricks-people-into-thinking-it-is-human/