Understanding Economic Behavior Using Open-ended Survey Data[*]

Ingar Haaland   Christopher Roth
Stefanie Stantcheva   Johannes Wohlfart

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Abstract

We survey the recent literature in economics using open-ended survey data to uncover mechanisms behind economic beliefs and behaviors. We first provide an overview of different applications, including the measurement of motives, mental models, narratives, attention, information transmission, and recall. We next describe different ways of eliciting open-ended responses, including single-item open-ended questions, speech recordings, and AI-powered qualitative interviews. Subsequently, we discuss methods to annotate and analyze such data with a focus on recent advances in large language models. Our review concludes with a discussion of promising avenues for future research.

Keywords: Open-ended Questions, Text Data, Methodology, Surveys, Large Language Models.
JEL Classification: C90, D83, D91

[*] Ingar Haaland, NHH Norwegian School of Economics, FAIR, CEPR, email: Ingar.Haaland@nhh.no; Christopher Roth, University of Cologne and ECONtribute, Max Planck Institute for Research on Collective Goods, CEPR, NHH Norwegian School of Economics; email: roth@wiso.uni-koeln.de; Stefanie Stantcheva, Harvard University, NBER, CEPR, email: sstantcheva@fas.harvard.edu; Johannes Wohlfart, University of Cologne and ECONtribute, Max Planck Institute for Research on Collective Goods, CEBI, CESifo, email: wohlfart@wiso.uni-koeln.de. We thank the editor (David Romer) and four anonymous referees for extremely constructive and helpful feedback. Maximilian Fell, Paul Grass, Hrishikesh Iyengar, Sarthak Joshi, Apoorv Kanoongo, Julian König, Nicolas Röver and Gregory Tham provided excellent research assistance. An earlier version of this review was circulated under the title "Measuring What Is Top of Mind" (Haaland et al., 2024). Roth and Wohlfart: Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1-390838866. Financial support from CEBI and the Danish National Research Foundation, grant DNRF134, is gratefully acknowledged. This work was partially supported by the RCN through its CoE Scheme, FAIR project No 262675.

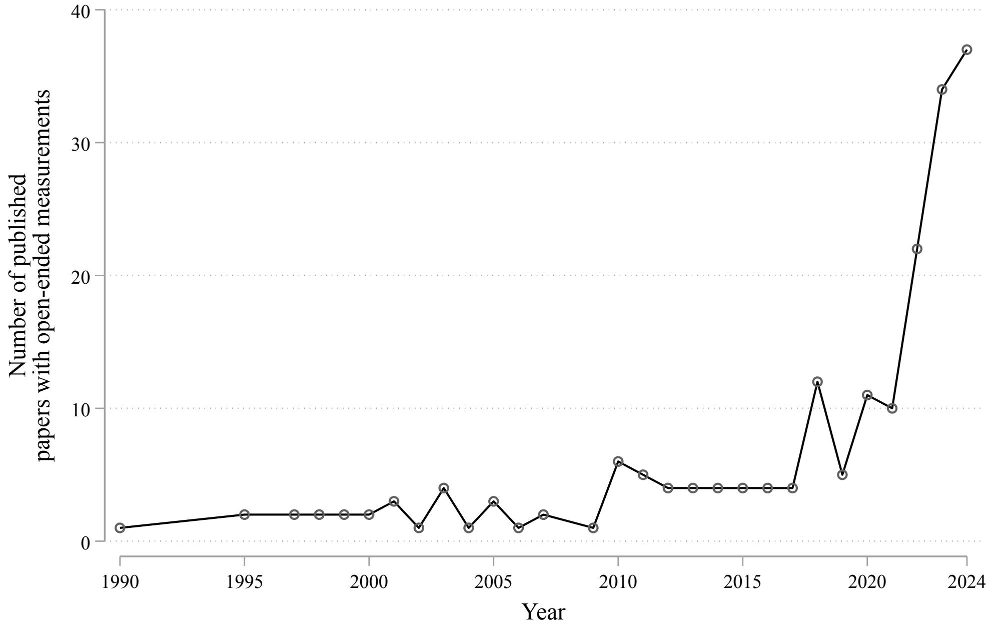
1 Introduction

Consider an individual who does not invest in the stock market, or who subscribes to a dominated health insurance plan. Or think of a firm manager who refrains from cutting employee wages even as the economy enters a recession. At first glance, these behaviors may seem puzzling—yet there could be plausible reasons behind them. How should one measure these reasons? One potential solution to this problem involves simply asking respondents open-ended questions about why they engage in the behavior of interest. Unlike structured survey questions offering respondents a set of pre-determined response options, open-ended questions do not prime individuals on any particular potential answer. These questions also do not require researchers to have prior knowledge about all relevant options. The qualitative text data resulting from open-ended response formats therefore provide a detailed lens into respondents' self-reported considerations.

In this paper, we review an emerging literature in economics that uses open-ended questions to better understand the mechanisms behind economic behaviors and expectations. As shown in Figure 1, open-ended survey data have become increasingly common in economics. Our review focuses on open-ended questions included in large-scale surveys, where participants are typically asked to write down their considerations in the context of a particular issue, decision, or prediction problem. Open-ended questions are applied to study topics such as attention allocation, reasoning, mental models, or verbal communication, and thus help to gain a deeper understanding of the mechanisms underlying economic choices and expectations.

Open-ended questions allow researchers to test predictions of influential theories of human behavior, such as theories of associative memory (Bordalo et al., 2024) or of the role of salience in attention allocation (Bordalo et al., 2025). They also let us paint a more realistic picture of the variables that individuals consider relevant when making choices or forming beliefs (Chinco, Hartzmark and Sussman, 2022). In addition, open-ended survey questions enable researchers to measure the motivations behind particular decisions (Braghieri, Schwardmann and Tripodi, 2024) or the perceived motives driving others' behaviors (Bursztyn et al., 2023). Open-ended questions are also crucial to understanding mental

Figure 1: Number of studies with open-ended measurements (including qualitative interviews) published in leading journals and working paper series between 1990 and 2024



Notes: This figure shows the number of studies with open-ended and qualitative text measurements published in leading journals since 1990. For 2024, publications and forthcoming papers as of mid-November are included. The figure is based on publications in leading journals (American Economic Review, American Economic Journal: Applied Economics, American Economic Journal: Economic Policy, American Economic Journal: Macroeconomics, Econometrica, Economic Journal, Journal of Development Economics, Journal of Political Economy, Journal of Public Economics, Journal of the European Economic Association, Review of Economics and Statistics, the Review of Economic Studies), the AEA Papers and Proceedings, and worker paper series (CEPR, CESifo, and NBER). To identify articles, we used Google Scholar to search for all articles published in these journals since 1990 containing the words "open-ended", "open", "qualitative interview", "qualitative survey" and then verified which of the search results featured an actual open-ended measurement. We also supplemented the figure with papers covered in our review that were not captured using this search algorithm.

models and economic narratives (Andre et al., 2022, 2025; Colarieti, Mei and Stantcheva, 2024; Stantcheva, 2024).

The techniques presented in this review can also be used to address policy questions, such as understanding which concerns loom the largest in voters' minds (Ferrario and Stantcheva, 2022), capturing the salient issues in public opinion (Geer, 1991), and characterizing people's first-order considerations when thinking about redistribution (Andre, 2025; Cappelen, Falch and Tungodden, 2024).

In this review, we proceed in three steps regarding open-ended survey data: its applications, how to collect it, and how to analyze it. Regarding the different applications, we cover ways of measuring motives and the reasoning behind decisions, mental models, narratives, and attention allocation. We also outline the usefulness of open-ended data to quantify the first stage in priming interventions and to measure information transmission, recall, and beliefs about experimenter expectations. Throughout our discussion, we provide examples from existing studies, explain the core advantages of open-ended questions for particular applications, and highlight specific points regarding the design and analysis in the different applications.

We next discuss the data collection process and important design considerations as well as the advantages and disadvantages of different ways of asking open-ended questions. We cover both survey questions to which participants respond in written text as well as new methods enabled by recent technological advances. These methods aim to collect rich data on people's considerations *at scale*. In particular, we discuss how speech recordings (Graeber, Roth and Schesch, 2024; Graeber, Noy and Roth, 2024) and AI-powered qualitative interviews (Chopra and Haaland, 2024; Geiecke and Jaravel, 2024) can be used to measure considerations. Compared to written text responses, speech recordings provide richer data, as they also contain nonverbal cues, such as emotions, while AI-powered qualitative interviews allow for clarification and follow-up questions, leading to more depth in responses.

Subsequently, we discuss different approaches to analyzing open-ended data collected through surveys or interviews. We start by discussing human coding, including the design of coding schemes, coding with the help of research assistants, and calculation of the intercoder reliability. We then proceed to Large Language Models (LLMs), which provide new opportunities for characterizing unstructured data in a nuanced and cost-effective way. Among other topics, we discuss practical issues related to annotating unstructured data using LLMs, including the use of Application Programming Interfaces (APIs). Lastly, we briefly review fully automated text analysis methods.

We conclude by laying out a series of open questions and avenues for future research. Specifically, we discuss the role of incentives in increasing effort, voice-based AI interviews, as well as the possibility of combining methods from neuroeconomics with open-ended questions to better understand conscious thought processes and the attentional foundations of decision making.[1] We will provide regular updates of relevant methodological developments in the online materials accompanying the paper.

Before proceeding, we address an important question: To what extent can mechanisms uncovered in open-ended responses, such as mental models, be considered genuine explanations of behavior? A long-standing critique in the social sciences and psychology argues that individuals' explanations of their decisions often represent ex-post rationalizations rather than authentic accounts of their decision-making processes (Berger et al., 2016; Machlup, 1946; Nisbett and Wilson, 1977). For example, Jerolmack and Khan (2014) highlight that survey-based explanations frequently reflect what respondents perceive as reasonable rather than the true drivers of their behavior. This perspective cautions against treating verbal responses as direct windows into decision-making mechanisms, as doing so risks confusing narratives constructed after-the-fact with the actual underlying factors. We thus caution readers to remain mindful of this caveat, recognizing that individuals may sometimes not be able to fully explain the reasons behind their behavior.[2]

Nevertheless, a growing literature in psychology and behavioral economics suggests that individuals are often able to accurately articulate essential elements of their decision-making processes (Ericsson and Simon, 1980, 1993; Morris et al., 2023; Sloman, 2009). For example, Hanna, Mullainathan and Schwartzstein (2014) illustrate that people's mental models significantly shape their choices. Handel and Schwartzstein (2018) emphasize that deeper insights into people's reasoning can inform the design of more effective economic policies and interventions. For instance, Handel and Schwartzstein (2018) highlight the importance of accounting for miscalibrated mental models when designing policies to help consumers avoid costly mistakes—such as selecting dominated health insurance plans or high-fee mutual funds. Even when the reasoning expressed in open-ended responses primarily reflects rationalizations, it still offers valuable insight into how individuals interpret their own behaviors and beliefs (Bruner, 1991).

This review builds on seminal work in economics that pioneered the use of qualitative

[1] Our review also relates to overview articles on attention in economics (Bordalo, Gennaioli and Shleifer, 2022; Enke, 2024; Gabaix, 2019; Loewenstein and Wojtowicz, 2025).

[2] Another concern with surveys is that they may not be predictive of real-world behaviors. As Colarieti, Mei and Stantcheva (2024) show, individuals are quite good at predicting their behaviors in familiar, everyday scenarios, and provide their rationales for them, making their stated choices reliable indicators of actual actions.

interviews and open-ended questions in the context of wage dynamics (Bewley, 1995, 1999), price setting (Blinder et al., 1998), inflation (Shiller, 1997), financial budgeting decisions (Morduch and Schneider, 2017) and home price expectations (Case and Shiller, 2003; Case, Shiller and Thompson, 2012).[3] Our paper also relates to research in survey methodology and on public opinions, where open-ended questions have been discussed as an alternative to closed-ended ones (Geer, 1988, 1991; Krosnick, 1999; Lazarsfeld, 1944).

Our review also builds on important work in other disciplines that have used qualitative data for a long time. For example, research in anthropology and sociology uses open-ended data obtained from qualitative interviews (Denzin and Lincoln, 2017; Emerson, Fretz and Shaw, 1995; Knott et al., 2022; Kvale, 1996; Patton, 2002). Sociologists and anthropologists have explored individuals' "mental models" through ethnographic methods, aiming to understand how cultural norms and social interactions shape cognition (Becker, 1998; Geertz, 1973; Holland and Quinn, 1987). We do not go in-depth into this type of research. The distinguishing feature of the work we cover in this review is the large-scale aspect of the data.

2 Major applications

In this section, we discuss different types of applications of open-ended survey data. Table 1 presents an overview of various applications including example questions. Appendix Tables A1–A7 provide an overview of papers in economics that use open-ended questions, organized by field of study.

Reasoning and (perceived) motives behind decisions Open-ended questions are particularly useful for exploring the reasoning and motives behind specific decisions. The open-ended nature of the questions allows respondents to express their motivations and lines of reasoning in a natural and unconstrained manner.

First, open-ended questions can be used to understand the considerations behind *decisions within experiments*. Such decisions could include redistribution decisions (Andre, 2025) or the willingness to pay for interacting with others (Braghieri, Schwardmann and Tripodi, 2024).

[3] For excellent reviews on qualitative interviews in economics, see Piore (2006) and Starr (2014). For reviews on the design of surveys and information provision experiments in economics, see Haaland, Roth and Wohlfart (2023), Stantcheva (2023) and Fuster and Zafar (2023).

Typically, researchers first ask respondents to make the decision or the prediction in question. Subsequently, respondents are asked to report the main considerations or reasons underlying their decision in an open-text box.

Second, open-ended questions can be used to characterize motives underlying *real-world decisions*. Applications include protesting property taxes (Nathan, Perez-Truglia and Zentner, 2025), stock market non-participation (Chopra and Haaland, 2024), the consumption of goods with externalities (Kaufmann, Andre and Kőszegi, 2024), spending and saving decisions (Colarieti, Mei and Stantcheva, 2024), or gun ownership (Alsan, Schwartzstein and Stantcheva, 2025). Researchers usually first elicit the behavior of interest using a structured survey question and subsequently pose an open-ended question asking participants why they behave in a specific way.

Third, open-ended responses can be leveraged for the measurement of inference about others' motives. In particular, respondents can be asked to explain why another respondent decided in a particular way. For example, Bursztyn et al. (2023) ask respondents why they think another respondent made a public posting on social media.

Narratives and mental models Another key application concerns the narratives and mental models individuals invoke in economic contexts. According to a common definition, narratives are causal accounts for why a specific event occurs (Shiller, 2017). Mental models are beliefs about the co-movement between different variables and the underlying mechanisms driving this co-movement (Andre, Schirmer and Wohlfart, 2024).

Open-ended measurements can be a powerful tool for understanding narratives and mental models. The most common applications are the following: first, asking respondents to explain the causes of a given phenomenon, e.g., asking respondents "which factors caused the increase in inflation" (Andre et al., 2025; Binetti, Nuzzi and Stantcheva, 2024); second, asking respondents about their perceived mechanisms underlying the relationship between different given variables, such as the effects of interest rate hikes on inflation (Andre et al., 2022) or the effects of "old news" on expected stock returns (Andre, Schirmer and Wohlfart, 2024); and third, measuring considerations about the broader consequences of a given change in a variable without specifying any particular outcome variable, such as the effect of inflation on the economy at large and on people's lives. For example, Stantcheva (2024) asks respondents "What were the most important impacts of inflation on your life?"

Researchers measuring subjective models and narratives are often interested in comparing respondents' reasoning with textbook models. The analysis of the data then requires an especially careful design of coding schemes that are able to capture subtle differences in reasoning (see Section 4).

Attention allocation Open-ended measurement approaches can be used to measure people's attention allocation—i.e., their allocation of cognitive resources across different topics or issues. For instance, such measurement can be applied to better understand which characteristics of an asset investors attend to when making investment decisions (Chinco, Hartzmark and Sussman, 2022; Wekhof, 2024), people's attention to different aspects of a statistical problem (Bordalo et al., 2025), or households' and firm managers' attention allocation across different economic variables (Link et al., 2024). Open-ended questions are attractive for measuring attention allocation, as respondents' attention is not mechanically drawn to topics that appear in response options.

While measuring motives, mental models, or narratives typically requires measuring respondents' full *explanations* of a certain decision, belief or event, eliciting attention allocation often merely requires capturing which *topics or issues* are top of respondents' minds in a given context (Ferrario and Stantcheva, 2022). This can be done by confronting survey respondents with a prompt on the context of interest. For instance, Link et al. (2024) measure households' and firm managers' attention to different economic topics by asking them "What topics come to mind when you think about the economic situation of your company/household?" On policy issues, Ferrario and Stantcheva (2022) ask "What are your main considerations about the Federal income tax?" The participants then write their responses into an open-text box. The topics raised in the open-text responses provide insights into respondents' attention allocation to different issues. Given that the interest lies in the topics or issues that are mentioned rather than in more concrete arguments and explanations, open-ended data on attention allocation often requires less nuanced coding, favoring automated methods (see Section 4).

Priming interventions Priming interventions are widely used in economic research (Cohn and Maréchal, 2016). Such interventions are typically used to exogenously draw respondents' attention to a particular issue or aspect of a decision problem. This allows researchers to study the causal effect of attention to a particular issue on beliefs, decisions or behaviors elicited later in the survey. The mechanisms underlying the effects of priming interventions, however, have been widely criticized for being a black box (Cohn and Maréchal, 2016). Open-ended questions open up the possibility of measuring how priming interventions affect attention allocation (Henkel, Oslislo and Schwerter, 2024).

A common approach to priming is to order survey questions differently such as to generate variation in the contextual cues treated and control respondents have been exposed to when making the decision or prediction of interest. For example, Alesina, Miano and Stantcheva (2023) use such an approach to study how attention to different issues affects attitudes towards immigration. An open-ended question can then be used to measure which issues are top of respondents' minds, e.g., when taking a specific decision within the experiment. The resulting text data then allows the researcher to estimate the "first-stage" effect of the priming intervention on the respondents' attention allocation. Structured questions are less suited for this purpose, as the included response options might themselves change respondents' focus, potentially interfering with the treatment variation created by the contextual cues. Structured questions may also be more likely to induce experimenter demand effects.

Open-ended questions cannot only be used to measure the impact of priming interventions—they can be the priming interventions. For instance, Stantcheva (2022) asks randomly selected subsamples of respondents a series of open-ended questions to consider the impacts of trade on their consumption bundles or on their jobs. The goal of these questions is to prime respondents to focus on either the consumption or the job impacts from trade. Algan et al. (2025) induce emotions such as anger or fear in respondents by asking them to describe with open-ended questions what makes them angry or happy about specific policy issues, such as immigration, trade, or tax policy.

Recall Open-ended questions can also be used to study memory and recall (Bordalo et al., 2024). Such applications proceed in similar ways as applications to attention allocation (discussed in Section 2): the respondents are exposed to a prompt or cue and are asked to write down their thoughts; however, the prompt concerns things that happened in the past. Open-ended measures appear particularly attractive for studying recall: closed-ended questions with response options indicating particular past events remind the respondents of these events by construction, making them inherently unsuited to understand respondents' natural recall process (Connor Desai and Reimers, 2018). Moreover, open-ended data reveal additional nuance about what is being recalled and provide the opportunity to detect memory distortions and confusion.

On the one hand, open-ended questions can be used to measure recall of *real-world experiences* people made in the past. For example, Jiang et al. (2024) ask retail investors to write down a past stock market episode that first comes to mind. They show that the stock market performance on the survey day shapes investors' recall, which in turn influences their beliefs about future returns.

On the other hand, open-ended questions can be used to study the recall of *information seeded in a baseline experiment*. For example, Graeber, Roth and Zimmermann (2024) use the following open-ended question: "Please tell us anything you remember about this product scenario. Include as much detail as you can. Most importantly, please describe things in the order they come to mind, i.e., the first thought first, then the next one etc." This enables the authors to study selective recall of stories versus statistical information. Reassuringly, their open-ended data yields similar conclusions as a structured incentivized task, suggesting that unstructured open-ended elicitations are a reliable measure of recall even in the absence of incentives for accuracy.

Information transmission Given that most communication relies on natural language, open-ended questions also lend themselves to studying information transmission. For example, questions asking subjects to record their response in a voice message have been used to study the causal impact of verbal explanations on social learning (Graeber, Roth and Schesch, 2024) and information transmission (Graeber, Noy and Roth, 2024). Graeber, Roth and Schesch (2024) tell respondents to "record an explanation that helps the other participant select the correct answer." Similarly, it is possible to study communication through writing in an open-text box (Grunewald et al., 2024).

Open-ended measurement mimics key features of communication in the real world and allows individuals to express their considerations, feelings, and experiences in their own words, without being constrained by predefined options. One feature that is special about open-ended questions in the context of communication is that one can provide respondents with incentives in a straightforward manner. For example, Graeber, Roth and Schesch (2024) incentivize people's recorded explanations by telling them that their payoff will depend on the accuracy of the choices made by the other respondent who will receive their recorded explanation before making their choice. As such, respondents have aligned incentives to communicate the most informative explanation to the other respondent.

Experimenter demand effects Experimenter demand effects are an important concern in survey-based research (de Quidt, Haushofer and Roth, 2018). Open-ended questions are increasingly used to mitigate concerns about experimenter demand effects. Specifically, respondents can be asked to guess the hypothesis that the researchers are testing in an open-ended question included at the end of the experiment. For example, participants are asked: "What do you think is the hypothesis that the researchers aim to test?" or "What do you think is the purpose of this study?". The open-ended nature of such questions ensures that respondents do not simply tick response options that are socially desirable, potentially giving a false impression of the prevalence of demand effects.

Testing for knowledge and understanding Open-ended survey questions can also be used to measure respondents' knowledge. Closed-ended questions with specific answer options often provide information that might inadvertently influence responses, making them less effective at gauging respondents' underlying knowledge (Brosius, Hameleers and van der Meer, 2022). For example, Stantcheva (2024) asks respondents to define what inflation is. When analyzing the data in such applications, it is important to specify clear criteria for what counts as a correct or false response.

Table 1: Applications of open-ended survey questions

Application	Type of measurement	Example questions
Reasoning and motives	Respondents are asked about reasons behind their decisions.	Why did you consume this news? Why did you engage in a political campaign?
Narratives and mental models	Respondents explain the relationship between two given variables, the evolution of a given variable, or the consequences of movements in a given variable.	Why do you think inflation increased to 8%? How do you think interest rate hikes affect subsequent inflation?
Attention allocation	Respondents list concerns, considerations or issues that come to mind when thinking about a topic.	What comes to mind when you think about government policies? What economic issues concern you most?
Measuring priming interventions' effects	Respondents describe which considerations are top of their mind after having been primed on a particular issue.	What considerations are on your mind right now? What is the first thing that comes to mind about immigration policy?
Priming through open-ended questions	Respondents are asked to think about an issue from a specific (priming) angle	When you think about immigration in the US, what makes you angry? What is the first thing that comes to mind about immigration policy?
Recall	Respondents are asked to recall past real-world experiences or information seeded in a baseline experiment.	What past stock market episode first comes to your mind? Please describe what you remember about this scenario.
Information transmission	Respondents communicate information (e.g., an explanation) to another respondent.	Please explain the reasoning behind your choice to another respondent.
Experimenter demand	Respondents guess the purpose or hypothesis of the study.	What do you think is the hypothesis that is being tested in this study?
Testing respondents' knowledge	Asking respondents to define or explain something	How would you define [concept] in your own words?

3 Collecting open-ended survey data

In this section, we discuss design considerations for open-ended questions in the context of surveys and qualitative interviews. We start with a discussion of single item open-text boxes—the most common way of collecting open-ended survey data and the main focus of this review—covering their advantages and disadvantages compared to more traditional closed-ended survey questions. A complementary review by Stantcheva (2023) covers guidance on the complete survey process. We then highlight the recent methodological advance of using speech recordings to measure considerations, which allows to capture rich contextual data such as non-verbal cues. Subsequently, we provide a brief overview of human-led qualitative interviews, before providing a more in-depth discussion of AI-powered interviews. Lastly, we briefly discuss approaches used in other social sciences.

3.1 Measuring written considerations in an open-text box

The most common approach to eliciting open-ended considerations in surveys is to invite participants to describe, in an open-text box, the key factors they consider when reflecting on a particular issue, forming a specific belief, or making a specific decision.

3.1.1 Design considerations

Cognitive costs One key issue to consider when designing open-ended questions is that they demand more cognitive effort from respondents than structured formats. This can lead to higher non-response rates and lower response quality if not managed carefully (Dillman, 2007; Millar and Dillman, 2012). To preserve high data quality, it is important to reduce the mental load on respondents as much as possible.

One potential strategy is to position open-ended questions early in the survey. Early placement may help engage respondents when they are likely to be more attentive and reduce fatigue, which can compromise data quality if open-ended questions are asked later. Indeed, research has shown that placing open-ended questions at the start of a survey leads to longer responses (Galesic and Bosnjak, 2009; Miller and Lambert, 2014). Additionally, limiting the number of open-ended questions in a single survey prevents overburdening respondents, which should reduce drop-outs and help preserve response accuracy.

Mode effects It is also important to consider the device respondents may use to complete the survey. Open-ended questions can be particularly challenging for respondents on mobile devices due to limited screen space and typing difficulties, which can lead to shorter, less thoughtful responses (Mavletova, 2013). If researchers are worried about these effects, they can encourage respondents to complete the survey with a computer.[4] Nevertheless, a major advantage of online surveys is the ability to reach broad and diverse samples, which is in no

[4] Note that some survey platforms allow restricting the survey to desktop participants, e.g., Prolific.

small part due to the use of mobile technologies. Thus, such restrictions need to be carefully weighed against the benefits of allowing surveys on mobile.

Gauging willingness to write Many studies using open-ended responses begin their surveys with a question to gauge respondents' general willingness to write, often using this question as a screening tool (e.g., Graeber, Roth and Zimmermann, 2024). This approach serves to filter out respondents who are disinclined to invest the necessary effort in open-ended responses or who are inattentive. While closed-ended questions can also be used as attention checks, they are more susceptible to participants guessing the right answers and allow little variation in the measured degrees of engagement and attention (Ziegler, 2022). Attention checks based on open-ended questions thus impose stricter screening criteria, enhancing overall data quality. The use of such screeners has to be weighed against the additional selection they produce.

Increasing respondent effort Smyth et al. (2009) provide evidence that simple motivational prompts, such as "This question is very important to our research. Please take your time answering it," increase response length and lead to a higher fraction of respondents elaborating their answers. Subjects that receive the motivational explanation also take more time when responding. Additionally, providing clear guidance on the expected length and format of responses should help reduce heterogeneity in response behavior (Züll, 2016). When participants know approximately how much text is expected (e.g., "Please respond in full sentences" or "Please spend 1–2 minutes on this question"), they should be more likely to respond thoughtfully and consistently.

Lastly, tailoring the visual layout of response boxes to the type of input needed enhances clarity and ease of response. For single-answer questions, a single entry box is usually sufficient. For multiple answers, offering separate fields for each response creates a structured layout, reducing the cognitive load associated with parsing multiple ideas in a single text box. When longer written responses are desired, using a larger text box can make the task feel more manageable and signal to respondents that a more detailed answer is appropriate. Indeed, Smyth et al. (2009) and Israel (2010) document that larger text boxes somewhat increase the response length for some groups of respondents.

Ex-post rationalization Another important consideration is minimizing the potential for ex-post rationalization, which can introduce biases (Nisbett and Wilson, 1977). In particular, participants might retrospectively make up reasons to justify their earlier responses rather than reporting genuine reasons. This concern about rationalization is particularly relevant when image concerns make particular reasons more desirable than others. To reduce this risk, one approach is to ask open-ended questions directly on the decision screen, potentially even before participants make their choice. This setup prompts participants to articulate their reasoning in real time, rather than rationalizing retrospectively. However, as noted by Imas, Kuhn and Mironova (2022), such a prompt may inadvertently influence behavior by increasing deliberation time, which could impact the naturalness of the decision-making process.

LLM-generated responses One concern with open-text data collection is that participants could use large language models (LLMs) to generate their responses, potentially compromising data integrity. Since these responses may not genuinely reflect participants' own thoughts or experiences, they could skew research results. While there exist detection tools to flag AI-generated text, these detection tools often have low accuracy (Akram, 2023) and might perform even worse as LLMs become more advanced. One attempt to limit LLM-generated responses is to prevent copy-pasting into response boxes, as implemented in Chopra and Haaland (2024). However, in some cases, respondents might legitimately use LLMs to edit or refine their open-ended text responses, making it potentially counterproductive to try to limit their use. A bigger concern in this regard is that responses from AI-based bots may become indistinguishable from human responses. As shown in Höhne et al. (2024), AI-based bots are able to pass common attention checks and populate open-ended questions in a meaningful way. They are also able to pass common bot protection measures, such as CAPTCHAs and hidden "honey pot" questions. These developments make it very important to recruit survey respondents from platforms with effective measures to deal with bots.

3.1.2 Advantages and disadvantages of open-ended questions

We next outline the main advantages and disadvantages of questions with an open-text response box compared to more traditional questions with structured response options. Table 2 provides an overview of the trade-offs involved when choosing between open-ended and closed-ended response formats.

Advantages of open-ended questions Compared to structured approaches, open-ended measurement of considerations offers several advantages.

First, open-ended questions allow respondents to freely express their considerations, not restricting them to a predefined set of structured response options (Geer, 1988; Kelley, 1983; RePass, 1971). This is especially important in settings where the researcher wants to discover novel factors and in settings where it is difficult for the researcher to predict respondents' spontaneous considerations ex-ante (Krosnick, 2018). Open-ended responses may also reveal misunderstanding or confusion on the part of participants and allow for qualitative insights that cannot be achieved with structured measures. Compared to closed-ended questions, which constrain the depth of responses but simplify and standardize them, open-ended questions allow for detailed, nuanced responses, often uncovering unexpected themes and providing a richer understanding of the respondents' perspectives (Hansen and Świderska, 2023; Krosnick, 2018).

Second, open-ended questions do not change people's considerations by informing them about potential lines of reasoning or drawing their attention to particular issues through the displayed response options.[5] This feature should alleviate concerns about potential confounds, such as social desirability bias or ex-post rationalization (Singer and Couper, 2017). For instance, when eliciting memories, asking responses to write down events they remember allows them to provide genuine recollections, whereas a structured list of response options may confound whether participants truly recall the event or are simply reminded of it (Connor Desai and Reimers, 2018). In the case of questions related to knowledge, open-ended measures do not prime respondents about magnitudes or signs and can thus better

[5] Of course, the question itself—even when presented merely with a text box—could prime subjects on the topic of the question. However, this issue is common across any type of survey question and seems hard to avoid. Structured questions *additionally* prime subjects on potential responses to the question.

capture the participants' actual knowledge (Brosius, Hameleers and van der Meer, 2022). This flexibility contrasts with closed-ended questions, where predetermined answers might miss key insights (Krosnick, 2018).

Third, open-ended questions can be asked directly on the screen eliciting the prediction or decision of interest, which allows researchers to document the respondents' considerations immediately after they have made their prediction. This potentially allows for a more precise measurement and might further mitigate ex-post rationalization. Structured questions are unsuited for being asked on the decision screen, as the content of the response options might change respondents' decision. As mentioned above, one caveat is that even the mere presence of the open-ended question might change the decision-making process by inducing more deliberation (Imas, Kuhn and Mironova, 2022).

Disadvantages of open-ended questions Open-ended measurement techniques also have a series of disadvantages. First, as a result of their unstructured nature, there is likely more scope for classical or non-classical measurement error as some respondents may be unwilling to exert effort when describing their considerations. The willingness to exert effort may vary systematically across different groups (Miller and Lambert, 2014). Even when respondents exert substantial effort, some responses may still be ambiguous and hard to interpret.[6] Open-ended questions are also more time-intensive, potentially increasing respondent fatigue, whereas closed-ended questions reduce fatigue risks by being quicker to complete (Dillman, Smyth and Christian, 2014).[7]

Another source of measurement error arises from the potentially large variation in the way individuals understand and respond to open-ended questions. This variation may affect the content of the answer and its length (Gómez, 2023). For instance, consider the setting in Andre et al. (2022), where respondents describe the considerations underlying their predicted effects of macroeconomic shocks on inflation and unemployment. In this setting, a respondent may write that they used their knowledge of economics without indicating

[6] As we review in detail in Section 3.3.2, AI interviews offer a promising avenue to partly dealing with this source of measurement error.

[7] These issues potentially introduce a bias–variance tradeoff: compared to structured formats, open-ended formats may be less subject to biases, e.g., due to priming, but feature a higher variance due to increased noise (Sinkowitz-Cochran, 2013).

which specific economic mechanism they had in mind. Another respondent may describe the full propagation channels of the shocks. This variability is reflected in a higher variance of responses compared to closed-ended questions, which offer standardized and consistent answers but may introduce bias due to constrained options (Reja et al., 2003; Sinkowitz-Cochran, 2013).

Next to measurement error, selective non-response bias is a prominent challenge for open-ended questions, as participants who choose not to answer open-ended questions may differ systematically from those who do, potentially skewing results. For instance, Reja et al. (2003) show that open-ended questions produce more missing data and inadequate answers than closed-ended ones. By contrast, Geer (1988) shows that almost all subjects in their setting respond to open-ended questions and that non-response is driven by disinterest in the specific question posed rather than an inability to answer such questions in general. Miller and Lambert (2014) provide a systematic analysis of non-response, which reveals that factors such as age, employment status, and race are related to the likelihood of responding to open-ended items. For instance, older, unemployed or retired respondents are more likely to provide answers. One way to mitigate non-response bias could be higher participation incentives (Dutz et al., 2022). Additional systematic evidence on how non-response bias to open-ended questions varies across different economic decision contexts would be helpful.

Finally, open-ended responses involve challenges in the analysis stage. While text analysis methods are straightforward to implement, it is often necessary to develop a coding scheme to exploit the full richness of the data (Saldana, 2021). Developing a coding scheme is a costly process and requires the researcher to make subjective choices that might not be fully replicable and could also be prone to potential researcher biases (Geer, 1991; Singer and Couper, 2017). There are also subjective judgments to be made when coding up the responses according to the scheme, potentially introducing additional noise and measurement error (O'Connor and Joffe, 2020; Saldana, 2021). Although LLMs can reduce the costs of annotating open-ended text data (Gilardi, Alizadeh and Kubli, 2023; Törnberg, 2024), they could also introduce biases. Therefore, comparing the LLM coding with human coders remains important, particularly for responses that require nuanced judgments beyond current LLM capabilities. This complexity contrasts with the ease of analyzing closed-ended questions.

Table 2: Comparison of open-ended and closed-ended questions

Aspect	Open-ended questions	Closed-ended questions
Depth of response	Allows detailed, nuanced responses, capturing subtle insights (Hansen and Świderska, 2023).	Constrains depth, produces standardized responses.
Ease of analysis	Complex to analyze, often requiring coding (Geer, 1991; Singer and Couper, 2017).	Easier to analyze quantitatively.
Respondent fatigue	Can increase fatigue due to longer, more involved answers (Dillman, Smyth and Christian, 2014).	Can be completed more quickly, reducing fatigue risk.
Flexibility	Adaptable to various contexts, uncovering unexpected themes.	Limited flexibility; predetermined answers may miss key insights (Krosnick, 2018).
Scalability	Scalability more challenging due to analysis complexity (Dutta and O'Rourke, 2020).	Highly scalable for large samples and repeated measurements.
Bias-variance trade-off	Lower bias but higher variance due to more noise in the open-ended data (Sinkowitz-Cochran, 2013).	Possibly biased by the options provided but lower variance (Reja et al., 2003); responses are standardized and consistent.
Effort variability	High; respondents may invest varying levels of effort, leading to heterogeneous response quality (Miller and Lambert, 2014).	Low; structured format limits variability in respondent effort, ensuring more consistent quality.
Non-response bias	Selective non-response bias is a prominent issue, as participants who choose not to answer open-ended questions may differ systematically from those who do, potentially skewing results (Reja et al., 2003).	Lower non-response bias; participants are more likely to respond due to the simplified format.

When to use open-ended vs. closed-ended questions Understanding the distinct advantages of each question type can guide researchers in selecting the most appropriate tool for their study objectives. Open-ended questions are particularly effective in exploratory phases, such as when generating hypotheses or gathering initial insights into a new topic (Krosnick, 2018). They allow respondents to provide insights that the researcher might not anticipate, revealing context-specific information or unique perspectives. However, they have traditionally been more resource-intensive given the high dimensionality of such data (Geer, 1991; Singer and Couper, 2017). While this has traditionally limited scalability, recent technological advances in online surveys and LLMs greatly reduce the cost of collecting open-ended survey data at scale.

In contrast, closed-ended questions offer streamlined, quantifiable data that can be readily analyzed and that is easier to compare across samples (Reja et al., 2003). This format is advantageous when the research objective is to test specific hypotheses or examine patterns across large groups. Open-ended questions are most appropriate when the diversity of potential answers cannot be captured through predefined options, when priming through provided response options is a concern, when responses require narrative detail that resists reduction to brief categories, and when gauging knowledge, as open-ended formats minimize the influence of random correct answers inherent in true/false setups (see the discussion in Fowler (1995)).

3.2 Measuring considerations with speech recordings

A recent innovation is to ask participants to record their considerations instead of writing them down (Graeber, Roth and Schesch, 2024; Graeber, Noy and Roth, 2024). Participants are prompted to verbalize their considerations in response to an open-ended question. Speech recordings thus capture real-time thought processes and articulation in a dynamic manner.

Design considerations Collecting speech recordings as part of a data collection process requires careful consideration of several critical factors. Providing participants with an initial practice opportunity or incorporating a speech recording into an attention check can help familiarize them with the recording process and ensure their equipment is functioning properly. For example, Graeber, Roth and Schesch (2024) ask respondents to record a voice message of a duration of at least 15 seconds as an initial attention check. This step allows participants to address any technical issues early, fostering confidence and reducing the likelihood of errors during data collection. Moreover, clear guidance should be provided on how to set up an optimal recording environment.

Another key consideration is addressing participants' privacy concerns and error recovery needs. Sharing voice data can feel more intrusive than submitting written responses, making it vital to communicate clearly about how recordings will be securely stored and used. Explicit consent must be obtained, with an emphasis on anonymizing data where possible to protect participant identity. Moreover, one potentially useful design option could offer participants the opportunity to correct errors in their recordings through a simple and accessible "re-record" feature. These steps can make the speech recording process more user-friendly and trustworthy.

Advantages of speech recordings Speech recordings have several advantages relative to written text responses. On top of the content that is also captured by writing in a text box, speech recordings capture the spontaneity and natural flow of considerations, which are often lost in written communication. Speech may be particularly effective at capturing what initially comes to mind. Beyond text alone, speech recordings capture more features than just text, including information about emotions, tone, emphasis, and natural disfluencies.[8] For instance, when eliciting narratives—the stories people tell to explain a specific event (e.g., the rise in inflation or past financial crises)—documenting the broader thought process and the emotional tone people use to discuss different relevant factors might give nuanced insights into their thinking. Galasso, Nannicini and Nozza (2024) study differences in responses to open-ended questions when they are either given through text or audio. Respondents who provide audio answers give longer, though lexically simpler, responses compared to those who type. Galasso, Nannicini and Nozza (2024) also document that oral responses offer more information and contain more personal experiences than written responses.

Disadvantages of speech recordings However, there are also potential disadvantages to this method. One potential concern is participant self-consciousness: awareness of being recorded might influence how participants express themselves, possibly leading to altered or restrained responses, though data from Graeber, Roth and Schesch (2024) suggest that participants feel comfortable recording themselves. Additionally, analyzing speech data can be more complex and time-consuming than written responses due to the need to interpret non-verbal cues, such as hesitation markers or disfluencies. Finally, technical limitations, such as poor audio quality or speech impediments, can pose challenges in ensuring clarity and usability of the recordings, although this rarely matters in practice (Graeber, Roth and Schesch, 2024; Graeber, Noy and Roth, 2024).

[8] For an excellent review on prosody (rhythm, stress, and intonation patterns of speech), see Wagner and Watson (2010).

3.3 Qualitative interviews

3.3.1 Qualitative interviews in the social sciences

Qualitative interviews allow individuals to articulate, in their own words, their perceptions and interpretations of the world around them (Knott et al., 2022). Designed to be "flexible, iterative, and continuous," these interviews evolve naturally rather than adhering to a rigid, pre-planned structure (Rubin and Rubin, 2011). Their adaptive nature and ability to explore emerging themes in depth make them particularly effective for hypothesis generation and understanding personal experiences, cognitive processes, and mental models.

In-depth interviews involve extended discussions with research subjects and can be structured, semi-structured, or unstructured, depending on the level of adherence to predetermined questions. Larger projects often use structured or semi-structured formats for comparability, while smaller projects may impose less structure to capture respondents' views more naturally. Ideally, interviews are recorded and transcribed for comprehensive analysis, though note-taking can be used if recording is not possible. Consistent, detailed records are recommended for systematic analysis. Interviews can be conducted in person, through video, voice, or text. Namey et al. (2020) show that there are no differences in the quality and quantity of information communicated through face-to-face compared to text-based interviews. Moreover, a text-based approach might have several advantages, such as a greater sense of privacy and control of the interview (Gibson, 2022).

Advantages and disadvantages compared to open-ended questions Qualitative interviews offer many advantages over pre-defined open-ended survey responses, particularly in their ability to capture depth and context (Knott et al., 2022; Patton, 2002). Unlike online survey questionnaires, interviews enable iterative questioning, allowing researchers to probe and clarify answers in real time. This process often uncovers hidden nuances, complex mechanisms, and contextual factors that simpler methods cannot address. Additionally, interviews provide a holistic view of participants' perspectives, situating responses within broader life circumstances, attitudes, or cultural contexts, making them especially valuable for understanding subjective experiences or intricate decision-making processes (Denzin and Lincoln, 2017). While qualitative interviews offer more richness than pre-defined open-ended questions, they also have some downsides. First, they are expensive and time-consuming to conduct, making them very difficult to scale. Second, they are prone to potential interviewer biases (Himelein, 2015). For instance, Stefkovics and Sik (2022) show that, when using qualitative interviews to understand overall happiness of individuals, the happiness of the interviewer strongly correlates with the respondents' measured level of happiness.

Prominent applications in economics Qualitative interviews have been used to study questions in labor economics and macroeconomics for a long time. In a classic study, Blinder et al. (1998) conduct interviews with business leaders to differentiate between different theories of price stickiness. Relatedly, Bewley (1999) conducts interviews with a large sample of executives, labor leaders, and other professionals to understand why businesses are not willing to cut wages during recessions when labor demand is low. While there are more recent prominent examples of qualitative interviews in economics (e.g., Bergman et al., 2024; Bustos et al., 2022; Duraj et al., 2024), they are still not commonly used among economists, who typically collect open-ended responses using survey questions without any adaptive probing.

Compared to other social scientists, economists typically would like to conduct interviews on larger and more representative samples, making the collections much more expensive. For instance, in an early discussion of interviews in economics, Bewley (2002) writes the following: "It is important that the sample be large, both to be confident of conclusions and because of the need for variety and key informants."

3.3.2 AI-conducted qualitative interviews

With recent advances in generative AI, it is now possible to conduct high-quality qualitative interviews with AI, making them low-cost and compatible with large-scale surveys. Chopra and Haaland (2024) introduce a framework for conducting qualitative interviews using an AI interviewer, leveraging the advanced capabilities of transformer-based large language models (LLMs). Relying on API integration with OpenAI's GPT-4, they conduct text-based interviews using a chat interface that mirrors text messaging applications. Their application can easily be integrated into standard survey software, such as Qualtrics, and allows researchers to conduct unlimited interviews in parallel at a marginal cost of less than $0.10 per interview for the API calls.

The AI interviewer is programmed to adhere to the methodological best practices inherent in qualitative research, such as using open-ended, non-leading questions. The key advantage of using AI-assisted interviews compared to a series of pre-defined open-ended questions is the capability for adaptive probing. Probing questions have two main purposes. First, they can resolve ambiguities when respondents provide answers that are vague or difficult to interpret. Second, they can be used to achieve breadth and depth of the conversation.

Quality of AI-conducted interviews A key question is whether AI-conducted interviews can be of high quality. Chopra and Haaland (2024) evaluate the quality of their AI-conducted interviews using several complementary strategies, including respondent engagement, human evaluation of the interview transcripts, the potential for making novel discoveries, and the predictive power for economic decisions. They find high respondent engagement throughout the interviews. Participants write 29 words per minute, almost 50% more than typical benchmarks from chat-based interviews with human interviewers (Namey et al., 2020).

Furthermore, in contrast to surveys with a series of open-ended questions, effort does not decline over the course of the interview. Respondents also rate the interview experience highly, with 96% indicating a preference to participate in another interview. 53% of the respondents report preferring an AI interviewer over a human one, while 21% express a preference for a human-led interview. A separate correspondence study that randomizes whether a study invitation is to a “40 minute-survey”, a “40-minute survey with a text-based interview with a human” or a “40-minute survey with a text-based interview with an AI” shows that the high satisfaction is not driven by selection effects: While there is no differential selection into an AI-conducted text-based interview compared to a regular survey, respondents are significantly less likely to sign up for a human-conducted text-based interview (Chopra and Haaland, 2024).

Another important quality metric is to what extent the AI interviewer aligns with its instructions. A team of trained human evaluators systematically hand-coded 12,000 interview questions and responses, showing a high alignment with the instructions: 95% of questions are open-ended, 94% are non-leading and neutral, and 84% of questions are considered high-quality according to textbook standards. The human evaluation also shows that hallucination of the AI is a close to non-existent problem, happening in only 0.01% of cases.

The hallmark of qualitative research is its ability to discover novel findings. In their main application, where they collect 385 AI-conducted interviews on stock market non-participation, Chopra and Haaland (2024) demonstrate that AI-led interviews can be used to generate novel hypotheses. They also compare AI-led interviews to a series of pre-defined open-ended questions, showing that AI-conducted interviews lead to richer insights that are qualitatively different from those observed from pre-defined open-ended questions. For instance, narratives, mental models, and subjective experiences are frequently discovered during interviews but are almost absent in responses to pre-defined open-ended questions. Furthermore, they run a follow-up study that shows that factors mentioned by respondents in the interviews predict economic behavior eight months later, suggesting that common concerns about uninformative “cheap talk” dominating the discourse in qualitative interviews are unwarranted.

Robustness across different interview settings Geiecke and Jaravel (2024) further demonstrate the robustness of the method through a series of AI-conducted interviews on measuring meaning in life, people’s political preferences, and decision-making in the context of educational and occupational choices. Respondents consistently rate the interview experience favorably, underlining how AI interviews can be flexibly adopted in different settings with high interviewee satisfaction. To assess the quality of their AI-conducted interviews, Geiecke and Jaravel (2024) work with trained sociologists who rate the quality of the AI-conducted interviews relative to a hypothetical human expert. The sociologists perceive the quality of the AI-conducted interviews as similar to what a hypothetical human expert could have achieved under similar circumstances, again demonstrating the robustness of the method.

Flexible implementation The implementation of AI interviews is flexible and the number of questions included depends on the goal of the interview. For instance, when surveying less literate populations or those with lower educational backgrounds, who may find it more difficult to articulate their considerations, it can be important to clarify ambiguous responses. Allowing an AI interviewer to ask a follow-up question to resolve ambiguities in the initial top-of-mind response might significantly increase the quality of the qualitative data at a relatively low cost (Chopra and Haaland, 2024). In other settings, a full interview with several follow-up questions to achieve additional breadth and depth might be desirable, but this depends on the setting, time budget, and other factors.

It is worth emphasizing that the AI-conducted interviews by Chopra and Haaland (2024) and Geiecke and Jaravel (2024) relied on carefully tested prompts that reflect best practices. Interview quality might deteriorate if interviews are conducted using prompts that have not been developed and validated according to best practice methods. However, both Chopra and Haaland (2024) and Geiecke and Jaravel (2024) use prompts that require only minimal adjustments to adapt them to different settings, making it possible for other researchers to conduct AI interviews without developing their own prompts from scratch. Open-source platforms for AI-conducted qualitative interviews are provided by both Geiecke and Jaravel (2024) and Chopra and Haaland (2024).[9]

Advantages and disadvantages compared to human-led interviews AI-assisted interviews inherit many of the same challenges as human-led qualitative interviews, such as a lack of comparability between respondents, a factor that is magnified compared to single open-ended questions. In addition to these, AI-assisted interviews face unique challenges, such as potential algorithmic biases (Rozado, 2024) and potential concerns about data privacy (Dell, 2025). Finally, an important concern is that selection into participating in an AI interview depends on trust in AI. This might induce significant selection biases by making less tech-savvy and more conservative respondents less keen to participate in AI interviews. Yet, Chopra and Haaland (2024) show that this does not seem to be a major concern in practice, as respondents in a correspondence are equally likely to sign up for a text-based AI interview as for a regular survey. Moreover, standard demographic characteristics do not predict differential selection into surveys compared to AI interviews. Taken together, these data counteract concerns about severe selection effects specific to AI interviews.

[9] The platforms are available on the following links: `https://github.com/friedrichgeiecke/interviews` and `https://github.com/fchop/interviews`.

While AI-conducted interviews offer high-quality data at a low cost, there are still some cases where a human-led interview may be a better choice. For example, in sensitive topics where privacy concerns are heightened and interviewees may need emotional support, a human-led interview may be necessary for ethical and practical reasons. Human-led interviews are also preferable in situations requiring responsiveness to emotional language and facial expressions.[10] However, as video-based AI-conducted interviews with human avatars become feasible and low-cost, the AI-based interview experience might further improve. Video-based interviews might also give rise to new dimensions of analysis, e.g., facial expressions and emotionality of language. Finally, while an experienced human interviewer may ask more high-quality questions and have more flexibility to develop and pursue hypotheses during interviews, these potential advantages must be weighed against the higher costs of human-led data collections. Furthermore, AI interviews might be a better choice when high consistency between interviews is considered important.

3.4 Similarities and differences to other social sciences

In what follows, we briefly discuss how other social sciences approach the collection of open-ended data compared to economics. Anthropologists focus on cultural context, using open-ended interviews as part of immersive fieldwork to understand beliefs and practices within specific cultural settings (Bernard, 2017; Spradley, 1979).[11] Anthropological interviews tend to be unstructured and exploratory, allowing researchers to adapt questions based on participant responses and emerging insights. In contrast, economists typically use interviews in a more structured manner, often designed to align with specific hypotheses or to complement quantitative data collections.

Sociologists emphasize social structures and patterns, often employing semi-structured interviews to link individual experiences to broader societal forces and to enable comparative analysis (Bourdieu, 1990; Weiss, 1994). These interviews often explore themes such as

[10] While Namey et al. (2020) do not find quality differences between face-to-face and text-based interviews, this may depend on the interview's context.

[11] Anthropological approaches have also been applied to economic questions. For example, Ho (2009) studies the culture of Wall Street investment banks, Venkatesh (2008) analyzes career ladders in urban gangs, and Levitt and Venkatesh (2000) examine the financial activities of a drug-selling street gang.

inequality, social mobility, and institutional barriers, providing rich qualitative data on lived experiences. Economists, while also interested in these topics, often approach interviews with a focus on understanding specific mechanisms or obtaining actionable policy insights.

Psychologists prioritize individual cognition and emotions, using structured interviews to explore psychological processes, often integrating them with experimental or clinical approaches (Kazdin, 2016; Kvale and Brinkmann, 2007). Behavioral and experimental economists have increasingly drawn on similar methods. For instance, interviews can be used to probe how individuals perceive probabilities, understand incentives, or frame decisions, complementing experimental approaches. However, economists often prioritize comparability across participants and replicability of findings, which can limit the depth of open-ended responses compared to the approaches used in psychology.

Despite these disciplinary differences, all four fields—anthropology, sociology, psychology, and economics—use open-ended data as a tool to gather rich qualitative insights. Moreover, all four fields rely on these methods for hypothesis generation, offering researchers a means to identify emergent themes and develop theories grounded in empirical observation.

4 Analyzing open-ended survey data

In this section, we review different methods for analyzing open-ended data. We begin with the most comprehensive approach—human coding based on a qualitative codebook—and discuss how the previously time- and resource-intensive process of coding open-ended data can be implemented at significantly lower costs by leveraging the capabilities of large language models (LLMs). We then discuss more traditional text analysis methods, such as keyness procedures that compare word frequencies across groups. The choice of method often depends on how important it is to preserve richness and capture subtleties in the data compared to the time and resource costs associated with managing a detailed coding procedure. We also highlight how to choose the best method for a given research application based on these considerations. Thereafter, we cover data analysis approaches from other social sciences. Finally, we discuss best practices for reproducibility when working with open-ended survey data.

4.1 Human coding

The most comprehensive way to analyze open-ended survey data involves human coding of scripts. This requires developing a coding scheme that can be applied to the data.

Creating a coding scheme There are two main approaches for creating a coding scheme from qualitative data. The first approach—inductive coding—starts with the data and creates the codes based on insights that emerge directly from the open-ended responses. The second approach—deductive coding—uses existing knowledge and theory to create a coding scheme. Whether to employ an inductive or deductive coding scheme depends on the goal of the study. The inductive approach, in which codes emerge from the data, is particularly useful for discovery and hypothesis generation. The deductive approach, in which codes might correspond to predictions from different economic theories, is better suited for hypothesis testing. It is also possible to have a coding scheme that includes both theoretically relevant codes as well as additional codes emerging from the data.

To create an inductive coding scheme, it is necessary to read through the open-ended responses to find common themes. During this process, it is common practice to create codes that stay close to how respondents talk about the concepts themselves (Corbin and Strauss, 2014). For instance, if respondents commonly talk about how they fear making large losses in the stock market, it is natural to include a code for "fear of making large losses" rather than frame it as "a high degree of risk aversion" (Chopra and Haaland, 2024). Or if respondents express concerns that "high taxes hurt the economy," that is a more intuitive code than "efficiency costs" (Stantcheva, 2021).

Depending on time, resources, and the purpose of the analysis, it might be advantageous to have two researchers independently read through responses to identify good codes and then work together on creating a set of final codes. During this process, it is common practice to combine closely related codes. The granularity of the final coding scheme depends on the research question and on how important it is to distinguish between subtle concepts in the data. After converging on a set of codes, the next step is to create a qualitative codebook that includes the final set of codes that have the desired depth and sufficient support in the data. The codebook should include example responses that illustrate how the codes should be applied. A comprehensive qualitative codebook—with both positive and negative examples of how to apply the code as well as a clear definition of the code—helps reduce disagreement between different coders and is especially important for applications with subtle distinctions. It is also key for LLM applications, as discussed in the next subsection.

Manual coding of the data When the codebook is created, the next step is to hand-code the data according to the codebook. This process is often done by a team of research assistants. To ensure a high quality of the manual coding of the open-ended data, we recommend implementing the following steps. First, all coders should carefully go through the codebook and be encouraged to ask clarifying questions if there are any ambiguities. Ideally, all involved coders participate in a joint training session and subsequently hand-code the same data independently to ensure that everyone has a similar understanding of the coding scheme. During this process, it is common to make refinements to the coding scheme based on feedback from the coders, e.g., by collapsing similar codes into a broader category or refining the definition of some codes to reduce ambiguity about how to apply the codes. Second, ensuring that coders are unaware of the research hypothesis can reduce the potential for biases in coding. In the case of hand-coding open-ended data collected following an intervention, it is important that the human coders are blind to the treatment assignment. Lastly, double-coding responses and resolving discrepancies through a third coder can reduce measurement error and mitigate the effect of biases of individual coders. Alternatively, conflicts in the initial codes can also be resolved by discussions of the initial set of coders, though frequent conflicts may indicate that the codebook might need refinement or that the coders need better guidance and training.

As we discuss in Section 4.2, it is becoming increasingly common to use LLMs to code open-ended data. While human coders are still preferred in certain cases, the presence of LLMs creates a potential agency problem: Research assistants might use LLMs for hand-coding. This is especially problematic in cases where the purpose of human coding is to create a human benchmark to examine the quality of the LLM coding. Researchers who rely on research assistants to code open-ended data should be aware of this issue. To mitigate this problem, researchers should clearly explain to research assistants why using LLMs defeats the purpose of the task.

Assessing the intercoder reliability (ICR) Another advantage of double-coding is that it allows for the calculation of the intercoder reliability (ICR), which measures the extent of overlap between different coders. On the one hand, calculating the ICR is useful when developing and refining a coding scheme. On the other hand, the ICR can be reported in the final paper as a measure of the quality of the data and coding procedure. While the ICR is a standard metric in other fields, such as sociology and anthropology, it is rarely reported in economics.

ICR requires at least two coders, with 10-25% of data typically coded by multiple individuals (O'Connor and Joffe, 2020). Common measures include Cohen's kappa, Krippendorff's alpha, Scott's pi, and Fleiss' K, with Krippendorff's alpha being the most flexible (O'Connor and Joffe, 2020). While a simpler measure like percent agreement might be more intuitive, it has the disadvantage of not taking into account agreement by chance. ICR scores improve with fewer codes and less complex questions but can decrease with nuanced or sophisticated topics. Miles and Huberman (1994) suggest 80% agreement on 95% of codes, and Neuendorf (2002) propose thresholds of 90% (widely acceptable) and 80% (commonly acceptable), but the optimal cutoff depends on the application and the goal of the exercise.

The ICR can be used to iteratively improve a coding scheme as follows: the ICR is calculated after several coders have coded the same batch of open-ended responses. Subsequently, the coding scheme is refined in discussions between the coders. Then, another batch of responses is coded by all coders, and the ICR is re-calculated. When the ICR has reached an acceptable level, the scheme is completed and used to code the final data, in many cases based on single-coding. However, as Hruschka et al. (2004) caution, repeated ICR testing can lead to "interpretative convergence," potentially reducing validity through the suppression of ambiguity or loss of nuance. One way of reducing this risk is to predefine and document interaction protocols (Hruschka et al., 2004).

Example applications Several studies have used hand-coding of open-ended responses to analyze unstructured text data. Andre et al. (2022) elicit respondents' reasoning when forecasting changes in unemployment and inflation in response to hypothetical macroeconomic shocks using an open-text question on the forecast survey screen. They classify the open-ended text responses into broad response type categories, such as whether responses mention considerations related to economic propagation mechanisms of the shocks or whether responses include general political or normative statements.

Andre et al. (2025) use hand-coding of respondents' open-ended explanations for why inflation in the US increased. They represent each respondent's explanation by its Directed Acyclical Graph (DAG). Thus, their hand-coding procedure not only identifies the respondents' perceived causal drivers of the inflation rate, but also the causal connections between different variables. For example, their coding scheme allows them to differentiate between perceived root causes and intermediary causes of inflation. Representing open-text data as DAGs brings these data into a quantitative format, and allows researchers to analyze open-text data using methods from graph theory and network theory.

Chinco, Hartzmark and Sussman (2022) pursue a different approach in the context of investment choices. They let survey participants themselves classify the open-text explanations of their considerations into structured categories, significantly reducing the costs of analyzing the data. The structured categories were selected based on open-text responses in pilot studies.

4.2 Using LLMs to code open-ended data

While human coding of open-ended responses allows the researcher to capture rich nuances and context from the data, it is very time- and resource-intensive, especially for large-scale data collections. Recent evidence suggests that LLMs can code open-ended data in a reliable and reproducible manner, outperforming crowd workers and making them a low-cost and easily scalable alternative to human coding of open-ended data (Gilardi, Alizadeh and Kubli, 2023). Several recent studies in economics leveraging frontier LLMs, such as OpenAI's GPT-4o or Anthropic's Claude 3 Opus, further demonstrate that they provide very similar results as human coding in many cases (Braghieri et al., 2024; Bursztyn et al., 2024; Chopra and Haaland, 2024; Link et al., 2024).

Developing a coding scheme with LLMs To use LLMs to code responses, it is first necessary to develop a coding scheme. As the reasoning abilities of frontier LLMs continue to improve and their context windows expand to allow them to analyze more open-ended responses simultaneously, they are becoming increasingly useful in the coding scheme development phase. While it is possible to rely exclusively on LLMs in this process by giving them access to the open-ended data and asking the model to suggest a classification scheme, it is still considered best practice that researchers familiarize themselves with the nature of the open-ended data collected and develop a coding manual by reading through at least a random subset of responses, as discussed in Section 4.1.[12]

After initially developing a coding scheme by reading through responses, a good next step can be to ask an LLM to generate its own coding scheme. The researcher can then compare and contrast the LLM-generated coding scheme and the human-generated one. The LLM might have identified subtle themes that humans might have missed, and vice versa, making a collaboration between humans and LLMs more powerful than either of the two alone. After the LLM has suggested its own scheme, a good follow-up strategy can be to give it access to the human-derived coding scheme and ask it to create suggestions for how to consolidate the two coding schemes. In the final step, the researcher—using their best judgment and understanding from a detailed reading of the open-ended data—should decide which suggestions to implement.[13]

Can LLMs completely replace human coding? While frontier LLMs can be a low-cost and easily scalable alternative to human coding, their performance can depend on the quality of the prompting, the type of LLM used, and the complexity of the setting (Rathje et al., 2024). Moreover, predicting the performance of an LLM across different contexts is challenging (Vafa, Rambachan and Mullainathan, 2024). It is therefore important, especially in novel or complex settings, to compare the LLM coding with human coding for a random subset of the

[12] For instance, Chopra and Haaland (2023) use an LLM to create a coding scheme and categorize open-ended responses from AI-conducted interviews. While the coding scheme looked reasonable at first sight and led to some informative insights, a detailed reading of the interview transcripts led to a much richer coding scheme that better captured the richness of the data, as reported in Chopra and Haaland (2024).

[13] While hallucinations—cases where the LLM "discovered" factors that are not supported by the underlying text data—used to be a common problem, it is becoming increasingly rare with recent frontier models. The researcher should still verify that all LLM suggestions incorporated in the final coding scheme are grounded in the open-ended data.

data (Ludwig, Mullainathan and Rambachan, 2024). If LLM coding and human coding align well on this random subset, it is reasonable to rely on LLM coding for the full data set.

To assess the degree of alignment with the human benchmark, it is standard practice to calculate F1 scores (Dell, 2025), which combine *precision* (true positives divided by true positives plus false positives) and *recall* (true positives divided by true positives plus false negatives) into a single metric ranging from 0 (worst score) to 1 (best score; perfect precision and recall). In addition to calculating an aggregate F1 score for all categories in the coding scheme, calculating individual F1 scores for each category allows researchers to identify specific categories where LLMs may struggle to match human performance. These insights can inform adjustments to the prompts guiding the LLM, such as incorporating additional examples to clarify proper classifications or refining variable definitions to improve the accuracy and reliability of the categorization. Furthermore, to avoid overfitting the prompt to the idiosyncrasies of the test data, it is good practice to refine prompts using a separate validation set and reserve the test set for final evaluation (Dell, 2025).

When working iteratively to improve prompts using F1 scores to assess the quality of AI coding, it is important that the underlying human coding is of high quality, as it serves as the ground truth for classification. Ideally, the human coding should be based on double-coded data, with any discrepancies between coders discussed and resolved. While a ground truth is necessary to evaluate the quality of LLM coding, researchers should recognize that human coding can be biased, even when there is high inter-coder agreement. Furthermore, the LLM may pay attention to relevant factors that humans overlook. For this reason, it is good practice to instruct the LLM to provide a brief explanation justifying its classification. The explanation can help determine whether the LLM made an error that calls for a refinement of the prompts or correctly classified the response, in which case the human coding protocol should be revised instead. Providing an explanation before the decision can also help enhance the quality of LLM coding through better model reasoning (Wei et al., 2022).

Implementing LLM coding at scale with an API When using LLMs for coding, it is standard practice to leverage an Application Programming Interface (API) to automate and document the workflow. The most common one is the OpenAI API which gives the user access to all of OpenAI's GPT models. Importantly, unlike interactions with ChatGPT, OpenAI API requests are not used for training data, which can be important for privacy reasons. When using the API, researchers must specify which model to use. Frontier models are typically more expensive but might be needed to achieve acceptable performance. With very large data sets—typically much larger than in most survey research applications—frontier models might be prohibitively costly, making more cost-efficient models preferable.[14] For a detailed discussion of different state-of-the-art LLMs, their sizes, and the trade-offs involved, see the regularly updated online version of Korinek (2023).[15]

Similarly to human research assistants, LLMs benefit from a comprehensive coding scheme that provides a clear definition of each category with clear examples of how the coding scheme should be applied. In addition to providing examples, it can be useful to include a justification for why the code should apply or not for a given example. How many examples to give and how detailed the justifications should be depends on the complexity of the coding scheme and how familiar the LLM is with the task at hand. For a very simple classification task, examples might not even be needed.

While it is often possible to provide an LLM with a full coding scheme and ask it to classify multiple codes simultaneously, especially with frontier models, it can sometimes improve performance to make separate API calls for each code. This could be especially useful when working with large and complex coding schemes or large text responses, such as full interview transcripts. While making separate calls is costlier and less time-efficient, it allows the LLM to focus on one classification task at a time, improving accuracy and consistency (Bursztyn et al., 2024; Chopra and Haaland, 2024; Link et al., 2024).

A practical example To get started with the API, the first step involves designing a prompt that incorporates the coding scheme and provides clear instructions for the model. The prompt should include a clear task description. For instance, Bursztyn et al. (2024) use the following prompt to categorize text responses about social media platform usage: "You

[14] In such cases, fine-tuning—where the researcher trains the model on an existing data set hand-coded by humans—might be necessary to achieve acceptable performance. While fine-tuning yields limited improvements for frontier models, it can enable smaller models to approach the performance levels of frontier models at much lower costs (Braghieri et al., 2024). However, fine-tuning is becoming increasingly redundant as frontier models become cheaper and more able.

[15] `https://www.aeaweb.org/articles?id=10.1257/jel.20231736`

will be supplied with a list of responses. The responses refer to the usage of different platforms, the platform will be indicated in parentheses at the end of the response. Please classify responses based on the coding scheme below. Each open-ended response can fall into multiple categories or none.” The prompts also included the full coding scheme, including category names, definitions, and illustrative examples. For instance, the category FOMO includes the following description: “Respondent mentions fear of missing out, feeling out of the loop, their wish to stay connected, or justifies usage through others’ usage.” and the following examples: “I feel compelled to keep ’in touch’ with what I perceive as being the culturally relevant ’thing’ at the moment. It breeds a sense of FOMO when you don’t use it.” and “Everyone else uses it so I feel that I will be missing out if I don’t.” Online Appendix B provides more details with Python code from the actual research process.

4.3 Traditional text analysis methods

While LLMs offer a scalable tool for analyzing open-ended data, traditional text analysis methods, such as dictionary-based approaches, topic modeling, keyness analysis, and machine learning classifiers, remain widely used in economics, as discussed in recent reviews (Ash and Hansen, 2023; Dell, 2025; Ferrario and Stantcheva, 2022; Gentzkow, Kelly and Taddy, 2019). As documented by Rathje et al. (2024), LLMs have the potential to outperform simple text analysis methods like dictionary-based approaches and match the performance of more advanced machine learning methods without requiring additional training data. Given their ease of use and the lack of existing training data for most open-ended survey applications, we believe LLMs will be the preferred choice over most existing text analysis methods for survey researchers. However, in cases involving large datasets where high-quality training data is available, or when the size of the text corpus makes LLMs prohibitively expensive, machine learning classifiers might be a better option (Dell, 2025).

4.4 Considerations when choosing between different procedures

Open-ended survey data can be analyzed through human coding, LLM coding, or traditional text analysis methods. The choice of method depends on factors such as the research objective and the nature of the data. In this section, we outline some key considerations to help guide the selection of the most appropriate approach for the question at hand.

Desired level of richness The first question one should ask is how important it is to exploit the full richness of the data. If it is important to capture subtle nuances and context from the open-ended responses, human coding or LLM coding might be preferable. For instance, if the research question is to understand how people reason about inflation (Andre et al., 2025; Binetti, Nuzzi and Stantcheva, 2024), traditional text analysis methods are unlikely to reveal the full richness of the responses. In other applications, where the purpose might be to test a very specific mechanism, more traditional text analysis methods, such as keyness analysis or a machine learning classifiers, might be sufficient to detect the relevant patterns in the data (Bursztyn et al., 2022).

Scalability, costs, replicability, and privacy considerations When conducting surveys with relatively small samples, human coding is often a convenient and cost-effective way of analyzing the data. For large-scale surveys with potentially several thousand participants, human coding can become prohibitively costly in terms of both time and resources. While LLM coding is often a viable alternative, there are still some general drawbacks with LLM coding that might make more traditional text analysis methods preferable. First, API requests can become expensive with large sample sizes or very elaborate coding schemes with many factors. Second, while API requests are typically not used for training data, it could still be problematic from a privacy perspective to send survey data to external servers. Third, results from the use of a commercial API might not be reproducible if the model used is discontinued. However, many of these potential issues can be mitigated by using open-source LLMs, such as Meta's LLama. These models can be run locally, allowing the user to run LLM queries without having to send data externally or pay for API costs. The open-source nature of the models also allows for full replicability. However, setting up such a system locally often requires significant computational resources and technical expertise (Dell, 2025).

4.5 Insights from other social sciences

Economists often approach qualitative data analysis with goals distinct from those of researchers in fields like sociology and anthropology. In this section, we discuss these differences and highlight how economists might benefit from adopting techniques commonly used in other disciplines.

Anthropologists and sociologists use tools such as Dedoose and NVivo to code and interpret qualitative data. Their capabilities—hierarchical coding, pattern visualization, and multimodal data handling—are distinct from typical economic software. Moreover, Dedoose's collaborative features support team-based coding, reflecting anthropological practices where multiple analysts bring diverse perspectives. One potential limitation of these tools is that they might be less suited to analyze datasets with a large number of observations. Yet, the integration of AI tools might mitigate these scale limitations going forward.

Anthropologists and sociologists often present their findings through detailed narrative accounts designed to immerse readers in the studied environment. These accounts incorporate direct quotes, anecdotes, and personal observations to vividly convey participants' perspectives (Bernard, 2017). Rather than prioritizing contextual depth, economic research emphasizes the identification and measurement of variables and patterns (Bardhan and Ray, 2006; Starr, 2014). A summary of these methodological differences across disciplines in the analysis of unstructured data is provided in Table 3. Incorporating some anthropological techniques, such as collaborative coding and in-depth contextual analysis, could offer an opportunity for economists to interpret qualitative data in a richer and more nuanced way.

4.6 Reproducibility

Concerns about low reproducibility of research results are paramount in economics and the social sciences more broadly (Camerer et al., 2016; Christensen and Miguel, 2018). Open-ended data poses several new challenges for reproducibility given large degrees of freedom in the analysis of such data. In particular, researchers have considerable degrees of freedom in devising coding schemes, which can be especially problematic for studies concerned with hypothesis testing.

Table 3: Comparing qualitative approaches in anthropology and sociology vs economics

Fields	**Anthropology & Sociology**	**Economics**
Data collection strategies	Focus groups, interviews, participant observation (Bernard, 2017); could be unstructured and driven by participants (Ashwin et al., 2022).	Surveys and textual analysis; generally top-down approach (Rao, 2023).
Sampling	Purposive; typically smaller samples focusing on specific populations for in-depth insights (Seawright and Gerring, 2008; Starr, 2014).	Random; large samples for statistical power.
Objective of data collection	Achieve saturation: collect data until no new themes emerge (Small, 2009)	Establish representativeness: aim for generalizable and replicable trends (Rao, 2023).
Role of researcher	Reflexive and often involved in data collection process; emphasizes the process and interpretation (Burawoy, 1998).	Objective; typically detached from their research subjects and focused on analysis (Rao, 2023).
Potential bias	More susceptible to researcher's influence; smaller sample sizes and thus not generalizable (Small, 2011; Starr, 2014).	Potentially less context-specific (Bardhan and Ray, 2006).
Analysis and inference	Emphasizes contextual complexity; seeks hidden meanings and patterns, richer descriptions of social phenomena (Geertz, 1973).	Focuses on variables and patterns that can be measured (Bardhan and Ray, 2006; Starr, 2014); often uses LLMs for analysis due to large samples (Ashwin, Chhabra and Rao, 2023).

Documentation of coding schemes One potential way to mitigate concerns about researcher degrees of freedom is a transparent, standardized, and detailed documentation of coding schemes. A comprehensive codebook that includes definitions and examples is crucial for ensuring that codes can be independently understood and applied by other researchers. Decision logs that provide a record of the rationale behind specific coding choices—especially ambiguous cases—can also be useful, at least for internal purposes. Such documentation not only makes the coding transparent, it also provides a basis for subsequent adjustments in the interpretation. Furthermore, in studies using LLMs for coding of open-ended responses, including the full prompts used for coding in an online appendix is good practice to encourage replicability and transparency around the results.

Pre-registration of coding schemes and LLM prompts Pre-registering coding schemes can mitigate concerns about researcher flexibility by specifying categories, definitions, and coding rules in advance. Pre-registration reduces post-hoc adjustments and enhances the credibility of findings but is mainly an option for studies concerned with hypothesis testing. For instance, a study testing whether a priming intervention successfully changes attention to a topic, as measured with an open-ended response, could benefit from a pre-registration. The pre-registration could include a coding scheme and the LLM prompt used to classify responses. However, a full pre-registration is not feasible in many applications where the focus is at least partly on discovery. For studies focused on hypothesis generation, a pre-registration could mainly be used to specify the coding procedures rather than the coding scheme.

Data anonymization Whether to publish the raw data alongside codes depends on the nature of the data and its potential sensitivity. In non-personal applications, such as expectations about macroeconomic variables, without identifiable or sensitive information, sharing raw text data is often both feasible and desirable. However, when it comes to open-ended data describing personal experiences, publishing the raw data may not be appropriate due to the risk of re-identification, even after anonymization. In such cases, researchers might instead provide detailed metadata, summaries, or illustrative examples that maintain the essence of the findings without exposing the original text. Sharing the analysis codes alone can still promote transparency and reproducibility by allowing others to understand and validate the methods. For sensitive qualitative datasets, access could be restricted through secure data repositories, requiring approval or agreements that prioritize ethical considerations. This approach balances the need for scientific openness with the responsibility to protect participants' privacy.

5 Conclusion and avenues for future research

This review provides an overview of how open-ended questions can be used to uncover mechanisms behind economic beliefs and behaviors. Given their wide applicability and advantages, we believe that open-ended survey data will continue to grow in popularity. For instance, the quest to better understand the foundations of belief formation and decision-making will likely spur more widespread use of these methods in economics. We conclude this review with a discussion of avenues for future research in the context of open-ended survey data.

New opportunities through LLMs The availability of LLMs, such as OpenAI's GPT-4 or Anthropic's Claude, provides new opportunities and dramatically reduces costs in the collection and analysis of open-ended data: LLMs can be used to conduct qualitative interviews at scale; LLMs can improve the analysis of open-ended data by better capturing the context, semantics, and sentiment of responses than existing tools; LLMs can be used to automatize the classification of open-ended data; and they offer a systematic, data-driven approach to generate (initial) classification schemes. We hope that this review lowers the barriers for researchers and practitioners who would like to make use of open-ended survey data.

Incentives As discussed in our review, one concern about open-ended questions is that respondents may exert low effort when writing their responses. Another concern is that effort levels may vary widely across respondents depending on their intrinsic motivation, which reduces interpersonal comparability.

A potential solution to these problems is the use of monetary incentives. Incentivizing open-ended responses is a complex challenge because there is typically no objective benchmark against which to evaluate them. More generally, unlike closed questions, where specific answers can be defined as correct or desirable, open-ended responses vary significantly in content, depth, and style, making it difficult to assess quality or value in a consistent, objective way. Without clear benchmarks, it is challenging to design incentive structures that reliably encourage respondents to provide thoughtful, meaningful answers rather than simply writing more or producing responses that may seem impressive but lack genuine insight. This lack of objective standards leaves open the question of how to best motivate quality responses in a way that aligns with research goals. It is conceivable, for example, that providing monetary incentives for more effortful responses distorts responses away from the true reasoning processes guiding behavior.

More generally, it remains an open question whether and how incentives can be used to increase the truthfulness of open-ended responses. While prior work emphasizes the importance of motivational prompts (Smyth et al., 2009), future research should examine whether incentives can be designed to enhance the truthfulness and accuracy of open-ended responses.

Voice-based AI interviews An emerging innovation in the field of interviews is the use of AI-driven systems to conduct semi-structured, voice-based interviews with respondents. In this setup, an AI interviewer interacts directly with respondents through natural conversation, leveraging voice technology to capture not only the content of their answers but also vocal nuances such as tone, pace, and emotion. Voice-based AI interviews can enable richer interactions by probing deeper into areas of interest based on both spoken words and vocal cues. By combining the conversational flexibility of AI with the expressive power of voice, this method opens new possibilities for understanding respondent sentiment and intent, making it particularly valuable for exploring complex topics in a scalable yet empathetic way. Eventually, adding videos to AI-conducted interviews can further increase their potential by allowing the AI interviewer to also pick up on facial expressions.

Neuroeconomics Combining methods from neuroeconomics with unstructured, open-ended responses presents a unique opportunity to deepen our understanding of belief formation, emotions, and considerations in decision-making contexts. Neuroeconomics provides tools to measure neural and physiological responses—such as brain imaging (fMRI or EEG), eye tracking, and skin conductance (Camerer, Loewenstein and Prelec, 2005)—capturing the immediate, often non-conscious, reactions that might accompany or precede verbalized considerations. Meanwhile, open-ended responses offer an introspective and narrative perspective, revealing subjective interpretations, emotional nuances, and the complexity of considerations that might not be apparent in more structured data. By integrating these approaches, researchers could measure both the internal processing and the explicit expression of considerations. For example, neuroeconomic methods might reveal brain areas activated during moments of conflict or ambivalence, which could then be connected to participants' own descriptions of doubt or conflicting considerations in their responses. This could illuminate how certain neural patterns correlate with specific ways of interpreting experiences or reasoning about decisions.

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Online Appendix:
Not for publication

A Additional tables

Table A1: Overview of studies: Political economy

Paper name	**Domain**	**Measurement**	**Analysis of text data**
Andre (2025)	Explanation of people's distributive choices	“Please explain why you made your choice the way you did.”	Hand-coding of responses.
Bursztyn et al. (2023)	Motives for choosing Tweet	“Why did you choose this Tweet rather than the other Tweet?”	Word counts and simple machine learning techniques.
Braghieri, Schwardmann and Tripodi (2024)	Reasons for self-selection into "echo chamber" and positive effects of cross-partisan communication	Conversation topics in a recorded and transcribed video chat, as well as reasons for the willingness to pay for the option to have a video chat.	Hand-coding of responses regarding willingness to pay and topic prediction using ChatGPT 3.5 turbo.
Bursztyn et al. (2020)	Beliefs about motives underlying xenophobic expression	“Why do you think your matched respondent chose to donate to Fund the Wall?” On top of this, the authors employ structured measures of beliefs about the matched respondent's type.	Pre-specified word counting procedure; Support Vector Machine classifier to predict structured belief measures based on text data.
Dechezleprêtre et al. (2025)	Considerations about climate change	“When thinking about climate change, what are your main considerations? What should [country] government do regarding climate change?”	Text analysis.
Galasso et al. (2024)	Anti-populist video ads regarding a populist referendum in Italy	Respondents were invited to share their considerations about a video in an open-ended question to compare how two videos are comparatively perceived.	Hand-coding and supervised text analysis (FEEL-IT)
Gründler and Potrafke (2020)	Attitudes towards fiscal rules	“What are your main considerations about fiscal rules?”; "What should be the goal of fiscal rules?"; "What are the main shortcomings of fiscal rules."	Word cloud and ML methods for sentiment analysis.
Hager et al. (2023*a*)	Voice and political engagement	4 Treatment groups with open-ended questions:“Would you like to tell us more about which issues we should particularly emphasize in the election campaign?(/Would you like to tell us more about which topics are particularly close to your heart?)(/+ After the completion of the survey, we will send you a summary of the results.)”	Hand-coding of responses.
Hager et al. (2023*b*)	Motives underlying change in effort in response to info	“Why would the results of the survey affect or not affect your decision? Please answer using whole sentences”	Human coding of scripts.
Hüning, Mechtenberg and Wang (2022)	Attitudes towards rent control	Discuss pro and cons of rent control	NLP and text analysis techniques.
Jessen et al. (2024)	Policy demand to reduce socioeconomic inequality in life expectancy	List as many measures as possible that the government could use to improve the life expectancy of the poor.	Word cloud.
König and Schmacker (2022)	Sin taxes, i.e., taxes on sugar-sweetened beverages (SSB)	4 Open-ended questions: 1st the general considerations of SSB taxes; 2nd regarding the goals; 3rd and 4th the benefiting respective losing groups.	Word cloud and keyness analysis.
Lang and Schneider (2023)	Influence of post-WWII German immigrant movement on nationalist sentiment and electoral responses	“What do you think is the significance of the fact that many Germans had experience of expulsion, flight, and immigration?”	Hand-coding of responses.
Liscow and Fox (2022)	Attitudes towards capital tax realization rule	Why preferred to defer taxation until sold respectively why preferred to tax before sold.	Word counting.
Luttmer and Samwick (2018)	Impact of policy uncertainty in social security on individual welfare	"We are interested in better understanding why you chose uncertain benefits around [B]% of the Social Security benefits you are supposed to get under current law over guaranteed benefits equal to [L]% of the Social Security benefits you are supposed to get under current law. Could you tell us the main reason for your choice?"	Hand-coding of responses.
Nathan, Perez-Truglia and Zentner (2025)	Reasoning for filling property tax complain or not.	“If you can, please explain why you will (or will not) protest in 2020.”	Handcoding of responses.
Stantcheva (2020)	Understanding, reason and learning about 4 economic policies: i) income, and ii) estate taxation, iii) health insurance, iv) trade	“What are your main considerations about [policy]...?” and more specific sub-questions regarding perceived goals and shortcomings, as well as the anticipated effects (e.g., which group would gain) from the specific policy.	Text analysis techniques (keyness analysis, topic analysis, word clouds).
Stantcheva (2021)	First-order concerns about income and estate tax	“When you think about federal personal income taxation and whether the U.S. should have higher or lower federal personal income taxes (/federal estate tax), what are the main considerations that come to your mind?”	Text analysis techniques (keyness analysis, topic analysis, word clouds).
Stantcheva (2022)	Attitudes towards trade	“When you think about trade policy and whether the U.S. should put some restrictions on trade with other countries, such as tariffs, what are the main considerations that come to your mind?” “What would be the effects on the U.S. economy if barriers to trade, such as tariffs, were increased?” “Which groups of people do you think would gain if trade barriers such as tariffs were increased?”	Text analysis techniques (keyness analysis, topic analysis, word clouds)

Table A2: Overview of studies: Political science

Paper name	Domain	Measurement	Analysis of text data
Breyer, Palmtag and Zollinger (2023)	Perceived status gains for women or minorities.	"E.g., Now think about the people who have tended to gain recognition compared to the past. How would you describe these people? What kind of characteristics, lifestyles, and opinions do these people have?"	Text analysis with a parsimonious dictionary.
Roberts et al. (2014)	Views on immigration; Intuition versus reflection in Public Goods Game; American National Election Survey	"Of the stories you read, what stories do you remember best? (If you don't remember the names, just describe the stories)."; "Please write a paragraph (approximately 8-10 sentences) describing a time your intuition/first instinct(/time carefully reasoning) led you in the wrong(/right) direction and resulted in a bad(/good) outcome."; "What has been the most important issue to you personally in this election?" and "What do you think is the most important political problem facing the United States today?"	Introduce their Structural Topic Model (STM), which relies on machine learning methods, and apply it to the three examples and compare it to hand-coding.
Rothschild et al. (2019)	Stereotypes about the two American parties	"Please write down four words that typically describe people who support the [Democratic/Republican] Party."	Structural Topic modelling.
Zollinger (2022)	Attitudes towards voter-party links	"If you imagine people with a lifestyle and opinions similar to your own, what kind of people would these be? How would you describe them?", "And someone who is not at all like you? Someone who lives completely differently and who has very different opinions? How would you describe them?"	Text analysis techniques (keyness analysis, latent semantic scaling)

Table A3: Overview of studies: Macroeconomics

Paper name	**Domain**	**Measurement**	**Analysis of text data**
An, Binder and Sheng (2023)	Gas price and inflation expectations	Asked respondents to describe the main considerations that come to their mind regarding the impact of the war on China's economy, overall prices in China, and gas prices in China.	Word cloud and hand-coding.
Andre et al. (2022)	Unemployment and inflation predictions	Ask respondents about their "main considerations in making the prediction" and about how they "come up with [their] prediction". On top of this, the authors employ structured measures of the considerations respondents had on their mind.	Human coding of scripts and simple word counting techniques.
Andre et al. (2025)	Narratives about the rise of inflation	Ask respondents "Which factors caused the rise in inflation?"	Human coding of text into DAGs.
Binetti, Nuzzi and Stantcheva (2024)	People's understanding of inflation	Ask respondents a series of qualitative questions about the relationship between inflation and economic activity, its causes, distributional impacts, and perceived consequences. For example, ' In your opinion, what are the primary causes of inflation?'	Hand-coding of responses.
Hommes, Pinter and Salle (2023)	Prior Knowledge of Public Finance	"Which risk(s) do you have in mind?" or "Which advantage(s) do you have in mind?"	Word cloud and classification.
Leiser and Drori (2005)	Inflation expectations	Ask participants to specify terms, concepts, or short phrases related to inflation.	Human coding of text and classification into broader categories.
Link et al. (2024)	Current economic situation	"What topics come to mind when you think about the economic situation of your company/household?"	Human coding of scripts and word counting.
Stantcheva (2024)	Causes and personal impact of inflation	E.g., "What were the most important impacts of inflation on your life?"; "When inflation gets very high, what do you think is the reason?"	Topic analysis and word clouds.

Table A4: Overview of studies: Labor economics

Paper name	Domain	Measurement	Analysis of text data
Abeler, Huffmann and Raymond (2023)	Incentive complexity and effort provision	“If someone were trying to get the most money, total, from [Period 3 and Period 4], what do you think would be the best approach?”	Hand-coding of responses.
Ayyar et al. (2024)	Gender attitudes influence on lifetime earnings.	“Imagine you are now 25 years old. Write about the life you are leading, your interests, your home life and your work at the age of 25. (You have 30 minutes to do so).”	Word-embedding model to identify gender attitudes in essays.
Capozza (2024)	Concerns of women regarding gender gap in salary negotiations	"Which factors do you think caused the gender gap in salary negotiation?"	Word cloud, keyness analysis and hand-coding.
Casarico, Schuetz and Uebelmesser (2024)	Causes of gender gap in earnings and pensions in Germany	“What do you think are the causes of the differences between men and women in gross annual earnings and retirement pensions?”	Word cloud and keyness analysis.
Dube, Naidu and Reich (2022)	Preferences for wages and non-wage amenities	Research Assistants conducted in-depth interviews with 87 employees	Define survey measures of dignity based on the topics mentioned in the interviews
Erkal, Gangadharan and Xiao (2022)	Default selection processes in leadership influence on gender gaps	“In Stage 1 of Experiment II, you chose the following method: (Method X / Method Y / Indifferent). Please explain your decision. ”	Incentivized (alignment with modal of other coders) hand-coding of responses by subjects.
Kaur et al. (2025)	Financial worries	“What makes you worry about money issues?”	Word clouds and text-counting.
Miano (2023)	Beliefs about on-the-job search	“Imagine you wanted to look for a new job at a new employer now, while still working at your current employer. Are there any issues that would make looking for a new job difficult for you now? What are the first ones that come to your mind?"”	Word cloud.
Oh (2023)	Labor supply decisions related to caste	During the follow-up survey, workers were asked why they turned down specific offers.	Surveyors classified free-form answers based on training.
Rodrik and Stantcheva (2021)	Beliefs about what makes a good job	“What is a good job?”	Text analysis techniques

Table A5: Overview of studies: Finance

Paper name	Domain	Measurement	Analysis of text data
Andre, Schirmer and Wohlfart (2024)	Prediction of Stock Market Returns	Ask respondents for their reasoning for their stock return predictions based on a pair of hypothetical scenarios involving stale news about future company earnings.	Word count and hand-coding of open-ended data.
Ba, Rivera and Whitefield (2023)	Forecasting the stock market impact of racial uprisings	"Please explain your prediction using 2 to 3 sentences."	Hand-coding of responses.
Bailey et al. (2019)	Mortgage leverage choice	Ask respondents why their mortgage leverage choice differs across hypothetical scenarios with different projected home price changes.	Overview of representative text responses
Bauer et al. (2024)	Experts' beliefs about climate risk pricing	"Which factors do you think cause a deviation from correct pricing of climate risks? Please respond in full sentences."	Hand-coding of responses.
Chinco, Hartzmark and Sussman (2022)	Stock investment decisions	Ask respondents what factors are most important to them when deciding what fraction of an endowment to invest in stocks	Self-classification of open-ended responses by survey participants.
Chopra and Haaland (2024)	Stock market non-participation puzzle	Conduct AI-assisted interviews with respondents, exploring their reasons for not investing in the stock market including an "what if" scenario and counterfactual reasoning.	Hand-coding 50 interviews and using these for OpenAI's API to query GPT-4 for code assignment.
Chopra, Roth and Wohlfart (2024)	Home Price Expectations	"How would this change in your expectations about future home prices affect your expectations about your household's future economic situation. Please explain why. Respond in full sentences."	Hand-coding of open-ended data.
Filippini, Leippold and Wekhof (2024)	Financial literacy	"Describe which characteristics you think distinguish sustainable financial products from conventional investments. Please write a short text of about three sentences"	Text analysis techniques (topic specific word counts)
Jiang et al. (2024)	Selective recall of past returns	"First think about the overall stock market movement since you opened an account. Since you started trading, what is the episode of market movement that first comes to mind? Please enter the starting month and ending month of this episode."	Hand-coding of dates.
Laudenbach et al. (2024)	Beliefs about the stock market	Ask respondents to describe in open text which specific historical episodes – if any – they had in mind when estimating the historical autocorrelation of aggregate stock returns.	Human coding of text responses into different historical episodes.
Wekhof (2024)	Intention-Behavior gap sustainable investments	Hypothetical investment scenario: "What criteria would be important to you when choosing a fund? Please write a short text with about 3 sentences."	Semi-manual classification approach from Houde and Wekhof (2023).

Table A6: Overview of studies: Behavioral economics

Paper name	Domain	Measurement	Analysis of text data
Arrieta and Nielsen (2024)	Explanation of people's lottery and charity choices	"Please write a message to another participant describing how you made your last five decisions."	Other respondents replicate choice with or without message, Robustness with GPT-4 which also classified text in procedural categories.
Bordalo et al. (2025)	Explanation of people's solving strategies for statistical problems	"Could you describe to us in your own words how you came up with your answer to the previous question?"	Classification with GPT-3.5 which specific features of the problem were attended to.
Bordalo et al. (2023)	Free Recall of shown words	"Please list up to 15 [category] that you remember seeing in the list of words we showed you. You do not have to fill in all 15 lines."	Hand-coding of responses.
Bursztyn et al. (2024)	Motives for preferring a world without Tiktok or Instagram and feelings about being the sole user to leave the platform	"You mentioned you would prefer to live in a world without [platform]. Why do you still use it?" and "How would you feel if you were the only one who deactivated [platform] and everyone else kept using it?".	Hand-coding of responses and AI based classification using LLM.
Castagnetti and Schmacker (2022)	Motivated information selection and updating	"Please explain, in general, how you decided between feedback modes across the five scenarios. For example, why did you choose one feedback mode over another? What specific characteristics of the feedback modes were you looking at?"	Hand-coding of responses.
Chopra, Haaland and Roth (2024)	Motives for (not) subscribing to newsletter	"Why did you (not) subscribe to the newsletter?"	Word counts and simple machine learning techniques.
Conlon (2024)	Role of rehearsal	Conversation with LLM which focus either on Successes or Failures in past academic experiences.	Conversation incetivized by engagement which was classified by LLM in a scale 0 to 100.
Agranov and Ortoleva (2017)	Motives for choices between lotteries	"In Part III of the experiment each question was asked to you three times. If you chose different options, could you please tell us why did you do it? (Please elaborate)."	Hand-coding of responses.
Elias, Lacetera and Macis (2023)	Attitudes towards sudden price increases and price regulation	'Using the slider below, please rate this scenario as: -10 (completely unfair) to +10 (completely fair)','We now ask you to select, among the two scenarios described above, the one that you would prefer to have in place in your country.','Please briefly describe in the space provided the main reason(s) for your answers and choice above'	Text analysis.
Graeber, Roth and Zimmermann (2024)	Memories about information provided	"Please tell us anything you remember about this product scenario. Include as much detail as you can. Most importantly, please describe things in the order they come to mind, i.e., the first thought first, then the next one etc."	Hand-coding of responses.
Graeber, Roth and Schesch (2024)	Verbal explanations of financial reasoning choices	"We are interested in how you would give advice in an informal conversation: You should share an explanation behind your response. Your recording will be played to a few other participants who will have to respond to the same question."	Transcribe transcripts by Phonic using Amazon Transcribe and GPT-4 for classification of transcribed text.
Graeber, Noy and Roth (2024)	Oral transmission of information using speech recordings	"Think about the first(/ or second) opinion you listened to about changes in house price growth in a large US city. We will now ask you to record a voice message summarizing this opinion."	Classify by hand-coding and GPT of responses whether level and reliability are transmitted.
Grunewald et al. (2024)	Potential reinforcement of motivated beliefs through ccommunication.	"[Quotes & Chat] To start the conversation and to give you some food for thought, here are two quotes by famous personalities: I think we are living in selfish times. — Javier Bardem, Hollywood actor and Oscar winner I'm just thankful I'm surrounded by good people. — Jon Pardi, singer and songwriter"	Word lists and bigram and trigram analysis.
Houser and Xiao (2011)	Communication influence on coordination game	Messages from Charness and Dufwenberg (2006).	Hand-coding of responses vs. incentivized (alignment with modal of other coders) hand-coding of responses .
Jabarian and Sartori (2024)	How the storytelling surrounding an information impacts the effectiveness of a survey eliciting reasoned preferences	Critical reasoning essays written by the respondents on the topic at hand.	Grading by doctoral-level psychologists determining whether the respondent is a critical or naive thinker.
Kaufmann, Andre and Kőszegi (2024)	Explanation of people's impact prediction on externalities	"Please explain why you chose this response.", "Please explain why you gave the same(/different) answer(/s) in the two situations." and "Please explain why you would be willing to pay money in situation 2 where the total impact would be zero."	Hand-coding of responses.
Martínez-Marquina, Niederle and Vespa (2019)	Provide incentivized advice to another participant for making a guess	"In the box below you can provide advice on what price you think the advisee should submit and a justification for your recommendation."	Hand-coding of responses.
Roth, Schwardmann and Tripodi (2024*a*)	Social Stigma and demand for psychotherapy	"Imagine a person with depression. What views about depressed people by others does this person worry about most?"	Hand-coding of responses.
Roth, Schwardmann and Tripodi (2024*b*)	Effectiveness and demand for psychotherapy	"What considerations do you have on your mind when choosing how much you would be willing to spend on 4 weeks of online therapy from BetterHelp? Please write 2-3 sentences. You may mention both downsides and benefits of buying therapy (if any were on your mind)."	Hand-coding of responses.
Saccardo and Serra-Garcia (2023)	Enable or limit their capacity to distort beliefs in moral dilemmas	"When you had to decide between learning about your commission Before or After getting information about the quality of Product B [A, if the order was flipped], how did you make this decision?"	Hand-coding of responses.
Tiezzi and Xiao (2016)	Market experiment evaluating the role of delaying externalities on support for taxes	""How did you decide to vote in favor or against the tax?" or "If your second vote was different from your first vote during the experiment, why did you change your mind?"	Incentivized (same coding with other randomly matched respondent) hand-coding by subjects.

Table A7: Overview of studies: Development economics and other areas

Paper name	**Domain**	**Measurement**	**Analysis of text data**
Ashwin et al. (2022)	Parent's aspirations for children in Bangladesh	Analysis of qualitative interview.	Developing supervised classification model trained with hand-coded subsample.
Ashwin et al. (2022)	Parent's aspirations for children in Bangladesh	Analysis of qualitative interview.	Using different LLMs (GPT-3.5 turbo and two Llama 2 versions) to compare to method from Ashwin et al. (2022).
Baird, McIntosh and Özler (2011)	Role of conditionality in cash transfers	Qualitative interview of random subsample.	Hand-coding of responses.
Burgstaller, Doerr and Necker (2023)	Tax credits influence on demand for legally provided services	"What reasons could there be for someone not claiming the government support?"	Hand-coding of topics which are used for keyness analysis.
Dillon et al. (2012)	Child labor	In the pilot phase, qualitative interviews with open-ended questions were conducted to solicit how respondents thought about the survey questions, why they chose the responses they did, and how they thought about concepts such as work, household production, and their primary activities.	Hand-coding of responses.
Houde and Wekhof (2023)	Investment in energy efficiency	"Describe the reasons why you decided (not) to carry out energy efficiency retrofits. Please write a short text of about 4 sentences."	Hand-coding and machine learning methods.
Jayachandran, Biradavolu and Cooper (2023)	Woman's agency	Semi-structured interview with open-ended questions.	Hand-coding of responses to calculate benchmark score.
Parker and Kozel (2007)	Poverty and vulnerability in India	'Semi-structured interview with open-ended questions.	Qualitative analysis methods are used to inform a quantitative survey.
Romero et al. (2022)	Direct vs. indirect management training	DWMS, an adaptation of the World Management Survey, was used for an interview that included 23 open-ended questions, such as " How do you keep track of what teachers are doing in the classrooms?"	Hand-coding of responses.

B API Implementation Details

To implement this workflow using the API of a language model, researchers can follow these steps. First, obtain access to the API, along with a programming interface such as Python. The coding scheme should be formatted for programmatic use, such as in JSON or YAML format. An example of a formatted coding scheme could look like the following:

```
- FOMO: Respondent mentions fear of missing out, feeling out of the loop,
  or justifies usage through others’ usage.
  Examples:
  - "I feel compelled to keep ’in touch’ with what I perceive as being
    the culturally relevant ’thing’ at the moment. It breeds a sense
    of FOMO when you don’t use it."
  - "Everyone else uses it so I feel that I will be missing out if I don’t."
```

Next, design the prompt to incorporate this coding scheme. Below is an example prompt:

```
You will classify text responses based on the coding scheme below. Each
response can fall into multiple categories or none. Use the categories’
names and definitions to make your decisions.

Coding Scheme:
- FOMO: Respondent mentions fear of missing out, feeling out of the loop,
  or justifies usage through others’ usage.
  Examples:
  - "I feel compelled to keep ’in touch’ with what I perceive as being
    the culturally relevant ’thing’ at the moment. It breeds a sense
    of FOMO when you don’t use it."
  - "Everyone else uses it so I feel that I will be missing out if I don’t."

Response to classify: "{response_text}"
```

This prompt can be programmatically passed to the latest available OpenAI model via the API. For instance, using Python with the GPT-4o model:

```
import openai

openai.api_key = "your-api-key"

def classify_response(response_text, coding_scheme):
    prompt = f"""
    You will classify text responses based on the coding scheme below. Each response can

    {coding_scheme}

    Response to classify: "{response_text}"
    """
    response = openai.ChatCompletion.create(
        model="gpt-4o",  # Use the latest recommended model
        messages=[{"role": "user", "content": prompt}],
        max_tokens=150,
        temperature=0
    )
    return response['choices'][0]['message']['content'].strip()

# Example usage
response_text = "I use this platform because all my friends are on it."
coding_scheme = """
- FOMO: Respondent mentions fear of missing out, feeling out of the loop,
  or justifies usage through others' usage.
  Examples:
  - "I feel compelled to keep 'in touch' with what I perceive as being
    the culturally relevant 'thing' at the moment. It breeds a sense
    of FOMO when you don't use it."
  - "Everyone else uses it so I feel that I will be missing out if I don't."
"""
classification = classify_response(response_text, coding_scheme)
print(f"Classification: {classification}")
```

Finally, classification results can be stored in structured formats such as CSV files or databases for further analysis. Researchers should ensure accuracy by comparing the model's classifications against manual coding, iteratively refining the prompt and coding scheme. This iterative approach enhances the method's robustness and applicability across diverse research contexts.