

Analyzing and Enhancing Clarification Strategies for Ambiguous References in Consumer Service Interactions

Changling Li^{2*} Yujian Gan^{1*} Zhenrong Yang³ Youyang Chen³
Xinxuan Qiu² Yanni Lin² Matthew Purver^{1,4} Massimo Poesio^{1,5}

¹Queen Mary University of London, UK ²Guangxi Normal University, China
³Guangxi University of Finance and Economics, China ⁴Jožef Stefan Institute, Slovenia
⁵University of Utrecht, Netherlands

Correspondence: m.poesio@qmul.ac.uk

Abstract

When customers present ambiguous references, service staff typically need to clarify the customers' specific intentions. To advance research in this area, we collected 1,000 real-world consumer dialogues with ambiguous references. This dataset will be used for subsequent studies to identify ambiguous references and generate responses. Our analysis of the dataset revealed common strategies employed by service staff, including directly asking clarification questions (CQ) and listing possible options before asking a clarification question (LCQ). However, we found that merely using CQ often fails to fully satisfy customers. In contrast, using LCQ, as well as recommending specific products after listing possible options, proved more effective in resolving ambiguous references and enhancing customer satisfaction.¹

1 Introduction

Clarification questions (CQ) have long been a focal point in dialogue research due to their various functions, with resolving ambiguities being one of the most crucial (Purver, 2004a; Boni and Manandhar, 2005; Ginzburg, 2012; Liu et al., 2014; Dhole, 2020; Lautraite et al., 2021; Testoni and Fernández, 2024). Previous studies have primarily examined whether models are capable of generating suitable clarification requests in response to ambiguities (Purver et al., 2001; Zhang and Choi, 2023; Deng et al., 2023). However, little attention has been paid to determining the most effective type of clarification request (Liu et al., 2014; Zhang and Choi, 2023). This gap in research prompts a significant question: What type of clarification request should intelligent customer service systems generate when addressing ambiguous references?

*These two authors contributed equally to this work.

¹You can find our data [here](#).

Dialogue 1:

A: I want the same pizza as last night.

B: What type of pizza would you like?

A: I want a Hawaiian pizza.

Dialogue 2:

A: I want a pizza.

C: What type of pizza would you like?

A: I want a Hawaiian pizza.

Table 1: Questions for general and specific references.

Before addressing this issue, it is necessary to clarify the definition of a CQ. Purver (2004b) defines a ‘clarification question/request’ in dialogue systems as a type of communicative action where one participant asks another to provide more information or to make their previous statement clearer. This typically occurs when the listener does not fully understand the speaker’s message due to ambiguity, vagueness, or missing information. In Dialogue 1 of Table 1, B provides an example of a CQ. However, Purver (2004b) believes that C in Dialogue 2 of Table 1 does not qualify as a CQ, but is merely an information request. This is because in Dialogue 2, C understands A’s message (a general, existentially quantified reference) but needs further information to clarify A’s needs. In Dialogue 1, B does not fully understand A’s message (a specific, definite reference), indicating ambiguity in A’s statement, and thus needs additional information to clarify. Unlike Purver (2004b), Rodríguez and Schlangen (2004) and Rieser and Moore (2005) consider both B and C to be CQs. Given that the subsequent dialogue content of B and C is similar, this paper adopts the same taxonomy and definition as Rodríguez and Schlangen (2004) and Rieser and Moore (2005).

Besides, we must define what an ambiguous reference is. An “ambiguous reference” in communication refers to a statement, word, or phrase whose

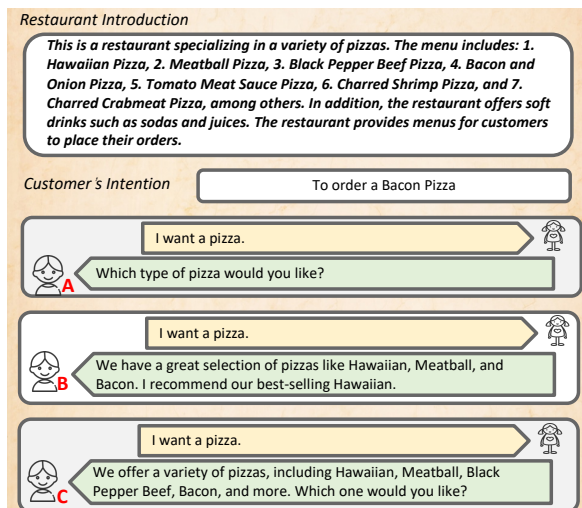


Figure 1: An example of a dialogue background with three different responses to an ambiguous reference. The girl represents the customer, and the boy represents the service staff.

meaning is not clear due to multiple possible interpretations (Eckert et al., 2003). In consumer service settings, an ambiguous reference can lead to confusion about product specifications, pricing, or customer intentions, which may hinder effective communication between the service staffs and customers. Effective clarification questions are essential in these scenarios to resolve ambiguities (Majumder et al., 2021).

Figure 1 illustrates an example of an ambiguous reference: a customer at a restaurant that serves various types of pizza orders a pizza but does not specify which kind. The figure also demonstrates several potential responses that the server might use to clarify this ambiguity. It is important to identify which response methods are commonly used by service staff and are favored by customers in practical scenarios. Addressing these questions is vital for the development of intelligent customer service systems.

To answer these questions, we collected 1,000 Chinese conversations from real-world consumer environments. Nearly every customer in these dialogues initiated at least one ambiguous reference. After organizing the data, we annotated each sentence to prepare the dataset for several uses: (1) training or evaluating a model’s capability to identify ambiguous references in conversations; (2) training or evaluating a model’s ability to resolve ambiguous references effectively through dialogue; (3) analyzing real-world service staff approaches to ambiguous references. Our analysis revealed that service staffs often use direct clarification questions

or list potential options before asking a clarification question to clear up any ambiguity, as demonstrated in responses A and C in Figure 1.

Our dataset highlights the response strategies typically used by service staff, yet these may not always align with what customers consider optimal. To gain deeper insights into customer preferences, we developed a questionnaire based on three response methods illustrated in Figure 1 and surveyed customers on their satisfaction with each response. The findings show that customers’ satisfaction levels with responses B and C are comparable and notably higher than with response A. This indicates that direct clarification questions are not the sole effective approach for addressing ambiguous references.

2 Dataset Construction

We gathered dialogue data from actual online and offline consumer interactions to explore how service staff addresses ambiguous references in customer inquiries. We compiled a dataset of 1,000 Chinese conversations, which were collected by four undergraduates over a period of three months, drawing on their personal shopping experiences and those of their peers.

2.1 Construction Principles

The dialogue dataset was constructed adhering to strict principles:

Authenticity: Every dialogue was directly drawn from actual consumer experiences, covering both successful and unsuccessful transactions.

Completeness: We ensured every conversation collected comprehensively included queries about products/services and responses from service staff.

Diversity: Dialogues span a range of online and offline scenarios, with offline scenarios including shops, restaurants, clothing stores, and other venues.

Privacy Protection: We rigorously anonymized all dialogues, removing or modifying any identifiable details, such as shop and brand names or personal identifiers.

2.2 Methodology for Dialogue Data Collection

Before we began data collection, we trained four data collectors to present requests with ambiguous references to service staff during their regular consumer activities, and to observe the responses. Once the transactions were complete—or if they

were terminated because the product or service was unavailable—the collectors exited the venues or ended the online sessions and reconstructed the dialogues from memory. It's important to note that all dialogues recorded are reconstructions based on actual conversations, and any personally identifiable information has been removed.

2.3 Pre-Analysis of Dialogues and Consumer Scenario Classification

After gathering approximately 300 dialogue samples, we performed an initial manual summary analysis. This analysis showed that service staff respond to customers' ambiguous requests using four main strategies: clarification questions, listing, listing followed by clarification questions, and information gathering, or they may choose to ignore the ambiguous reference. Specifically, clarification questions (*CQ*) directly address the ambiguity, as illustrated in response A of Figure 1. Listing (*LIST*) involves detailing potential options, as depicted in response B of Figure 1. Listing followed by clarification questions (*LCQ*) combines listing options with clarification questions, as seen in response C of Figure 1. Information gathering (*IG*) involves asking questions that do not directly relate to the ambiguity, such as inquiring about the customer's preference for spicy or sweet flavors within the context of the ambiguous reference shown in Figure 1. Ignoring the ambiguous reference (*IAR*), like *IG*, overlooks the need for clarification; however, unlike *IG*, responses here are declarative rather than interrogative.

Additionally, we observed that different consumer environments may influence the responses. From the analysis of dialogue samples, we classified the consumer environments into five main categories: those with only a menu, only product displays, both a menu and product displays, neither menus nor product displays, and online shopping. The first category, labeled as '*MENU*', includes scenarios found typically in restaurants where customers can see the menu but not the actual food. The second, '*PROD*', refers to environments like supermarkets where only product displays are available. The third category, '*M&P*', applies to fast food outlets where both menus and food are visible in display counters. The fourth, '*NO-M&P*', includes service-oriented settings such as barber shops and mobile repair stores, where neither menus nor products are displayed. Lastly, the '*OL*' category encompasses purely online shop-

ping. These first four categories are associated with offline consumer settings, while the last category specifically pertains to online shopping.

2.4 Dataset Annotation Steps

Documenting consumer dialogues is merely the initial step; they also require detailed annotation. This involves categorizing responses from service staff, briefly describing the consumer scenario as illustrated by the restaurant example in Figure 1, and identifying the type of consumer scenario. The steps for organizing and annotating this data are as follows. Step 1: Load the dialogue into a data annotation platform and record the time, city location, and specific consumer scenario, along with a concise description of it. Step 2: Meticulously annotate each sentence in the dialogue by category, including '*CQ*', '*LIST*', '*LCQ*', '*IG*', '*IAR*', 'ambiguity' (if the customer raises an ambiguous reference), and 'none' (if it doesn't fit into any of the previous categories), resulting in a total of seven categories. Step 3: Perform internal cross-validation within the team. Discuss any discrepancies in annotations during team meetings and make final decisions collaboratively.

3 What type of clarification question do service staff prefer to use?

Table 2 illustrates how service staff respond to requests with ambiguous references across various scenarios based on the dataset introduced in Section 2. The reason the total responses exceed the number of dialogues in the dataset is that an ambiguous reference can include multiple elements needing clarification. In most instances, service staff predominantly rely on clarification questions, including both *CQ* and *LCQ*, which constitute approximately 90% of all responses. Except in the *PROD* scenario, the frequency of using either *CQ* or *LCQ* is similar, indicating no clear preference among service staff. However, in locations where only products are displayed (*PROD*), it appears that service staff more frequently opt for *LCQ*. This approach may be necessary because similar items are not always on adjacent shelves, thus listing items from various locations helps staff better understand customer needs and guide them accurately. Furthermore, since customers lack menus and neither party may directly see the required items, *LCQ* could also improve the customer's sensory experience.

Among the remaining response types—*LIST*,

Scenario	Total	<i>CQ</i>	<i>LIST</i>	<i>LCQ</i>	<i>IG</i>	<i>IAR</i>
Offline						
<i>MENU</i>	485	0.449	0.049	0.476	0.021	0.004
<i>PROD</i>	624	0.405	0.050	0.514	0.027	0.003
<i>M&P</i>	404	0.505	0.010	0.483	0.002	0
<i>NO-M&P</i>	58	0.483	0.017	0.448	0.051	0
Online						
<i>OL</i>	828	0.430	0.087	0.448	0.023	0.012

Table 2: Response Strategies by Service Staff Across Different Scenarios: Row headers distinguish online and offline scenarios as detailed in Section 2.3. The ‘Total’ column sums counts from five response strategies, each defined in the remaining column headers with explanations also in Section 2.3.

IG, and *IAR*—none directly involve clarification questions. *LIST* is the predominant method within these, and while it does not directly seek clarifications, it demonstrates that service staff have detected the ambiguous references in customer communications and are attempting to resolve the ambiguity in a non-questioning manner. Conversely, *IG* and *IAR* indicate a failure by service staff to accurately identify the ambiguity. Fortunately, occurrences of these latter two responses are infrequent in real-world scenarios.

4 What type of clarification questions do consumers prefer to receive?

In the last section, we explored the preferred response types to ambiguous references from the perspective of service staff. This section shifts focus to customer preferences regarding the responses they receive from service staff. We conducted a hybrid online and offline survey to analyze these preferences, utilizing the Tencent Questionnaire mini-app for creation and distribution. The survey was primarily distributed in the Guangxi region of China. A total of 413 questionnaires were issued, and all were returned with valid responses.

4.1 Questionnaire Design

The survey encompasses gathering basic information from participants and assessing their satisfaction with responses provided by service staff across various consumer settings. We designed 10 scenarios for this purpose, split evenly between online and offline, each offering three distinct responses from service staff for evaluation. This diverse scenario approach helps mitigate potential biases in ratings due to specific environmental or stylistic responses. The three response types assessed in-

	<i>LIST</i>		<i>CQ</i>		<i>LCQ</i>	
	Mean	Std	Mean	Std	Mean	Std
Both	4.048	0.94	3.492	1.04	4.059	0.93
Online	4.077	0.93	3.458	1.05	3.992	0.91
Offline	4.019	0.95	3.526	1.04	4.123	0.94

Table 3: Mean and Standard Deviation for Three Response Strategies: Detailed explanations of the strategies are provided in Section 2.3. ‘Both’ represent both online and offline.

clude *CQ*, *LIST*, and *LCQ*. While *LIST* is less frequently used, assessing *LIST* helps determine which aspects of the *LCQ* are most valuable to customers. Satisfaction ratings are captured on a 5-point Likert scale, ranging from 1 (strongly dislike) to 5 (strongly like), ensuring that preferences are accurately quantified. For detailed content of the questionnaire, see Appendix C.

4.2 Questionnaire Data Analysis

Table 3 shows customer satisfaction rating with three distinct response types from service staff across various scenarios. A key takeaway from Table 3 is that satisfaction with mere clarification questions is the lowest, even less than the satisfaction with listing potential options, which are infrequently used by service staff. Furthermore, satisfaction levels for *LIST* and *LCQ* are similar, both substantially higher than for mere clarification. This suggests that in responses incorporating both listing and clarification, the listing aspect is deemed more crucial than clarification. Additional evidence comes from online scenarios, where satisfaction with listing alone marginally surpasses that with *LCQ*. Consequently, it is apparent that consumers prefer service staff to explicitly and exhaustively outline all options.

We next performed a one-way analysis of variance (ANOVA) on the data from Table 3 to delve deeper into the satisfaction differences across various response types in different scenarios. Initially, we analyzed dialogues from both online and offline. The analysis revealed that for comparisons between *LIST* versus *CQ* and *LCQ* versus *CQ*, the resulting *p*-values were nearly zero. This led us to reject the null hypothesis of no significant differences, demonstrating notable satisfaction disparities among these response types. In contrast, the *p*-value between *LIST* and *LCQ* was 0.85, which did not warrant rejecting the null hypothesis, indicating no significant satisfaction differences be-

tween these two types of responses. Moreover, when comparing online to offline data, the p -values for *LIST*, *CQ*, and *LCQ* were 0.03, 0.05, and 0, respectively. These findings highlight significant variations in satisfaction rating between online and offline, emphasizing the necessity for tailored customer service dialogue designs for each scenario. This implies that strategies effective in offline settings may not necessarily translate well to online interactions, and vice versa. For a more detailed analysis, Appendix B categorizes the data by age and educational level.

4.3 Key Takeaways

Building on the analysis, we offer the following three key insights:

- While simple clarification questions can resolve ambiguous references, they are not the most effective approach.
- Listing combined with clarification stands out as the best strategy for dealing with ambiguous references.
- Businesses can effectively resolve customer ambiguities by combining the listing of potential choices with actions like suggesting new releases, which typically maintains high levels of customer satisfaction.

5 Conclusion

This study analyzed service staff responses to ambiguous references using data from 1,000 customer interactions and feedback from 413 customer questionnaires. The results show that while simple clarification questions resolve ambiguities, they do not achieve high customer satisfaction. In contrast, strategies combining listing with clarification questions or others increase customer satisfaction. Future research should continue to analyze our dataset to develop more sophisticated responses that could outperform those by human service staff.

6 Limitation

This research is confined to a Chinese-language dialogue dataset, with the analysis restricted to surveys conducted within China. Consequently, the findings may not be directly applicable to other linguistic contexts. Furthermore, the relatively small sample of participants over the age of 65 in our questionnaire might not accurately reflect the broader opinions of this demographic.

7 Acknowledgements

We thank the anonymous reviewers for their helpful comments. Yujian Gan, Matthew Purver and Massimo Poesio acknowledge financial support from the UK EPSRC under grant EP/W001632/1, and Purver also from the EPSRC under grant EP/S033564/1 and from the Slovenian Research Agency (ARRS) core research programme Knowledge Technologies (P2-0103).

References

- Saeid Amiri, Sujay Bajracharya, Cihangir Goktolga, Jesse Thomason, and Shiqi Zhang. 2019. [Augmenting knowledge through statistical, goal-oriented human-robot dialog](#).
- Negar Arabzadeh, Mahsa Seifkar, and Charles L. A. Clarke. 2022. [Unsupervised question clarity prediction through retrieved item coherency](#).
- Marco De Boni and Suresh Manandhar. 2005. [Implementing clarification dialogues in open domain question answering](#). *Natural Language Engineering*, 11:343–361.
- Yang Deng, Lizi Liao, Liang Chen, Hongru Wang, Wenqiang Lei, and Tat-Seng Chua. 2023. [Prompting and evaluating large language models for proactive dialogues: Clarification, target-guided, and non-collaboration](#).
- Kaustubh D Dhole. 2020. [Resolving intent ambiguities by retrieving discriminative clarifying questions](#).
- Claudia Eckert, Martin Stacey, and Christopher Earl. 2003. [Ambiguity is a double-edged sword: similarity references in communication](#). In *Proceedings of the 14th international conference on engineering design*.
- Yue Feng, Hossein A. Rahmani, Aldo Lipani, and Emine Yilmaz. 2023. [Towards asking clarification questions for information seeking on task-oriented dialogues](#).
- Jonathan Ginzburg. 2012. *The Interactive Stance: Meaning for Conversation*.
- Ryan Blake Jackson and Tom Williams. 2020. [Enabling morally sensitive robotic clarification requests](#).
- Hadrien Lautraite, Nada Naji, Louis Marceau, Marc Queudot, and Eric Charton. 2021. [Multi-stage clarification in conversational ai: The case of question-answering dialogue systems](#).
- Alex Liu, Rose Sloan, Mei-Vern Then, Svetlana Stoyanchev, Julia Hirschberg, and Elizabeth Shriberg. 2014. [Detecting inappropriate clarification requests in spoken dialogue systems](#).

- Bodhisattwa Prasad Majumder, Sudha Rao, Michel Galley, and Julian McAuley. 2021. [Ask what’s missing and what’s useful: Improving clarification question generation using global knowledge.](#)
- Matthew Marge and Alexander I Rudnicky. 2019. Miscommunication detection and recovery in situated human–robot dialogue. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 9(1):1–40.
- Matthew Purver. 2004a. The theory and use of clarification requests in dialogue.
- Matthew Purver, Jonathan Ginzburg, and Patrick G T Healey. 2001. [On the means for clarification in dialogue.](#) *Proceedings of the Second SIGdial Workshop on Discourse and Dialogue* -.
- Matthew Richard John Purver. 2004b. *The theory and use of clarification requests in dialogue.* Ph.D. thesis, University of London King’s College.
- Verena Rieser and Johanna Moore. 2005. Implications for generating clarification requests in task-oriented dialogues. In *Proceedings of the 43rd Annual Meeting of the ACL*, pages 239–246, Ann Arbor.
- Kepa Rodríguez and David Schlangen. 2004. Form, intonation and function of clarification requests in German task-oriented spoken dialogues. In *Proceedings of the 8th Workshop on the Semantics and Pragmatics of Dialogue (Catalog)*, pages 101–108, Barcelona.
- Alberto Testoni and Raquel Fernández. 2024. [Asking the right question at the right time: Human and model uncertainty guidance to ask clarification questions.](#)
- Tom Williams, Fereshta Yazdani, Prasanth Suresh, Matthias Scheutz, and Michael Beetz. 2019. Dempster-shafer theoretic resolution of referential ambiguity. *Autonomous Robots*, 43:389–414.
- J Wyatt. 2005. Planning clarification questions to resolve ambiguous references to objects. In *Proceedings of the 4th IJCAI workshop on knowledge and reasoning in practical dialogue systems, Edinburgh, Scotland*, pages 16–23.
- Michael J. Q. Zhang and Eunsol Choi. 2023. [Clarify when necessary: Resolving ambiguity through interaction with lms.](#)

A Relate Work

A.1 Ambiguous Reference

Researchers are interested in conversational agents facing the challenge of ambiguous reference (Eckert et al., 2003). For instance, Wyatt (2005) aims to design robots capable of engaging in task-directed conversations with humans about ambiguous references in tabletop scenes. Marge and Rudnicky (2019) presents a method for robustly handling miscommunication between people and robots in task-oriented dialogues, supporting the detection and

recovery from situated grounding problems related to referential ambiguity and impossible actions. Williams et al. (2019) initially provides recommendations for designers of robots that need to generate such requests and further demonstrates that a Dempster-Shafer reasoning component, when combined with probabilistic reference resolution, can address both pragmatic and referential uncertainties.

A.2 Clarification Questions in Dialogues

The generation of clarification questions is vital in dialogue system research, enhancing system accuracy and user experience. Literature in this area covers various aspects: optimal timing for posing questions, task-oriented models for different scenarios, and ethical frameworks for clarification.

Arabzadeh et al. (2022) introduced an unsupervised learning method for predicting when to pose clarification questions based on retrieval item consistency and contextual similarity, showing superior generalization over neural network methods. Feng et al. (2023) developed a multi-attention sequence-to-sequence model that integrates contextual information and task knowledge to improve the specificity and accuracy of clarification questions in task-oriented dialogue systems. Further, Amiri et al. (2019) combined semantic parsing with probabilistic dialogue management to enhance knowledge base quality and human-robot interaction by generating goal-oriented clarification questions. Meanwhile, Jackson and Williams (2020) introduced a moral reasoning strategy in robots to ensure ethical responses when initiating clarification questions, integrating a moral assessment module into the robot architecture. In large language model applications, Deng et al. (2023) implemented the Proactive Chain-of-Thought (ProCoT) scheme to augment goal planning in reasoning chains, significantly improving the handling of clarification and goal-oriented questions.

B Further Analyzing Questionnaire Data

In addition to overall lower satisfaction with *CQ* than with *LIST* and *LCQ*, *CQ* consistently ranks below both in satisfaction across all ten consumer scenarios in the questionnaire. Satisfaction levels between *LIST* and *LCQ* fluctuate. *LIST* occasionally achieves slightly higher satisfaction than *LCQ*, particularly in online scenarios, similar to the general trend in Table 3.

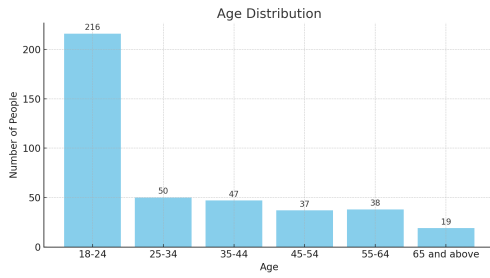


Figure 2: Age Distribution of Questionnaire Respondents

Figure 2 displays the age distribution of survey participants, predominantly ranging from 18 to 24 years old. Upon segmenting participants by age, it becomes apparent that all groups express the lowest satisfaction with *CQ*. Older participants increasingly favor *LCQ*, with satisfaction for *LIST* nearly as high. Distinctly, those aged 65 and above, while also least satisfied with *CQ*, perceive less difference between *CQ* and *LIST* responses compared to other age groups, showing almost no preference between these response types.

We performed analogous analyses based on gender and educational levels, revealing that irrespective of gender or educational classification, respondents showed a marked preference for *LIST* and *LCQ*, consistently *CQ* the lowest. Besides, females tended to rate responses higher than males across the board. Furthermore, there was a clear trend of increasing satisfaction with all three response types as educational attainment rose.

C Questionnaire

Questionnaire

01 Required Your age: (single choice)
Under 18, 18-24, 25-34, 35-44, 45-54, 55-64, 65 and above

02 Required Your gender: (single choice) Male, Female

03 Required Your education level: (single choice)
Middle school and below, High school or vocational school, Associate degree and undergraduate, Master's degree and above

04 Required Your occupation: (single choice)
Student, Educator, IT Industry, Healthcare, Government Agency, Freelancer, Retired, Farmer, Public Institution, Enterprise, Other

Score 1 to 5: 1 - Very dissatisfied, 2 - Dissatisfied, 3 - Neutral, 4 - Satisfied, 5 - Very satisfied

05 Required: Assume you are at a breakfast shop and want to buy a char siu bao.
You say, "I want to buy a bun." Please rate the following responses from different salespeople:
A: "What kind of bun would you like?"
B: "We have meat bun, char siu bao, red bean paste bun, and three delicacies bun. Which one would you like?"
C: "We currently have meat bun, char siu bao, red bean paste bun, and three delicacies bun."

06 Required: Assume you are at a cake shop and want to buy a cheese cake.
You say, "I want to buy a cake." Please rate the following responses from different salespeople:
A: "Hello, we have three flavors: original, cheese, and taro. You can choose any."
B: "Hello, what kind of cake would you like?"
C: "Hello, we currently offer signature original cake, cheese cake, and taro cake. Which one would you like?"

07 Required: Assume you are at a department store and want to buy an oil-control shampoo.
You say, "I want to buy a shampoo." Please rate the following responses from different salespeople:
A: "Hello, what effect do you need from the shampoo?"
B: "Hello, we currently have shampoos with oil control, smoothing, and color protection effects. These three are very popular."
C: "Hello, we have shampoos mainly for oil control, smoothing, and color protection. Which one would you like?"

08 Required: Assume you are at a yogurt drink shop and want to buy a strawberry yogurt.
You say, "I want to buy a cup of yogurt." Please rate the following responses from different salespeople:
A: "Our peach, strawberry, and avocado flavored yogurts are very popular. You can choose any."
B: "Our signature flavors are peach yogurt, strawberry yogurt, and avocado yogurt. Which flavor would you like?"
C: "What kind of yogurt would you like?"

The questions 9 and 10 are omitted here...

11 Required: Assume you are consulting an online customer service representative and want to buy a 20-inch suitcase.
You say, "I want to buy a suitcase." Rate the responses from different CSRs:
A: "We have suitcases in various sizes: [18-inch Link] [20-inch Link] [22-inch Link] [24-inch Link]. Which one would you like?"
B: "Our store has 18-inch, 20-inch, 22-inch, and 24-inch suitcases.
For more details and to order, please click: [18-inch Link] [20-inch Link] [22-inch Link] [24-inch Link]."
C: "What size of suitcase would you like?"

12 Required: Assume you are consulting an online customer service representative and want to buy a double-door refrigerator.
You say, "I want to buy a refrigerator." Rate the responses from different CSRs:
A: "Hello, we have French four-door, double-door, and T-type three-door refrigerators.
For more details and to order, please click: [French Four-door Link] [Double-door Link] [T-type Three-door Link]."
B: "Hello, we have these three types of refrigerators: [French Four-door Link] [Double-door Link] [T-type Three-door Link]. Which one would you like?"
Customer Service C: "Hello, what type of refrigerator would you like?"

13 Required: Assume you are consulting an online customer service representative and want to buy a Y brand facial cleanser.
You say, "I want to buy a facial cleanser." Rate the responses from different CSRs:
A: "Hello, what brand of facial cleanser would you like?"
B: "Hello, our store has R brand, T brand, and Y brand facial cleansers.
For more details and to order, please click: [R Brand Link] [T Brand Link] [Y Brand Link]."
C: "Hello, our store has [R Brand Link] [T Brand Link] [Y Brand Link] facial cleansers.
Which one would you like?"

14 Required: Assume you are consulting an online customer service representative and want to buy an M brand hair dryer.
You say, "I want to buy a hair dryer." Rate the responses from different CSRs:
A: "Hello, our store has [M Brand Link] [H Brand Link] [P Brand Link] hair dryers.
Which one would you like?"
B: "Hello, what brand of hair dryer would you like?"
C: "Hello, our store offers M brand, H brand, and P brand hair dryers.
For more details and to order, please click: [M Brand Link] [H Brand Link] [P Brand Link]."

Figure 3: Survey Questionnaire on Customer Preferences for Response Styles.