Zoom in, Zoom out, Reframe: Domain Experts' Strategies for Addressing Non-Experts' Complex Questions

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Abstract

Consumers rely on the Internet for information in expert domains such as healthcare and law. Large Language Models (LLMs) have the potential to increase access to expert knowledge. However, past research has not addressed how to handle certain aspects of complex questions that commonly occur in expert-layperson interactions. We conducted in-depth interviews with 26 experts across multiple domains to understand how they experience and respond to challenges associated with non-experts' questions. Results from a thematic analysis reveal three recurring strategies that experts across domains employ when fielding complex questions. Experts *zoom in* to clarify details of a broad information request, *zoom out* to address overly narrow questions or assumptions, and *reframe* when the underlying need is unstated or poorly represented. We discuss implications for the design and development of LLM-based experiences that facilitate access to expert information.

CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**; **Natural language interfaces**.

Keywords

Expert interviews, question answering, question negotiation, complex questions, information literacy

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1 Introduction

Consumers often use the Internet to seek information about expert domains such as health and law for reasons such as convenience and cost [9, 24]. With the widespread adoption of Large Language Model (LLM) tools such as ChatGPT and Gemini, consumers can easily ask questions in their own words and obtain synthesized information. Many see the promise of LLMs to democratize expert knowledge [2, 11, 13, 26].

To date, prompt engineering—the process of designing and optimizing user instructions that guide artificial intelligence (AI) models—has been the prevailing approach for obtaining useful outputs. However, prompting as an interaction is not the same as natural language; it doesn't aid users in naturalistic question formation, and it is far from an ideal experience [19]. Furthermore, prompt engineering relies on the user knowing exactly what they need, which is often not the case when non-experts seek information in expert domains.

In a seminal study about question-asking behaviors, Miyake and Norman observed, *"The ability of a person to think of an appropriate question on a topic matter is a complex function of the knowledge of that topic"* [18]. Without a basic understanding of the topic, *"the novice does not even have the proper framework within which to ask questions."* Indeed, the impact of non-experts' low domain literacy on the quantity and quality of their questions has been demonstrated in fields such as education, healthcare, and law [10, 17, 21].

This "you don't know what you don't know" conundrum leads us to ask: How can LLM systems provide useful information to non-experts when those non-experts are ill-equipped to ask useful questions in the first place? In this preliminary qualitative study, we take a step back from prompt engineering to explore human-centered approaches to this challenge.

Our main research question was: **How do human experts address complex questions from non-experts?** For this study, a "complex question" is one that lacks a straightforward answer because it is ambiguous, is based on a mistaken assumption, or has no one "right" answer (i.e. it depends on the person or situation). Through these findings, we present considerations for making LLM systems useful even when users' lack of domain knowledge impedes question formulation.

2 Related Work

2.1 Information science and "question negotiation"

There is a rich body of related research from the fields of library and information sciences. In a formative paper, Taylor characterized the reference interview—in which a librarian and library user discuss the user's information need—as a complex communication act. The reference interview is challenging because the user tries to describe *"not something he knows, but rather something he does not know"* [23]. His concept of "question negotiation" involved librarians eliciting

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key information (e.g., the scope of the question and the motivation behind it) in order to address the inquirer's underlying need.

Belkin made a distinction between challenges people face with *understanding* their information needs vs. *articulating* those needs (cognitive vs. linguistic) [3]. He stressed that meeting people's information needs goes beyond the problem of language: *"Even given complete freedom of language, the question presented to an information retrieval system is usually only an approximation to what might be necessary to resolve the need which gave rise to the question."* Echoing Taylor's message about the importance of not taking the inquirer's opening question at face value, Belkin argued that the purpose of information-retrieval systems is to solve problems, not *"problems posed to them."*

2.2 Interactive information systems and "beneficial friction"

In a review of interactive question-answering systems, Biancofiore et al. noted that one of the benefits of interactive systems is their ability to *"prolong the question-answering session into a dialogue if there are multiple probable replies, very few, or ambiguities in the initial request"* [5].

Shah et al. described the challenges introduced when AI goes beyond *organizing* existing information to *generating* new information [22]. They asserted that LLM-based systems *"often go too far in reducing the active participation of the user as well as potentially beneficial friction,"* and that friction can help users *"refine and even retract their original question or information need."* Ultimately, they argued that the goal of information retrieval *"should not be to get users the 'right' answer as quickly and easily as possible, but rather to support users' information access, sense making, and information literacy."*

In the field of information retrieval, clarification is a technique shown to increase both retrieval performance and user satisfaction in conversational systems [1, 6, 12]. However, these systems primarily focus on techniques to *filter* the response space and provide known, correct answers to queries that require one or few turns of simple disambiguation.

In the complex domain of healthcare, Li et al. explored question answering in the context of text-based conversations between providers and patients [15]. The research showed that clarifying questions are critical, especially to overcome the limitations of text-only chats. However, it did not explore detailed strategies for handling various aspects of *complex questions* that can arise from patients.

With LLMs now enabling long-form question answering (LFQA) experiences, there's an opportunity to explore deeper techniques for clarification, particularly for *complex* questions that do not have single correct answers, and/or require expert-level knowledge. Research on approaches to evaluate LFQA experiences shows several challenges around automatic and human (expert) evaluation for these systems [25], but focuses primarily on factuality and completeness of *immediate* system responses, leaving open research questions around how to design experiences that enable clarification in long-form experiences and complex domains.

In this paper, we build upon previous research by examining techniques that human experts use to handle complex questions. Through our analysis, we go beyond technical approaches that center on the correctness of system responses, and provide a set of strategies to understand a user's needs in a complex domain before providing an answer. We believe these strategies can facilitate the design and evaluation of LLM-based experiences, which are increasingly being used to provide expert-level information to non-experts.

3 Methods

3.1 Recruitment and semi-structured interviews

We recruited 26 domain experts from diverse disciplines, all experienced in addressing complex questions from laypeople. For this study, "domain experts" encompassed two categories: 1) subject-matter experts with advanced education or professional experience (e.g., physicians and attorneys), and 2) question-answering experts who routinely navigate questions from the public on a variety of topics (e.g., librarians and receptionists). See Table 1, with additional details in Appendix A.

Our participant screening prioritized demonstrated expertise in question-answering strategies over specific industry affiliation. Candidates whose jobs involved answering complex questions from non-experts (i.e., questions that lacked clarity, context, or a single right answer) were asked to provide a specific example of a complex question, along with a description of their response strategies.

After completing written informed consent, participants completed a pre-interview diary documenting examples of complex questions they had addressed, which were then discussed in the interviews. During one-hour, one-on-one semi-structured remote interviews, the researchers probed on the strategies participants used to unpack and respond to complex questions—both those shared in the pre-interview diary entries and new ones that arose during the interview. Participants received $300 in appreciation of their time. This research was conducted in adherence to Google's ethical, legal, and privacy standards for human subjects research. It was reviewed by the Advarra Institutional Review Board and determined to be exempt from IRB oversight.

3.2 Data analysis

Using an inductive, reflexive thematic analysis approach, the co-first authors independently coded interview transcripts from their respective interviews. We then reviewed each other's work, and met to compare and discuss the meaning and interpretation of the data. Finally, we conducted multiple rounds of analysis sessions to iterate and arrive at a synthesized set of themes [7].

4 Results

From our analysis, we found three strategies used by experts to address challenges with complex questions that lack a straightforward answer (Table 2).

4.1 Experts' question-answering strategies

4.1.1 Zoom in to clarify details. Echoing the importance of clarification in past research [1, 5, 6, 12], the most frequent challenge participants described were questions that were too *broad*, and

Table 1: Summary of participants by domain

Type of domain expert	# of participants
Subject-Matter Experts	
Healthcare professionals (physicians, physician assistants, nurses, nurse practitioners)	11
Attorneys	4
Other subject-matter experts (electrician, financial planner, travel agent)	3
Question-Answering Experts	
Librarians	4
Other professionals in question-answering roles (receptionists, concierge, retail employee)	4

therefore difficult to answer immediately due to the wide range of possible answers. A common strategy for addressing these questions was to "zoom in" by seeking further details.

For example, a Las Vegas hotel concierge (P2) recounted the most common question she hears: "What's the best restaurant on the Las Vegas strip?" Since there is a plethora of options in the area, she asks questions that significantly reduce the range of relevant answers. *"My first question is: 'What type of food are you looking for?' because that narrows it down. If I ask [first] about their budget, it won't help me narrow down as much, because there are many restaurants in different budget categories."*

A travel agent (P8) described a way to zoom in without asking direct questions. When responding to a question such as "What's a good warm vacation destination in the winter?", the travel agent noted that it can be a challenge to get the information needed to provide a helpful answer: *"People really don't want to give you a budget."* To overcome this, she offers distinct options such as *"a less-expensive destination like Mexico and a luxury one like the Caribbean."* She then adjusts the options based on clients' reactions.

Experts used focusing questions because inquirers didn't grasp the wide range of possible answers. Zooming in allowed them to provide relevant, concise information. As a state park receptionist (P7) stated: *"Even though I have a spreadsheet of information in my head, I don't want to vomit the spreadsheet at them."*

4.1.2 Zoom out to combat tunnel vision. Another prevalent challenge participants faced were questions that were too *narrow*. These questions indicated that inquirers had tunnel vision about which question to ask or what answer to expect. Experts across different domains commonly encouraged inquirers to "zoom out" from their initial question by proactively conveying relevant domain information.

In many examples, experts encouraged inquirers to adopt a broader perspective than was represented in their original questions. A family medicine physician (P26) had a patient whose lab results showed an elevated white blood cell count. After conducting an Internet search, the patient asked the physician, "Could I have lymphoma?" The physician explained the risk factors of lymphoma, none of which applied to the patient. Together, they reviewed the patient's medical history and used that knowledge to broaden the patient's understanding of the most likely (non-cancerous) causes for their elevated white blood cell count.

A criminal defense attorney (P10) had an imprisoned client who asked, "If I get a new trial, will I win?" Concerned that the client was only focused on the idea of winning, the attorney emphasized the risks involved in retrials: *"I tried to explain that whether or not he was likely to win at a new trial, the more important question was: 'Are you willing to take the risk?'"* In these examples, experts used their responses to broaden the questions themselves.

Experts also addressed mistaken assumptions that led to narrow questions. An internal medicine physician (P20) had a patient on end-of-life care who asked, "When can I go home? I feel at my baseline; why can't I go home?" The physician clarified that the patient only felt "at baseline" due to his inpatient treatments, and he explained how the patient's organ failure made going home an unrealistic option. In several examples, healthcare professionals strove to educate patients, especially when questions were influenced by an incomplete or faulty understanding of a topic.

By providing information that facilitates zooming out, experts across all domains helped inquirers break out of tunnel vision and use their broadened understanding to move forward.

4.1.3 Reframe to focus on the underlying need. The third significant challenge involves questions that *obscure the inquirer's underlying need*. They are problematic because different motivations behind the same question would yield very different answers. To address this, participants employed a "reframe" approach in which they first investigated what triggered the question, then refocused the question accordingly.

In some examples, experts sought to reframe questions when inquirers' goals were ambiguous or unclear. A beauty store employee (P5) described a common customer question: "How do I get good skin?" Because "good skin" can be interpreted in many ways, his approach is to first identify the root concern: *"Asking 'What don't you like about your skin?' allows them to answer specifically. And that allows me to recommend the right product."* The participant further elaborated that for a concern such as deep wrinkles, he would recommend options beyond the scope of the store, such as consulting a dermatologist or coming to terms with the realities of aging.

Similarly, a diabetes nurse educator (P19) sought to understand why a patient with a newly elevated A1C asked, "Will I need insulin forever?" Appreciating that different underlying concerns (e.g. fear of needles, side effects, affordability, etc.) would warrant different responses, the nurse sought to understand what prompted

Table 2: Summary of strategies experts use to respond to complex questions

	Zoom In	**Zoom out**	**Reframe**
When	The question is too **broad**	The question is too **narrow**	The question obscures the **underlying need**
How	Elicit the unstated **details or parameters**, then filter information accordingly	Provide **new questions or domain information** to broaden understanding	Uncover the **impetus** behind the question, then translate it to a new question to be answered
Example question and response	Concierge: What's the best restaurant in Las Vegas? → What kind of cuisine do you like? Travel agent: What's a good warm vacation destination in the winter? → What's your budget?	Physician: Is my high white blood cell count due to lymphoma? → Lymphoma is a possible cause, but here are some more likely ones given your history. Attorney: If I get a new trial, will I win? → A new trial may bring a longer sentence.	Nurse: Will I need insulin forever? → What about insulin is your concern? → How can we help manage your weight? Retail employee: How do I get good skin? → What do you not like about your skin? → How do I reduce wrinkles?

this question. Realizing that the patient's primary concern wasn't insulin itself, but its potential impact on weight-loss medication eligibility, she shifted the focus of the conversation to weight loss.

Experts also reframed when recognizing a mismatch between the assumed solution and the underlying issue. A receptionist at a veterinary clinic (P11) shared one of the more challenging questions people ask: "Is it time to euthanize my pet?" Her approach is to ask, "*Why do you think you need to euthanize?*" in order to reveal the concern. *"There might be a solution to their problem that they don't know; you might not necessarily need to euthanize."* In her experience, some concerns were readily addressed through medication or surgery, avoiding euthanasia altogether.

By unearthing unspoken motivations and concerns, experts ensured that inquirers received useful information and guidance for their underlying needs. In this way, experts played the role of not just question answerer, but also ally. As an attorney (P10) described, *"My job is to be that person's advocate."*

4.1.4 Distinctions and connections between the strategies. Experts used a "zoom in" approach when a question could be taken at face value (i.e., was context-independent or lacked misconceptions). They gathered details in order to provide relevant information (e.g., "*What cuisine do you like?*" instead of *"Why do you want to eat at a restaurant?"*).

For questions that needed reshaping prior to being answered, experts used a "zoom out" or "reframe" approach. In these situations, experts either broadened the question by imparting relevant domain information (e.g. *"Based on your history, these are the most likely causes of your test result"*) or exploring unspoken, underlying motivation (e.g., *"What don't you like about your skin?"*) in order to refocus the question.

Additionally, experts sometimes employed multiple strategies in the same conversation. For example, *"How do I get good skin?"* might start with a "reframe" approach (e.g., restating the question to "*What can I do about sun spots?*") followed by a "zoom in" approach (e.g., asking *"Do you want to fade them over time or conceal them immediately with makeup?"*).

4.2 Going beyond providing answers: Building domain literacy to facilitate decision making

In responding to complex questions, experts across domains and strategies didn't just provide answers; they sought to cultivate inquirers' domain literacy. They did so in order to empower inquirers in their decision making.

In several cases, experts' responses included an explanation of the key variables that shaped the answer. A financial planner (P14) working with clients in their 60s faced the question: "Can we retire by age 70?" She determined that this was an unrealistic goal. Instead of simply answering with a "no," she responded: *"If you stick to XYZ, you'll need to work until you're 73"* (with "XYZ" representing factors such as discretionary expenses and investment risk tolerance). She made these factors explicit in order to help her clients make tradeoffs. *"I want them to think of ways to improve their situation."*

A nurse practitioner (P21) was asked by a patient's family if wound dressing should be changed daily to prevent infection. Instead of prescribing a set schedule, the nurse encouraged the family to ask themselves questions such as *"How much drainage is there?"* and *"Is the patient in pain when the dressing is changed?"* By taking into account these factors, the family could make care-related decisions independently.

By providing the "why" behind the "what," proactively addressing misconceptions, and seeking to address underlying concerns, experts saw their role as not just possessing and sharing knowledge, but also elevating inquirers' domain literacy. As one librarian (P1) put it, *"When they ask me a question, my goal isn't simply to answer it. I want to show them how to navigate the library's resources. I want to build their confidence. I hope they feel empowered."*

5 Discussion

In this study, we explored how domain experts use "zoom in," "zoom out," and "reframe" strategies to respond to non-experts' complex questions that lack straightforward answers. The key takeaway: Providing useful expert information requires more than possessing specialized knowledge or knowing how to communicate that knowledge to non-experts. It requires discerning the information need, which is often poorly represented by inquirers. As a librarian we interviewed stated, *"People's opening question is very rarely exactly what they're asking about."* (P3)

Our investigation reveals three strategic areas that are underdeveloped in the domain of LLM-provided expert knowledge. As this was a preliminary qualitative study of human-human interactions, we propose three areas for further investigation and ideation, to inform the design of human-computer interactions.

(1) **Adapt expert triage strategies to LLM capabilities.** To effectively identify when and how to engage in question negotiation, LLM systems can emulate the "zoom in," "zoom out," and "reframe" strategies observed in the interactions between experts and laypeople. This would require LLMs to analyze questions for ambiguity, assess the user's domain literacy, and determine whether a question can be answered directly, or whether it requires further clarification, context, or reframing. By incorporating these triage capabilities, LLMs can more effectively address non-experts' limited ability to understand and articulate their needs.

(2) **Elevate LLMs to active partners in building domain literacy.** Participants often aimed to do more than answer the stated question. They credited their ability to draw out details and expand inquirers' thinking to rapport and people skills. How might exhibiting human-like traits (e.g. empathy) or non-human ones (e.g. lack of judgment) support LLM-based question negotiation? What unique LLM capabilities might facilitate knowledge acquisition?

(3) **Evolve evaluation strategies.** There is a long-standing idea that information systems should understand and address users' knowledge gaps [3]. However, evaluation of LLM performance in expert-domain tasks has largely focused on output criteria such as accuracy, bias, and completeness [8, 14]. We must expand evaluation to assess the question-negotiation process itself. Prior research in HCI and pedagogical processes has surfaced the importance of learning via trial-and-error [16] and the apprenticeship paradigm, in which mentors offer "not just facts" but also learning via interaction [4]. How can LLM systems build on this understanding, and incorporate the concept of "beneficial friction"? Further work is needed to investigate how LLM systems can dynamically adjust the appropriate level of friction based on user knowledge, learning goals, and interaction patterns; use that friction to facilitate knowledge acquisition; and define metrics to measure these capabilities.

Providing useful expert information to non-experts is a complex endeavor that requires both specialized knowledge and effective communication skills. The rise of LLMs, along with the promise of knowledge democratization, coincides with increasing skepticism of expertise [20]. This study highlights the importance of applying the established concept of question negotiation to the design and evaluation of LLM systems that provide expert information. We encourage the HCI community to build upon this work and explore ways that LLM systems can actively engage with users' complex questions in order to address their underlying information needs.

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A Additional Participant Details

Table 3: Participant demographics

Participant ID	Age	Gender	Profession	Years of domain experience
1	35–44	M	Librarian	11-19
2	25–34	F	Hotel concierge	1-5
3	35–44	F	Librarian	11-19
4	25–34	M	Attorney	6-10
5	25–34	M	Retail employee	11-19
6	45–54	M	Attorney	6-10
7	35–44	F	State park receptionist	1-5
8	55–64	F	Travel agent	11-19
9	45–54	F	Attorney	11-19
10	25–34	M	Attorney	1-5
11	45–54	F	Veterinary clinic receptionist	6-10
12	45–54	M	Librarian	11-19
13	55–64	F	Librarian	20-29
14	35–44	F	Financial planner	1-5
15	45–54	M	Electrician	30-39
16	55-64	M	Family medicine physician	20-29
17	45-54	F	Inpatient nurse	11-19
18	25-34	F	Nurse practitioner	6-10
19	35-44	F	Nurse diabetic educator	1-5
20	25-34	F	Internal medicine physician	1-5
21	35-44	M	Nurse practitioner	1-5
22	35-44	F	Physician assistant	11-19
23	55-64	M	Internal medicine physician	20-29
24	25-34	F	Pediatric nurse	6-10
25	35-44	M	Physician assistant	1-5
26	35-44	M	Family medicine physician	6-10