# A Learning Support System Using Question Generation Based on Oral Reading Behavior when Reading English Manga

Sotaro Takaguchi[1], Motoi Iwata[2], and Koichi Kise[1]

[1] Graduate School of Informatics, Osaka Metropolitan University, Sakai, Japan
sg22120o@st.omu.ac.jp, kise@omu.ac.jp
[2] Department of Digital Media, Kyoto Tachibana University, Kyoto, Japan
iwata-m@tachibana-u.ac.jp

**Abstract.** This study proposes an interactive English learning support system that generates questions based on learners' oral reading behaviors while reading English manga. The proposed system uses speech and eye-gaze information collected during oral reading to detect speech balloons that learners may not fully understand. Balloon-level features are extracted from the collected data, transformed into labels through outlier detection, and incorporated into prompts for a large language model to generate questions adapted to learners' comprehension states. We conducted an experiment comparing the proposed method with a baseline method using comprehension tests and questionnaires. The results suggested that the proposed method helped learners notice ambiguities in understanding and improved the detection of speech balloons that learners felt they did not understand. These findings indicate the potential of using reading behaviors to support interactive English learning adapted to learners' comprehension states.

**Keywords:** English learning · Large language models · Oral reading · Eye-gaze information · Question generation

## 1 Introduction

As globalization progresses, improving English proficiency has become increasingly important for Japanese learners. Interactive learning has attracted attention as an effective approach for deepening learners' understanding [4]. However, interactive learning generally requires a dialogue partner, making continuous implementation in everyday learning environments difficult.

Recent advances in large language models (LLMs), such as ChatGPT, have enabled AI-based interactive learning support. Li et al. developed EDEN, an interactive English learning system using LLMs [5]. Their study showed that empathetic feedback generated by LLMs can improve learners' motivation. However, effective support remains difficult unless systems can appropriately identify which parts learners have difficulty understanding. Therefore, incorporating information that reflects learners' comprehension states into interactive learning systems is important.

In this study, we focus on reading behaviors during oral reading as indicators of learners' comprehension states. When learners experience comprehension difficulties, changes may appear in reading behaviors such as speech and eye-gaze information. By using these reading behaviors as inputs to LLMs, it becomes possible to generate questions that reflect learners' comprehension difficulties and provide interactive learning support adapted to learners' comprehension states.

To naturally obtain such reading behaviors, we focus on oral reading. Previous studies have shown that oral reading is effective for improving reading comprehension and reading speed [11]. In addition, English manga are approachable learning materials that can enhance learners' motivation and provide opportunities to learn practical English expressions used in daily conversation [3].

Based on the above, this paper proposes an interactive English learning support system that automatically detects speech balloons that may not be well understood by learners based on speech and eye-gaze information collected during oral reading of English manga and generates questions for those speech balloons using an LLM.

All of the experiments and work described in this article were done with the permission of the research ethics committee of the Graduate School of Informatics, Osaka Metropolitan University.

## 2 Related Work

### 2.1 Relationship Between Speech Information and Reading Comprehension

Chung et al. investigated the relationship between prosodic features during oral reading and reading fluency and reading comprehension among Taiwanese children [1]. Their study showed that prosodic features in oral reading are closely related to both reading fluency and reading comprehension.

### 2.2 Relationship Between Eye-Gaze Information and Reading Comprehension

Underwood et al. showed that eye fixation patterns and visual inspection behaviors, such as regressions and rereading, are strongly related to reading comprehension and reading speed [10]. In particular, fixation duration and fixation frequency were found to reflect text comprehension, suggesting that eye-gaze information can serve as an objective indicator of cognitive load and comprehension during reading.

Shimoda et al. analyzed eye movements while learners read English texts with different levels of difficulty and reported that fixation behaviors are related to learners' English proficiency [8].

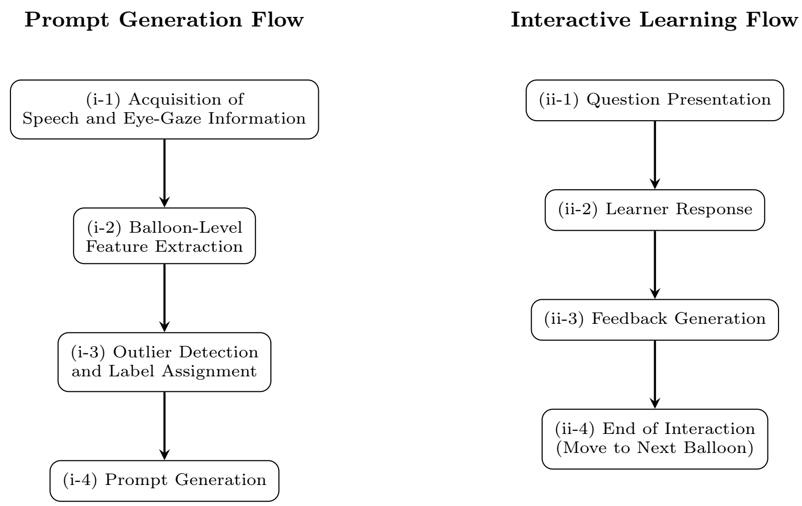


**Fig. 1.** Processing flow of the proposed system (left: prompt generation flow, right: interactive learning flow)

### 2.3 Relationship Between Speech Information, Eye-Gaze Information, and Reading Comprehension

Takaike et al. demonstrated that combining speech information and eye-gaze information enables effective estimation of speech balloons containing unknown words in translated Japanese manga [9].

## 3 Proposed System

### 3.1 Overview

The proposed system aims to support interactive English learning adapted to learners' comprehension states by generating questions for speech balloons that may not be well understood based on speech and eye-gaze information collected during oral reading of English manga. Figure 1 shows the overall structure of the proposed system.

The proposed system is implemented as a web application in which learners read manga, perform oral reading, and engage in interactive learning. GPT-4o provided by OpenAI is used as the LLM.

The system consists of two flows: (i) prompt generation flow and (ii) interactive learning flow. In the prompt generation flow, speech and eye-gaze information are collected during oral reading, balloon-level features are extracted, outlier detection and label assignment are performed, and prompts are generated using the manga synopsis, speech balloon text, and labeled features. In the interactive learning flow, generated prompts are input to the LLM, questions are presented to learners, learners answer the questions, and the LLM generates feedback.

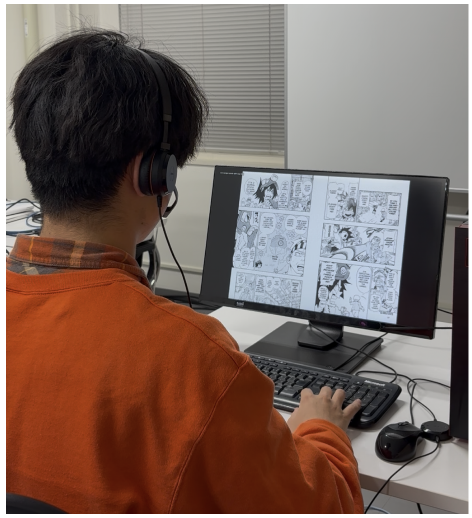

**Fig. 2.** Example of the oral reading environment (*Barrage* Episode 1, © Kohei Horikoshi / Shueisha)

### 3.2 Acquisition of Speech and Eye-Gaze Information

Learners are asked to orally read one episode of English manga displayed on the learning web application while speech and eye-gaze information are collected during oral reading. In the learning web application, a two-page spread of the manga is displayed as a single image with a resolution of 2732 × 2048 pixels.

To accurately obtain eye-gaze information, learners are instructed to maintain a stable head position during oral reading. A headset and an eye tracker are used to collect speech and eye-gaze information, respectively. The headset is used to reduce variations in recording quality caused by changes in the distance between the microphone and the learner's mouth.

The collected speech data are stored in WAV format, while eye-gaze data are stored as logs containing gaze coordinates and timestamps. Figure 2 shows the oral reading environment.

### 3.3 Balloon-Level Feature Extraction

Next, speech and eye-gaze information corresponding to each speech balloon are identified using the method proposed by Takaike et al. [9], and 47 balloon-level features are extracted for each speech balloon.

Among these 47 features, the proposed system uses four features that were reported to contribute to unknown-word estimation in the study by Takaike et al., excluding text features and frequency-analysis-based speech features such as MFCCs (we will use the text features for baseline method in Sect. 4). The four features used in this study are shown in Table 1.

**Table 1.** Balloon-level features used in the proposed system

| Sensor Information | Feature | Description |
|---|---|---|
| Eye-Gaze Features | Number of Fixations | Number of fixations within a speech balloon |
| | Balloon Fixation Duration | Duration of fixations within a speech balloon |
| | Average Saccade Velocity | Average velocity of saccades within a speech balloon |
| Speech Feature | confidence(min) | Minimum word confidence score obtained from IBM Watson speech recognition |

```
-----------------------------------
episode: ep01
page: 1
speech balloon: 5
confidence(min): noraml
number of fixations: normal
average saccade velocity: large
balloon fixation duration: normal
-----------------------------------
```

**Fig. 3.** Example of feature label assignment

### 3.4 Outlier Detection and Label Assignment

To convert the extracted features into a format that can be easily interpreted by the LLM, the four features described in the previous subsection are transformed into labels.

First, outliers are detected for each feature using Isolation Forest [6], which is capable of detecting anomalous values. In this study, outliers do not represent globally abnormal values, but rather values that are unusual within a single oral reading session of an individual learner.

When an outlier is detected, the feature value is compared with the average value within the session. If the value is larger than the session average, the feature is labeled as "large," while values smaller than the average are labeled as "small." If no outlier is detected, the feature is labeled as "normal." Figure 3 shows an example of label assignment for the four features.

### 3.5 Prompt Generation

The prompt used for question generation consists of the following elements:

- Text of each speech balloon


**Fig. 4.** Example screenshot of the learning web application during interactive learning

– Synopsis of the manga episode
– Instructions for question generation
– Labels assigned to speech and eye-gaze features

The synopsis was generated using ChatGPT based on the text of all speech balloons in the episode.

The instructions direct the LLM to generate questions related to vocabulary, content understanding, and inference based on the manga text. The prompts also instruct the LLM to use labels assigned to speech and eye-gaze features only as hints for question generation and not to mention them explicitly to learners. The detailed prompts used in this study are provided in Appendix A.

### 3.6 Interactive Learning Flow

Figure 4 shows an example screenshot of the learning web application during interactive learning.

Generated prompts are input to the LLM, and questions are presented for target speech balloons. Learners answer the generated questions, and the LLM generates feedback or additional questions based on the responses.

By repeating this interaction process, learners deepen their understanding of the target speech balloons. The interaction ends when sufficient understanding is achieved, after which the system moves to the next target speech balloon.

## 4 Experiment

### 4.1 Experimental Setup and Procedure

Participants learned using both the proposed method and the baseline method, and the methods were evaluated using a comprehension test and questionnaires.

The experimental procedure was the same for both methods: (1) participants orally read one episode of English manga, (2) engaged in interactive learning by answering generated questions, (3) completed a comprehension test and questionnaires, and (4) selected speech balloons that they felt they did not understand.

Participants used a headset and an eye tracker in both methods to maintain consistent experimental conditions.

### 4.2 Experimental Conditions

Two methods were compared in this experiment: the proposed method and the baseline method. Both methods used an LLM for question generation and involved interactive learning in which learners answered generated questions. However, the prompts input to the LLM differed between the methods.

- **Proposed Method:**
  The prompt included the manga synopsis, the text of each speech balloon, instructions for question generation, and labels assigned to speech and eye-gaze features after outlier detection. Questions were generated for speech balloons in which outliers were detected.
- **Baseline Method:**
  The prompt included the manga synopsis, the text of each speech balloon, instructions for question generation, and a list of target speech balloons selected using text features. Four text features were used: the number of words, average word frequency, minimum word frequency, and maximum word frequency, where these four text features were useful ones in Takaike's method. Outlier detection was performed for each feature, and speech balloons detected as outliers for at least one feature were selected as question generation targets.
  These text features were used only for target selection and were not included in the prompt input to the LLM.

Table 2 shows the differences in prompt components between the proposed method and the baseline method.

### 4.3 Evaluation Method

As an objective evaluation, a comprehension test was conducted after reading, and the number of correct answers was calculated. All questions were four-choice multiple-choice questions about the manga content.

As a subjective evaluation, questionnaires using a seven-point Likert scale were conducted to evaluate factors such as burden of oral reading, difficulty of the learning material, appropriateness of question generation locations, and quality of generated questions.

NASA-TLX [2] was used to evaluate subjective workload, and IMI [7] was used to evaluate motivation.

**Table 2.** Prompt components in the proposed method and the baseline method

| Prompt component | Proposed method | Baseline method |
|---|---|---|
| Instructions for question generation (different between the proposed and baseline methods) | ○ | ○ |
| Synopsis of the manga episode | ○ | ○ |
| Text information for each speech balloon | ○ | ○ |
| Labeled speech and eye-gaze features | ○ | – |
| List of target speech balloons selected from text features | – | ○ |

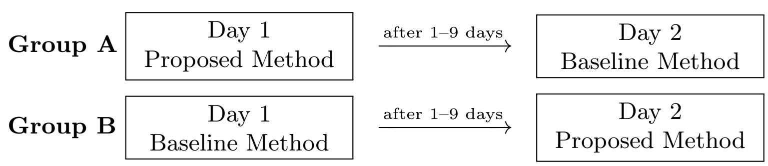


**Fig. 5.** Overview of the experimental schedule

To evaluate the detection accuracy of speech balloons that participants did not understand, Recall and Precision were calculated based on the agreement between speech balloons selected by participants and speech balloons selected as question generation targets by each method.

### 4.4 Experimental Setting

The experiment was conducted using a desktop PC. Speech information was collected using a headset, and eye-gaze information was collected using an eye tracker.

The participants were 12 Japanese university students (age: $20.25 \pm 1.29$). The experiment was conducted after informed consent had been obtained.

The experiment consisted of two sessions of approximately 1 hour and 30 minutes each. Participants received an Amazon gift card worth 1,000 yen per hour as compensation.

Since all participants experienced both methods, order effects could influence the results. Therefore, the order of the methods was counterbalanced across participants. Group A experienced the proposed method first, whereas Group B experienced the baseline method first.

The interval between the two sessions ranged from 1 to 9 days depending on participants' schedules. Figure 5 shows the experimental schedule.

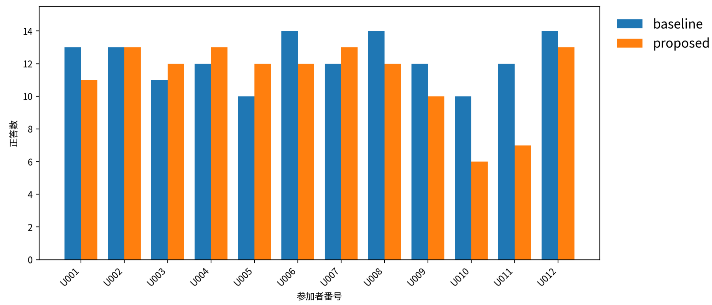


**Fig. 6.** Number of correct answers for each participant in the proposed method and the baseline method

## 5 Results and Discussion

### 5.1 Test Results

Figure 6 shows the number of correct answers in the comprehension test for each participant.

Four participants achieved higher scores with the proposed method, whereas seven participants achieved higher scores with the baseline method, and one participant obtained the same score in both methods. This result suggests that the effectiveness of the proposed method varies among participants.

To investigate the relationship between comprehension test scores and subjective evaluation indices, the differences between the proposed and baseline methods were calculated as follows:

$$\Delta S = S_{\text{proposed}} - S_{\text{baseline}}, \qquad \Delta X = X_{\text{proposed}} - X_{\text{baseline}},$$

where $S_{\text{proposed}}$ and $S_{\text{baseline}}$ represent the numbers of correct answers in the comprehension test for the proposed and baseline methods, respectively. Similarly, $X_{\text{proposed}}$ and $X_{\text{baseline}}$ represent the NASA-TLX and IMI scores for the proposed and baseline methods, respectively.

Spearman's rank correlation coefficient was calculated using data from 12 participants. A positive correlation was found between $\Delta S$ and IMI Interest/Enjoyment ($\rho = 0.74, p = 0.005$). Negative correlations were also found between $\Delta S$ and NASA-TLX Temporal Demand ($\rho = -0.68, p = 0.015$) and Frustration ($\rho = -0.61, p = 0.036$).

These results suggest that participants who evaluated the proposed method as more enjoyable and less frustrating tended to achieve higher comprehension test scores.

### 5.2 Questionnaire Results

For the questionnaire item "*The speech balloons for which questions were generated were parts that I felt were difficult to understand*," nine participants gave

**Table 3.** Correlations between differences in correct answers and subjective evaluation indices

| Index (difference) | Spearman's $\rho$ | $p$-value |
|---|---|---|
| IMI Interest / Enjoyment | 0.74 | $0.005^{**}$ |
| NASA-TLX Temporal Demand | -0.68 | $0.015^{*}$ |
| NASA-TLX Frustration | -0.61 | $0.036^{*}$ |

$^{*}p < 0.05$, $^{**}p < 0.01$

**Table 4.** Recall and Precision for detecting speech balloons that were not understood

| Metric | Baseline method | Proposed method |
|---|---|---|
| Recall | $0.112 \pm 0.088$ | $0.274 \pm 0.221$ |
| Precision | $0.195 \pm 0.157$ | $0.187 \pm 0.116$ |

higher ratings to the proposed method. In addition, six participants gave higher ratings to the proposed method for the item "*The questions helped me notice my misunderstandings or misreadings*."

Five participants also gave higher ratings to the proposed method for the item "*After being asked the questions, I realized that I had not fully understood the content*."

These results suggest that question generation based on reading behaviors may help learners notice ambiguities in understanding and that reading behaviors are appropriately reflected in the generated questions.

The questionnaire results also provide indirect evidence regarding the educational value of the generated questions. Six participants gave higher ratings to the proposed method for noticing misunderstandings or misreadings, and five participants gave higher ratings for realizing insufficient understanding. These results suggest that the generated questions may help learners recognize misunderstandings and insufficient comprehension.

### 5.3 Detection Accuracy of Speech Balloons That Were Not Understood

Participants selected speech balloons that they felt they did not understand after learning with each method. These selections were treated as the ground truth, and agreement with the speech balloons detected by each method was evaluated using Recall and Precision:

$$\text{Recall} = \frac{TP}{TP + FN}, \qquad \text{Precision} = \frac{TP}{TP + FP},$$

where TP, FN, and FP represent the numbers of true positives, false negatives, and false positives, respectively.

The proposed method achieved higher Recall (0.274) than the baseline method (0.112), indicating that the proposed method detected more speech balloons that participants felt they did not understand.The Recall of the proposed method exceeded that of the baseline method for 9 of the 12 participants.

On the other hand, Precision slightly decreased in the proposed method (0.187) compared with the baseline method (0.195), indicating an increase in false detections. Six of the 12 participants showed higher Precision with the proposed method than with the baseline method.

These results suggest that using reading-behavior features enables the detection of more speech balloons that learners felt they did not understand compared with using text features alone, although false detections also increased.

The observed true-positive and false-positive cases suggest that eye-gaze and speech features may reflect multiple types of comprehension difficulties. In some cases, speech balloons associated with large reading-behavior deviations contained expressions that required understanding grammatical relationships and distinctions between related expressions, suggesting that the features may capture difficulties related to sentence interpretation and syntax. In other cases, the selected speech balloons contained potentially unfamiliar words, suggesting that the features may also reflect vocabulary-related difficulties. However, the current study did not systematically classify the types of comprehension difficulties reflected in reading behaviors. Further analysis is needed to clarify the relationship between reading behaviors and different types of comprehension difficulties.

### 5.4 Limitations and Future Work

One limitation of this study is that speech balloons that participants reported as not understood were treated as the ground truth. Future work should introduce objective balloon-level comprehension measures to evaluate understanding more directly. In addition, the evaluation was conducted using a limited number of participants and manga episodes. Future studies should investigate the effectiveness of the proposed method using a larger number of participants, multiple manga titles, and episodes with controlled difficulty levels. Furthermore, the current study focuses on English learning support using manga as learning material. Incorporating manga-specific information, such as visual context, panel structure, character identity, and facial expressions, may further improve question generation and should be explored in future work.

## 6 Conclusion

In this study, we proposed an interactive English learning support system that automatically detects speech balloons that may not be well understood by learners based on speech and eye-gaze information collected during oral reading of English manga, and generates questions for those speech balloons using an LLM.

Experimental results showed that although some participants achieved higher comprehension test scores with the proposed method, other participants achieved higher scores with the baseline method, suggesting that the learning effect of the proposed method varies among individuals. However, analysis of the relationship between differences in comprehension test scores and differences in subjective evaluation indices revealed significant correlations with IMI Interest/Enjoyment and NASA-TLX indices such as Temporal Demand and Frustration. These results suggest that participants who evaluated the proposed method as more enjoyable and less temporally demanding or frustrating tended to achieve higher comprehension test scores with the proposed method.

In addition, the questionnaire results suggested that question generation based on reading behaviors may effectively support learners' comprehension. Regarding the detection accuracy of speech balloons that learners did not understand, the proposed method tended to detect more speech balloons that participants felt they did not understand than the baseline method. On the other hand, false detections of speech balloons that participants had actually understood also increased, revealing a trade-off in detection accuracy.

These results suggest that the proposed system has the potential to support interactive English learning by utilizing reading behaviors such as speech and eye-gaze information to generate questions that reflect learners' comprehension states.

Future work includes improving feature selection and detection methods to reduce false detections, generating questions according to learners' English proficiency levels, and evaluating long-term learning effects.

**Acknowledgements** This work is partially supported by JSPS KAKENHI Grant Number 24K02962 and 25K15179.

## References

1. Chung, W.L., Bidelman, G.M.: Acoustic features of oral reading prosody and the relation with reading fluency and reading comprehension in taiwanese children. Journal of Speech, Language, and Hearing Research **65**(1), 334–343 (2022)
2. Hart, S.G., Staveland, L.E.: Development of nasa-tlx (task load index): Results of empirical and theoretical research. In: Hancock, P.A., Meshkati, N. (eds.) Human Mental Workload, pp. 139–183. Elsevier (1988)
3. Howell, P.: Using manga in teaching english as a foreign language. Hiroshima Studies in Language and Language Education **17**, 195–204 (2014)
4. Kitada, N., Nishimura, K.: Classroom practices for interactive learning and their analysis (in japanese). Naruto University of Education (2021)
5. Li, S., Shao, T., Yu, Z., Hirschberg, J.: EDEN: Empathetic dialogues for english learning. In: Findings of the Association for Computational Linguistics: EMNLP 2024. pp. 3492–3511. Association for Computational Linguistics, Miami, Florida, USA (2024). https://doi.org/10.18653/v1/2024.findings-emnlp.200, `https://aclanthology.org/2024.findings-emnlp.200/`
6. Liu, F.T., Ting, K.M., Zhou, Z.H.: Isolation forest. In: Proceedings of the 2008 IEEE International Conference on Data Mining. pp. 413–422. IEEE (2008)
7. Ryan, R.M., Koestner, R., Deci, E.L.: Intrinsic motivation inventory: A self-report measure of intrinsic motivation and extrinsic motivation. Tech. rep., University of Rochester (1997)

8. Shimoda, A., Tsuchida, Y., Toyama, S., Hokabe, K., Murakami, Y.: Evaluation of english proficiency based on eye-gaze analysis during reading comprehension (in japanese). IPSJ SIG Technical Reports **2019-INTERACTION-2**(76), 1–6 (2019)
9. Takaike, T., Iwata, M., Kise, K.: Estimation of unknown words using speech and eye gaze when reading aloud comics. In: Pattern Recognition, Computer Vision, and Image Processing: ICPR 2022 International Workshops and Challenges. pp. 91–106. Springer (2023)
10. Underwood, G., Hubbard, A., Wilkinson, H.: Eye fixations predict reading comprehension: The relationships between reading skill, reading speed and visual inspection. Language and Speech **33**(1), 69–81 (1990)
11. Yukimaru, N.: Effects of oral reading instruction on the improvement of english reading comprehension for japanese university students (in japanese). Language Education Center Journal, Seinan Gakuin University (2011)

# A Instruction Prompts Given to the LLM

In this study, instruction prompts for question generation were included as part of the input to the LLM. This appendix presents the actual prompts given to the LLM. Since variables such as the work title, episode title, speech balloon text, and other information were embedded in the prompts, they are represented here using placeholders: `<WORK>` (work title), `<EPISODE>` (episode title), `<SYNOPSIS>` (synopsis), `<BALLOON_TEXT>` (target speech balloon text), `<METRICS_LINES>` (list of outlier indicators), and `<PLAN_JSON>` (design JSON).

## A.1 Prompts Used in the Proposed Method

### Design JSON Generation

```
You are a tutor who supports oral reading-based English manga learning.

Input: a synopsis, speech balloon text, and outliers in reading behavior
related to this speech balloon (states of indicators derived from
eye-gaze and speech information).

Objective: Based on the outliers in reading behavior, estimate what the
learner is likely to have difficulty understanding, and determine what
kind of question should be asked specifically for that estimated difficulty.

Important: The relationship between indicators and comprehension
difficulties is not based on fixed rules. Infer reasonably each time from
the combination of textual features (vocabulary, syntax, referents,
context dependency, amount of information, etc.) and the indicators.

Output must be JSON only. Do not include explanatory text. Strictly follow
the following schema:
```

```
{
  "unknown_part": "The part that the learner is likely to have difficulty understanding
  (e.g., word meaning, sentence structure, referent, situation understanding,
  inference, etc.)",
  "because": "The reason for this judgment based on the outliers
  (e.g., low confidence, etc.; keep it short)",
  "question_direction": "The direction of the question that should be asked to check
  this comprehension difficulty (e.g., confirming the meaning of a difficult word,
  paraphrasing, checking the subject and predicate, etc.)"
}
```

The following information, including the work title, synopsis, speech balloon text, and outlier indicators, was added as user input to the above instruction prompt.

```
[Work] <WORK> / [Episode] <EPISODE>
[Synopsis]
<SYNOPSIS>

[Target speech balloon text]
<BALLOON_TEXT>

[Outliers in reading behavior (indicator states)]
- <METRICS_LINES>
```

**Question Generation**

```
You are a tutor who supports oral reading-based manga learning.

Based on the given speech balloon text, synopsis, and eye-gaze and speech
indicators detected as outliers, ask questions step by step to deepen the
learner's understanding.

Output in Japanese. Ask only one question per turn. Make the question
specific and tied to the text. Do not fabricate facts that are not written
in the text.

Important: The design JSON given below represents the point that the learner
is estimated not to understand and the direction of the question to ask,
based on outliers in the learner's reading behavior.

You must follow this design JSON when generating questions and responses
to the learner. The purpose is to examine the unknown_part.

However, the design JSON only determines the purpose of the question
(what should be checked). The way the question is formed must follow the
```

```
Question Construction Guide below.

[Work] <WORK> / [Episode] <EPISODE>
[Synopsis]
<SYNOPSIS>

[Target speech balloon text]
<BALLOON_TEXT>

[Indicators detected as outliers in this speech balloon]
- <METRICS_LINES>

[Design JSON]
<PLAN_JSON>

Question Construction Guide:
1) Vocabulary and expressions: Ask about the meaning and usage of words
   and expressions in the text.
2) Content understanding: Check understanding of characters, situations,
   and events based on the text.
3) Inference: Ask learners to distinguish what can and cannot be inferred
   from the text.
```

### A.2 Prompt Used in the Baseline Method

```
You are a tutor who supports oral reading-based manga learning.
Based only on the given speech balloon text and synopsis, ask questions
step by step to deepen the learner's understanding.
Output in Japanese. Ask only one question per turn. Make the question
specific and tied to the text. Do not fabricate facts that are not written
in the text.

[Work] <WORK> / [Episode] <EPISODE>
[Synopsis]
<SYNOPSIS>

[Target speech balloon text]
<BALLOON_TEXT>

Question Construction Guide:
1) Vocabulary and expressions: Ask about the meaning and usage of words
   and expressions in the text.
2) Content understanding: As much as possible, check understanding of
   characters, situations, and events based on the text.
3) Inference: Ask learners to distinguish what can and cannot be inferred
   from the text.
```