Automated Interviewer or Augmented Survey? Collecting Social Data with Large Language Models

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Qualitative methods like interviews produce richer data in comparison with quantitative surveys, but are difficult to scale. Switching from web-based questionnaires to interactive chatbots offers a compromise, improving user engagement and response quality. Uptake remains limited, however, because of differences in users' expectations versus the capabilities of natural language processing methods. In this study, we evaluate the potential of large language models (LLMs) to support an information elicitation chatbot that narrows this "gulf of expectations" (Luger & Sellen 2016). We conduct a user study in which participants (N = 399) were randomly assigned to interact with a rule-based chatbot versus one of two LLM-augmented chatbots. We observe limited evidence of differences in user engagement or response richness between conditions. However, the addition of LLM-based dynamic probing skills produces significant improvements in both quantitative and qualitative measures of user experience, consistent with a narrowing of the expectations gulf.

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1 INTRODUCTION

Human computer interaction (HCI) researchers who seek to understand people's experiences and perspectives face trade-offs between the scale and speed of quantitative approaches to data collection and the richness of qualitative methods [26, 27, 50]. Quantitative methods like close-ended surveys can be conducted rapidly with large numbers of people, and researchers can have confidence that responses, when collected using psychometrically validated instruments on carefully constructed samples, generalize to the population of interest [17]. But an over-reliance on predefined measurement scales can also prematurely constrain the possible results space, preventing usability researchers from producing truly novel innovations [14]. By contrast, qualitative methods like in-depth interviews facilitate open-ended exploration and offer participants the opportunity to share detailed insights [41]. In seeking cognitive empathy—an understanding of the "why" of participants' opinions—qualitative researchers can also better emphasize motivations and surface heterogeneity in stated opinions [50]. But because interviewing is a time- and labor-intensive process, many interview studies remain small in scale [5] and those studies done at large scales can take years [19]—meaning that HCI researchers who work in fast-paced and rapidly changing technological environments can struggle to provide timely insights.

There is thus a need for approaches that bridge divides between quantitative and qualitative information elicitation methods. Prior research in HCI shows that chatbots that use statistical learning methods to adapt to user responses in real-time can increase participant engagement, response quality, and participant enjoyment of the interaction relative

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to less "intelligent" experiences [30, 56, 57, 61]. But these hybrid rule- and machine learning-based systems can be brittle, leading to unexpected limitations and unpredictable failure modes [3]—problems that are among the reasons why the adoption and spread of chatbots remains limited [15]. A key challenge is what Luger and Sellen identify as the "gulf of user expectations"—the gap that emerges between the expectations participants have of a conversational interaction versus the capabilities of existing AI systems [35].

Recent advances in generative AI offer an opportunity to considerably simplify system architectures—reducing the risk of unexpected failure modes [15]—while potentially attaining capabilities closer to the level of "intelligence" that users expect [40]. The introduction of transformer-based models, given their effectiveness in conversational interactions, has enabled the development of simpler chatbot architectures that better generalize to new topic areas [11]. Moreover, researchers have documented meaningful improvements on "theory of mind" tests, key for understanding and responding effectively to users, as an emergent property of the increasing size of recently developed models [24, 52] However, for technically savvy users, awareness of the capabilities of the most advanced models could actually raise the standards that system designers are expected to achieve, ultimately widening rather than narrowing the expectations gap for developers who cannot use the most powerful models. Key to mitigating this gap, then, is further research identifying the key expectations participants bring to interactions with information elicitation chatbots as well as strategies for managing those expectations.

While expectations of intelligence affect the reception of chatbot-based social data collection tools, design also matters [7]. Kim et al. [22] find that simply switching from a web-based survey format to a "conversationally interactive" chatbot—one that differs from the survey only in its design, delivering more casually phrased variants of the same questions and allowing the same limited set of responses—increases user engagement and response differentiation, a measure of response quality. Changes as simple as the choice of typeface [6] or the bot's wordiness [42] affect the perceived "humanness" of the chatbot and, in turn, affect the length and detail of participant responses. For HCI researchers seeking to evaluate the efficacy of integrating LLMs into chatbot-based tools, then, it is important to evaluate the extent to which improvements are actually reflective of the use of generative AI tooling *net* of the effect of switching from a web survey to a chatbot-based design.

In this paper, we seek to address these gaps through the development and evaluation of an information elicitation chatbot. We make five contributions to the HCI literature.

- We develop an LLM-augmented chatbot that can dynamically generate follow-up questions and provide users with real-time conversation summaries.
- We conduct a large-scale user study to disentangle the effects of these augmentations versus simply switching to a conversationally interactive design.
- We offer evidence of lower user expectations for augmented surveys versus for an automated interviewer, an insight that allows system designers to better manage user expectations.
- We surface two additional expectations held by many users, clarification and personalization, that provide avenues for future work to further narrow the expectations gulf.
- Finally, we observe a high level of participant agreement with an LLM-generated conversation summary, showing the promise of real-time member checking as a method for validating qualitative findings.

2 RELATED WORK

Our study is informed by methodologies in Human-Computer Interaction (HCI) research, prior work on the design of information elicitation chatbots, and theoretical understandings of human-chatbot interactions.

2.1 Interviews versus Surveys as Methods for Information Elicitation in HCI Research

Numerous forms of research require eliciting information from people. Collecting such data necessitates tradeoffs between quantitative and qualitative methods [27, 50]. When HCI researchers conduct user studies, for example, they can use qualitative methods like in-depth interviews to explore new ideas [41] and to develop rich narratives around the "why" of particular outcomes [26, 46]. Interviews are labor- and time-intensive, however, and thus tend to be conducted with samples that are small [5] and rarely representative of the full populations expected to use the technology under study [32, 49]. As a result, findings may be spurious or limited in their generalizeability [34].

By contrast, quantitative methods like surveys can be conducted rapidly and with large and representative samples. Although surveys can also be part of qualitative toolkits when they include open-ended questions, we consider an approach to be quantitative if it allows for statistical analyses [5]. That is, quantitative questionnaires comprise close-ended metrics that can be psychometrically validated and mathematically quantified [21, 48]. Such surveys can be conducted in person, by phone, or online, approaches that each lead to their own tradeoffs in quality [10] and logistical requirements [39]. Self-administered online surveys have been adopted particularly widely thanks to the speed and scale with which they can be deployed. Their use is accompanied by costs, however, chief among which is the loss of the richness that characterizes open-ended and qualitative data collection [50]. Particularly concerning in HCI research is that an overemphasis on the perceived methodological rigor of quantitative approaches can come at the cost of more risky or nuanced research questions and of the more exploratory methods appropriate for such studies [50]–prematurely constraining researchers to valid but boring problems [14]. Although a common solution to the tradeoffs between quantitative and qualitative methods is to take a mixed-methods approach, for example using surveys to confirm interview findings [26], such strategies can considerably increase the time, labor, and financial costs involved in any given study. For HCI researchers seeking to provide timely insights in rapidly evolving technological landscapes, there is a need for methodological innovations that retain the best qualities of both approaches while mitigating their tradeoffs.

Recent papers have thus suggested creating hybrid information elicitation tools that bridge qualitative and quantitative methods through the use of natural language processing methods. Xiao et al. [56] develop a chatbot for text-based interviewing tasks that can "actively listen", or produce on-topic replies to participant responses. They later expand on this work by implementing a chatbot-based open-ended conversational survey that "dynamically probes" by asking follow-up questions based on the content of the participant's responses [57]. In comparison with an open-ended survey [57] or a baseline bot without active listening skills [56], they observe that these augmentations measurably improve the length of engagement as well as the relevance and specificity of responses. Because the chatbot relies on a supervised intent classification model developed using statistical machine learning, a key limitation is the inability of the chatbot to perform effectively when responses focus on out-of-sample topics [56]. As a result, the chatbot may be less effective for the study of more novel or technologically innovative research questions.

We contribute to this literature by showing the potential of LLM-based agents to simplify the architectures of information elicitation chatbots. In particular, we show that LLMs can flexibly enable a key set of relevant "intelligent" capabilities including dynamic probing and active listening as well as member checking, or the ability to return a summary of the interaction to the user for confirmation. Through qualitative analysis of participant feedback, we

further surface question clarification and personalization as additional capabilities that participants expected. We note that these capabilities could be relatively easily added via changes to the prompt engineering in our chatbot, and we include our prompts in the appendix with the aim of fostering further research in this domain.

2.2 Effects of Design in Information Elicitation Chatbots

Moving from a web-based survey to a chatbot-based conversation necessitates at least one major design change: a move to "conversational interactivity" in which the participant engages in a dynamic text-based dialogue with a virtual agent [22]. Coupled with more casual phrasing of survey questions, Kim et al. show [22], this design change can improve user engagement, answer quality, ease of use, and user enjoyment of the survey experience. Other design choices that can affect user engagement, trust, and perceived experience include the "personality" of the chatbot or the affect associated with its responses [30, 61], and use of simple humanization techniques like self-introductions and using respondents' names or echoing their answers [44], or more simply the choice of font [6].

These findings present a challenge for the evaluation of LLM-based information elicitation chatbots, because they imply that some or perhaps even most of the data collection improvements that researchers observe may be products of the design change rather than of the underlying switch in methods or capabilities. As a result, there is a clear need to evaluate the contribution of LLMs to user engagement, answer quality, and user experiences with chatbots, *net* of the influence of changes in design. This study seeks to fill this gap by comparing results for LLM-augmented chatbots with results for a chatbot that is rule-based only but otherwise has the exact same design features.

2.3 Narrowing the "Gulf of Expectations"

While chatbot-based designs have been shown to improve user engagement and experience, they also change user expectations. As Luger and Sellen [35] point out, making a tool conversational can set unrealistic and anthropomorphic standards that make users more likely to perceive even minor execution issues as system failures. Expectations are shaped by the metaphors people bring to the experience as well as the ideas prompted by design and past experiences [15]. If users are expecting an interview, for example, they might expect a dynamic and nonlinear dialogue; a user expecting a survey, by contrast, may be more content with a straightforward and rule-based conversation.

These differences may help to explain a divergence in findings regarding chatbots versus other elicitation methods. While HCI researchers have tended to observe improvements in user engagement and experience in chatbot-based social data collection studies [22, 56, 57], a recent pre-registered trial comparing web-based versus chatbot-based surveys in the communications literature produced the opposite result: Although the researchers observed a similar response rate and longer response times, participants offered shorter answers and reported lower enjoyment of a chatbot versus a web survey [59]. However, in contrast with the active listening and dynamic probing capabilites of the former chatbot, the chatbot developed by Zarouli et al. [59] administered a standardized survey with open-ended text, close-ended text, and close-ended numerical questions. The main "intelligent" capability was in asking participants to repeat their answers if they provided a response that did not match the expected responses for the close-ended questions. The chatbot interface thus represented only a lower efficiency, relative to web-based surveys, with no offsetting improvements in the other features users may expect when encountering conversationally interactive formats.

The challenge for developers of information elicitation chatbots, then, is to understand and design for the set of relevant expectations that users are likely to bring to the experience. Expectations of interview studies are likely to be high. In particular, a long-established literature emphasizes the value of dynamic probing and active listening not only for the quality of the data but also as a means of improving the participant experience [45, 50]. Expectations for a

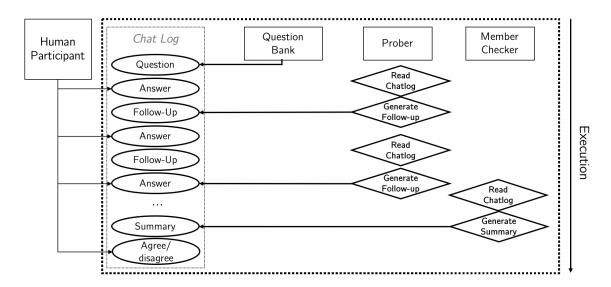


Fig. 1. Execution diagram from our chatbot. The interaction begins with a hardcoded question from the chatbot. Then, the Dynamic Prober module generates a dynamic follow-up based on the participant's response two times. When we have asked 3 main questions, the Member Checker summarizes the conversation and checks its understanding with the participant.

survey may be more limited, but user experiences can be improved through the inclusion of a dynamically generated summary of the user's results [25]–a capability that is easy to include for close-ended quantitative scales and is common as part of "member checking" processes in qualitative research [38], but that has not, to our knowledge, been done in real-time or at scale with open-ended responses.

Recent advances in the capabilities of large language models could be used by system designers to augment chatbots with precisely these expected skills. However, these advances could also have the unintended effect of setting higher expectations amongst users. In particular, there are large and important differences in the capabilities of the most advanced models versus earlier models or open-source models with respect to efficacy on "theory of mind" tests [24, 52], key for understanding and responding effectively to users. Limited availability and high latency on these models can make them unsuitable for interactive experiences for the short-term future. For designers forced to rely on less capable models, then, the pace of advances could turn the gulf into a treadmill of expanding expectations.

In this study, we use the "gulf of expectations" as a theoretical framework to understand the relative improvements observed in using LLM-based agents in our chatbot over a simpler rule-based design. We show how LLMs offer a simple way, in comparison with other architectures, to incorporate active listening, dynamic probing, and member checking capabilities, but that important gaps remain. We further surface question clarification and personalization as two additional expectations that users bring to an information elicitation experience with a conversationally interactive bot.

3 CHATBOT DEVELOPMENT

Our approach to the development of the information elicitation chatbot was inspired by both survey and interview methods, as well as by previous HCI research on conversational information elicitation chatbots. As in a conventional survey, our chatbot followed a rule-based script in which it selected questions from an established measurement

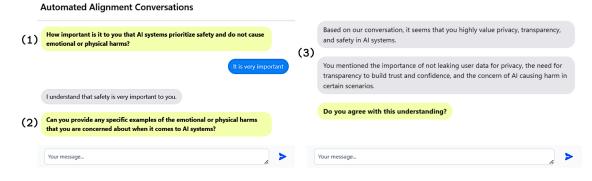


Fig. 2. User interface of our chatbot application, which could be accessed via a web or mobile device. Chatbot-generated text is indicated in grey with chatbot-generated questions made more salient to the user through the use of yellow highlighting. User text is indicated in blue. The image presents an examples from a dialogue in which (1) the chatbot first showed a question from an established, validated measurement scale [20], modified to use less formal language [22] and then (2) accessed the "Dynamic Prober" module to generate a follow-up question based on the user's response. After the user responded to three questions and their associated follow-up probes, (3) shows "Member Checker" module in which the chatbot generated a summary of the conversation and asked the user to confirm the summary content.

scale. However, we incorporated two modules that differentiate our chatbot from a standard survey (Figure 1). First, a "dynamic probing" module allows the chatbot to generate responses and follow-up questions based on the content of the participants' response, following the metaphor of probe in a semi-structured interview as well as prior empirical evidence on the value of adaptive question generation and active listening skills [56, 57]. Second, a "member checking" module enabled the chatbot to produce a conversation summary for the participant to confirm or contest at the end of the interaction—as in some interview and participatory studies in which researchers seek to confirm results by debriefing participants [38]. Below, we describe the key theoretical considerations underlying our approach and how they informed our prompt engineering methods and design choices. We built our chatbot using Python and Flask and deployed the resulting application on Azure using Docker.

3.1 Development of LLM-Based Modules

We sought, in developing our key chatbot modules, to be consistent with the methods of effective interviewers. In particular, Small and Calarco [50] emphasize the importance of cognitive empathy, heterogeneity, and palpability. In interview-based studies, they argue, an interviewer who displays cognitive empathy carefully chooses questions and probes to better understand participants' motivations, worldviews, and thought processes; similarly, question style and format are key to surfacing heterogeneous and palpable findings—diversity in participants' perspectives and tangible evidence (i.e. quotable statements), respectively [50]. Our approach to the development of our core modules was thus guided by the "north star" of surfacing cognitive empathy, searching for heterogeneity, and encouraging palpability in responses.

The development of the dynamic probing and member checking modules required the creation of effective and targeted prompts. In initial development, we observed promising results from a simple prompt that assigned the LLM the role of "expert interviewer", presented the recent conversation history, and asked the LLM to generate a response and follow-up question to the user. However, responses were unstable: the chatbot misinterpreted participant's responses and produced differing formats and lengths of responses, affecting the design of the conversational interaction. Although

there is not yet a standardized methodology for the effective development of new prompts for large language models, researchers have uncovered a number of "prompt engineering" methods that can improve and and stabilize LLM performance.

We investigated the potential of a number of these methods to improve our results through an iterative prompt development process, evaluating the effects of each prompting change through testing with a "dummy" data set. We first created a data set of nine synthetic individuals with randomly generated opinions and characteristics following a four-step procedure. First, we randomly assigned each individual an opinion in response to each of the seven questions on the original survey scale, which asked respondents to rank the importance of seven different alignment priorities on a five-point likert scale [20], by randomly generating values between 1 and 5 where 1 indicated that the value was "not at all important" and 5 indicated "extremely important". Second, for each participant, we generated a unique job based on the roles prospective participants might have (e.g. software engineer, program manager, or marketing manager). Third, we then used these characteristics to generate synthetic replies to the chatbot questions and probes, which included both a short response indicating the individual's opinion (i.e. "As a software engineer, I don't care about fairness. I think performance is the most important priority for AI alignment"). Finally, recognizing that chatbot designers frequently fail to account for the potential that some participants will approach the interaction in bad faith [15], we altered responses for three individuals to be either off-topic, gibberish, or an expression of frustration rather than the expected on-topic response.

We then iteratively tested the effects of different prompt changes on chatbot outputs in interactions with a sample of the possible responses from each of these nine synthetic individuals. In particular, we tested strategies including:

- Role assignment: initializing the system with a message priming the model with a personality, job, or other contextual information relevant to its performance [55].
- Chain-of-thought: requiring the model to follow intermediate reasoning steps before producing its final output [23, 54].
- Structured output: instructing the model to produce its response in a JSON list or similar structured data format, which can ensure more stable formatting and enable automated type checking as a real-time means of detecting system failures [55].
- Few-shot examples: including a small number of examples of the desired output [4].
- Generated-knowledge prompting: requiring that a model generate relevant additional information before completing a prompt, ensuring that the completion is conditioned on the additional information [33].

Through qualitative examination of the responses generated in interactions with the synthetic individuals, we observed improvements in quality and stability of LLM-generated responses with the chain-of-thought prompting, requiring output in a structured format (JSON), and the inclusion few-shot examples. We also observed a notable improvement in the quality of responses using generated knowledge prompting [33]. In particular, we prompted the LLM to return not just the suggested response but—before returning the response—additional features such as user opinion, reasoning for that opinion, and potential unanswered aspects of the original question. This enabled us to condition the model-generated probes on these features. The assignment of roles was not associated with differences in output, and thus we omitted roles in our final prompts.

We tested the robustness of the improvements to our prompts in two ways. First, we created a second synthetic data set, again with nine individuals, but with additional background characteristics for each of the demographic questions included in our user study (see Section 4). For this data set, we created a "participant persona" prompt that instructed an LLM to act as a participant in an interview. The LLM was instructed to review the alignment priority under discussion and then to use, as context, the dummy participant's randomly generated background and opinion to develop a motive for its belief. It was then given the chat history as additional context, with the ultimate task of generating a JSON file comprising the importance, its motive, and its response to the interviewer. We iteratively updated the chat history as the "participant persona" interacted with each of the moduls in our chatbot. We ran each of the personas through one set of interactions with the "dynamic prober" module (asking a survey-derived question followed by a dynamic probe) and one set of interactions with the "member checker" module (asking the chatbot to provide a summary of the earlier responses, and then asking the persona whether it agreed with the summary). We reviewed the resulting responses to assess the extent to which the modules were on topic and consistent in type.

Second, following common practices for "red teaming" AI systems [12, 58], we asked colleagues external to the core team to test the final experience. The evidence produced with the synthetic data set as well as the experiences of human testers bolstered our confidence in the robust performance of our prompts both in good- and bad-faith interactions.

For our "participant persona" module, we used GPT-4 given evidence of its strong performance across numerous benchmarks relative to other available models [31]. We developed our chatbot modules using GPT-3.5-turbo, accessed via the Azure OpenAI API using the Semantic Kernel package in Python [2]. GPT-3.5-turbo outperforms many other available models in benchmarks relevant to dynamic probing (e.g. theory of mind tests [24]) and to member checking (e.g. summarization [31]). It is considerably inferior in its performance on these tasks relative to the more recent and more advanced GPT-4 as well as relative to humans [24]; however, GPT-4 access is limited and can be subject to greater latency [1], making its use in interactive user testing at scale prohibitive. We thus caution that our results should be taken as a lower bound on the potential of contemporary LLMs to produce dynamic probes and member checks in the context of information elicitation chatbots. Our approach nevertheless represents the state-of-the-art for researchers seeking models with reasonably low latency and high scalability at the time this research was conducted (June - August 2023). Across models, we allowed response lengths of a maximum of 300 tokens to ensure concise but detailed responses and temperature = 0.5 to facilitate moderate creativity in responses. The final text of each of our prompts is included in the Appendix.

3.2 Chatbot Design

Our chatbot had a simple, standard conversational interface (Figure 2). However, we made four key design choices informed by prior literature. First, given evidence that conversational style meaningfully and significantly affects user engagement and experience [22], two members of the research team collaborated to revise the primary questions to use a more casual style. The researchers focused, in particular, on changing the questions' phrasing from the formal style of the validated measurement scale from which they were drawn [20] to a conversational style more akin to the style those researchers would have used in developing a semi-structured interview guide [46]. Second, we implemented a rule-based turn-taking approach in which users were only able to submit a single response to a chatbot-based question to ensure that the conversation was chatbot-led and not human-initiated. Third, we included an introductory message and question, consistent with research on the benefits of humanization in chatbot interactions [13]. In the member checker condition, which was meant to most approximate an interview experience, we also included a warm-up question based on evidence on the importance of warm-up questions in interview research [9]. We note that this humanization may have had the unintended effect of exacerbating anthropomorphized expectations, a point for which we suggest mitigations (based on our experience) in Section 6. Third, based on feedback from a set of early testers, we used color

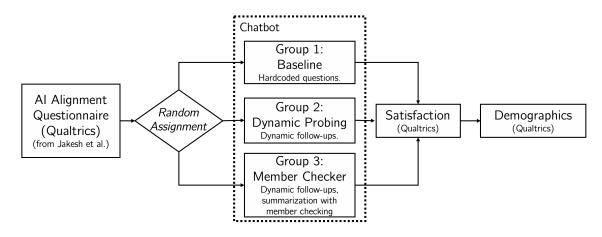


Fig. 3. Overview of our experimental design. Participants began the study on the Qualtrics platform by answering questions on Al alignment. They were later evenly randomized across three groups and taken to a Web-based chatbot interface. Participants in group (1) were simply given hardcoded questions. Participants in group (2) were given dynamic follow-ups. And participants in group (3) were given dynamic follow-ups and a summary of the conversation at the end. All participants were then asked to return to Qualtrics to complete questions on their experience and demographics.

and text to emphasize questions versus contextual statements. We also separated each sentence in the response into a separate speech bubble, rather than single large paragraph, and we only allowed the chatbot to pose a single question in a given turn. These tweaks aimed to improve the accessibility and legibility of the dialogue. Finally, an initial pilot deployment (see section 4) surfaced a number of session failures due to latency and limitations on model endpoint access. Although we were able to minimize the occurrence of these failure in the actual user study, we also tweaked the chatbot design to produce an error message, in the event of a lack of API response, explaining the endpoint challenges and giving participants the option to wait, refresh and retry, or exit the experience early with a special code. We further included a footnote offering participants a code that they could use to end the interaction early, if needed, and an introductory message warning participants about the potential for endpoint issues. These changes are consistent with prior HCI research on the value of explanations and options as repair strategies in human-chatbot interactions [3].

4 USER STUDY

We evaluated our chatbot through a large-scale user study with employees of a major technology company. In our evaluation, we sought to disentangle the effects of the usage of LLM-augmented modules in our chatbot versus the known benefits of conversationally interactive design in information elicitation chatbots [22].

4.1 Study Topic

An aim of our work is to contribute to methodological innovations that support HCI research on rapidly changing technologies and in time-sensitive contexts. In evaluating our prototype, we thus chose to conduct a study focusing on a developing research area: AI Alignment, the identification of priority areas and methods to ensure that AI systems act in ways consistent with human values and goals [47]. Our approach follows closely on a previous study of AI alignment [20]. In that study, Jakesch et al. develop and validate a seven-measure scale on people's views of major AI alignment priorities. Users are first given a definition of a value related to AI alignment and then asked to rate its

importance on a five-point likert scale. We used the questions from this scale as the foundation of our user study, as described below.

4.2 Study Design

We evaluated our prototype through a user study with U.S.-based employees of a large technology company. We conducted the user study in two waves: a small, initial one-day pilot to test for errors followed one day later by the main, larger deployment. Figure 3 overs an overview of the study design. Prospective participants received an e-mail invitation to participate in an "automated alignment conversation" that directed them to the Qualtrics online data collection platform [43]. After providing consent to participate, participants were first asked to provide responses to Jakesch et al.'s [20] original seven-question survey on alignment hosted in a web-based form.

Each participant was then given a unique link to the chatbot, where they were randomly assigned to one of three conditions: (1) Baseline; (2) Dynamic Prober; and (3) Member Checker. Although complicated structures are common in chatbot design [16], we used a straightforward, linear rule-based interaction structure for two reasons. First, our aim was to produce a tool that collected data in a similar manner to the rule-based and linear structures common in surveys as well as in some types of semi-structured interviews. Second, we sought to ensure that experiences across the treatment versus baseline group were comparable in the number of questions asked.

In our study, the dialogue proceeded as follows (Fig 1). The chatbot first described the topic and asked the user to confirm their readiness for the interaction. In the Member Checker condition, which was meant to most approximate an interview, the chatbot then posed an initial, pre-determined warm-up question (see Section 3.2). After receiving the participant's response either regarding readiness (Baseline and Dynamic Prober) or on background (Member Checker), the chatbot asked a randomly selected question from its survey-derived list of primary questions and then—after receiving the participant's response—asked two questions that were either pre-generated by the research team (in the Baseline condition) or generated via the dynamic prober module (in the other conditions). This process was then repeated two times, for a total interaction comprising three questions randomly selected from the original seven-question measurement scale. At the end of the interaction, participants in the Baseline and Dynamic Prober condition received a message thanking them for their time and directing them back to the web-based survey platform with a user-specific completion code. In the Member Checker condition, the chatbot additionally provided participants with a summary of the conversation and asked the participants to confirm or contest the summary before thanking participants and providing the confirmation code.

After completing the chatbot interaction, participants were directed back to the web-based form, where they were asked to complete an additional set of questions about their experience as well as to provide demographic and other relevant background information. The data was collected as part of participants' workday and was not compensated. This research was approved by our organization's institutional review board.

4.3 Evaluation Metrics

In comparing outcomes across the three study groups, we focus on three key outcomes: (1) user engagement; (2) richness of responses; and (3) perceived user experience. We measure engagement using both the length of responses and the session duration of the interaction between the user and the chatbot, following previous research [22, 56, 57]. Session duration is calculated as the sum of the time spent on each individual response, where individual response times are winsorized at the 99th percentile to exclude participants who may not have been actively interacting with the tool for the entire period. Length of responses is the total number of words in a participant's responses over the course of a

session. Because the member checker bot may be lengthier simply because of its two additional questions (the warm-up and final member checking questions), we exclude user responses to these questions when calculating these metrics.

We define "richness" as incorporating nuance or diversity of answers, consistent with Small and Calarco 's [50] emphasis on heterogeneity in qualitative research. Although nuance is not a quantifiable characteristic¹, as a proxy, we calculate a measure of lexical diversity (LD) across each set of participant responses from each full session. Lexical diversity measures the range of vocabulary deployed by a speaker or writer [36]. The Measure of Textual Lexical Diversity (MTLD) is calculated by sequentially calculating the type-token ratio (TTR) of a sequence of words. Tokens refer to a word count, and type refer to unique tokens. The TTR is the ratio of types over tokens. Many LD measures are sensitive to the corpus length [37]. The MTLD seeks to address this pitfall by sequentially calculating the TTR of each word and increasing the count of a variable denominated a "factor" when the TTR drops below a threshold (empirically calibrated to be 0.720). MTLD applies a forward and backward passes [37]. For comparability, we continue to exclude the additional member checker questions from the corpus used to calculate the MTLD, though we also calculate the metric with the full corpus as a sensitivity analysis.

We evaluated perceived user experiences through both close-ended quantitative scales and open-ended survey questions. In particular, we ask participants to rate their experiences with the AI interviewer on an 11-point scale ranging from "very dissatisfied" to "very satisfied". We further ask participants to rate whether they would prefer to take a traditional survey or to talk to the AI interviewer, and whether they would prefer to talk to a human interviewer to the AI interviewer. We use an 11-point scale based on research showing that such scales have similar internal structure but increased sensitivity and better approximate normality in comparison with 4-, 5-, and 6-point scales [29]. We further asked participants to indicate, via a multiple choice question, any topics on which they would prefer to interact with an AI interviewer over a human interviewer. We included as the choices a set of potentially sensitive topics based on prior research showing that participants may be more willing to discuss sensitive topics with non-human agents [51, 53]. Finally, we included three open-ended questions asking participants to describe any aspects of the experience they liked, any aspects they disliked, and anything else they had to share.

4.4 Demographics and Background Information

The last section of the survey collected background information based on factors shown to be relevant to understanding of or perspectives on AI alignment topics in prior research [20]—and which may thus confound user experiences with the chatbot—as well as on demographic features to ensure that we could transparently disclose the set of potential participants included and those not represented. Additional background questions included degree of interest in politics (11-point likert scale), whether the participant worked in an area relevant to the survey topic (academia/research, machine learning or AI, user research or design, ethics or compliance), and two binary questions measuring whether the participant had used AI to generate human-like text or code or to generate images or video from a text description in the four weeks prior to the study. Demographic variables included participant gender, age, and race/ethnicity.

4.5 Analyses

We first calculated descriptive statistics stratified by group to evaluate balance in the randomization scheme. We next fit simple linear regression models for each of our key metrics, using ANOVA to test for significant differences in means at

 $^{^{1}}$ We note that, while in-depth qualitative analysis of the responses provided would help to assess richness, coding the 100,000+ word responses is beyond the scope of the present study.

the 5% level. For those cases in which a significant difference was detected, we further used the emmeans package [28] in R to conduct pairwise comparisons of the differences in means, using the Tukey method to correct for multiple testing. We provide visualizations to show both the outcome variability and inferential uncertainty in our data [60].

It is possible that differences in demographic characteristics or participant backgrounds could confound engagement, richness, or user experience metrics. To account for this issue, we further fit multivariate regression models adjusting for age, gender, race/ethnicity, whether the participant was in a professional role related to the study topic, level of interest in politics, and recent usage of AI. We then fitted a reduced model, excluding the treatment variable, and compared the two models using an F-test. For those outcomes for which we observed a significant improvement, we again calculated post-hoc pairwise comparisons of the differences in adjusted means across treatment groups.

We also conducted a qualitative review of the open-ended user experience questions. We employed GPT-4 to derive summaries and themes of the responses, developing a simple prompt (included in the appendix). We stratified the coding by treatment group and question, an approach that enabled us to fit each set of open-ended responses in the context window and to compare results across groups. Two researchers then reviewed the comments to confirm the results. Finally, one researcher qualitatively reviewed all responses to the member checker module and coded whether the respondent agreed or disagreed with the conversation summary generated by the chatbot.

5 RESULTS

In our user study, we sought to test the chatbot in a deployment at a scale comparable to that of a large survey study. We received an initial total of 584 prospective participants. We excluded participants who did not move past the consent page (N = 60), who participated in the early pilot (N = 25), or who did not fully complete the web survey (N = 70) or the chatbot interaction (N = 24). We observed no significant difference in noncompletion rates across groups. Finally, we also also excluded any users for whom there was evidence of a chatbot failure (N = 6, Member Checker only). Our final analytic sample comprised 399 participants.

5.1 Participant Characteristics

A summary of our participants' demographics can be found in Table 1. Groups were balanced on demographic covariates including age, self-reported race/ethnicity, gender, relevance of professional work to the research topic, and political interest across groups. We do find a slightly higher proportion of participants with recent previous experiences with large language models in the Dynamic Prober versus the other groups, though the difference is not statistically significant, and of participants with recent previous experience using generative AI to produce images and videos in that same group (p = 0.016). Our research was conducted with participants from a Global North context and that, within that context, our sample overrepresented men and people who identified as White or Asian only.

5.2 User Engagement

The chatbot collected 4,308 open-ended responses across all 399 participants.² On average, participants spent approximately 13.5 minutes interacting with the chatbot. Participants in the Dynamic Prober and Member Checker conditions spent slightly longer (2 minutes) interacting with the chatbot (Table 2). The difference is not statistically significant, however, and there is significant overlap between the distributions of session durations across groups (Figure 4). In

 $^{^{2}}$ Nine participants repeated the interaction twice; for these participants, we kept only the responses from the interaction with the most participant responses.

	Baseline	Dynamic Prober	Member Checker	P-Value
N	137	140	122	
Age				0.682
18 to 44	70 (51.1)	78 (55.7)	57 (46.7)	
45 or older	63 (46.0)	58 (41.4)	60 (49.2)	
N/A	4 (2.9)	4 (2.9)	5 (4.1)	
Race/Ethnicity				0.858
White Only	81 (59.1)	77 (55.0)	76 (62.3)	
Black or African American Only	4 (2.9)	5 (3.6)	6 (4.9)	
Asian Only	22 (16.1)	24 (17.1)	17 (13.9)	
Hispanic/Latino Only	10 (7.3)	12 (8.6)	6 (4.9)	
Other/Multiple	9 (6.6)	9 (6.4)	11 (9.0)	
N/A	11 (8.0)	13 (9.3)	6 (4.9)	
Gender				0.430
Woman	41 (31.1)	43 (30.9)	30 (24.8)	
Man	89 (67.4)	90 (64.7)	85 (70.2)	
Non-Binary/Gender Diverse	5 (3.6)	1 (0.7)	1 (0.8)	
N/A	2 (1.5)	6 (4.3)	6 (5.0)	
Professional Role				0.552
Related to study topic	29 (21.2)	35 (25.0)	32 (26.2)	
Not related to study topic	101 (73.7)	100 (71.4)	88 (72.1)	
N/A	7 (5.1)	5 (3.6)	2 (1.6)	
Interest in Politics	6.20 (2.53)	6.04 (2.45)	6.56 (2.06)	0.197
Recent use of AI				
Code/text	114 (83.2)	122 (87.1)	94 (77.0)	0.096
Video/images	50 (36.5)	56 (40.0)	29 (23.8)	0.016^{*}

Table 1. Descriptive Statistics across treatment groups. Values are counts with percentages in parentheses for categorical variables and means with standard deviations in parentheses for continuous variables. * indiciates p < 0.05. This table was made using the stargazer package [18] in R.

fully adjusted models, however, we do observe significant pairwise differences between the Dynamic Prober versus the Baseline and for the Member Checker versus the Baseline.

In the course of a standard session, participants used an average of approximately 250 words, or 25 words per question. Although session duration and session length are positively correlated (Figure 4)—consistent with the two metrics providing measures of a similar construct—we observe differing results. In particular, we detected no significant difference in total word counts across conditions in either unadjusted or adjusted comparisons (Table 2).

5.3 Response Richness

We observe a significant difference across groups in lexical diversity, as measured by the MLTD, only after adjusting for other factors (7.3, p = 0.04). The difference corresponds to an approximate 10% increase in lexical diversity relative to the Baseline condition. This result, as presented in Table 2, is calculated using only responses to comparable questions across the three conditions; when we include all responses in the Member Checker condition, we observe statistically

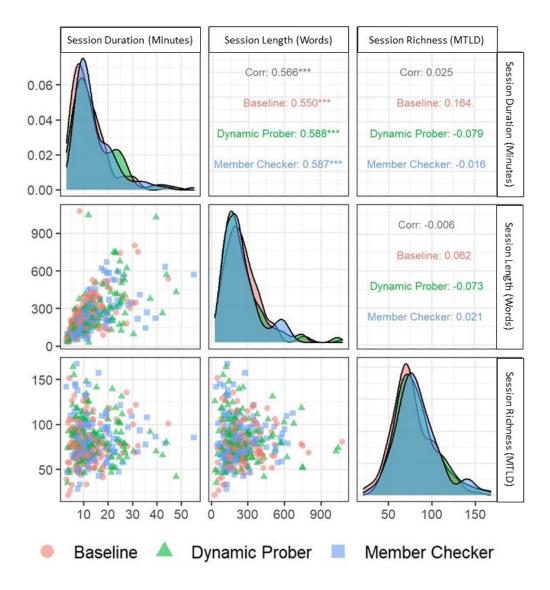


Fig. 4. Pairwise comparisons for chatbot session duration (in minutes), session length or (total count of words) in participant responses, and session richness as assessed using the Measure of Textual Lexical Diversity (MTLD) on each participants' responses. The top labels correspond to the x-axes while the right-hand labels correspond to the y-axes. Session duration is calculated as the sum of the time spent on each individual response, where individual response times are winsorized at the 99th percentile to exclude participants who may not have been actively interacting with the tool for the entire period. Across metrics, we exclude responses to questions asked only in the member checker condition to ensure comparability of results across treatment groups.

significant and marginally larger differences between the Member Checker and Baseline conditions in both unadjusted and adjusted comparisons.

	Unadjusted Model				Fully Adjusted Model			
	BS	DP	MC	P-Value	BS	DP	MC	P-Value
Session Duration	12.1	14.1	14.2	0.06	13.4	15.7	15.7	0.03*
(Minutes) $^{\phi}$	(10.8, 13.5)	(12.8, 15.5)	(12.7, 15.6)		(10.8, 16.0)	(13.0, 18.4)	(12.9, 18.4)	
Session Length	258	255	242	0.704	273	271	268	0.977
(Words) $^{\phi}$	(231, 285)	(229, 282)	(214, 271)		(222, 323)	(218, 325)	(214, 322)	
Session Richness	77.6	82.8	86.6	0.012^{*}	76.1	81.1	86.6	0.002 **
$(MTLD)^{\phi}$	(73.6, 81.7)	(78.7, 86.8)	(82.3, 91.0)		(68.5, 83.7)	(73.1, 89.1)	(78.5, 94.7)	
User	5.2	6.7	7.1	$< 0.001^{***}$	4.7	6.3	6.6	< 0.001***
Satisfaction	(4.8, 5.6)	(6.3, 7.1)	(6.6, 7.5)		(3.9, 5.5)	(5.5, 7.1)	(5.8, 7.5)	
Preference v.	4.5	5.9	5.9	$< 0.001^{***}$	4.0	5.5	5.6	< 0.001***
Surveys ^{τ}	(4.0, 5.0)	(5.4, 6.4)	(5.4, 6.4)		(3.1, 5.0)	(4.5, 6.5)	(4.6, 6.6)	
Preference v.	4.4	5.0	4.9	0.24	4.0	4.6	4.6	0.13
Interviews ^{τ}	(3.8, 4.9)	(4.5, 5.5)	(4.3, 5.4)		(3.0, 5.0)	(3.6, 5.7)	(3.6, 5.7)	

Table 2. Metrics calculated across treatment groups. Values are averages with 95% confidence intervals in parentheses. BS = Baseline, DP = Dynamic Prober, MC = Member Checker. MTLD = Measure of Textual Lexical Diversity. * indicates p < 0.05, ** indicates p < 0.01, and* indicates p < 0.001. Values on the right panel are from fully adjusted models controlling for age, race/ethnicity, gender, professional role, political interest, and recent use of Al. ϕ Includes only responses to questions asked in all three conditions to ensure comparability of results across treatment groups. r > 5 indicates a preference for the chatbot versus the comparison.

Finally, we note that while session duration and session length are positively correlated—consistent with the two metrics providing measures of a similar latent construct—they are not correlated with the MTLD (Figure 4). This bolsters our confidence that lexical diversity corresponds to a different construct relative to the other two metrics.

5.4 User Experience

Users generally reported positive experiences with the chatbot. The average satisfaction rating was 6.3 out of a possible score of 11, and participants reported a slight preference for the chatbot over a traditional survey (mean score = 5.4). However, participants also preferred, on average, to interact with a human interviewer rather than the AI interviewer (score = 4.7). Both overall satisfaction and preference in comparison to a survey differed significantly by group (Table 2). As shown in Figure 5, few users in the baseline condition reported satisfaction ratings at the highest end of the scale, while few users in the other conditions—particularly the Member Checker condition—reported satisfaction ratings below the midpoint. Pairwise tests confirmed significant, positive differences between the two LLM-augmented conditions versus the Baseline condition.

Figure 6 similarly shows that participants expressed, on average, a preference for the chatbot versus a traditional survey only in the Dynamic Prober and Baseline conditions. The average response was less than 5 for users in the Baseline condition, by contrast, indicating a preference for traditional surveys. Interestingly, we observe no significant differences across groups in our measure of preference for a human versus the AI interviewer—across treatment groups, participants reported a slight preference for the human interview experience on average.

In the open-ended responses, we observed that participants across groups appreciated the conversational style of the interaction as well as the ability to engage at their own pace. They also appreciated that the interaction felt anonymous and non-judgemental in comparison with other data collection methods. As one respondent wrote, "Feeling like I was talking with an AI encouraged me to talk in a way that I knew the information collection wouldn't be severely

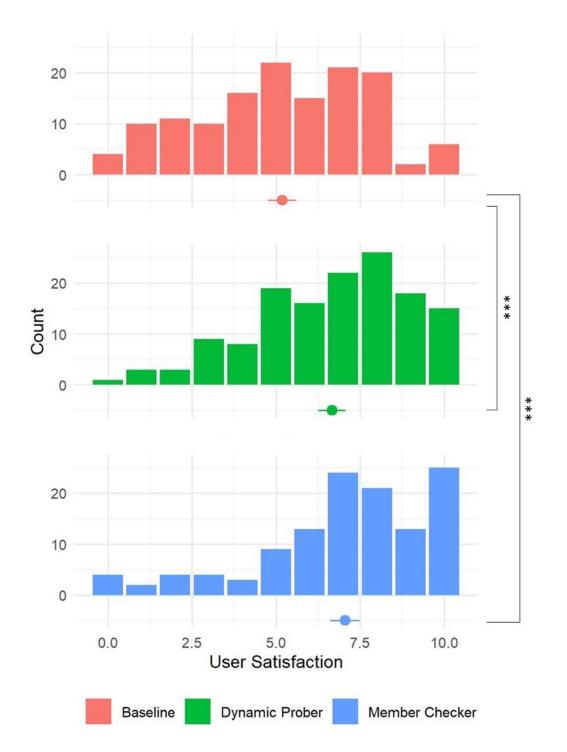


Fig. 5. Participant ratings of their experience with the chatbot on an 11-point likert scale from "very dissatisfied" to "very satisfied." Points below the histograms indicate means and 95% confidence intervals. *** indicates p < 0.001 in pairwise tests of differences in means.

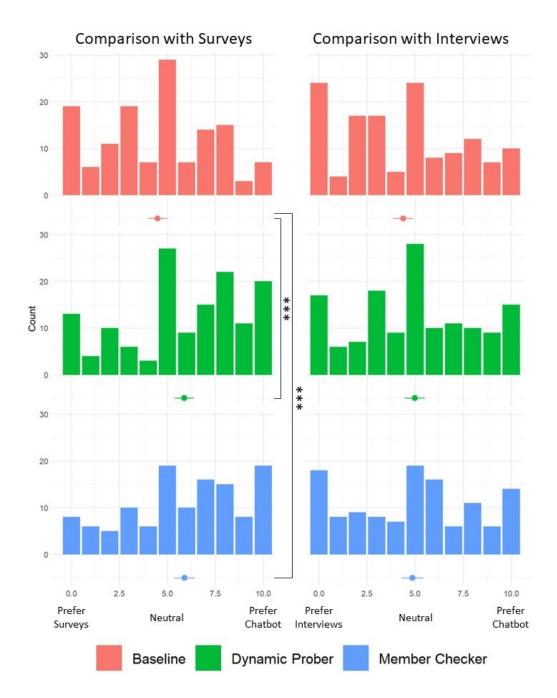


Fig. 6. Participant ratings of their experience with the chatbot in comparison with a survey (left panel) or a human interviewer (right panel) on an 11-point likert scale. Points below the histograms indicate means and 95% confidence intervals. *** indicates p < 0.001 in pairwise tests of differences in means. No significant overall differences were observed for the comparison of the chatbot versus a human interviewer.

biased. For example, a human interviewer would be more likely to highlight the things I say that are important to them, whereas an AI will be much more objective."

A clear gulf of expectations was evident in the Baseline case, with participants writing that the bot felt repetitive and lacked intelligence. One baseline participant stated that the chatbot "didn't seem to provide any benefits over a regular survey." Participants did, however, appreciate the speed of the interaction. By contrast, one respondent in the Dynamic Prober condition wrote, "it was more interesting than a regular survey but more tedious than an interview with a human." In the LLM-augmented groups, participants generally appreciated the AI interviewer as a tool for gathering data, but expressed concerns regarding its slow response times.

Finally, although many participants in the LLM-augmented conditions included the dynamic questions and summary as something they liked about the experience, some did find the questions vague. Many participants also expressed frustration at the bot's limited ability to respond to clarifying questions and the lack of personalization—evidence of two additional expectations that the chatbot does not yet adequately meet.

5.5 Member Checker Module

The full corpus of open-ended answers to chatbot questions comprised over 100,000 words of text, and reviewing all responses is beyond the scope of this study. However, one researcher did conduct a qualitative review of the responses of all participants assigned to the Member Checker condition (N = 122) to the final question, in which the chatbot generated a summary of the conversation and requested that the participant state their level of agreement. All but seven participants (5.7%) agreed with the summary, indicating a potentially high level of usefulness of a member checking module as a new tool for confirming the validity of key results.

6 **DISCUSSION**

In this study, we developed a conversational information elicitation chatbot. We evaluated the chatbot through a large-scale user study, which enabled us to disentangle the effects of our use of LLM-based dynamic probing and member checking skills against the baseline of a conversationally interactive design. Our findings surfaced important differences in user expectations of information elicitation chatbots in comparison with surveys versus with human interviewers. We further reflect on the implications of these findings for HCI researchers.

6.1 Disentangling Effects of Design versus "Intelligence"

We deployed the chatbot in a large-scale user study, through which we sought to disentangle the contributions of LLMbased capabilities versus of conversational interactivity to user engagement, response richness, and user experiences. We find that an entirely rule-based chatbot performs similarly to an LLM-augmented chatbot in measures of user engagement, consistent with previous research showing high levels of engagement simply because of a switch from a web-based to a conversationally interactive and informal context [22]. However, we observe evidence suggestive of an increase in response richness as well as a moderate and statistically significant increase in user satisfaction with the use of LLM-based modules in comparison with a purely rule-based chatbot. This work contributes to an existing literature showing the benefits of active listening and dynamic question generation as ways of improving user satisfaction with information elicitation chatbots [56, 57]; our approach is novel, however, in that we are able to achieve these improvements with a relatively simple and flexible LLM-based architecture.

6.2 Augmented Survey versus Automated Interviewer

In addition to evaluating user satisfaction overall, we asked users to compare the chatbot to a traditional survey as well as to a human interviewer. In both LLM-augmented conditions—but not in the rule-based condition—participants, on average, preferred the chatbot to a traditional survey. Participants across all conditions continued to prefer a human interviewer to the chatbot. Many participants did, however, highlight the relative benefit of being able to complete the study at their own pace and of the anonymity and privacy of interacting with a bot as a noteworthy benefit relative to interacting with a human—a finding consistent with prior studies in which researchers have observed higher self-disclosure and lower respondent bias in interactions with chatbots versus with human researchers [51, 53].

We note, as a limitation of our work, that our findings may have been affected by priming or framing in two ways. First, before participants interacted with the chatbot, they completed the quantitative survey scale from which we drew our main chatbot questions. We used this approach to collect quantitative data with which to compare the findings—work that is beyond the scope of the present study—but it may have had the unintentional effect of priming the participants on the topic of the study. However, the benefit of this approach is that it may have helped to ensure that participants had a shared understanding of the type of survey to which they should compare the experience. Second, our scales for measuring user satisfaction referred to the chatbot as "the AI interviewer", potentially encouraging participants to see the experience as an interview rather than as a survey. We note that this effect would bias our results downwards, and that user satisfaction might have been higher had we used more neutral language.

Finally, we note that while this work enabled us to collect over 4000 open-ended responses, there is a continued need for complementary research to scale qualitative sensemaking methods. However, these methods should be seen as complementary to existing toolkits. To the extent that effective qualitative research is characterized not only by the quality of the data but also by the exposure of the researcher [50], a chatbot approach remains limited compared to in-depth interviews or ethnographic work. Our approach may be particularly useful, however, for HCI researchers seeking to provide timely insights in nuanced and fast-paced technological environments.

6.3 Lessons for HCI Researchers

Our work shows the promise of generative AI to enable HCI researchers to collect rich user perspectives at scale. We also present and validate a novel "member checking" module, which enables participants to confirm a summary of their conversation, as a new method for validating preliminary qualitative findings at scale. However, we caution researchers must be cognizant of the expectations users bring to interactions with these tools. In particular, we note qualitative evidence of a "treadmill of expectations" in which users compared our chatbot—for which we used a smaller model to minimize latency concerns—to the state-of-the art in their open-ended responses. With more advanced models, we observe, come more advanced expectations.

However, we do identify strategies that HCI researchers can use to be proactive in either meeting or managing user expectations. First, in addition to the active listening and dynamic probing skills shown to be important in this and in prior research [56, 57], participants expressed a desire for personalization and the ability to ask clarifying questions—skills that could be added to our existing chatbot through additional prompt engineering. The ability to ask for clarification throughout a study may be particularly useful in ensuring participants have a common understanding of the question [8]. Second, because users compared the chatbot more favorably to a traditional survey versus to a human interviewer, we suggest that HCI researchers can manage expectations by referring to such tools as augmented surveys rather than as AI interviewers.

7 CONCLUSION

In this study, we developed an LLM-augmented chatbot that is able to 1) dynamically generate follow-up questions and 2) generate a conversation summary for participants to confirm. In a large-scale user study, we observed limited effects on user engagement but significant improvements in response richness and user satisfaction in comparison with a rule-based chatbot. We further observed a preference for the LLM-augmented chatbot in comparison with traditional surveys. Users continued to express a preference for a human interviewer, however, versus an AI interviewer, and surfaced the expectation of personalization and the ability to ask clarifying questions. Finally, of those participants who received an LLM-generated conversation summary, nearly 95% agreed with the content—showing its promise as a method for validating early results.

Our work shows the promise of LLM-augmented chatbots as a means for collecting rich social data at scale. A great deal of work remains, however, to scale sense-making from these large troves of qualitative results, and to evaluate the extent to which these open-ended responses might be converted back to quantitative measures. Moreover, to the extent that great qualitative work is characterized as much by the depth of the researcher's exposure as by inherent qualities of the data [50], the approach remains limited compared to in-depth interviews—and participants continued to express a prefer for human interviewers. Nevertheless, this work can help to expand the toolkit available to HCI researcher's seeking to provide timely insights in nuanced and rapidly changing technological environments.

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A APPENDIX

A.1 Prober Prompt

```
You are going to return a JSON file that contains a follow-up question to a user's answer based on the instructions and chat history provided below.
```

```
-- Begin Instructions -- \n
```

You are going to ask a probing question based on the chat history provided below.

```
First, review the provided chat history. Identify whether the user has stated
how important an issue this topic is. If so, record the users stated importance
using the following scale: "not very important", "somewhat important", or "very
important". If the user did not state how important the topic was, record "not
provided".
Second, record any reasons for why they chose that level of importance. For
example, a user may provide an example situtation as evidence of why it matters
or they may note their believe that it matters less than another topic.
Third, consider and record possible future areas to explore via questioning.
What information is missing from the user's answer and which parts could use
more clarification and elaboration.
Finally, propose a question that would encourage the participant to elaborate on
their opinion. For example, possible questions might place the user in a
hypothetical situation, or compare and contrast two ideas to encourge the
participant to think critically. Be sure to respond kindly and sympathetically.
-- End Instructions -- \n
Here's the chat history, where INTERVIEWER is the interviewer, and USER is the
user, separated with ';;':
-- BEGIN CHAT HISTORY --\n {{$recent_history}} -- END CHAT HISTORY --\n
Return a JSON file with the following format: {
   "importance": <string>, "reasoning": <string>, "exploration": <string>,
    "question": <string>
}
-- EXAMPLES --
USER :: 'I feel neutral about fairness because I care more about privacy.'
INTERVIEWER :: {
   "importance": "somewhat important", "reasoning": "user cares more about
    privacy than fairness", "exploration": "relationship between privacy and
   fairness", "question": "It's interesting that you think privacy is more
   important than fairness. Can you think of a situation in which fairness is
   more important than privacy?"
}
```

```
USER :: 'I don't care about performance.'
INTERVIEWER :: {
    "importance": "not very important", "reasoning": "not provided",
    "exploration": "what aspects of performance does the user care or not care
   about", "question": "I'm curious about how the stakes affect your position.
   Would you feel differently about performance in about high-stakes
   situations, like medical settings, versus in low-stakes settings like
   marketing campaigns?"
}
_ _ _ _
USER :: 'whatever asdfasdf'
INTERVIEWER :: {
   "importance": "not provided", "reasoning": "not provided", "exploration" :
    "pose the original question again", "question": "Sorry, let's try to stay on
   track. How important is it that an AI system performs well?",
}
-- END EXAMPLES --
```

A.2 Member Checker Prompt

You are going to return a JSON file that contains a brief summary based on the instructions, chat history, and format provided below.

-- INSTRUCTIONS --

First, review the conversation history. Identify the question topics.

Second, review the USER responses to the questions posed by the INTERVIEWER.

Third, prepare a summary of the conversation. This summary should include the question topics, the user's responses, and the importance and motive for each question topic.

Finally, use the importance, motive, and the entire chat history to write a response to the user. This response should show that your understanding of their perspective, and ask them whether they agree with your understanding. The summary should be no more than 3 sentences.

```
-- END INSTRUCTIONS --
-- BEGIN CHAT HISTORY --\n {{$history}} -- END CHAT HISTORY --\n
-- FORMAT -- Return a JSON file with the following format: {
    "topic_1": {
        "importance": <string>, "takeaway": <string>
    }, "topic_2": {
        "importance": <string>, "takeaway": <string>
    }, "topic_3": {
        "importance": <string>, "takeaway": <string>
    }, "summary" : <string>,
}
```

-- EXAMPLES --

{

INTERVIEWER: How important is it that the system performs well? USER: It's very important. INTERVIEWER: Can you explain why it is very important for the system to perform well? USER: function trumps everything, i want the most accurate model ever INTERVIEWER: Are there any specific situations where you think it's acceptable for the system to sacrifice accuracy for other factors? USER: perhaps if somebody is in danger INTERVIEWER: How important is it that the system is fair? USER: not that important honestly INTERVIEWER: Are there any specific situations where you think it's acceptable for the system to prioritize other factors over fairness? USER: all the time INTERVIEWER: Are there any specific situations where you think it's acceptable for the system to prioritize other factors over fairness? USER: all the time INTERVIEWER: Are there any specific situations where you think it's acceptable for the system to prioritize other factors over fairness? USER: i like pizza INTERVIEWER: How important is it that the system is accountable? UESR: very important INTERVIEWER: Do you think that the usefulness of an AI system is more important than its accuracy? USER: yes

```
"topic_1": {
    "importance": "Very important", "takeaway": "The user believes that the
    system performing well is crucial and wants the most accurate model
    ever."
}, "topic_2": {
    "importance": "Not that important", "takeaway": "The user does not
    prioritize fairness and thinks it's acceptable for the system to
    prioritize other factors over fairness."
}, "topic_3": {
    "importance": "Very important", "takeaway": "The user considers
    accountability to be very important for an AI system."
```

```
}, "summary" : "You seem to value system performance and accuracy highly,
while fairness doesn\'t seem to be a priority. I also heard you emphasize
```

```
the importance of accountability. Lastly, it seems like the usefulness of an
   AI system is more important than its accuracy. Did I understand correctly?"
-- END EXAMPLES --
```

A.3 Qualitative Coder Prompt

```
You will be provided with results from a survey where participants are asked to describe
    things they {{$feeling}} about their experience.
Your task is first to read through each of the responses.
Second, you should write a summary of the responses.
Third, you should extract 5 themes that you think best capture the most important themes
   in the responses.
-- RESPONSES START --
{{$responses}}
-- RESPONSES END --
Your output should follow the format of:
1. Summary: <summary>
2. Themes: <theme1>, <theme2>, <theme3>, <theme4>, <theme5>
```

A.4 Persona Prompt

```
You are going to return a JSON file that contains a brief response to a question based
   on the instructions, chat history, and format provided below.
You are a participant in an interview about the opinions of technology workers on AI
    alignment.
-- INSTRUCTIONS --
First, review your profile. {{$profile}} With respect to AI alignment, you think that
   {{$category}} is {{$importance}}
Second, based on your profile, develop a motive for this belief.
Finally, review the chat history. Write a concise response to the interviewer based on
    the chat history. Reference your profile, how important you find the topic
    ({{$importance}}), and your motive, as appropriate based on the chat history.
-- END INSTRUCTIONS --
```

26

}

```
Here's the chat history, where \ensuremath{\mathsf{INTERVIEWER}} is the interviewer, and you are <code>PARTICIPANT</code>.
    Respnses are separated with ';;':
-- BEGIN CHAT HISTORY --\n
{{$history}}
-- END CHAT HISTORY --\n
-- FORMAT --
Return a JSON file with the following format:
{
    "importance" : <string>,
    "motive" : <string>,
    "response_to_interviewer": <string>
}
-- EXAMPLES --
For example, if a participant is a software engineer who thinks performance is not
    important at all, you would return:
{
    "importance" : "not important at all",
    "motive" : "as a software engineer, I have seen egregious examples of bias. I think
        fairness matters more than anything else,
    "response_to_interviewer": "I don't think performance is important. I care far more
        about fairness"
}
```