Beyond Stars: Enriching Restaurant Reviews with Interactive Follow-Up Analysis

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***Abstract*—This paper proposes a follow-up interaction system designed to enhance restaurant reviews and evaluates its effectiveness through empirical analysis. Restaurant reviews serve as a critical source of information for customers when selecting dining options and significantly influence a restaurant's reputation and patronage. However, many reviews are missing some points to be reviewed, often omitting important aspects of the dining experience. To address this issue, this study introduces a system leveraging ChatGPT to identify missing elements in reviews and prompt reviewers to include them through follow-up interactions, thereby enriching the content of reviews. The experiment observed participants as they refined their reviews using the system's feedback. We analyzed the originally described elements, the system-identified absent elements, and the elements added after follow-up interactions. The results demonstrated that follow-up interactions effectively increased the amount of information in reviews and ensured a comprehensive coverage of multiple perspectives, including food, restaurant environment, and reviewer experiences. Additionally, we conducted statistical analyses to examine co-occurrence patterns between review elements and assess the fairness of the system's suggestions for absent elements. The findings highlighted the potential of this system to improve the quality of user-generated content. We believe that it would enable consumers to access detailed and reliable reviews while providing restaurants with actionable customer feedback to enhance their services.**

***Keywords*-Follow-up interaction; computational approach for food and eating activities; Large Language Model-supported system.**

I. Introduction

When selecting a restaurant from numerous options, customers frequently refer to restaurant reviews posted on websites. These reviews directly reflect the experiences and impressions of reviewers who have actually visited the restaurants. The review is a precious source of restaurant information for customers. If reviewers themselves can enrich their reviews, the information can be helpful for both restaurants and customers. Previous work showed this concept of this idea and the result of primary analysis in reviewing restaurants [1]. This paper analyzes a more comprehensive evaluation of the system's effectiveness and provides deeper insights into the implications of follow-up interactions. Moreover, we will discuss the potential applications of the proposed system in practical settings in detail.

Reviews significantly influence customers' impressions of restaurants before their visit, and the content of these reviews can greatly affect the restaurant's patronage [2]. Restaurants undertake various approaches to attract customers through reviews: offering the first drink, a plate of desserts, and optional services for free, such as writing a review or posting photos and videos with some specific tags.

Restaurants try to attract customers through some initiatives. Let us consider that the handled content differs between writing reviews and posting tagged photos and videos. Reviews primarily deal with text, while photos and videos mainly involve visuals and sounds. The text in reviews can detail various aspects of the experience in the restaurant. The reviews can tell not only the taste, smell, and texture of the food but also the ambiance and environment of the restaurant, its location, and the attitude of the staff. Moreover, they sometimes provide the circumstances leading up to the reviewer's visit and individual events for each reviewer in the restaurant. These types of information are helpful for customers to select a restaurant. Luca's research underscores the significance of user-generated content and examines how reviews influence consumer decision-making [3]. This study has revealed that a one-star increase in the average rating of a review could boost the revenue of independent restaurants by 5-9%. Additionally, it has been noted that restaurants with a higher number of reviews were generally perceived as more reliable by customers. Göral has identified four primary reasons why customers read reviews [4]: "risk reduction," "search time reduction," "avoidance of buyer's remorse," and "group influence." Moreover, Göral has highlighted that reviews allowed restaurants to track customer opinions, as providing a substantial benefit to the establishments. These related studies have collectively demonstrated that reviews are beneficial both to customers and restaurants. On the other hand, photos and videos may not offer as much detailed information as reviews. They can provide attractive and impressive visual information, e.g., the appealing appearance of food [5], and customers' facial expressions after eating. To attract customers through visually appealing content, restaurants have been making various efforts to make their dishes look more appetizing.

Reviews are potentially able to provide much valuable information for customers, but most of them do not provide sufficient details about the restaurant. Just one word like "good" or "bad" can not be a source to be referred to. Accordingly, so many customers focus on photos and videos, and then restaurants emphasize visual and sound content as an advertisement. It is not too much to say that this trend ignores something that can not be recorded in photos and videos. If the review can be improved as its potential, the customers can receive more information for aspects not shown in photos and videos, e.g., smells of coffee and the kindness of staff. We thus investigate the following research questions;

RQ 1 What memory challenges do customers face when detailing a restaurant?
RQ 2 What types of information can be missed in reviews?
RQ 3 Does the follow-up interaction enrich the description in reviews?

In this paper, we ask reviewers to describe their dining experience twice. From the investigation, we study what they remember and what is easy to describe from different perspectives. When reviewing a dining experience, the memories the reviewer recalls are not text but sensory information from their senses: visual, auditory, olfactory, gustatory, and tactile inputs. For RQ 1, this study explores how reviewers verbalize and express these memories in text, what information is easier or harder to recall, and what information can be expressed in text but not in photos or videos, and vice versa. By clarifying these aspects, we aim to understand the trends in review writing and consider how to enrich the content of reviews based on these findings. To investigate RQ 2 and RQ 3, we prepare the follow-up system introducing ChatGPT. As a review is input, the system identifies aspects that exist and do not exist in the review. The system shows the follow-up question to encourage reviewers to detail the missed aspects in mind. The aspects in the original and revised reviews are comparatively analyzed. Then, we consider the effectiveness of follow-up interaction in enriching reviews. The organization of this paper is as follows: Section II will provide an overview of related work, summarizing existing studies on restaurant reviews and follow-up interactions. Section III will present this research's basic idea, explaining the follow-up system's background and objectives. Section IV will detail the proposed method, describing the mechanism of the follow-up interaction in depth. Section V will outline the experimental settings and data collection methods to ensure the reproducibility of the study. Section VI will present and analyze the experimental results, discussing the findings in detail. Finally, Section VII will conclude the study and discuss future challenges and directions.

II. Related Work

Restaurants can be classified into numerous segments, with criteria: the level and quality of service, customer participation in the dining experience, price, quality of food, and ambiance [6]–[9]. Based on these criteria, restaurants can be categorized into fast food, casual dining, fine dining, and business food service. There are many elements unique to each segment, while common elements (e.g., accessibility, menu diversity, and a certain level of cleanliness) exist across the segments. Existing papers discussed which restaurant segment can meet customer expectations and what elements enhance customer satisfaction [10]–[12]. These studies have shown that casual dining restaurants adequately meet customer expectations, and the quality of food and restaurant services significantly impacts customer expectations. It has also been confirmed that the price of food affects customer satisfaction, especially in fast food and casual dining restaurants [13], [14].

Let us focus on the unique elements of each restaurant segment. It is evident that aspects like food quality, restaurant service, and price are crucial elements for relatively low-priced dining options. These elements are related to the customer's dining experience and their overall experience in the restaurant. There are many studies that have used different aspects necessary for customer satisfaction in reviews, extracting various evaluations of restaurants from reviews [15]–[20]. These studies have enabled the automatic evaluation of restaurants based on reviews and feature extraction. They analyzed elements necessary for customer satisfaction in restaurants from various points of view.

However, these studies do not enrich the content of reviews to enhance the customer experience. We can find many papers analyzing restaurant reviews in various ways. Jurafsky et al. have identified four key aspects commonly found in reviews: food quality, service, ambiance, and price [21]. Their study has highlighted that these aspects are the most critical factors for customers when evaluating restaurants. Additionally, Rita et al. have explored how these four aspects are treated within reviews, revealing the impact of Michelin star ratings on customer emotions by comparing reviews before and after the acquisition of stars [22]. Yan et al. have further examined how these four aspects influence consumer satisfaction and the intention to revisit [23]. Some studies have proposed analytical methods for analyzing restaurant reviews while conducting the analysis. Xue et al. have developed a neural network-based approach that simultaneously classifies aspect categories and extracts aspect terms from restaurant reviews [24]. Lohith et al. have utilized Latent Dirichlet Allocation (LDA) and Bidirectional Encoder Representations from Transformers (BERT) for aspect extraction and sentiment analysis in restaurant reviews [25].

Despite these advancements, existing studies have primarily focused on extracting and analyzing review elements rather than improving the content of the reviews themselves. While significant progress has been made in understanding customer satisfaction and behavior through reviews, a gap has remained in enhancing the depth and completeness of reviews to capture the dining experience better. This gap is significant, as reviews are critical resources for both consumers and restaurants. However, they often lack sufficient detail to be truly informative. By addressing this limitation, our research aims to enrich the descriptive quality of reviews through follow-up interactions. We advance the state-of-the-art in review analysis and content generation to fill the void left by prior studies. The aspects extracted from restaurant reviews in previous studies will be comprehensively covered in Section IV-A. In addition to these previously studied aspects, this paper includes specific aspects frequently observed in Japanese restaurant reviews, as identified by the authors through independent analysis of dining review websites.

III. Basic Idea

This study analyzes 1) what aspects are likely to be described in reviews, 2) in what order they are typically described, and 3) what content is recalled through follow-up interaction. It aims to identify points that satisfy customers and encourage them to write reviews, enriching customer experiences and restaurant management strategies. Furthermore, by identifying the elements customers look for in restaurants from reviews.

The proposed system introduces ChatGPT to point out missing elements in reviews. Many studies have explored the use of conversational generative Artificial Intelligence (AI), mainly focusing on interactive prompt-feedback loops. In these systems, users input prompts, receive AI-generated feedback, and interactively refine their prompts based on the feedback received. This iterative loop continues until the final output aligns with the user's intentions. Such interactive systems not only assist users in precisely articulating their intent but also enhance comprehension and communication of data. These systems have been successfully applied to improve writing clarity, generate creative content, and provide detailed explanations in various contexts. The iterative refinement process ensures that the AI-generated content meets users' specific needs and expectations, demonstrating the versatility and power of these tools in diverse applications. This paper investigates the effectiveness of follow-up interaction in enriching the content of reviews, making them more comprehensive and informative.

The proposed approach utilizes ChatGPT, a leading conversational AI, to identify and address missing elements in restaurant reviews. This study explores the impact of follow-up interactions on making reviews more detailed and informative. Our approach, which incorporates ChatGPT, leverages the latest advancements in AI technology. It demonstrates how interactive systems can enhance user-generated content. The system provides users with specific feedback, guiding them to refine and enrich their reviews. This innovative approach ensures that the reviews are comprehensive and meet the needs of potential customers. Our work exemplifies the practical applications of advanced AI technologies, highlighting their transformative potential in optimizing the generation and effective utilization of user feedback within real-world contexts.

In the following subsections, we will describe preliminary knowledge for this paper. The background for writing and reading reviews would justify the concept of the proposed method.

A. The Role of Reviews for Consumers and Restaurants

As mentioned in Section II, reviews are not merely a collection of subjective customer opinions; they serve as a critical source of information that influences other consumers' decisions. Reviews, particularly in restaurants, attract new customers and significantly encourage repeat visits from existing patrons. Positive reviews function as an effective form of advertising, enhancing the restaurant's reputation, though negative reviews may deter potential customers, thereby impacting the business's operations. Reviews thus hold substantial importance in a restaurant's marketing strategy and overall success.

Additionally, reviews are invaluable in helping consumers identify dining establishments that align with their preferences and expectations, reducing the risks associated with trying new places. Reviews, therefore, directly affect both the perception and success of restaurants.

B. Perspectives Present or Absent in the Review

Restaurant reviews typically cover several essential aspects, including food quality, service, ambiance, and pricing, as described in Section II. These categories, which are detailed in Table I, help consumers evaluate a restaurant and make decisions regarding whether to dine there. However, it is relatively uncommon for all of these aspects to be addressed thoroughly in a single review. Many reviews tend to focus heavily on just one or two elements, while other essential details are left out. For instance, a reviewer might discuss the quality of the food in great detail, describing flavors, portion sizes, and the arrangement of the dishes. However, he/she might neglect to mention the level of service they received or the restaurant's atmosphere. In some other cases, reviewers focus on secondary details, such as the appearance of the restaurant's exterior, its interior decor, or special events happening at the time of their visit –like a Christmas fair or a Japanese food festival. While these details may be interesting, they often come at the expense of addressing the core elements that most readers are looking for, such as the food itself or how well the staff treated them during their visit.

One main reason for these omissions is that most reviews are written in an unstructured, free-form style. Reviewers freely write whatever stands out to them without needing to follow any specific format. Though this flexibility allows for more personalized reviews, it also means that important aspects of the dining experience might be unintentionally left out. Without a set structure guiding the content, reviewers might skip over crucial details that would otherwise be valuable to readers and restaurant owners alike.

C. The Need for Enriched Review Content through Follow-up Interaction

To relieve the issue of incomplete reviews, this study introduces a system that leverages conversational AI, specifically ChatGPT, to facilitate follow-up interactions. These interactions are designed to prompt reviewers to consider and include overlooked aspects by enhancing the comprehensiveness of the reviews. The proposed system benefits restaurants by providing them with more accurate and useful feedback. It also helps consumers make more informed decisions and ensures that reviews are more detailed and multi-faceted. Moreover, enriched reviews generated through this iterative process increase the trustworthiness and persuasiveness of the content. It is supposed to offer superior value to future customers seeking reliable information and businesses aiming to improve based on detailed feedback. The iterative nature of follow-up interactions ensures that the generated content aligns closely with the reviewer's intent and the readership's needs by making the reviews more relevant and actionable.

The proposed approach highlights the importance of follow-up interactions in the review process. By addressing missing

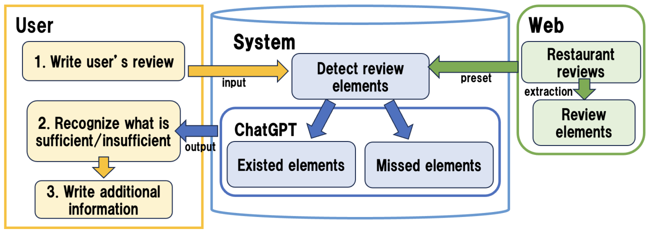

Figure 1: The framework and interaction of the proposed system. The system incorporates ChatGPT to learn from review elements extracted from reviews. It identifies review elements contained within reviews, categorizing them into existing elements and missed elements. Users input their original reviews into the system, and then they recognize the existing and missed elements based on the feedback. Subsequently, users input additional reviews as taking into account suggestions from the system.

TABLE I: The review elements contained in restaurant reviews. Each element is assigned an index. The review elements are organized from three perspectives: food, restaurant, and reviewer. These elements are based on a specific Japanese restaurant review site.

ID	Food	ID	Restaurant	ID	Reviewer
1	taste	8	place	16	when
2	texture	9	budget/price	17	who
3	appearance	10	interior/decoration	18	why
4	smell	11	staff	19	feeling
5	ingredients	12	customer	20	event
6	volume	13	season	21	user age
7	food combination	14	history of store	22	hunger level
		15	limited event	23	satisfaction

elements in user reviews, the quality of the content may be significantly improved. This result benefits future customers, who gain access to more accurate and detailed information when making decisions. These benefits are practical for the businesses themselves as well. Businesses can leverage these enriched reviews to better understand customer feedback, make targeted improvements, and enhance their marketing efforts.

IV. Proposed Method

Figure 1 shows the framework of the proposed system and its interaction. In Section IV, we developed a system to detect existing/absent elements in reviews and to enrich reviews through follow-up interaction. The review elements are preset to ChatGPT with prompt engineering.

A. Elements in Restaurant Reviews

This paper defines the elements in restaurant reviews as encompassing all aspects related to dining; we consider that the experience of dining out includes before and after visiting the restaurant itself. To empirically extract these elements, the first author conducted a systematic survey of restaurant reviews on a popular dining website [26].

This involved analyzing a diverse range of reviews to identify common themes and descriptors used by customers. The extracted elements reflect the holistic dining experience and are represented in Table I, which are presets in the proposed system. For analytical clarity, these elements were categorized into three perspectives: food, the restaurant's environment, and the reviewer's experience. This categorization was based on the frequency and significance of mentions in the reviews, allowing us to distill the most impactful aspects of the dining experience as perceived by customers.

Note that the elements were heuristically selected for this paper. It is not crucial to the goal of our study, which is to investigate the effectiveness of follow-up interaction in enriching reviews. Although, the data-driven approach to preparing the elements will be our future work.

B. Follow-up Interaction with ChatGPT

The system introduces ChatGPT as a conversational model of Large Language Models: LLM.

We set the following prompts to ChatGPT;

[PROCEDURES]

Please assist in creating a restaurant review. Follow the steps outlined below to provide support in writing restaurant reviews.

1) Inform the participants by saying, "Please enter your review."
2) Have the participants input their review.
3) Detect which elements of the review are present based on the input of participants, identifying which of the following categories each element belongs to: {about the food}, {about the environment}, {about the reviewer}.
4) Briefly communicate to the participants the detected elements from their review.
5) Inform the participants of any missing elements, ensuring that there are at least three elements mentioned in the review under each category {about the food}, {about the environment}, {about the reviewer}.

The elements of restaurant reviews described in Section IV-A are preset to ChatGPT. We conducted prompt engineering for ChatGPT to detect existing and absent elements from an input review. When participants input their dining experiences at a restaurant, the system identifies which elements exist in the review. The system represents all elements included in a review for each perspective. Also, the system represents more than three absent elements for each perspective if the review does not include all of the elements in Table I completely. After representing these, the system suggests that the reviewer should add the absent elements to enrich the review comprehensively. Note, users may add any descriptions other than absent elements suggested by the system.

We observed how the system works through test cases in advance. Reviews randomly selected from a website were input into the proposed system. It was confirmed that the proposed system successfully identified some existing and absent elements in nine reviews out of ten reviews. One error case only represented existing elements but did not show absent elements as a suggestion. For such error cases, the proposed system could represent correct absent elements as the experimenter additionally prompted “detect the absent elements” as a problem solver. Therefore, we decided to constantly monitor the interaction in the experiment and appropriately prompt the problem solver if the system would unexpectedly work.

V. Experimental Settings

In Section V, using the proposed system described in Section IV, we experimented with writing restaurant reviews. The reviews written by participants and their interaction with the proposed system were analyzed from various points of view.

A. Procedures

The experiment was conducted in three steps, shown in Figure 1. The procedures of the experiment were as follows;

1) Each individual participant had a dining experience.
2) The participant wrote a review about his/her dining experience and took the feedback from the proposed system.
3) The participant wrote additional information to enrich the description in the review according to the system’s suggestions.

We studied the reviews written by the participants for each element and perspective based on the profiles of the participants.

B. Participant Profiles

A profile survey was conducted on 26 participants before writing the review and interacting with ChatGPT. The survey included six items: the participant’s age, gender, experience with writing reviews, the timing of the dining experience mentioned in the review, the amount paid at the restaurant, and the timezone of the dining experience. These participant profiles were designed with reference to the reviewer profiles on Tabelog [26], a popular restaurant review site in Japan. Table II shows the profile survey of participants.

In our experiment, the survey investigated the degree of familiarity with writing reviews in addition to basic information about the participants. We asked whether or never the participants had written reviews regularly or spontaneously for some exogenous incentives (e.g., for a reward). This survey aimed to clarify whether familiarity with writing reviews leads to differences in the review aspects focused on. The survey on the timing of the dining experience mentioned in the review was designed with four options: within one week, two weeks, three weeks, and four weeks. This questionnaire would clarify whether the elapsed time since the dining experience influenced the review aspects focused on. The survey on the amount paid at the restaurant was conducted with four options: below 2,000 JPY, between 2,001 and 4,000 JPY, between 4,001 and 6,000 JPY, and above 6,000 JPY. This questionnaire was prepared to study whether there was a relationship between the amount paid and the review aspects focused on. The survey on the timezone of the dining experience had three options: morning, noon, and evening. We used the result of this survey to clarify whether there was a relationship between the timezone and the review aspects focused on.

VI. Results

Table III shows the results of the experiment. In the table, for each participant, originally described elements, originally absent elements suggested by the system, and added elements by follow-up interaction are listed as the index of review elements. This table represents what each participant included in their restaurant reviews and in what order. Figure 2 statistically summarizes the review elements input by participants as described in Table III, categorized by the IDs explained in Table I. Figure 3 presents the statistical summary of the “originally absent elements suggested by the system” from Table III, highlighting the review elements that participants were prompted to add during the follow-up interaction. This figure illustrates the frequency with which the system pointed out each review element as missing. In Section VI, we study the overall review elements through the interactions. Moreover, we focus on the participants’ profiles, the timing of the dining experience, and the amount paid to consider the interaction of writing reviews with follow-up interaction more deeply.

A. Discussions for Review Elements through Follow-up Interactions

This section studies the overall results of the experiment. We focus on the trends in originally described elements, originally absent elements suggested by the system, and added elements by follow-up interaction. It was confirmed that food, restaurant, and reviewers were all described in the originally described and added elements in the reviews. Moreover, through follow-up interaction, the users added not only the suggested elements but also other elements. From these results, the follow-up interaction provided by the proposed system helped reviewers enrich their reviews as informative and comprehensive. These results follow RQ 1, RQ 2 and RQ 3.

Comparing the summary statistics in Figure 2 and Figure 3 suggested the effectiveness of the system. Specifically, when we compare the originally described elements with the originally absent elements suggested by the system, it is evident that certain review elements (such as those with IDs 3, 8, 10, 11, and 17) were frequently missed in the original reviews and were consistently highlighted by the system as absent. This demonstrates that the system effectively fulfilled its role in identifying and suggesting absent elements, confirming its proper functioning. Additionally, the lack of significant bias or trend in the elements the system identified suggests that it treated all review elements fairly. However, we also noticed that elements with IDs like 1 and 19, which were already commonly included in the original reviews, were also flagged by the system. This indicates a redundancy in the system’s feedback, highlighting an area that requires improvement to make the system more efficient.

TABLE II: This table represents the profiles of the participants. The leftmost column displays the participant ID. The profile information includes age, gender, experience writing restaurant reviews, the timing of the reviews mentioned, dining budget (in Japanese Yen), and the time of day the dining experience occurred. These participant profiles are based on reviewer information from Tabelog, a Japanese restaurant review site.

ID	Age	gender	Experience	When	Budget(JPY)	Timezone
1	21	M	Voluntary	1 week ago	1-2,000	Evening
2	21	M	No experienced	4 weeks ago	4,001-6,000	Evening
3	20	M	No experienced	1 week ago	1-2,000	Evening
4	22	F	Voluntary	4 weeks ago	2001-4,000	Evening
5	22	F	Exogenous	1 week ago	1-2,000	Daytime
6	20	M	No experienced	3 weeks ago	2001-4,000	Evening
7	20	M	No experienced	2 weeks ago	1-2,000	Evening
8	20	M	Exogenous	1 week ago	1-2,000	Daytime
9	20	M	No experienced	1 week ago	1-2,000	Evening
10	19	M	No experienced	1 week ago	1-2,000	Evening
11	20	M	No experienced	1 week ago	1-2,000	Evening
12	20	M	No experienced	1 week ago	1-2,000	Evening
13	20	M	No experienced	4 weeks ago	1-2,000	Evening
14	20	M	No experienced	1 week ago	2,001-4,000	Evening
15	24	F	No experienced	1 week ago	1-2,000	Evening
16	21	M	No experienced	1 week ago	1-2,000	Daytime
17	23	M	Exogenous	1 week ago	1-2,000	Evening
18	51	F	Exogenous	4 weeks ago	1-2,000	Evening
19	21	M	No experienced	3 weeks ago	1-2,000	Evening
20	22	M	No experienced	1 week ago	1-2,000	Daytime
21	22	M	No experienced	1 week ago	1-2,000	Daytime
22	23	M	No experienced	1 week ago	2,001-4,000	Evening
23	23	M	No experienced	1 week ago	2,001-4,000	Evening
24	22	M	Voluntary	1 week ago	6,001-	Evening
25	22	M	No experienced	1 week ago	1-2,000	Evening
26	24	F	Exogenous	2 weeks ago	2,001-4,000	Evening

Let us compare the added elements following the follow-up interaction with the originally absent elements suggested by the system. The comparison results suggest that participants actively incorporated the suggested absent elements into their reviews. This further underscores the effectiveness of the follow-up interaction in enriching the review content.

Throughout both originally described and added elements, it was confirmed that there were highly co-occurred elements: taste and texture, taste and ingredients, and taste and food pairing. The frequent co-occurrence of these elements suggested a natural inclination among reviewers to link sensory experiences when describing their dining experiences. This might reflect the expectations of the audience, who likely rely on these descriptions to imagine the food more vividly. Co-occurrence of taste and texture happened in reviews listing the characteristics of the dish. This co-occurrence revealed that when reviewers discuss the texture of a dish, they almost always relate it back to the taste. That is to say, it suggested that these two elements are deeply interconnected in the diner's experience. It is believed that texture, which can enhance or diminish the taste, often determines the satisfaction level of the dining experience. Therefore, the frequent mention of these co-occurrences underlines their importance in restaurant reviews. For co-occurrences of taste and ingredients, Reviews explaining ingredients in the dish and what taste the ingredients had included the co-occurrence of taste and ingredients. Pairing of taste with ingredients further emphasizes the detailed nature of the reviews in general. When reviewers discuss specific ingredients, they tend to describe how these ingredients contributed to the overall flavor profile of the dish. This suggested that readers of such reviews might be particularly interested in understanding what a dish contains and how each component contributes to the dining experience. Taste and food pairing co-occurred in reviews describing the combinations of ordered dishes on that day, including combinations of their tastes. The frequent mention of taste and food pairing suggested that reviewers often considered the harmony of flavors between different dishes. This could indicate that the dining experience was often evaluated as a whole, where the interplay of different tastes across dishes contributes significantly to the overall satisfaction. This insight is crucial for restaurants as it highlights the importance of creating a cohesive menu where dishes complement each other.

The total number of elements throughout interactions indicated that taste-related elements were most frequent in both originally described and added reviews. Almost all reviews mentioned the taste of the food. It thus suggested that the taste was the easiest element to describe in reviews rather than others. This emphasis on taste may reflect a broader cultural or psychological tendency to prioritize flavor over other sensory experiences when discussing food. It may also point to the fact that taste is one of the most memorable aspects of a meal, which reviewers are eager to share with others. Many reviews started with a description of taste and went to others. From these results, there might be a common idea among reviewers that "restaurant reviews should have descriptions of taste."

TABLE III: This table represents the experimental results, including the originally reviewed elements they entered into the system, the absent elements output by the system as feedback, and the added elements that participants entered after receiving feedback. The colors in the table indicate different perspectives: blue for food, red for the restaurant, and orange for the reviewer. The far left column lists each participant's ID. The sequence of the numbers in the table corresponds to the order of review elements as they appear in the reviews and feedback.

Participant's ID	Originally described elements	Originally absent elements suggested by the system	Added elements by follow-up interaction
1	1 19 5 4	9 11 17	10 9 11 8 12 17 15
2	16 9 19 1	11 12 8	12 8
3	8 9 1 2 7 6 23 19	3 4 11 12 16 17 18	16 18 11
4	9 17 7 1	8 2 3 15 22	2 1
5	2 1 10 19	3 4 11 12 13 15 17 22 23	16 17 22 23 11
6	10 18 19 7	1 5 6 8 9	6 7 9 11 19
7	8 10 19 13 1 12	16 17 18 19 20	1 13 6 9 11 14 15 16 19 21
8	11 1 7 9	5 9 16 23	16 12 7 9
9	8 5 1	10 11 16 17	16 17 8 10 11
10	17 9 6 23 8 14 1 13 14 15	5 3 4 7 11	5 3 4
11	1 9 22 7	8 10 13 15	10 19
12	1 2 5 6 17 9 19	8 10	8 10
13	1	4 5 21 22 23	7 6 23
14	1	3 17 10 19	3 5 17 19
15	16 18	1 2 3 5 6 7 8 9 10	7 1 9 8 19 11
16	8 16 12 7 1 18 19	2 3 9 11 13 18 20 21	18 9
17	16 12 1 2 6 18 19	8 9 19 20	8 9
18	8 2 1 5 7 19 3 2 23	4 17 19	4 19 10 17 12
19	16 17 12 19 1	5 10 12 13 17	9 1 5 10 12 13
20	1 2 6	8 9 10 11 12 14 15 18 20 21	16 12 10 11 23
21	1 19	1 5 6 19	1 5 6 23
22	8 17 16 1 11 10	3 7 6 10 20 22 23	6 23 10
23	17 9 19 6 1	12 13 14 15	11 15 1
24	1 17 7 18 19	22 23 16	17 20 9 18 11 16
25	3 2 5 1 10 11 19	1 8 16	10 16 1
26	8 1 19	10 9 7	11 9

Starting with taste suggested that reviewers naturally saw it as the most important part of their experience, shaping the rest of the review. This approach could serve as a guiding principle for restaurants looking to improve their reviews. The taste of their dishes is consistently exceptional and may significantly enhance their overall ratings; our experimental data objectively shows that, though it is no surprise.

Focusing on elements only in the original descriptions, we found that reviews commonly included tastes and budget/price, i.e., elements related to foods. The frequent mention of budget/price and taste indicated that participants were concerned not only with the food's quality but also with its value for money. This could be especially relevant in settings where customers are particularly price-sensitive. Understanding this correlation can help restaurants better position their offerings to meet customer expectations. Such elements were easily described with reviewers' feelings before and after eating. The descriptions of reviews actually explained the taste and price in relation to the reviewer's feelings. These results suggested that taste and price were significant points when evaluating restaurants.

Let us focus on added elements after the proposed system suggested absent review elements in a review. The added reviews commonly include not only elements related to taste but also ones related to the restaurant's environment: place and budget/price. This shift towards including more environmental factors, such as place and budget/price, after receiving feedback suggested that these elements were often overlooked initially but yet crucial to the overall dining experience. Although the system did not suggest, reviewers additionally mentioned elements related to taste through the follow-up interaction. The spontaneous addition of taste-related elements, even when not prompted by the system, underscored the centrality of taste in reviewers' minds. This suggested that, regardless of the guidance provided, taste remains the most salient feature for most reviewers, likely due to its direct impact on their sensory experience. This result also supported the idea that reviewers emphasized taste-related elements in reviews. The consistent emphasis on taste-related elements reflected its dominant role in shaping the dining experience. This finding may guide future enhancements of the review system, which should focus more on effectively capturing and articulating these sensory experiences. We confirmed that elements concerning place were not commonly mentioned in originally described reviews, which were added after follow-up interaction. Moreover, added reviews included more elements related to staff and interior/decoration. The results showed the elements concerning the restaurant were increased after follow-up interactions. The addition of elements related to place, staff, and interior/decoration after the follow-up interaction suggested that these factors, while important, might not initially be top-of-mind for reviewers. However, when

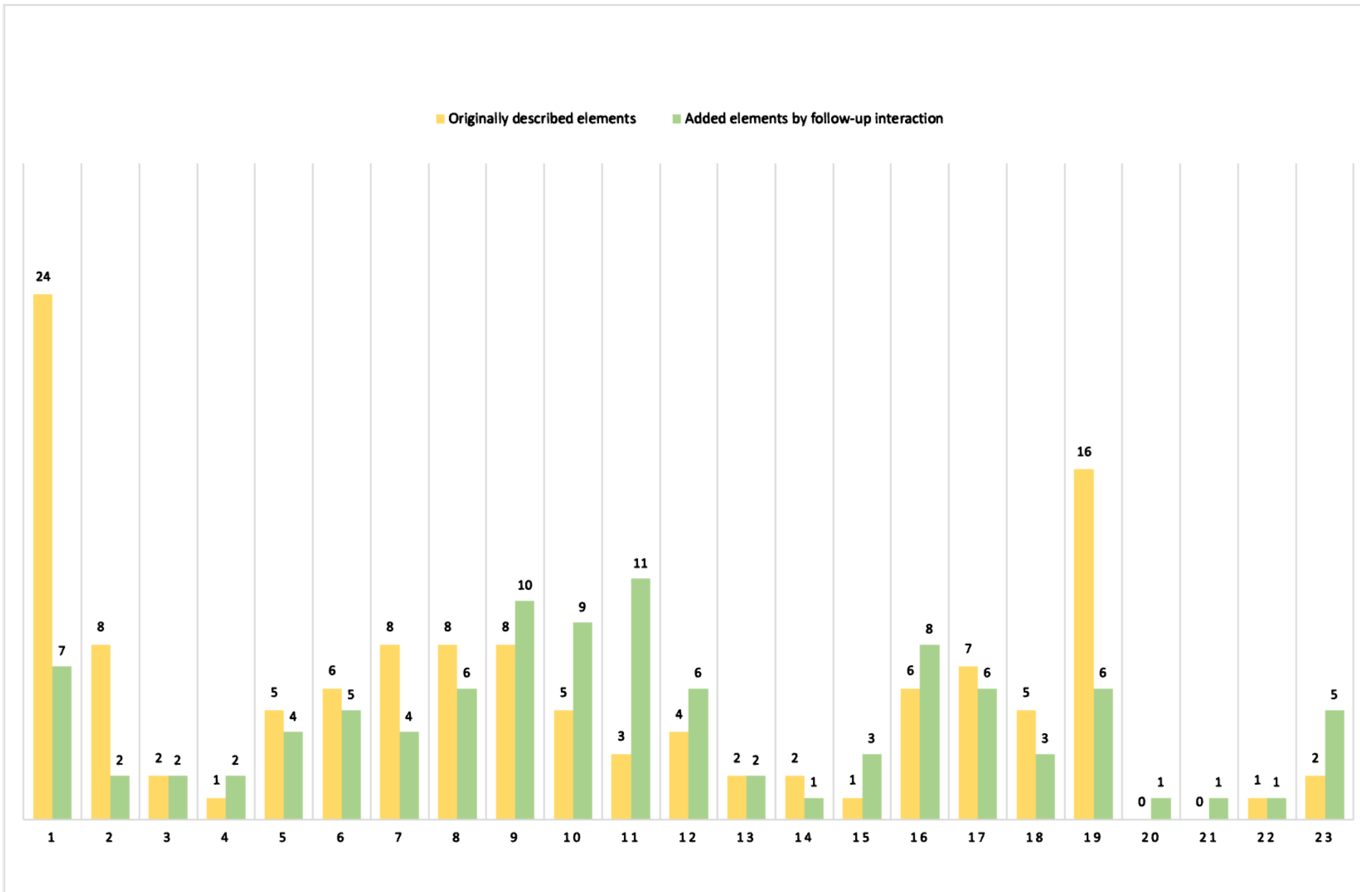

Figure 2: The summary statistics of review elements identified in participants' restaurant reviews. The chart categorizes the elements into "Originally described elements" and "Added elements by follow-up interaction" based on the experimental results listed in Table III. The yellow bars represent elements that participants initially included, while the green bars indicate elements that were added after the system's follow-up suggestions. The horizontal axis in this figure represents the review elements ID, where IDs 1-7 correspond to aspects related to food, IDs 8-15 correspond to aspects related to the restaurant, and IDs 16-23 correspond to aspects related to the reviewer. The vertical axis shows the frequency of occurrence for each review element in the reviews. Consequently, this figure allows for the observation of the distribution and enrichment of review content resulting from the follow-up interactions. The high frequency of taste-related elements and the increase in elements related to the restaurant's environment post-interaction are particularly noteworthy.

prompted, reviewers recognized their value in shaping the overall dining experience. This finding is significant as it shows that the follow-up interaction successfully encourages a more holistic review, which could be more useful for potential customers.

B. Discussions for Profiles of Participants

We focus on the reviewers' profiles shown in Table II. In the following discussion, we consider the experience of writing reviews, the timing of the experience, and the amount paid at the restaurant. By focusing on the reviewers' profiles, we could gain a deeper understanding of the background factors that influenced the content of reviews. Note that all the participants were in their twenties, their genders were unbalanced and not sufficiently evident for discussion, and most visited restaurants in the evening. The following discussions regarding the results in Table I are thus limited to these profiles.

1) Experience for writing reviews: It was found that there were no significant differences between voluntary and exogenous elements in the originally described and added elements for those who experienced writing reviews. So, it suggested that the experience of writing a review had a more significant meaning than the desire to write one. Participants without review writing experience often described elements of their satisfaction in their reviews. In contrast, reviews from participants with writing experience less frequently mentioned their satisfaction; it seemed that satisfaction was not crucial for experienced reviewers.

Let us focus on the originally described elements. Participants with review writing experience included food-related elements, particularly mentioning taste after an introduction of

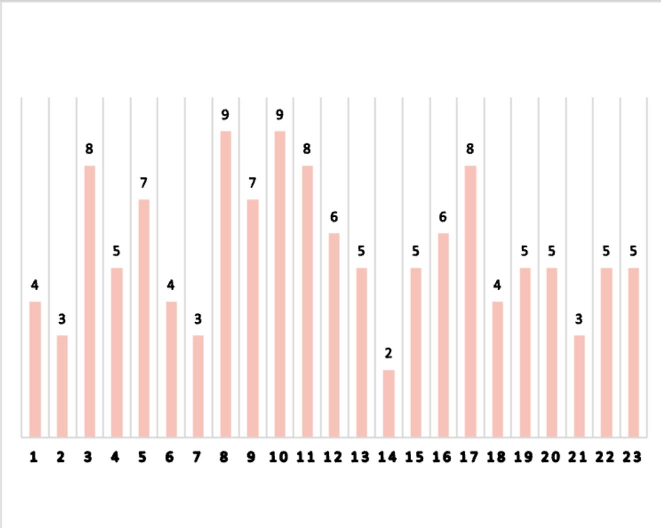

Figure 3: The frequency with which the system identified missing elements in participants' original reviews and suggested their inclusion. The horizontal axis represents the review elements ID, while the vertical axis indicates how often the system provided feedback on missing review elements.

the reviewer or context of dining. These participants mentioned multiple perspectives of dining (i.e., food, restaurant, and reviewer) in a review, though those with no experience in writing reviews mentioned a few elements. On the other hand, reviewers who are inexperienced in writing reviews tend to describe fewer elements. Their common perspective of their reviews was the "reviewer" him/herself. They described how they felt the taste and the context of dining without any preambles. Inexperienced reviewers tended to provide simple impressions based on their senses and experiences, resulting in a more personal narrative. This indicated that their reviews were more subjective and might offer less helpful information for readers. Additionally, their reviews' lack of consistency and reliability could make it harder for readers to use these reviews for decision-making. In contrast, participants lacking prior review writing experience often produce more subjective reviews, with a stronger emphasis on personal feelings and intuitive reactions. Such reviews may offer less value to other readers who seek an overall assessment of the restaurant.

For added elements after the follow-up interaction, experienced participants in writing reviews improved the review to include more elements about the restaurant, while elements for food were less. The review, which consisted of originally described and added elements, covered all types of perspectives in restaurant reviews. Inexperienced reviewers could also improve their reviews by adding some elements that are absent from their original ones. It was suggested that the follow-up interaction could improve the reviews; it seems to be effective for even experienced reviewers.

2) Timing of dining experience: Originally described reviews differed between the dining experience and the timing of writing reviews. Participants who dined more than two weeks ago tended to focus more on the restaurant and reviewer perspectives. It suggested that the passage of time might influence the reviewer's focus. In contrast, participants who had dined within a week concentrated more on 'food.' This indicates that recent memories may encourage more detailed descriptions of taste and texture, while older memories shift attention towards more abstract aspects of the experience.

These results implied that recent experiences led to more detailed memories of the food itself, whereas older memories tended to emphasize the environment and context of the dining experience. Therefore, it is considered that the timing of the review can significantly affect its content.

3) Amount paid: We discuss the experimental results by focusing on the amount paid at the restaurants mentioned in the reviews. The reviews' tendencies differed between amounts paid less than 2,000 JPY and paid more than 2,001 JPY. This fact helped us better understand how the amount paid influences the content and focus of the reviews. For instance, when less was paid, the reviews primarily focused on the quality and value of the food, while higher payments led to a broader evaluation of the overall dining experience, including the environment.

The participants who had paid less than 2,000 JPY often mentioned elements for food in the original and added reviews. This result suggested that when budget constraints were in play, reviewers were more likely to focus on the value of the food, emphasizing its quality and quantity. The participants who had dined economical foods did not focus on restaurant and user perspectives. It seems that the important aspect of experiences was food itself for economic foods. Participants who paid more than 2,001 JPY included mentions of food, restaurant, and user perspectives. This result indicated that these reviews were more organized and provided a comprehensive assessment of the dining experience. Higher payments likely elevated the reviewer's expectations, leading to greater attention to various aspects beyond just the food. It seemed that they focused on not only food but also the environment and context of dining for the experience with expensive costs. It suggested that the overall satisfaction in more expensive dining experiences relied heavily on multiple factors, including service and ambiance. These findings suggested that the payment should not be just for food but for the overall dining experience. When restaurants set higher prices, they must ensure that all aspects of the experience, including service and ambiance, meet customer expectations to justify the cost.

VII. Conclusion

This study has investigated writing reviews with follow-up interaction. In this paper, we have set the following research questions;

- RQ 1 What memory challenges do customers face when detailing a restaurant?
- RQ 2 What types of information can be missed in reviews?

RQ 3 Does the follow-up interaction enrich the description in reviews?

The answers to each research question have been as follows;

Ans. 1 Without differences of experience, it is hard for customers to detail all perspectives of a dining experience by him/herself.

Ans. 2 Perspectives for restaurants and users tend to be absent. Especially in restaurants with less amount paid, the customers focused more on taste.

Ans. 3 Follow-up interaction as pointing out the absent elements is effective in revising the reviews in the written reviews. Adding descriptions enriches reviews from multiple perspectives.

These answers follow the RQ 1, RQ 2, and RQ 3 that could not be followed in related works.

In the future outlook of this paper, we identify several challenges that need to be addressed to enhance the robustness and validity of our research findings;

1) Validation of the results across broader demographics and provide more generalizable insights.
   - Increasing participant numbers.
2) Eliminating any biases that could arise from uneven participant demographics and heuristically prepared review elements.
   - Balancing participant profiles.
   - Resolving empirical basis for review elements.
3) Detailed analysis of how participants engage with interaction prompts for a deeper comprehension of the effects of interaction models.
   - Observation of participant interaction: which prompts elicit the most informative responses and how participants navigate the review process.
4) Developing strategies to handle and accurately process unclear or suboptimal review inputs.

These steps will significantly contribute to the refinement of our experimental design. We believe that the AI-supported review system ultimately leads to more comprehensive and informative restaurant reviews that can better serve consumers and restaurant management.

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