UTTER

Unified Transcription and Translation for Extended Reality (UTTER)

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D7.2 – Second prototype evaluation report

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Abstract

This report summarizes the evaluation of the second prototypes for two use cases of the UTTER project, the customer service assistant and the meeting assistant. The first part of the report focuses on the evaluation of two different features of the customer service assistant: machine translation with contextual information and emotion recognition in customer service conversations. The second part of the report focuses on the evaluation of the meeting assistant, *TiM*, in particular its accuracy, robustness and safety aspects.

1 Evaluation of the customer service assistant use case

1.1 Second year prototype

The goal of this use case is to build a multilingual customer support assistant that empowers a human customer assistant agent to provide support in any language. The assistant is able to produce fit for purpose translations that take into account the context of the conversation. The assistant is empathetic, and takes into consideration the customer satisfaction for producing translations.

In the 2nd year prototype, we integrated Tower (Alves et al., 2024), a translation-oriented LLM developed within UTTER, into the demonstration code, enabling it for two main tasks: machine translation at sentence-level and beyond sentence-level (i.e. considering previous turns in the conversation) and grammar error correction. A video with a demonstration of the prototype is available.[1]

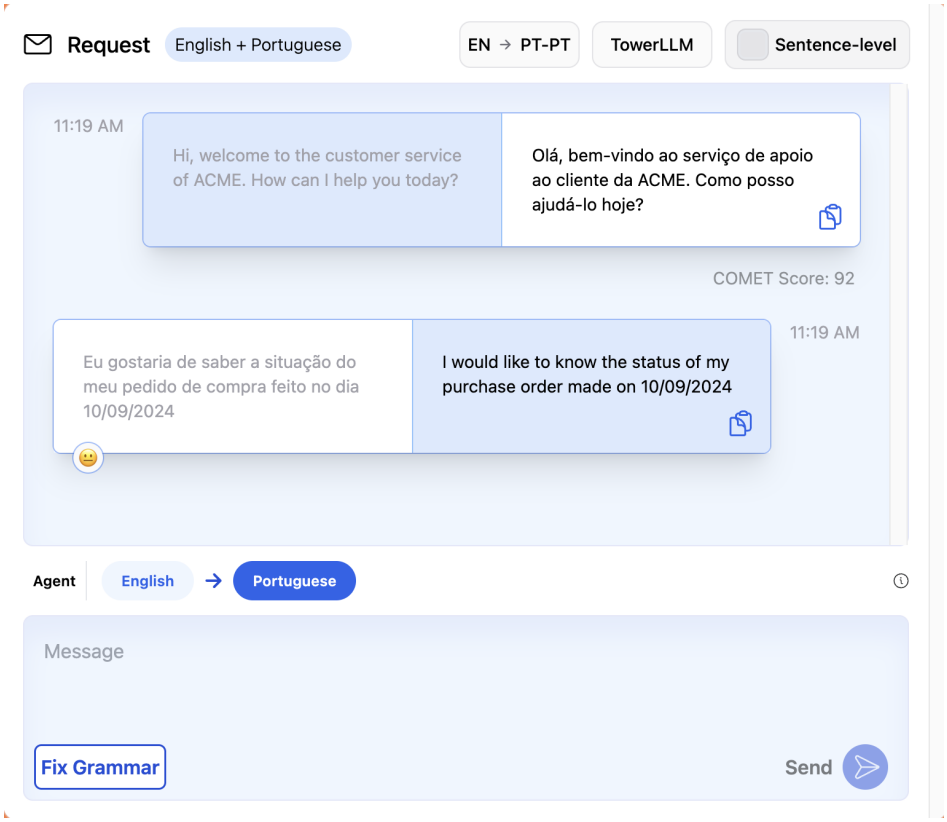

Figure 1: Customer service assistant 2nd year prototype.

For the evaluation, we focused on two main parts of the assistant: machine translation with context given by the previous sentences, and emotion recognition with LLMs developed within UTTER during the last year.

1.2 Machine Translation

The objective of this evaluation is to assess the performance of both open-source and proprietary large language models (LLMs) in translating bilingual conversations between a customer and

[1] https://drive.google.com/file/d/15tjdK8-ulwchg_qoe5UrlkJr2PB4sRAo/view?usp=drive_link

an agent in a customer service chat setting. We focus on understanding how well these models handle the translation of entire conversations within their context, rather than translating individual sentences in isolation. The conversations are bilingual in that the customer writes in one language (non-English) and the agent writes in a language different from the one spoken by the customer (English). The evaluation is performed for the language directions that UTTER focuses on (English, German, French, Portuguese, Korean and Dutch).

1.2.1 MT systems and approaches

In this evaluation we have considered the following machine translation approaches:

- Pre-trained multilingual machine translation model: Meta's NLLB-3.3B (Costa-jussà et al., 2022) parameters[2] with beam search decoding (beam size: 4).
- Proprietary LLM-based service: Following the recent release of stronger GPT models, we evaluate GPT-4o[3] in the translation of bilingual chat conversation setting.
- TowerInstruct (Alves et al., 2024), a state-of-the-art LLM specialized for MT and related tasks developed by Unbabel and Instituto Superior Tecnico as part of UTTER. For the experiments in this report we use TowerInstruct-7B-v0.2[4] with greedy decoding.
- TowerChat[5], a model finetuned on top of TowerBase-7B.[6] TowerChat has been trained with the concatenation of TowerBlocks[7] dataset and the entire training dataset of the WMT Chat Shared task, using context-aware prompts (Figure 2). This training process equips the model with the capacity to better understand and leverage conversational context, enabling it to generate high-quality translations for conversational settings.

For the LLMs, namely, GPT-4o, TowerInstruct and TowerChat, two different prompts are used. One prompt passing only one sentence to translate and another prompt that incorporates contextual information into the prompt, specifically, the entire previous bilingual conversation is provided as the context in the prompt. The prompt with context information is shown in Figure 2.

1.2.2 Data

The dataset used to conduct this evaluation is the one used for the 2024 WMT Chat Shared task (Mohammed et al., 2024), the MAIA 2.0 corpus. It consists of real bilingual customer support data for five language pairs. It builds on the dataset released in the 2022 WMT Chat Shared task edition (Farinha et al., 2022) and it includes two additional language pairs: Dutch and Korean. The dataset encompasses dialogues across diverse topics, including account registration issues, payment and delivery clarifications, and after-sale services in various industries such as retail and gaming. The new dataset was automatically anonymized using Unbabel's proprietary anonymization tool,

[2] Model available at https://huggingface.co/facebook/nllb-200-3.3B
[3] The version of the model used was gpt-4o-2024-08-06.
[4] Model available at https://huggingface.co/Unbabel/TowerInstruct-7B-v0.2.
[5] This system is going to be fully described in a forthcoming publication in the 2024 WMT Conference in the Chat Shared Task, detailing the approach with additional analyses and experiments.
[6] https://huggingface.co/Unbabel/TowerBase-7B-v0.1
[7] https://huggingface.co/datasets/Unbabel/TowerBlocks-v0.2

```
Context: {context}
Translate the following {source_lang} source text to
{target_lang}, given the context.
{source_lang}: {source_seg}
{target_lang}: {target_seg}
```

Figure 2: Instructions with contextual information for bilingual conversational translation tasks. Parts in red are included only when a context is available. Parts in blue are only included for training TowerChat thus, in inference the model is asked to perform prompt completion.

customer	Hallo, ich komme nicht in meine Sum up pos was denn no App rein Hello, I can not get into my sum up pos what then no app
agent	I am sorry to hear that. Es tut mir leid, das zu erfahren.
agent	Let me see what I can do for you Lassen Sie mich sehen, was ich für Sie tun kann.
agent	Could you please tell me what error message you can see while logging in to your POS? Könnten Sie mir bitte sagen, welche Fehlermeldung Sie sehen können, während Sie sich bei Ihrem POS anmelden?
customer	Wenn ich auf die App gehe, erscheint dieses Gerät hinzufügen. When I go to the app, it shows Add this device.
agent	Could you please try to connect the App with the POS? Könnten Sie bitte versuchen, die App mit dem POS zu verbinden?
customer	die App ist die PRS-ORG pos app the app is the PRS-ORG app
customer	ich habe die Frage daher nicht verstanden so I did not understand the question
agent	Could you please elaborate on your query? Könnten Sie bitte Ihre Anfrage näher erläutern?

Table 1: An example of a EN-DE conversation between a *customer* and an *agent* from MAIA dataset.

followed by a manual validation performed by expert linguists, to comply with the General Data Protection Regulation (GDPR). Table 1 provides an example of a bilingual conversation from this dataset.

We use the same test sets made available for the 2024 WMT Chat Shared Task.[8] Table 2 presents the data's statistics, including the number of segments, conversations, and average conversation length. As reported in Mohammed et al. (2024) the test sets were created by selecting conversations that exhibit the highest counts of context-dependent discourse phenomena tags, as extracted using Multilingual Discourse Aware (MuDA) tagger (Fernandes et al., 2023).

1.2.3 Results and Discussion

We report the results with the systems and data described in Section 1.2.1. For that, we use COMET-22 (Rei et al., 2022) automatic reference-based evaluation metric.

[8] https://github.com/WMT-Chat-task/chat-task-2024-results/tree/main/test

Lang. Pair	test			
	# segments	# conversations	# length	# words
EN-NL	2k	58	34.7	10.2
EN-PT	2k	73	27.9	8.8
EN-DE	2k	67	30.5	9.4
EN-KO	2k	42	47.2	9.6
EN-FR	2k	65	32.2	10.1

Table 2: Dataset statistics with the number of segments (# segments), number of conversations (# conversations), average conversation length (# length), and average number of words per turn (# words) for each language pair considering both directions (en-xx and xx-en). Note that for ko customer parts, we considered the English reference translation to calculate the number of words.

Model	From English					
	German	French	Portuguese (Brazil)	Korean	Dutch	Average
NLLB	90.56	91.06	86.33	87.26	87.86	88.61
GPT-4o w/o context	**92.74**	92.43	93.01	92.26	92.68	92.62
GPT-4o w/ context	92.49	92.62	93.4	93.06	93.08	92.93
TowerInstruct-7B w/o context	91.71	91.89	91.9	91.64	91.3	91.68
TowerInstruct-7B w/ context	92.61	92.08	93.03	91.76	93.02	92.5
TowerChat w/o context	92.36	92.26	93.89	93.73	92.81	93.01
TowerChat w/ context	**92.74**	**92.64**	**94.53**	**94.16**	**94.09**	**93.63**

Table 3: Evaluation using COMET-22 for language directions translating from English.

For translation directions coming from English, for almost all systems, adding the conversation context to the prompt helps improving translation quality, on average, across language pairs. The biggest gains are obtained by TowerInstruct-7B (approximately 0.81 COMET points). The best model across all language pairs is TowerChat using prompts with contextual information, surpassing even GPT-4o.

For translation directions that produce English, the best model is also TowerChat for all languages except Dutch, in which GPT-4o is slightly better (Table 4). In average across all language pairs, TowerChat has the best performance, and it is improved when using contextual information in the prompt. In this direction, the usage of contextual information in the prompt is beneficial for 3 out of 5 language pairs but the differences in COMET-22 scores are smaller compared to when the same systems are translating from English.

TowerChat presents superior performance on bilingual customer service conversation translation when compared to TowerInstruct-7B. Even though TowerChat was finetuned with a diverse set of instructions covering multiple translation-related tasks (in TowerBlocks), it is more specialized towards the customer service translation task and content type. TowerInstruct-7B is a very strong model not only for this content type but also for tasks such as grammar error correction and automatic post-editing as shown in the experiments described in Alves et al. (2024).

It is important to highlight the strong performance of both TowerInstruct-7B and TowerChat. COMET-22 scores above 90 indicate very high translation quality, placing these models in the "very

Model	To English					
	German	French	Portuguese (Brazil)	Korean	Dutch	Average
NLLB	89.03	89.18	86.1	88.05	88.45	88.16
GPT-4o w/o context	92.16	92.18	91.4	93.24	93.07	92.41
GPT-4o w/ context	91.94	91.17	91.18	90.6	**93.27**	91.63
TowerInstruct-7B w/o context	92.08	92.78	90.43	93.13	92.45	92.17
TowerInstruct-7B w/ context	92.07	92.44	91.42	93.05	92.89	92.37
TowerChat w/o context	**92.28**	**92.79**	91.06	94.69	92.78	92.72
TowerChat w/ context	92.24	92.67	**92.09**	**94.98**	93.06	**93.00**

Table 4: Evaluation using COMET-22 for language directions translating into English

good" to "excellent" translation quality range. Their performance is on par or better than GPT-4o. Little is known about GPT-4o implementation details such as architecture, number of parameters and data, but it is assumed to be significantly larger than previous OpenAI models.[9]

1.3 Emotion Recognition in Conversation

Part of the role of the customer service assistant is to enable the customer service agent to understand if the customer is satisfied with the service they are providing. The final goal would be to have a system that is able to recognize the emotion of the customer towards the conversation. A first step was made in the first year prototype to understand how current sentiment analysis approaches fare with the content type of bilingual chat conversations. The conclusion was that emotion recognition models based RoBERTa, an encoder-only large pre-trained language model, performed better at this task than proprietary LLM-based service (GPT-3.5) that are more recent and trained on more data. This year we evaluate an early checkpoint of EuroLLM-9B (Martins et al., 2024), a multilingual large language model developed within UTTER, and compare with the finetuned RoBERTa model presented last year and GPT-3.5 in the emotion recognition setting.

1.3.1 Data

The evaluation is performed using the MAIA (Farinha et al., 2022) dataset, as in the previous year. The MAIA dataset has unique attributes such as being composed of bilingual conversations between an agent and a customer in a customer service scenario. The utterances in the dataset were annotated with one of the following emotions: empathy, happiness, dissappointment, confusion, frustration, anger, anxiety and neutral for the cases in which no emotion was observed in the utterence. These are important for the objectives of UTTER, in particular the customer service assistant. The model testing is conducted exclusively on the MAIA dataset, and the number of segments for each data split is detailed in Table 5.

1.3.2 Experimental Settings

We evaluate three different systems in the customer service emotion recognition setting.

[9] https://explodingtopics.com/blog/gpt-parameters

- Proprietary LLM-based service, GPT-3.5. This system is prompted with the sentence intended for classification and examples similar to the sentence being classified (few-shot examples with in-context learning). As shown in last year's evaluation, the context of the conversation (previous sentences) does not improve the performance of this model as effectively as using similar examples. Hence, we concentrate on prompts with few-shot examples obtained using RAG.

- TowerInstruct-Mistral,[10] is similar to the model used for machine translation experiments in Section 1.2.1. This is a Mistral-based model of 7B parameters (Jiang et al., 2023) that follows the Tower approach for expanding the languages supported, using continued pretraining as described in Alves et al. (2024). After this first step of training the model is finetuned with translation-related tasks instructions, using the same set as the model used in Section 1.2.1. The goal is to asssess if it is able to perform emotion recognition to some extent.

- EuroLLM-9B, a multilingual LLM currently being developed by UTTER partners that supports 35 different languages including all European Union official languages (Martins et al., 2024). This is an early version of the model that is going to be made available later during the project. It has been pretrained with around 4T tokens of textual data and has been finetuned with instructions for several multilingual tasks. This model is also prompted with the sentence intended for classification, along with examples that are similar to the sentence being classified.

- The model described in (Dias et al., 2022), which leverages a RoBERTa model to facilitate Emotion Recognition in Conversation (ERC). It can exploit the conversational context to enhance text comprehension but it cannot leverage similar examples as generative models. This model is finetuned only on the MAIA training data referred in Section 1.3.1.

The prompt used for the LLMs is presented in Figure 3. The [Examples] are selected using a procedure that identifies a given number of similar sentences to the [Utterance to classify] along with their respective emotions. The similar sentences are retrieved from the training data of the MAIA dataset.

1.3.3 Results and Discussion

The evaluation was carried out on the MAIA test sets. Results are presented in Table 6 for all three systems averaged acrross all language directions (including agent and customer). The best approach overall (averaging all classes equally) is obtained by RoBERTa with a context of four

[10] https://huggingface.co/Unbabel/TowerInstruct-Mistral-7B-v0.2

	en-de			en-pt		
	Agent	**Client**	**Total**	**Agent**	**Client**	**Total**
# segments (MAIA dev)	808	782	1,590	497	336	833
# segments (MAIA test)	1490	1488	2,978	1091	798	1,889
# segments (MAIA training)	5285	6139	11,424	3485	2759	6,244

Table 5: Dataset sizes for emotion recognition for training, development and test sets.

```
You are an emotionally intelligent assistant for customer support.
Classify the emotion of the utterances with AT MOST ONE OF THE
FOLLOWING EMOTIONS: empathy, happiness, neutral, disappointment, confusion,
   frustration, anger, anxiety.
Here you have some examples similar to the utterance to classify:
[Examples].
If you do not identify the emotion from the emotions list or the
message is empty, please answer neutral.
Utterance: [Utterance to classify]
Emotion:
```

Figure 3: Emotion Recognition Prompt

previous sentences ($c = 4$). The next model is GPT-3.5 using RAG with 20-shots with comparable results to the RoBERTa model trained on MAIA data. Interestingly GPT-3.5, TowerInstruct and EuroLLM-9B benefit from few-shot examples in the prompt, achieving higher classification performances when compared to their zero-shot runs. GPT-3.5 Macro F1 goes from 28.99 without few-shot examples to 42.65 with 20 similar examples in the prompt. Similarly, TowerInstruct goes from 16.25 Macro F1 without few-shot examples to 24.18 with 20 examples in the prompt and EuroLLM-9B goes from 18.68 Macro F1 without few-shot examples to 32.62 with 10 similar examples in the prompt. TowerInstruct lags behind the other models, likely because the instruction set used to finetune the model is more focused on translation-related tasks and therefore presents less task diversity. EuroLLM-9B was finetuned

The main challenge for all models are the Anger and Frustration classes, that present a much lower classification perfomance than other classes. This issue is especially pronounced in the EuroLLM-9B model, which shows a particularly poor performance on the Anger class. The main focus of the instruction set used for finetuning EuroLLM-9B was to equip the model with the ability of performing a diverse number of tasks across all the languages it supports. The occurrence of emotion recognition or emotion awareness data was not designed as a goal and therefore is very minimal. The results indicate that this model could benefit from emotion recognition data and that would likely lead to improvements on emotion recognition in conversation tasks.

Interestingly, the RoBERTa model finetuned on the MAIA training data achieves better performance than GPT3.5 even though it is a much simpler model of around 125M parameters. This is the model currently integrated in the demonstration prototype for the emotion awareness recognition, as it is cost effective and presents good performance.

2 Evaluation of the meeting assistant use case

2.1 Second year prototype: TiM (Trust in Me)

We have developed the second prototype of our UTTER meeting assistant, also known as *TiM*. This prototype is showcased in greater detail in a YouTube presentation.[11] *TiM* remains a "smart assistant

[11] https://www.youtube.com/watch?v=zFXqhFqlDPI

Model	Macro F1	Empathy	Happiness	Disappointment	Confusion	Frustration	Anger	Anxiety	Neutral
GPT3.5, $e = 0$	28.99	31.24	23.66	31.39	29.72	18.72	10.26	3.33	83.62
GPT3.5, $e = 10$	40.9	53.68	34.33	33.7	36.49	29.27	**15.73**	37.16	89.79
GPT3.5, $e = 20$	42.65	54.81	37.78	33.9	40.48	**29.68**	17.2	40.36	86.99
TowerInstruct-Mistral, $e = 0$	16.25	19	12.5	1	0	2.5	12	0	83
TowerInstruct-Mistral, $e = 10$	22.81	30.5	24.5	12	12.5	2	3	13	85
TowerInstruct-Mistral, $e = 20$	24.18	31.5	30.5	15.5	17.5	2	0	11	85.5
EuroLLM 9B, $e = 0$	18.68	14.5	32.5	28	9	2	0	0	63.5
EuroLLM 9B, $e = 10$	32.62	36.5	35	26.5	36	21	0	22.5	83.5
EuroLLM 9B, $e = 20$	31.07	33.115	34.5	23.5	39	15	0	17.5	86
XLM-RoBERTa, $c = 0$	42.24	67.44	43.22	23.6	38.17	16.72	7.77	53.24	89.83
XLM-RoBERTa, $c = 1$	43.46	65.93	**45.02**	31.18	36.22	17.27	11.24	50.58	89.92
XLM-RoBERTa, $c = 2$	41.32	68.31	43.57	22.32	35.26	15.13	4.89	54.12	90.16
XLM-RoBERTa, $c = 3$	42.28	69.32	40.77	23.96	35.26	15.13	4.89	**58.47**	90.52
XLM-RoBERTa, $c = 4$	**45.5**	**70.55**	44.86	**36.06**	**42.95**	16.8	8.18	53.76	**90.86**

Table 6: F1 scores for all the classes in the MAIA test set. Bold results are the highest. e refers to the number of similar few-shot examples included in the prompt. c refers to the number of previous sentences given to the RoBERTa model

that can attend meetings on your behalf." Users can interact with *TiM* to retrieve information about meetings they attended or even those they missed.

In the first year, we focused on building a general-purpose, LLM-powered assistant designed to answer meeting-related questions in a friendly and informal context. However, this assistant was not yet ready for deployment, as real-world applications pose significant challenges. These challenges include handling questions that may be:

- Beyond the assistant's intended scope,
- Inappropriate,
- Or ambiguous.

Our objective this year was to refine *TiM* into a robust and reliable meeting assistant that can operate effectively in more demanding, real-world scenarios. Figure 4 illustrates the architecture of our meeting assistant prototype developed in the second year of the UTTER project. The user interface remains based on *Streamlit*,[12] and the assistant can be powered by various LLMs. To enhance safety, we have implemented an LLM-based pre-filter for each user query. This pre-filter is designed to retain only those queries that are relevant, based on a set of criteria specified in a JSON file. Examples of these filters will be provided in the evaluation section. Overall, the novel features of this year's prototype compared to last year's include the following:

- Clearly defined boundaries for the assistant's mission and filtering of inappropriate user requests (evaluated in this report),
- Access to a broader range of LLMs (evaluated in this report):
  - Remote (OpenAI),
  - Local server (Big Llama models),
  - Local computer (Small & Quantized Llama models)

[12] https://streamlit.io

- Self-reflection on the agent's own responses (not evaluated in this report).

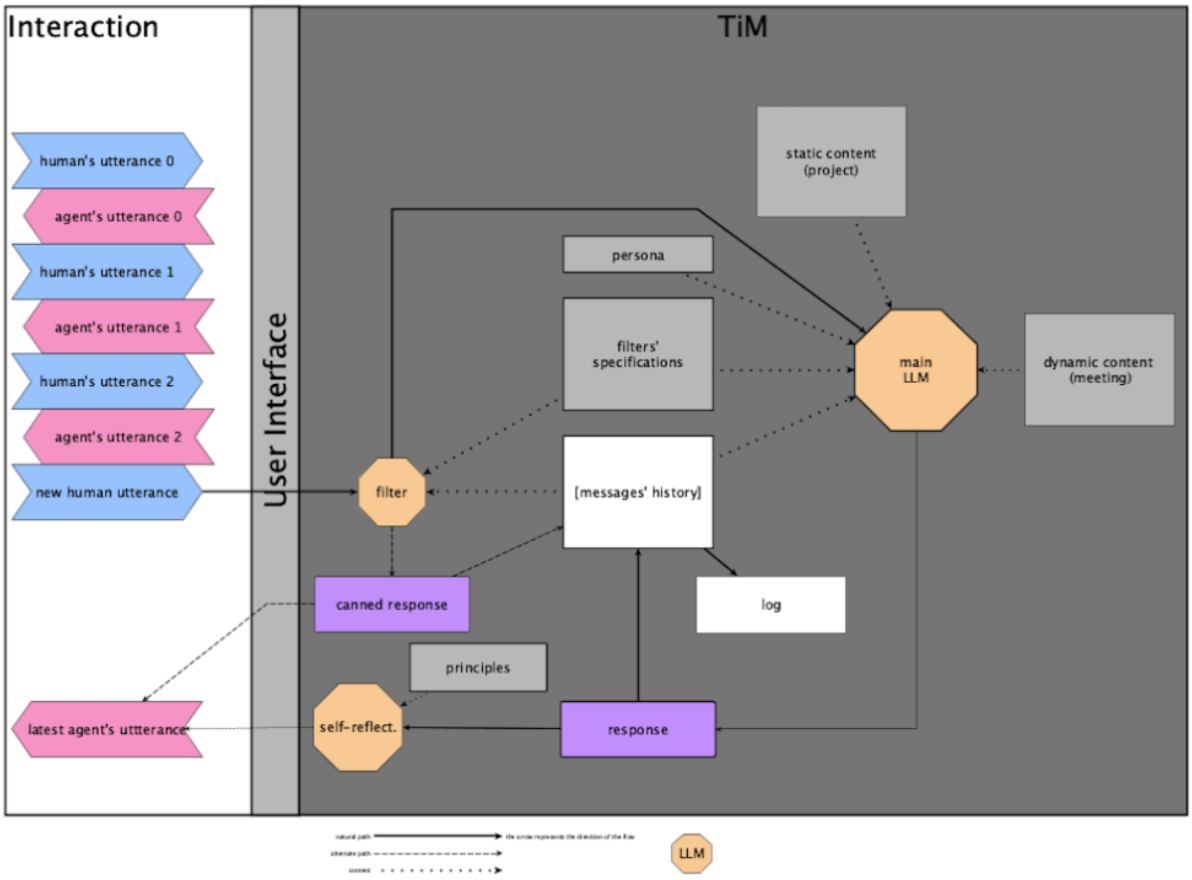

Figure 4: Architecture of TiM, the second year prototype

This section is dedicated to the evaluation of our second meeting assistant. Specifically, we assess *TiM* along the following axes:

- **Accuracy:** we utilize our ELITR-Bench dataset[13] to evaluate the performance of our meeting assistant with various closed and open LLMs, including some of the latest models.
- **Robustness:** we augment ELITR-Bench with noisy versions of the meetings' transcripts and evaluate the robustness of various LLMs to noisy text,
- **Safety:** we create a small dataset of hundred utterances, categorized as either *appropriate* or *inappropriate* requests according to filters we established. We then evaluate the effectiveness of several LLM-based filters in detecting and filtering out irrelevant or toxic requests.

2.2 Evaluate accuracy of TiM when powered with different LLMs

We follow the methodology we described in the UTTER mid-term report and in our ELITR-Bench publication (Thonet et al., 2024). Our benchmark, ELITR-Bench, augments the existing ELITR

[13] https://github.com/utter-project/UTTER-MS9-meetingdata/tree/master/ELITR-Bench

corpus by adding 271 manually crafted questions with their ground-truth answers, as well as noisy versions of meeting transcripts with different levels of Word Error Rate. We evaluate recent long-context LLMs on ELITR-Bench dataset using a GPT-4-based evaluation that was also presented and evalidated in Thonet et al. (2024).

QA and Conversation settings. The proposed ELITR-Bench is available in two settings. In **ELITR-Bench-QA**, we designed for each meeting a set of stand-alone questions (along with their answers) that can be addressed solely based on the meeting transcript, without additional context. We also designed a modified **ELITR-Bench-Conv** version where questions are to be asked in sequence, in a pre-defined order within a conversation. In this setting, some of the questions contain pronominal references or ellipses, for which previous conversational context (i.e., previous questions and answers) must be used to answer properly. For example, the question "*What is challenging about testing the demo system at the students firm fair?*" from the QA setting is replaced in the Conv setting with "*What is challenging about this event?*", where the answer to the previous question in the conversation was "*The students firm fair*". Such questions have been obtained by manually re-writing the Conv questions into QA questions by resolving coreferences. The number of QA/Conv differentiating questions is 16 (out of 141) for the dev set and 17 (out of 130) for the test set.

Evaluation protocol. The evaluation on ELITR-Bench is conducted as follows. For each meeting, a prompt containing the transcript and detailing the assistant's task is formed. Then, questions are appended to the initial prompt to drive the conversation about the corresponding meeting. We consider two ways to do this: (i) the *single-turn mode*, where only a single question is tackled in the conversation (i.e., the prompt is re-initialized for each new question), or (ii) the *multi-turn mode*, where all the questions related to a meeting are asked successively within a single conversation. Given the stand-alone nature of questions in ELITR-Bench-QA, one can adopt either the single-turn or multi-turn modes for this setting, whereas for ELITR-Bench-Conv it only makes sense to use the multi-turn mode as some questions are inter-dependent. In our evaluation methodology, given a question integrated in the aforementioned prompt, the response generated by an LLM is evaluated automatically using a GPT-4 judge,[14] following the standard practice in LLM evaluation (as discussed in Thonet et al. (2024)). Specifically, we adopted a score rubric-based evaluation methodology (Kim et al., 2024) in which a generated response is evaluated on its proximity to the ground-truth answer, given the associated question and a score rubric that details the quality criteria expected at each score level (ranging from the lowest score of 1 to the perfect score of 10).

Compared models. In our experiments on ELITR-Bench, we compared responses generated by 12 LLMs with long-context capabilities. We included both commercial models and open-source long-context models in our benchmarking:

- **GPT-3.5**, **GPT-4** (OpenAI, 2023) and **GPT-4o**[15] are powerful commercial LLMs from OpenAI that have obtained state-of-the-art performance on a wide range of LLM benchmarks.

[14] Our GPT-4 judge is based on the gpt-4-0613 checkpoint, for its cheaper cost compared to gpt-4-turbo models. Pilot experiments with different GPT-4 judges led to similar evaluation scores.

[15] https://openai.com/index/gpt-4o-system-card/

Table 7: Summary of the long-context models compared. *Vicuna models are provided with a 16K context limit, but it was extended to 32K using RoPE extrapolation (Su et al., 2024).

Model	Context limit	Backbone	Link
GPT-3.5 (turbo-16k-0613)	16K	-	https://platform.openai.com/docs/models/gpt-3-5-turbo
GPT-4 (1106-preview)	128K	-	https://platform.openai.com/docs/models/gpt-4-and-gpt-4-turbo
GPT-4o	128K	-	https://platform.openai.com/docs/models/gpt-4-o
LongAlpaca-7B	32K	LLaMA-2-7B	https://huggingface.co/Yukang/LongAlpaca-7B
LongAlpaca-13B	32K	LLaMA-2-13B	https://huggingface.co/Yukang/LongAlpaca-13B
LongChat-7B-v1.5	32K	LLaMA-2-7B	https://huggingface.co/lmsys/longchat-7b-v1.5-32k
Vicuna-7B-v1.5	16K*	LLaMA-2-7B	https://huggingface.co/lmsys/vicuna-7b-v1.5-16k
Vicuna-13B-v1.5	16K*	LLaMA-2-13B	https://huggingface.co/lmsys/vicuna-13b-v1.5-16k
LongAlign-7B	64K	LLaMA-2-7B	https://huggingface.co/THUDM/LongAlign-7B-64k
LongAlign-13B	64K	LLaMA-2-13B	https://huggingface.co/THUDM/LongAlign-13B-64k
LLaMA-3.1-8B	128K	LLaMA-3.1-8B	https://huggingface.co/meta-llama/Meta-Llama-3.1-8B-Instruct
Phi-3-small	128K	Phi-3-small	https://huggingface.co/microsoft/Phi-3-small-128k-instruct

We used the gpt-3.5-turbo-16k-0613, gpt-4-1106-preview, and gpt-4o-2024-05-13 checkpoints,[16] which enable a context length of 16K tokens for GPT-3.5 and 128K for GPT-4 and GPT-4o.

- **LongAlpaca-7B** and **LongAlpaca-13B** were obtained by fine-tuning LLaMA-2 models using the LongLoRA technique on the LongAlpaca dataset, both introduced in Chen et al. (2024). Their context size limit is 32K.
- **LongChat-7B-v1.5** is the LLaMa-2 version of the original LongChat-7B model (Li et al., 2023), trained on curated conversation data with rotary position embeddings (RoPE) (Su et al., 2024). It enables a context of at most 32K tokens.
- **Vicuna-7B-v1.5** and **Vicuna-13B-v1.5** were obtained by fine-tuning LLaMA-2 on the user-shared ShareGPT conversations, similarly to the original Vicuna model (Chiang et al., 2023). Their context length is 16K – which we extrapolate to 32K at inference time using RoPE (Su et al., 2024), to enable processing the longer meeting transcripts.
- **LongAlign-7B** and **LongAlign-13B** are based on the LongAlign recipe (Bai et al., 2024) by fine-tuning LLaMA-2 models on synthetic long sequences using a compact batching strategy. Their maximum context size is 64K tokens.
- **LLaMA-3.1-8B** is the latest iteration (at the time of writing) of the LLaMA family of models from Meta AI. This model enables a context limit of 128K due to its native long-context fine-tuning. We used the instruction-tuned version of the model in our experiments.
- **Phi-3-small** is the 3rd model of the Phi family of LLMs from Microsoft (Abdin et al., 2024).

We summarize the details of the different long-context LLMs in Table 7. We provide for each model its context size limit in tokens, its backbone model (i.e., the pre-trained model used for the fine-tuning), and the link to the model checkpoint on Huggingface for open-source models or the link to the relevant OpenAI documentation for proprietary models.

[16] https://platform.openai.com/docs/models/

The inference was done on a single A100 GPU with 80GB memory. In preliminary experiments, we also attempted to include the Mistral-7B-Instruct-v0.2[17] model in our study, as this model supports a context of up to 32K tokens. However, running this model on ELITR-Bench led to a GPU out-of-memory error on the A100, and thus we discarded it.

Main results The main results of the benchmarking on ELITR-Bench are reported in Table 8. The compared models are evaluated in three settings that combine the ELITR-Bench-QA or ELITR-Bench-Conv question set with the single-turn mode (i.e., one question asked per conversation) or multi-turn mode (i.e., all questions related to one meeting asked in a single conversation).[18] For each of the three considered settings, we report the results on the dev set, the results on the test set, and their mean. Given the extensive cost of GPT4-based evaluation, we performed a single seeded run for the dev set and three seeded runs for the test set. For the latter, we report the average score over the three runs.

Looking at the three settings in Table 8, we observe that GPT-4 and GPT-4o dominate over all other approaches with an average score that is always above 8.[19] GPT-3.5 obtained a slightly lower average score – around 7 – and was also beaten by the two recent open-source LLMs, LLaMA-3.1-8B and Phi-3-small with LLaMA-3.1-8B coming out on top. These three models notably outperformed the LLaMA-2-based LLMs. Among the latter, differences are smaller with scores close to 6 on the single-turn setting, and ranging from 4 to 6 on the multi-turn settings. Nonetheless, we can note that Vicuna-13B-v1.5 is the LLaMA-2-based approach that performed the most favorably overall on the three settings. Interestingly, the results in the single-turn and multi-turn modes show large discrepancies for LLaMA-2-based models – even when the question set is exactly the same, for ELITR-Bench-QA. This seems to indicate that these LLMs get distracted by the previous questions and answers, which affects their performance. In contrast, GPT-4/4o is able to maintain its performance between the single-turn mode and the multi-turn mode. The same can be observed for LLaMA-3.1-8B and Phi-3-small, suggesting that recent open-source long-context LLMs are able to successfully handle multi-turn conversations, unlike their predecessors. Comparing the results of the QA and Conv settings in the multi-turn mode, we found only minimal differences. This can be explained by the small number of questions that differ between QA and Conv (16 for the dev set and 17 for the test set).

Results by question type and answer position In this paragraph, we provide the full results split by question type and answer position obtained on ELITR-Bench-QA's test set in the single-turn setting. The results are given in Table 9. Looking at the global model performance over the different question types and answer positions, we do not identify any clear trend highlighting a question type or position answer as notably easier or harder. However, the *Who* questions seem to be on average slightly easier to answer. In contrast, the *What* questions were comparatively more challenging than other types for the best performing models (GPT-3.5, GPT-4, GPT-4o, LLaMA-3.1-8B, and Phi-3-small). This is not surprising as *What* questions sometimes require complex answers that go beyond simply listing entities, dates or numbers. Interestingly, LLaMA-2-based models struggled the most with the *How many* questions. Although the amount of such questions is very limited (8 in

[17] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.2

[18] Single-turn ELITR-Bench-Conv is omitted as some questions in the Conv setting are context-dependent (i.e., rely on previous questions or answers) and thus could not be asked independently.

[19] While one might argue that GPT-4 is unfairly advantaged due to the use of a GPT-4 judge, we have observed (experiments not reported here) that the dominance of this model is observed for other evaluators as well.

Table 8: Results on different ELITR-Bench settings. The reported numbers correspond to the average scores from 1 to 10 (higher is better) obtained by a GPT-4 evaluator, on a single seeded run for the dev set and 3 seeded runs for the test set. Boldface numbers correspond to the best performance among proprietary or open-source models. The results for GPT-3.5 are omitted in the multi-turn setting as the context length exceeded the 16k limit of this model.

Model	Single-turn			Multi-turn					
	ELITR-Bench-QA			ELITR-Bench-QA			ELITR-Bench-Conv		
	Dev	Test	Mean	Dev	Test	Mean	Dev	Test	Mean
GPT-3.5	7.04	7.44	7.24	-	-	-	-	-	-
GPT-4	8.21	8.39	8.30	**8.53**	**8.42**	**8.47**	**8.53**	8.36	8.44
GPT-4o	**8.53**	**8.44**	**8.48**	8.33	8.38	8.36	8.48	**8.41**	**8.45**
LongAlpaca-7B	5.89	5.60	5.75	4.53	4.84	4.68	4.70	4.58	4.64
LongAlpaca-13B	6.17	6.25	6.21	4.76	4.71	4.73	4.74	4.74	4.74
LongChat-7B-v1.5	6.60	5.78	6.19	5.85	4.17	5.01	5.21	4.31	4.76
Vicuna-7B-v1.5	5.42	5.61	5.51	4.68	4.61	4.65	4.67	4.69	4.68
Vicuna-13B-v1.5	5.92	6.52	6.22	5.52	5.67	5.60	5.42	5.78	5.60
LongAlign-7B	6.11	6.46	6.28	5.43	4.47	4.95	5.04	5.06	5.05
LongAlign-13B	6.27	6.33	6.30	4.65	5.33	4.99	4.81	4.95	4.88
LLaMA-3.1-8B	**7.70**	**7.83**	**7.76**	**7.77**	**7.81**	**7.79**	**7.80**	**7.78**	**7.79**
Phi-3-small	7.31	7.34	7.32	7.67	7.52	7.59	7.53	7.38	7.46

the test set) which calls for caution on tentative interpretations, this seems to suggest that LLaMA-2 models are notably less proficient at dealing with quantities and numbers than GPT models and more recent open-source LLMs such as LLaMA-3.1 and Phi-3.

With respect to the answer position, past work reported a "lost in the middle" effect (Liu et al., 2023), stating that the middle of a model's context tends to be overlooked more often than the beginning or end of the context. To further investigate this phenomenon in our dataset, we conducted a statistical hypothesis test on the scores obtained by each individual model. Specifically, we ran a one-tailed Welch's t-test (Welch, 1947) with the following alternative hypothesis: "The average score for questions with middle-position answers is lower than the average score of other questions". The p-values obtained for each model's set of scores are given in Table 10. Interestingly, we observe that the "lost in the middle" hypothesis is statistically verified (p-value < 0.05) for only two models: LongChat-7B-v1.5 (p-value = 0.032) and Vicuna-7B-v1.5 (p-value = 0.046). While we do not have a clear explanation about which of these two models' characteristics caused that effect, these models have in common that they are based on LLaMA-2-7B and were trained by the same LMSYS organization. It is then possible – although purely hypothetical – that the specific fine-tuning recipe followed by LMSYS on LLaMA-2-7B for these two models led to the "lost in the middle" effect.

2.3 Evaluate robustness of TiM to noisy text

Noisy versions of the meeting transcripts. To evaluate the robustness of long-context language models (LLMs) to noisy text, we generated multiple noisy versions of the ELITR meeting transcripts by simulating various levels of automatic speech recognition (ASR) noise. We utilized a large corpus of over 500,000 ASR transcripts aligned with reference texts, derived from the LibriSpeech corpus (Panayotov et al., 2015) and decoded using the Google Cloud Speech-to-Text

Table 9: Results by question type and answer position on the test set of ELITR-Bench-QA in single-turn mode. The number N below a subset indicates the corresponding subset size. Boldface numbers correspond to the best performance among proprietary or open-source models.

Model	Question type				Answer position			
	Who (N=45)	What (N=57)	When (N=20)	How many (N=8)	Begin (N=43)	Middle (N=34)	End (N=22)	Several (N=31)
GPT-3.5	7.91	6.94	7.68	7.79	7.33	7.45	7.76	7.37
GPT-4	8.56	**8.29**	8.28	8.29	**8.36**	8.29	8.32	**8.57**
GPT-4o	**8.68**	8.12	**8.60**	**8.92**	8.17	**8.67**	**8.42**	8.56
LongAlpaca-7B	5.35	5.37	6.35	6.79	5.81	5.80	4.97	5.53
LongAlpaca-13B	7.19	5.47	6.47	6.00	5.93	5.95	6.85	6.59
LongChat-7B-v1.5	6.88	4.94	6.33	4.17	6.41	4.91	5.89	5.77
Vicuna-7B-v1.5	6.13	5.65	5.40	2.88	5.89	5.21	4.96	6.12
Vicuna-13B-v1.5	6.96	6.68	5.48	5.54	6.35	6.41	6.55	6.87
LongAlign-7B	6.93	6.33	6.00	5.88	7.09	6.39	6.47	5.66
LongAlign-13B	6.08	6.74	5.97	5.75	6.71	6.21	6.33	5.95
LLaMA-3.1-8B	**8.18**	**7.53**	7.53	**8.67**	**7.95**	**7.60**	**8.00**	**7.77**
Phi-3-small	7.67	6.78	**7.85**	8.25	7.57	7.36	7.06	7.22

API. The dataset includes annotated transcription errors and is available from the RED-ACE ASR Error Detection and Correction dataset.[20] We merged the train, development, and test sets into a single .jsonl file, containing 525,308 lines, and used it to create 86,148 substitution rules. Each rule specifies a token and a probability distribution over similar tokens (or an empty character) that can replace it. An example of a such a substitution rule is as follows:

```
{"earlier": {"early": 0.4651, "Elliot": 0.0233, "Early": 0.0233, "Hurley": 0.0233, "earliest": 0.1860, "earrings":
    0.0233, "other": 0.0465, "early.": 0.0233, "earlier.": 0.0698, "Julia": 0.0233, "area": 0.0233, "audio":
    0.0233, "Aaliyah": 0.0233, "Italia": 0.0233}}
```

These rules enable the simulation of noisy transcripts from existing 'clean' transcripts, targeting specific Word Error Rate (WER) levels of 20%, 40%, 60%, 80%, and 100%. However, the actual WER achieved after noise injection is generally lower than the intended target, meaning that even at a target WER of 100%, some correct answers can still be inferred. The actual WER values corresponding to different target levels are presented in Table 11.

Below is an example of GPT-4's response to the same question when provided with transcripts from the same meeting but with varying levels of noise in the long-context window. The answers below correspond to the question *"Who is going to register for the [PROJECT2] conference?"*:

- **Ground Truth (GT):** [PERSON3]
- **WER 0.2:** (PERSON3) is going to register for the [PROJECT2] conference.
- **WER 0.4:** The transcript does not explicitly state who will register for the [PROJECT2] conference.

[20] https://huggingface.co/datasets/google/red_ace_asr_error_detection_and_correction

Table 10: Results of a one-tailed Welch's t-test on the alternative hypothesis "The average score for questions with middle-position answers is lower than the average score of other questions", to verify the presence or absence of a "lost in the middle" effect (Liu et al., 2023). Boldface numbers denote statistically significant results (p-value < 0.05).

Model	p-value
GPT-3.5	0.466
GPT-4	0.372
GPT-4o	0.754
LongAlpaca-7B	0.713
LongAlpaca-13B	0.265
LongChat-7B-v1.5	**0.032**
Vicuna-7B-v1.5	**0.046**
Vicuna-13B-v1.5	0.469
LongAlign-7B	0.409
LongAlign-13B	0.413
LLaMA-3.1-8B	0.308
Phi-3-small	0.541

Table 11: Comparison of target Word Error Rates with the effective Word Error Rates obtained by the noise injection procedure, averaged over all dev and test meeting transcripts.

Target WER	Effective WER
20.00	20.99
40.00	37.41
60.00	50.07
80.00	61.86
100.00	71.13

- **WER 0.6:** Based on the transcript, (PERSON3) indicated that they can register for the [PROJECT2] conference.
- **WER 0.8:** Based on the transcript, it is not entirely clear who specifically is going to register for the [PROJECT2] conference.

We observe that GPT-4 remains robust to text noise across several noise levels for this query. It is important to note that a poor response at WER=0.4 and a better response at higher noise levels can occur because the target WERs (noise levels) are calculated for the entire meeting transcript. Various segments of the transcript, especially the relevant ones, may be impacted in diverse ways or remain unaffected at different noise levels.

Experimental results on robustness. In Section 2.2, we studied how long-context LLMs fare at answering questions when having access to relatively clean meeting transcripts. However, in many practical scenarios, the quality of the transcripts might be degraded due to different factors: e.g., the audio recording conditions, the presence of accented speech, or simply the lacking capabilities of

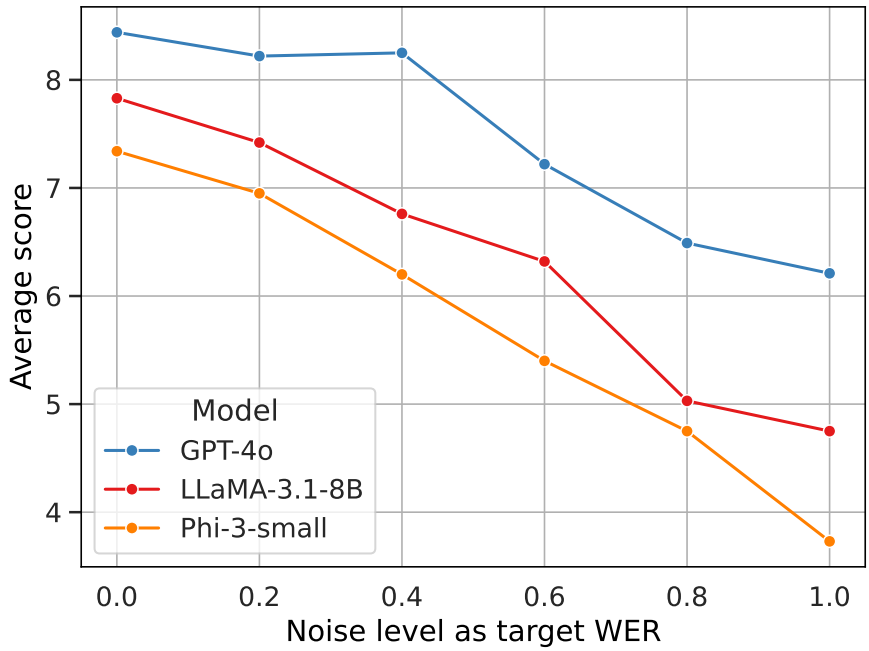

Figure 5: Comparison of the scores obtained for GPT-4o, LLaMA-3.1-8B, and Phi-3-small using transcripts with varied levels of noise on the test set of ELITR-Bench-QA in single-turn mode. Indicated levels of noise correspond to the target Word Error Rates set in our noise injection procedure.

the ASR model. We then sought to understand how robust long-context LLMs are in the presence of a noisy transcript. For that purpose, we tested the three best-performing models from Table 8 – i.e, GPT-4o,[21] LLaMA-3.1-8B, and Phi-3-small – on the test set of ELITR-Bench-QA in single-turn mode, using transcripts with varied levels of noise. The results are reported in Fig. 5. In this experiment, a single seed is used to limit the cost incurred by GPT-4-based evaluation.

We observe in Fig. 5 that while the gap between the two open-source models and GPT-4o is small on the clean transcript (around 1 point), it widens significantly as noise level is increased. Interestingly, GPT-4o also seems to be more resistant to mild noise (0.2 and 0.4) in comparison to other models. Even at very high noise levels (0.8 and 1.0), its average score remains above 6 which is similar to the performance of LLaMA-2-based models from Table 8. All in all, we conclude that while the most recent open-source long-context LLMs approach GPT-4/4o capabilities on clean transcripts, there remains an important gap when noisier context is used.

2.4 Evaluate safety of TiM

We want our assistant to effectively reject user requests that are inappropriate or irrelevant for a meeting assistant. To achieve this, we have defined safety filters which are natural language guidelines outlining acceptable requests. These filters will be used by the LLM to identify and filter out unsuitable requests.

Table 12 provides an overview of the *config.json* file, which outlines key parameters governing the assistant, including those necessary safety filters. The three filters used in our evaluation are listed under the 'filters' key. Additionally, the 'utterer' key specifies the LLM responsible for generating

[21] Given the similar performance of GPT-4 and GPT-4o, we only retained GPT-4o due to its lower cost.

responses to user inputs, while the 'filterer' key designates the LLM used to filter out inappropriate requests based on the predefined filters. We are using a specific prompt for our LLM-based filter, as shown in Table 13.

Key	**Value**
`"welcome"`	"Hi, I'm TiM your meeting assistant!"
`"human"`	"User"
`"assistant"`	"Tim"
`"help"`	"Sorry you missed the last meeting! Ask any legitimate questions, in English, French or Korean."
`"utterer"`	"openai-gpt-4o"
`"filterer"`	"openai-gpt-3.5-turbo"
`"filters"`	"be expressed in English, French, or Korean", "not contain toxic content", "contain questions and utterances expected for a conversational meeting assistant such as: greetings, questions about meetings or projects, clarification, acknowledgment, and closure"
`"filter_emoji"`	":bell:"

Table 12: The `config.json` file outlines various aspects of the assistant, including the necessary safety filters.

You only act as a binary filter in front of a conversational agent. Your response to the utterance is OK if it respects the following guidelines and KO otherwise.
Guidelines: a valid (OK) utterance should:
[Add the content of "filters" here]
Always add a short explanation after OK or KO about your decision. Now give your response for the following utterance:
[Add user utterance to be processed here]

Table 13: The prompt used for the LLM-based filters

Dataset for evaluating filters' accuracy We built a dataset for evaluating filters' efficiency on two real UTTER meetings transcripts that took place on November 14th, 2022, and January 16th, 2023, respectively. The first meeting has 57 queries, among which 24 are irrelevant, while the second meeting has 44 queries, with 20 being irrelevant. Below, we present examples of relevant and irrelevant queries based on the filters defined in the JSON file shown in Table 12.

```
{Hello, who attended the meeting?} {[OK]}
{How much is 2 + 2?} {[KO]}
{Did Laurent Besacier participate?} {[OK]}
{He was AGAIN on vacations!} {[KO]}
{I cannot t remember what WP8 is, can you please remind me?} {[OK]}
{Merci pour l'information, c'etait utile.} {[OK]}
{Who cares about this stupid project anyway?} {[KO]}
{Pourquoi est-ce que tu es si nul dans ce travail?} {[KO]}
```

LLM	Meeting 1 (November 14th, 2022)			Meeting 2 (January 16th, 2023)		
	gpt4-o	gpt3.5	llama3.1	gpt4-o	gpt3.5	llama3.1
acc %	**100**	94.7	94.7	**97.7**	95.5	95.5
false alarm %	**0**	9.1	6.1	**4.2**	8.3	8.3
miss %	**0**	0	4.2	**0**	0	0

Table 14: Results on Filters' Accuracy: accuracy (*acc*) is defined as the number of correctly labeled utterances divided by the total number of utterances. The false alarm rate (*false alarm*) represents the proportion of relevant utterances incorrectly labeled as irrelevant; the miss rate (*miss*) indicates the proportion of irrelevant utterances incorrectly labeled as relevant.

Experiments on filters' accuracy We evaluate 3 LLMs as filterers: **GPT-3.5**, **GPT-4o** and **LLaMA-3.1-8B**. The results of our evaluation are presented in table 14. GPT-4o offers the best performance, but using it to filter every utterance in the chatbot could be costly. More affordable models, such as GPT-3.5 and LLaMA-3.1-8B, can be viable alternatives as they also demonstrate respectable performance.

2.5 Conclusion

We have evaluated our second meeting assistant, *TiM*, across multiple dimensions: accuracy, robustness, and safety. The key finding is that recent open models, such as LLaMA-3.1-8B, outperform GPT-3.5 on our meeting assistant benchmark, though they still fall short of GPT-4o's performance. These smaller open models also show promising results in filtering irrelevant requests, demonstrating good safety capabilities. However, our experiments on robustness to text noise reaffirm the superiority of the closed GPT-4o model in this regard.

3 Conclusion

This document describes the second prototypes evaluation built for the two use cases of the UTTER project, the Customer Service Assistant (Section 1) and the Meeting Assistant (Section 2). For the customer service assistant use case, the main finding is that open-model-based approaches such as Tower perform very well when translating bilingual conversations in customer service contexts, even surpassing strong closed LLMs. Regarding emotion recognition in conversations encoder-based approaches (RoBERTa) are still very competitive with LLMs, with comparable performance to proprietary LLM-based services, and with very large performance gap compared to open-weights alternatives. For the meeting assistant use case the main finding is that open models such as LLaMA-3.1-8B outperform GPT-3.5 on the meeting assistant benchmark while still falling short of GPT-4o performance.

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D7.2 Second prototype evaluation report