Meetalk: Retrieval-Augmented and Adaptively Personalized Meeting Summarization with Knowledge Learning from User Corrections

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Abstract

We present **Meetalk**, a retrieval-augmented and knowledge-adaptive system for generating personalized meeting minutes. Although large language models (LLMs) excel at summarizing, their output often lacks faithfulness and does not reflect user-specific structure and style. Meetalk addresses these issues by integrating ASR-based transcription with LLM generation guided by user-derived knowledge. Specifically, Meetalk maintains and updates three structured databases, Table of Contents, Chapter Allocation, and Writing Style, based on user-uploaded samples and editing feedback. These serve as a dynamic memory that is retrieved during generation to ground the model's outputs. To further enhance reliability, Meetalk introduces hallucination-aware uncertainty markers that highlight low-confidence segments for user review. In a user study in five real-world meeting scenarios, Meetalk significantly outperforms a strong baseline (iFLYTEK ASR + ChatGPT-4o) in completeness, contextual relevance, and user trust. Our findings underscore the importance of knowledge foundation and feedback-driven adaptation in building trustworthy, personalized LLM systems for high-stakes summarization tasks.

1 Introduction

Large Language Models (LLMs) have shown impressive capabilities in performing summarization and generation tasks across a wide range of domains. However, a fundamental question remains: How do LLMs utilize knowledge, unstructured, in real-world applications, and how can we ensure that this knowledge is personalized, accurate, and faithful? This question is especially critical in the context of automated meeting minutes generation, where information needs to be not only complete and concise but also aligned with domain-specific writing norms and user preferences.

Although existing approaches have used LLM to generate abstractive meeting summaries, they often fall short in two key areas: (1) the inability to adapt to user-specific structural and stylistic knowledge and (2) the tendency to produce hallucinated or generic outputs due to weak grounding. Furthermore, traditional systems lack mechanisms for learning from user feedback, leading to repeated errors and suboptimal long-term performance in repetitive meeting contexts.

In this work, we propose **Meetalk**, an adaptive meeting minutes generation system that addresses these challenges by tightly integrating *retrieval-augmented generation* (RAG), user-driven knowledge modeling, and hallucination-aware design. Specifically, Meetalk builds and updates structured knowledge bases, including chapter allocation mappings and writing style templates, learning from user-provided examples and edits. At inference time, these personalized knowledge modules are retrieved and injected into LLM prompts to guide faithful and stylistically consistent generation. In addition, we incorporate uncertainty indicators such as "[Not Sure]" labels to make the confidence of the model interpretable to users, thus enabling human-AI collaboration in mitigating hallucinated content.

To evaluate Meetalk, we conducted a controlled user study in five real-world meeting scenarios. Compared to a strong baseline (iFLYTEK ASR + ChatGPT-4o), Meetalk consistently improves output completeness, contextual relevance, and user trust, while significantly reducing time and cognitive load. Our findings suggest that adaptively modeling and utilizing user-specific knowledge not only enhances generation quality, but also provides a promising paradigm for deploying trustworthy, personalized LLM-based systems in professional workflows.

2 Backgrouond

2.1 Text-to-Minutes: Evolution from Extractive Methods to Large Language Models

Early research on meeting summarization primarily employed extractive methods (Tur et al., 2008) (Riedhammer et al., 2008) (Tixier et al., 2017), though studies indicated a human preference for abstractive summaries in conversational content (Goyal et al., 2022) (Murray et al., 2010). The rise of LLMs has brought strong semantic capabilities to tasks like meeting minutes generation (Cao et al., 2024), but factual consistency remains a key issue. Studies show that nearly 30% of summaries generated by seq2seq models contain inaccuracies (Cao et al., 2018)(Kryściński et al., 2019). LLMs also face challenges in adapting to subjective preferences, crucial for meeting minutes. Biermann et al.(Biermann et al., 2022) found that users prefer tools that align with their writing styles, but Ippolito et al.(Ippolito et al., 2022)(Lin et al., 2024) noted LLMs struggle to maintain organizational or individual style and format, further complicating their use in this context. Therefore, to develop an accurate and personalized meeting minutes tool, we propose leveraging the capabilities of LLMs while implementing strategic system designs to enhance accuracy and adapt to personal preferences.

2.2 Adaptively Personalized Minutes: RAG and Summary-based Prompt Engineering

User preference modeling plays a crucial role in understanding and adapting to user preferences, thereby enabling the generation of personalized meeting minutes. Researchers have applied machine learning-based user preference modeling in various specific domains. Yang et al. proposed a kernel probability model for color theme evaluation (Yang et al., 2024). Ma et al. introduced CRNN-SA for extracting user music preferences from listening history (Ma et al., 2022). Ma et al. developed SmartEye, a deep learning system that generates real-time photo composition suggestions based on users' previous photos and feedback (Ma et al., 2019).

Recent advancements in LLMs have highlighted the potential of Retrieval-Augmented Generation (RAG) in user preference modeling (Lewis et al., 2020). RAG enhances LLM performance by providing relevant external information, reducing hallucinations, and improving response accuracy. Summary-based prompt engineering for adaptive personalization leverages the power of text summarization to create dynamic, user-tailored prompts (Ait Baha et al., 2023). This approach abstracts essential information conveniently without capturing sensitive details (Friedman et al., 2013). While users often struggle to distill key features to refine their prompts, employing LLMs to extract these features and automatically incorporate them into subsequent prompts offers a convenient solution (Ait Baha et al., 2023). Recent studies have shown that such adaptive systems can significantly improve engagement and satisfaction in various applications, from recommendation (Lyu et al., 2023) systems to personalized learning platforms (Ait Baha et al., 2023).

In the context of personalized meeting minutes, RAG and summary-based prompt engineering can be employed for retrieving users' sample meeting minutes and learning from user modifications on the minute's output.

3 System Design

3.1 Design Goals (DGs)

Motivated by the findings of formative study and existing research, we aim to design an adaptively personalized meeting minutes generation tool with the following **design goals (DGs)**:

DG1. To ***improve minutes quality*** while ***reducing time*** spent on meeting minute generation.

DG2. To integrate users' ***personal preferences*** in meeting minute formats and writing styles.

DG3. To leverage an adaptive approach that streamlines the process for repetitive meeting tasks, ***improving efficiency over time***.

DG4. To enhance the ***visualizations for trustworthiness***, increasing user confidence in the generated minutes.

3.2 Overall Workflow

Meetalk's workflow can be visualized in Figure 1, beginning with the user uploading a sample meeting minutes file and the meeting audio to be processed. The system analyzes the sample file to *suggest* three key components: the Table of Contents (ToC), Chapter Allocation Database, and Writing Style Database. These components serve as adaptive references for the subsequent processing steps, allowing Meetalk to tailor its output to each user's specific needs and preferences.

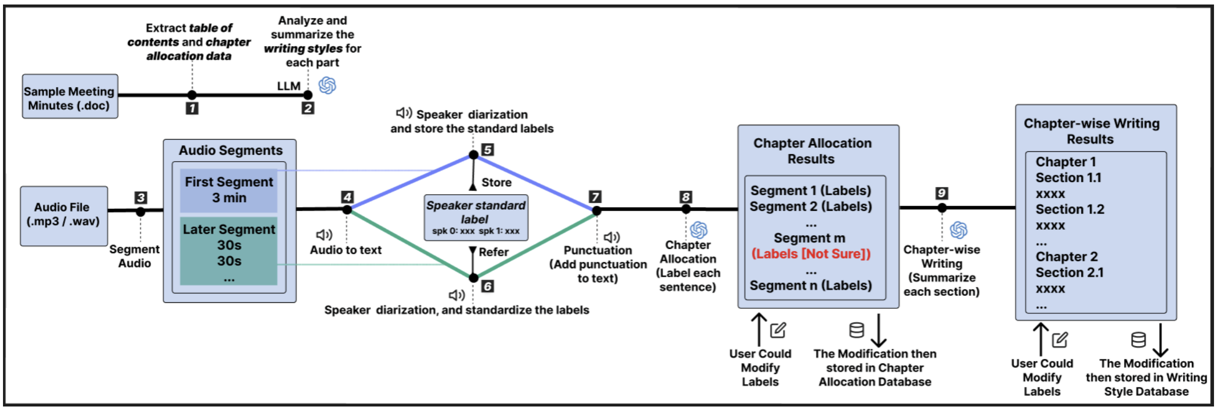

Extract *table of contents* and *chapter allocation data*
Analyze and summarize the *writing styles* for each part
Sample Meeting Minutes (.doc)
LLM
1
2
Speaker diarization and store the standard labels
Audio Segments
First Segment 3 min
Later Segment 30s 30s ...
Audio File (.mp3 / .wav)
3
Segment Audio
4
Audio to text
5
Store
Speaker standard label
spk 0: xxx spk 1: xxx
Refer
6
Speaker diarization, and standardize the labels
7
Punctuation (Add punctuation to text)
8
Chapter Allocation (Label each sentence)
Chapter Allocation Results
Segment 1 (Labels)
Segment 2 (Labels)
...
Segment m
(Labels [Not Sure])
...
Segment n (Labels)
User Could Modify Labels
The Modification then stored in Chapter Allocation Database
9
Chapter-wise Writing (Summarize each section)
Chapter-wise Writing Results
Chapter 1
Section 1.1
xxxx
Section 1.2
xxxx
...
Chapter 2
Section 2.1
xxxx
...
User Could Modify Labels
The Modification then stored in Writing Style Database

Figure 1: Meetalk's main process: Steps 1-2 sample file data analysis and suggestion, 3-7 transcribe audios, 8 allocates chapters, and 9 involves chapter-wise writing.

Next, Meetalk processes the meeting audio using ASR, dividing it into segments for *transcription, speaker diarization, and punctuation*. As each segment is processed, Meetalk performs *chapter allocation* by referring to the Chapter Allocation Database, labeling the text according to the existing ToC or creating new chapters or sections as necessary. If users find the chapter allocation results inaccurate, they can pause the process and *modify* the chapter allocation labels as easily as editing text. By confirming the modifications, these *changes are incorporated* into the Chapter Allocation Database for future reference.

Once all audio is processed and allocated, Meetalk *generates content for each section* based on the Writing Style Database and the allocated text. Similarly, if users are unsatisfied with the generated results, they can directly modify the content. By confirming the modifications, Meetalk will analyze the modified parts at a high level and *update the Writing Style Database* accordingly.

Throughout this process, Meetalk offers two LLM options: OpenAI ChatGPT API (supporting all available versions), and a locally hosted LLAMA3:8b. This flexibility allows users to choose their preferred LLMs for various needs, balancing factors such as performance, privacy, and cost.

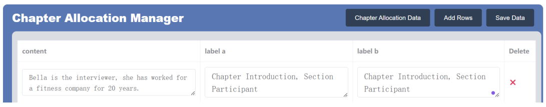
3.3 Databases

Meetalk features three core databases. First, the **Table of Contents Database (ToC)** is responsible for storing the organizational structure of meeting records, specifically the chapters and sections. Second, the **Chapter Allocation Database** archives historical associations between contents and specific chapters and sections. Third, the **Writing Style Database** establishes guidelines and stores details for diverse writing styles. The writing styles for different sections are displayed alongside their corresponding sections in the ToC. These three components can be populated through three methods. *The first method is Referencing to Sample Files*: Meetalk processes reference documents by examining their chapter layouts, recognizing the content within, and summarizing the writing style characteristics. *The second method is Manual User Input*, where users can manually enter data for all three databases. *The third method involves Learning from User Modifications*, Meetalk learns and updates the databases based on user modification on the output. These processes will be explained in detail in a subsequent section.

3.3.1 Chapter Allocation Database

The Chapter Allocation Database is organized into three columns: content, Label A, and Label B. Both label columns follow the format "Chapter xx, Section xx," serving to denote the hierarchical chapter and section to which the content belongs. The inclusion of two labels is based on our rigorous testing results. We conducted a systematic study using a random sample of 200 sentences from meeting transcripts, analyzed in conjunction with their corresponding table of content. Two editors independently labeled each sentence, considering its contextual placement (Cohen's Kappa = 0.92, agreement ratio = 96.5%). Analysis of these labels revealed that 78% of sentences corresponded to a single section, while 22% belonged to two different sections. Therefore, we've included a second label column to accommodate these dual-labeled sentences. For content requiring more than two labels, users can split the same content item into multiple rows for input, allowing additional labels to be assigned to that content. For example, a content item needing 4 labels can be entered in two rows, with 2 labels assigned to each row.

To allow users conveniently update the databases, as shown in Figure 2, Meetalk provides users with the flexibility to edit table contents, add new entries, and modify chapter allocation outputs. While minor changes need to be made, our database can keep track on the preferences based on these changes. After editing and confirming the edits, users could click the “Save Data” button to upload the edited database and save it as the current chapter allocation database.



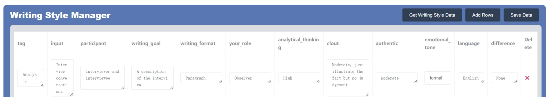
content	label a	label b	Delete
Bella is the interviewer, she has worked for a fitness company for 20 years.	Chapter Introduction, Section Participant	Chapter Introduction, Section Participant	×

Figure 2: Chapter Allocation Databases, with buttons to get chapter allocation data, add rows, delete rows and save data.

The content column of the Chapter Allocation Database is stored as embeddings (referred to as "content embeddings" below). For each entry of the "content" column, an embedding is generated using the *large multilingual E5 text embedding model* (referred to as *"multilingual-e5-large"* below). The multilingual-e5-large model supports 93 languages, primarily English, enabling Meetalk to process meeting minutes in multiple languages, thereby enhancing its global applicability. These embeddings are crucial as they provide a mathematical representation of the text, facilitating later comparison and retrieval.

3.3.2 Writing Style Database

To empower users with the capability to utilize and preserve precise and tailored writing tags, we have defined eleven indicators categorized into three main types: Five for **Writing Context**, five for **Summary Variables**, and one **Difference**.



tag	input	participant	writing_goal	writing_format	your_role	analytical_thinking	clout	authentic	emotional_tone	language	difference	Delete
Analysis	Interview conversations	Interviewer and interviewee	A description of the interview	Paragraph	Observer	High	Moderate, just illustrate the fact but no judgement	moderate	formal	English	None	×

Figure 3: Writing Style Databases, with 11 columns and buttons to get writing style data, add rows, delete rows, and save data.

Writing Context encompasses the foundational elements necessary for creating the writing piece. These indicators were derived from a comprehensive formative study on meeting minutes requirements across diverse industries, including: **Input:** The scenario of the meeting. **Participant:** The individuals or groups involved in the meeting, including their roles and relevance to the discussion topics. **Writing Goal:** The primary objective of the meeting minutes, such as informing, decision-making, or action planning. **Writing Format:** The required structure or style of the meeting minutes, such as paragraphs, bullet points, or numbers. **Your role:** The viewpoints or roles that need to be represented in the minutes.

Summary Variables are mainly derived from LIWC 2022 definitions, including: **Analytical Thinking:** Measures logical and hierarchical thinking patterns. **Clout:** Reflects social status, confidence, or leadership abilities. **Authenticity:** Indicates honesty, personal disclosure, and genuineness. **Emotional Tone:** Assesses overall emotional tone of the writing. **Language:** *English, Spanish, Traditional Chinese, etc.*

And finally, the **Difference** variable is created to store comparisons between user modifications and original text.

The Writing Style Manager interface includes three main buttons to interact with the writing style data. The *"Get Writing Style Data"* button retrieves the current tag data from the database. Users may then add, delete, or edit rows, uploading their changes using the *"Save Writing Style Data"* button. With this approach, we enable dynamic and iterative improvements in writing style prediction and generation.

4 Knowledge Integration and Utilization in Meetalk

In the era of large language models (LLMs), the ability to effectively ground generation on structured and personalized knowledge is crucial to enhancing output accuracy and trustworthiness. Meetalk addresses this challenge by incorporating a retrieval-augmented and user-adaptive knowledge pipeline into its summarization workflow. This section details how Meetalk constructs, retrieves, and updates knowledge to enable personalized, faithful, and hallucination-aware meeting minutes generation.

4.1 Knowledge as Structured Memory

We conceptualize knowledge in Meetalk as a structured memory composed of three user-specific databases: the Table of Contents (ToC) database, the Chapter Allocation database, and the Writing Style database. These databases are derived from user-provided sample minutes or previous interactions, and encode the organizational structure, topical segmentation, and preferred linguistic style for each meeting domain. Unlike static templates, these knowledge modules dynamically evolve as users revise system outputs.

4.2 Retrieval-Augmented Prompting

To ensure faithful and stylistically consistent generation, Meetalk employs retrieval-augmented generation (RAG) techniques at multiple stages. During chapter allocation, each segment of transcribed audio is embedded and matched against prior content in the Chapter Allocation database to suggest contextual labels. Similarly, in the writing stage, the system retrieves style exemplars from the Writing Style database to construct section-specific prompts. These retrieved signals act as grounding knowledge, guiding the LLM to produce outputs aligned with both the user's structural expectations and domain-specific discourse.

4.3 Knowledge Updating via User Feedback

To support long-term adaptability, Meetalk treats user modifications as implicit knowledge updates. After each editing action—whether modifying chapter boundaries or rewriting section texts—the system summarizes the difference and updates the corresponding database entry. In doing so, Meetalk implements an interactive knowledge editing loop that enables continual refinement of the structured memory without requiring explicit reprogramming or prompt engineering from the user.

4.4 Hallucination Awareness and Uncertainty Markers

To further enhance trust and mitigate hallucinations, Meetalk integrates a lightweight hallucination-aware mechanism. When the system detects uncertain or low-confidence segment-label mappings—based on retrieval inconsistencies or model disagreement—it marks them with a "[Not Sure]" tag in the interface. This allows users to prioritize checking potentially unreliable content, offering a human-AI collaboration path for factuality verification. These uncertainty annotations can also be logged for future benchmarking or fine-tuning, supporting broader efforts in hallucination detection and correction in knowledge-intensive generation tasks.

In summary, Meetalk transforms user interactions into a dynamic knowledge lifecycle: acquiring knowledge from user examples, injecting it via retrieval-augmented prompting, refining it through feedback, and regulating output trustworthiness through uncertainty cues. This design provides a concrete pathway for realizing knowledgeable, user-aligned LLM applications in high-stakes domains such as meeting documentation.

5 Evaluation

To evaluate the effectiveness of Meetalk in supporting the generation of meeting minutes, we conducted a *within-subject study* comparing Meetalk with the conventional approach to automate meeting minutes. As our baseline, we selected *iFLYTEK real-time ASR combined with ChatGPT-4o*. Participants were asked to complete **two tasks**, using the baseline method and Meetalk respectively.

To validate the optimization of our system for handling the repetitive nature of meetings, participants in each task processed **three meeting audios** from a specific scenario, generating meeting minutes in a consistent format. To assess the generalizability of Meetalk, we selected **five different scenarios** and invited participants who were familiar with these scenarios to complete the tasks.

Through these comparisons, we seek to evaluate whether Meetalk outperforms the baseline method in addressing the design goals derived from literature and the formative studies.

Eighteen (N=18) participants are invited to this study, with five different real-world scenarios included: **legal consultations**, **study abroad counseling**, **academic discussions**, **mock interviews**, and **company pitches**. Participants generally span moderate to high levels of expertise within their respective fields.

It is noteworthy that all participants demonstrate high frequency of meetings and substantial usage of language models in their professional contexts, underscoring the relevance of this study to contemporary professional practices. If the audio contains private conversations, any mentions of real names have been cut out beforehand, and this removal does not affect the main content of the meeting.

5.1 The Baseline Method

The baseline method combines two powerful tools: Using iFLYTEK ASR to generate transcript from the meeting audios, and using OpenAI's ChatGPT-4o to write meeting minutes from transcripts. This approach requires users to switch between two separate tools and incurs significant costs.

5.2 Study Procedure

A remote study session for each participant lasted up to 3 hours, divided into three parts: **the pre-study survey, the main study itself, and the post-study interview.** Participants accessed Meetalk via a web browser on a researcher-provided computer through remote control software. Simultaneously, the experimenter communicated with the participants via Zoom or Lark video conferencing.

As for the main process, initially, communicate with the participant to ensure they understand the relationship and purpose of the above materials, as well as the workflow of using Meetalk. Then, proceed with two tasks while recording the time taken for each: ***Task 1:*** Using the three transcripts produced by iFLYTEK, create meeting minutes similar to the sample meeting minutes file using ChatGPT4o for each transcript. Instruct participants to pay close attention to the format and writing style, aiming to match the sample meeting minutes as closely as possible. Participants are allowed to use various tools within ChatGPT4o to accomplish this task. ***Task 2:*** On Meetalk, upload the sample meeting minutes file and click "suggest". Allow participants to freely modify the suggested database. Then, instruct them to click "submit" for chapter allocation, again allowing free editing. Finally, have them click "write" and permit further modifications as needed. Remind participants that their edits will be saved to the database, which may influence the processing of subsequent audio files.

6 Results

In this section, we analyzed objective and subjective results by combining the final study minutes, post-study questionnaires, and screen recordings captured during the process. The subjective ratings on minutes' quality and the ML GUI Heuristics are presented in Figure 4.

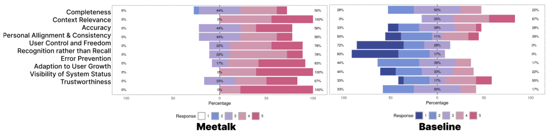


Figure 4: **Ratings for Meetalk(left) and the baseline(right) method** of the subjective 5-point Likert rating results on minutes' quality and user experience based on the ML GUI Heuristics.

6.1 Q1: Meetalk *improves writing quality* while *reducing time*

We recorded the time taken by 18 participants to complete two distinct tasks in this study. The average time for each scenario was calculated and visualized in Figure 5. Overall, Meetalk consistently utilizes less time than the baseline method across all scenarios, (p = 0.0169, Cohen's d = 1.7629), with an average time reduction of 33.9%.

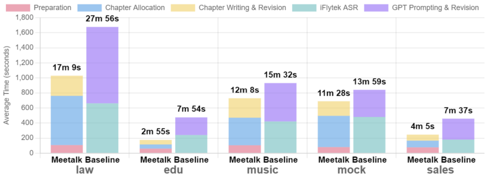


Figure 5: **Meetalk and the baseline method average time comparison** in five studied scenarios. Within a bar, the different colors show the specific time proportion of each stage. It is evident from the figure that the total time used by Meetalk is lower than that of the baseline method.

As shown in 1, the Flesch-Kincaid Reading Ease scores indicate that Meetalk's output has no significant difference on the readability level compared to the baseline's output (p = 0.0688, lower scores indicating easier-to-read text. Regarding word count, Meetalk consistently demonstrates a higher word count percentage across all domains compared to the baseline (p = 0.0114, Cohen's d = 1.9815). This substantial difference in word count percentages indicates that Meetalk consistently produces more extensive content than the baseline, suggesting more detailed or comprehensive responses in each domain.

Based on the participants' ratings of minutes quality, Meetalk-generated minutes generally outperformed those produced by the baseline method on **completeness** (Mean = 3.56 > 2.94, p = 0.0022, Cohen's d = 1.1093), **Context Relevance** (Mean = 4.44 > 3.94, p = 0.0244, Cohen's d = 0.7864), and **Accuracy**(Mean = 4.00 > 2.89, p = 0.0010,

Domain	Law		Edu		Music		Mock		Sales	
	Meetalk	Baseline	Meetalk	Baseline	Meetalk	Baseline	Meetalk	Baseline	Meetalk	Baseline
Flesch-Kincaid Reading Ease **Mean (SD)**	14.03 (0.23)	13.26 (0.55)	16.47 (1.72)	15.20 (2.08)	15.18 (2.83)	10.81 (1.69)	15.88 (1.92)	16.38 (2.87)	18.00 (1.44)	13.36 (2.27)
Word Count Percentage	3825/17945 =21.32%	869/17945 =4.84%	774/1500 =51.6%	476/1500 =31.73%	3566/13012 =27.41%	873/13012 =6.71%	841/4406 =19.09%	151/4406 =3.42%	1480/3595 =41.17%	551/3595 =15.32%

Table 1: Comparison of Meetalk and Baseline across **Flesch-Kincaid Reading Ease** (The lower, the easier to read) and the **word count**

Cohen's d = 1.1971).

- **Completeness:**

Meetalk's score generally outperforms the Baseline's score. Even though both methods cover the main idea, Meetalk provides more details and in-depth explanations, resulting in more comprehensive and complete content. This difference can be attributed to the different approaches Meetalk takes in processing the long transcript. Meetalk accurately extracts all sentences related to a specific section. Then, in a single LLM process, it focuses only on these sentences and rewrites them. By focusing on a specific section, Meetalk can provide richer, more relevant content within a limited generation space. In comparison, the baseline method adopts a full-text summarization, although it touches on the solution part, but only provides an overall summary. It is constrained by the token limit of the LLMs, resulting in limited space allocated to the solution part in the summary.

- **Conext Relevance:** Likert results show that Meetalk consistently achieves slightly higher context relevance scores compared to the baseline method. The low relevance in the baseline method may be attributed to overgeneralization. When processing large amounts of text, language models often attempt to synthesize broad summaries, resulting in vague or generic statements that lack specific, pertinent details (Liu & Lapata, 2019). This tendency towards overgeneralization leads to output that, while broadly related to the input, fails to address the nuances of the given query, significantly reducing its relevance and utility to the user.

- **Accuracy:** Users rated Meetalk's accuracy slightly higher than the baseline's. User feedback indicated that while both methods generally handle explicit numerical data well, the baseline often introduces logical errors that reduce overall accuracy. This issue likely stems from the limitations of traditional summarization techniques in handling long-form content (Liu & Lapata, 2019), which adapted by the baseline method.

6.2 Q2: Meetalk *allows user-driven customization to address personal preferences*

Two metrics in the ML GUI heuristics framework showed noteworthy results. The **Personal Alignment & Consistency** metric showed a positive trend favoring Meetalk over the baseline method (Mean = 3.72 vs. 2.83, p = 0.1887, Cohen's d = 0.4472), although the difference was not statistically significant. More compellingly, the **User Control and Freedom** metric demonstrated a highly significant advantage for Meetalk (Mean = 4.11 vs. 1.83, $p < 0.0001$, Cohen's d = 1.9031). These results strongly suggest that Meetalk effectively empowers users to tailor their reading experience according to individual preferences and habits, particularly in terms of providing enhanced control and freedom.

Through user-driven customization, the system achieves alignment consistency by ensuring that formats and writing styles are consistent with both sample files and user preferences. By allowing users to define their own formats and create writing style tags, the system maintains a seamless alignment with users' desired outcomes and expectations. By allowing users to edit or delete suggested content, and to modify Meetalk's output as needed, Meetalk ensures a high degree of user control and freedom.

6.3 Q3: Meetalk *streamlines repetitive meeting tasks with adaptive learning*

Given the repetitive nature of meeting minutes tasks, it's crucial for a system to leverage this characteristic to enhance efficiency. Our study revealed that Meetalk significantly outperformed the baseline method in three critical areas: **recognition rather than recall** (Mean 3.94 > 1.67, $p < 0.0001$, Cohen's d = 2.5820), **error prevention** (Mean 4.33 > 2.72, $p < 0.0001$, Cohen's d = 1.9437), and **adaptation to user modification** (Mean 4.67 > 2.61, $p < 0.0001$, Cohen's d = 2.2194). These results strongly indicate that Meetalk effectively empowers users to tailor their meeting minutes experience, leveraging the repetitive nature of the tasks to enhance overall efficiency and user satisfaction.

Function **suggestion** significantly enhances this aspect. P3 noted, *"Meetalk's ability to suggest table of contents and writing styles from sample files is incredibly helpful. I don't have to remember everything or keep separate databases."* P12 added, *"It's much easier than the baseline where we had to maintain our own databases and then figure out how to prompt ChatGPT correctly."* This automated suggestion feature allows users to focus more on minutes creation and understanding rather than tedious memorization and retrieval.

6.4 Q4: Meetalk *enhances visualizations for trustworthiness*

The trustworthiness of meeting minutes generation is paramount to its usefulness. Meetalk outperformed the baseline in both **Visibility of System Status** (Mean 4.00 > 3.28, p = 0.0198, Cohen's d = 0.8165) and **Trustworthiness** (Mean 4.78 > 2.89, p < 0.0001, Cohen's d = 2.2356), according to participant ratings.

• **Visibility of System Status:** Meetalk provides visibility into three key areas: databases, progress of the chapter allocation process, and final results. P5 commented, *"With Meetalk, I can see everything from the databases being used to how far along the process is. It's so much more transparent than just seeing input and output like with the baseline."* P11 added, *"Being able to track the chapter allocation process in real-time gives me a sense of control and understanding that I didn't have with ChatGPT."* The high degree of visibility allows to reduce uncertainty about system behavior. Users are better able to anticipate and adjust processes, resulting in greater efficiency and accuracy, making participants more confident and proactive in using LLMs.

• **Trustworthiness:** The enhanced visibility of system status, coupled with Meetalk's ability to indicate uncertainties, fosters a true collaboration between human and AI. P2 noted, *"I appreciate that Meetalk shows me what it's unsure about. It feels like we're working together, rather than me just correcting a finished product."* P14 elaborated, *"The constant feedback during the process makes me trust Meetalk more. It's not just a black box spitting out results."*

This approach to transparency and collaboration significantly increases trustworthiness. As P8 summarized, *"With Meetalk, I feel like I'm part of the process, not just an end-user. That makes me trust the results much more than I did with the baseline system."*

7 Conclusion and Discussions

Meetalk addresses the challenges of long meeting minutes generation through innovative chunking and adaptive personalization. By performing ASR on 30-second audio segments and labeling transcribed content for section allocation, Meetalk enhances completeness and relevance, allowing users to review and modify labels in real-time. This process reduces input length for LLMs, improving the quality of summaries. Additionally, the system's flexibility accommodates various data types and user preferences through RAG and summary-based prompt engineering, enabling natural adaptation to user behavior. Meetalk's design also includes an authenticity assessment mechanism that boosts user trust with feedback labels like "[Not Sure]." Overall, Meetalk's approach and principles can be generalized to other AI-driven applications beyond meeting note-taking, enhancing user engagement and facilitating multimodal processing tasks.

In conclusion, this study introduces Meetalk, an innovative adaptive AI system for personalized meeting minutes generation. By addressing key challenges in automated minute-taking, including effectively adapting to personal preferences, Meetalk represents a significant advancement. The system's unique features, such as chapter allocation, chapter-wise writing, and adaptive learning from user modifications, offer a flexible and user-centric approach to generate meeting minutes. Our comprehensive user study across diverse real-world scenarios demonstrates Meetalk's effectiveness in producing high-quality, personalized minutes while enhancing user experience and trustworthiness. These findings validate Meetalk's practical applicability, and further contribute valuable insights to the broader domain of personalized AI-assisted text processing and summarization. As organizations continue to rely heavily on meetings for information exchange and decision-making, systems like Meetalk have the potential to significantly improve productivity and communication effectiveness. Future research can build upon this foundation, further exploring the integration of adaptive personalization in various professional contexts and expanding the capabilities of AI-assisted documentation systems.

Limitations

One limitation for our work is that we chose personal computers as the primary device for Meetalk in the user study, since we consider their common use as meeting minute tools. However, we believe that one of Meetalk's core functionality, namely converting speech into structured meeting minutes, can be applicable to other devices, particularly smartphones, which might offer more convenience in audio recording and uploading. Nevertheless, using the system on smaller screens may require UI adjustments, and the user experience could differ. For instance, content review and manual editing might face more challenges, which potentially increases the need for automated support.

Another limitation lies in the failure to use locally deployed LLMs for the user study. Although we include LLAMA3:8b in the design of Meetalk, we still used GPT-4o in our user study in order to be consistent with the most commonly used methods mentioned by the participants in the formative study.This choice, while facilitating a direct comparison of the results, also limits our understanding of how the localized models perform in real-world applications. Future research could explore similar user studies using localized models such as LLAMA3:8b to validate the effectiveness of our proposed approach in real privacy-constrained environments.

Furthermore, we employed the Flesch-Kincaid Reading Ease score and word count percentage as objective measures to assess the quality of the meeting minutes produced. While readability is a crucial aspect of meeting minutes and it provides valuable insights, it does not include all dimensions of content quality. Additionally, word count percentage could somehow refelect the completeness of Meetalk's generated minutes, but we did not measure the quality of the large word counts. Both these two measures provide extra results to triangulate with the subjective assessment of text quality.

Lastly, Meetalk, as a research prototype, has inherent limitations. Our system relies on advanced LLMs like LLAMA3:8b or ChatGPT-4, both requiring significant computing resources. In our experiments, we either deployed LLAMA3:8b locally on a 24GB NVIDIA RTX 4090 GPU or used the ChatGPT-4o API. What's more, the 8k limit of one-sentence summarization, might lead to information gap, in concluding the meeting scenarios. Additionally, the ASR component lacks an interactive learning process, which means the transcription errors can't be automatically corrected based on user modifications. Currently, the system doesn't support real-time audio input, only allowing for audio file uploads. Furthermore, while powerful, the LLM-based text generation is not 100% accurate and can occasionally produce hallucinations or inaccuracies in the generated content.

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A System Design

B Meetalk overall introduction

C Participant information

D System UI

E Meetalk and Baseline result comparison examples

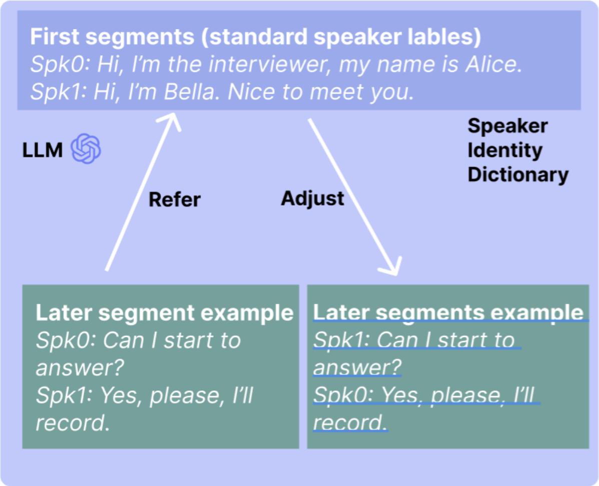

First segments (standard speaker lables)
Spk0: Hi, I'm the interviewer, my name is Alice.
Spk1: Hi, I'm Bella. Nice to meet you.
LLM
Speaker Identity Dictionary
Refer
Adjust
Later segment example
Spk0: Can I start to answer?
Spk1: Yes, please, I'll record.
Later segments example
Spk1: Can I start to answer?
Spk0: Yes, please, I'll record.

Figure 6: Meetalk's speaker diarization example in an interview scenario: The initial segment identifies Speaker 0 as the interviewer and Speaker 1 as the interviewee, storing their utterances in a **Speaker Identity Dictionary**. In later segments, even if speakers are initially mislabeled due to isolated analysis, the system corrects these labels by referencing the Dictionary, ensuring consistent speaker identification throughout the interview.

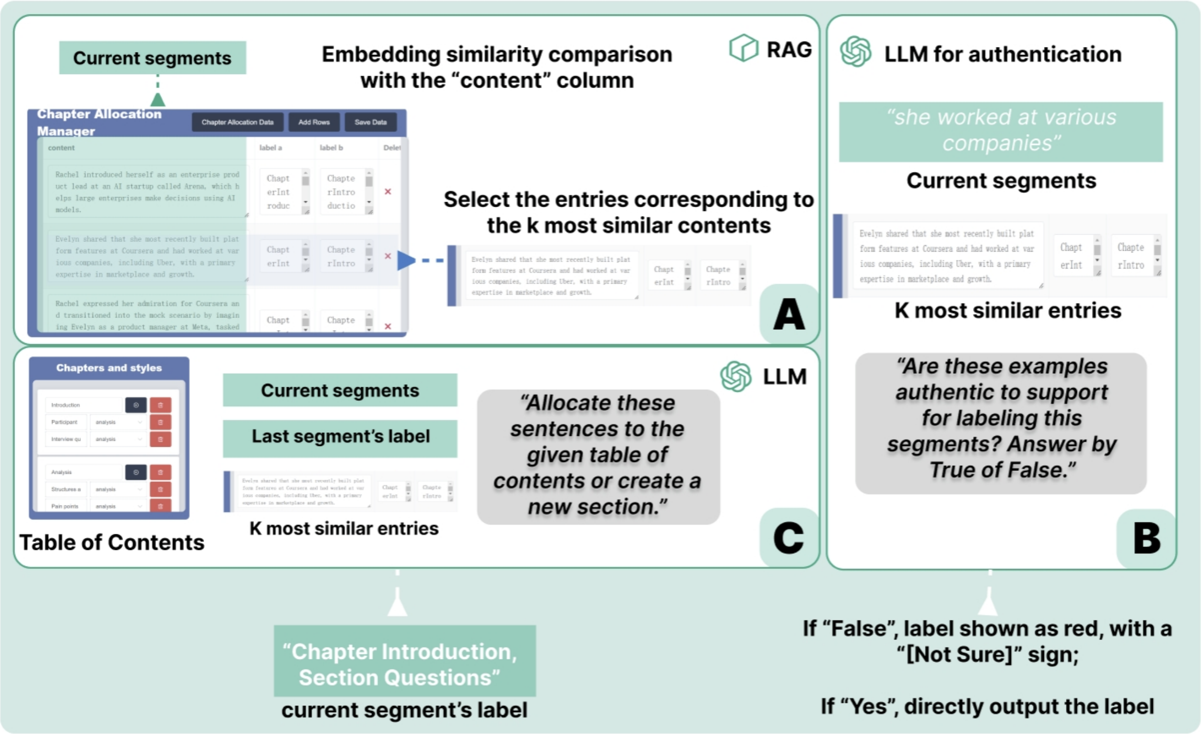
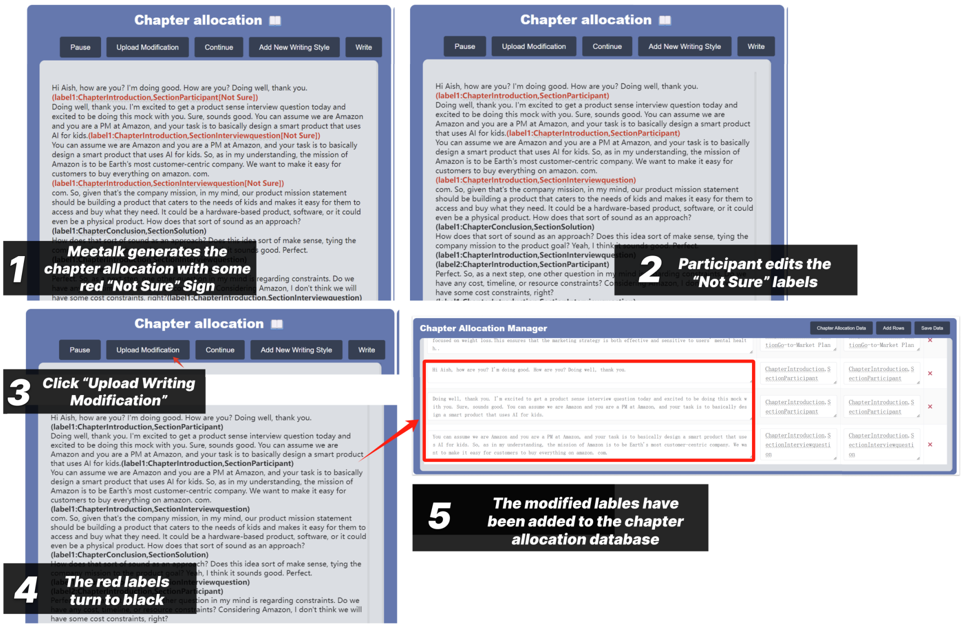

Current segments
Embedding similarity comparison with the "content" column
RAG
Chapter Allocation Manager
Chapter Allocation Data
Add Rows
Save Data
content
label a
label b
Select the entries corresponding to the k most similar contents
A
LLM for authentication
"she worked at various companies"
Current segments
K most similar entries
"Are these examples authentic to support for labeling this segments? Answer by True of False."
B
Chapters and styles
Table of Contents
Current segments
Last segment's label
K most similar entries
LLM
"Allocate these sentences to the given table of contents or create a new section."
C
"Chapter Introduction, Section Questions"
current segment's label
If "False", label shown as red, with a "[Not Sure]" sign;
If "Yes", directly output the label

Figure 7: Chapter Allocation Procedure. **Step A**: Retrieve two entries with similar contents to the current segments. **Step B**. Leveraging an LLM to judge whether the retrieved two entries are authentic or not. If False, the label will be shown as red with a "[Not Sure]" sign. **Step C**. Request: Prompt ToC, current segments, last segment's label, and the retrieved two entries to an LLM, for generating the label for the current segment.



Chapter allocation

Pause | Upload Modification | Continue | Add New Writing Style | Write

Hi Aish, how are you? I'm doing good. How are you? Doing well, thank you.
(label1:ChapterIntroduction,SectionParticipant[Not Sure])
Doing well, thank you. I'm excited to get a product sense interview question today and excited to be doing this mock with you. Sure, sounds good. You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids.(label1:ChapterIntroduction,SectionInterviewquestion[Not Sure])
You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids. So, as in my understanding, the mission of Amazon is to be Earth's most customer-centric company. We want to make it easy for customers to buy everything on amazon. com.
(label1:ChapterIntroduction,SectionInterviewquestion[Not Sure])
com. So, given that's the company mission, in my mind, our product mission statement should be building a product that caters to the needs of kids and makes it easy for them to access and buy what they need. It could be a hardware-based product, software, or it could even be a physical product. How does that sort of sound as an approach?
(label1:ChapterConclusion,SectionSolution)
How does that sort of sound as an approach? Does this idea sort of make sense, tying the ... it sounds good. Perfect.
(label1:ChapterIntroduction,SectionInterviewquestion)
Perfect. So, as a next step, one other question in my mind is regarding constraints. Do we have any ... Considering Amazon, I don't think we will have some cost constraints, right?(label1:ChapterIntroduction,SectionInterviewquestion)

1 *Meetalk generates the chapter allocation with some red "Not Sure" Sign*

Chapter allocation

Pause | Upload Modification | Continue | Add New Writing Style | Write

Hi Aish, how are you? I'm doing good. How are you? Doing well, thank you.
(label1:ChapterIntroduction,SectionParticipant)
Doing well, thank you. I'm excited to get a product sense interview question today and excited to be doing this mock with you. Sure, sounds good. You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids.(label1:ChapterIntroduction,SectionParticipant)
You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids. So, as in my understanding, the mission of Amazon is to be Earth's most customer-centric company. We want to make it easy for customers to buy everything on amazon. com.
(label1:ChapterIntroduction,SectionInterviewquestion)
com. So, given that's the company mission, in my mind, our product mission statement should be building a product that caters to the needs of kids and makes it easy for them to access and buy what they need. It could be a hardware-based product, software, or it could even be a physical product. How does that sort of sound as an approach?
(label1:ChapterConclusion,SectionSolution)
How does that sort of sound as an approach? Does this idea sort of make sense, tying the company mission to the product goal? Yeah, I think it sounds good. Perfect.
(label1:ChapterIntroduction,SectionInterviewquestion)
(label2:ChapterIntroduction,SectionParticipant)
Perfect. So, as a next step, one other question in my mind is regarding constraints. Do we have any cost, timeline, or resource constraints? Considering Amazon, I don't think we will have some cost constraints, right?

2 *Participant edits the "Not Sure" labels*

Chapter allocation

Pause | Upload Modification | Continue | Add New Writing Style | Write

3 *Click "Upload Writing Modification"*

Hi Aish, how are you? I'm doing good. How are you? Doing well, thank you.
(label1:ChapterIntroduction,SectionParticipant)
Doing well, thank you. I'm excited to get a product sense interview question today and excited to be doing this mock with you. Sure, sounds good. You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids.(label1:ChapterIntroduction,SectionParticipant)
You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids. So, as in my understanding, the mission of Amazon is to be Earth's most customer-centric company. We want to make it easy for customers to buy everything on amazon. com.
(label1:ChapterIntroduction,SectionInterviewquestion)
com. So, given that's the company mission, in my mind, our product mission statement should be building a product that caters to the needs of kids and makes it easy for them to access and buy what they need. It could be a hardware-based product, software, or it could even be a physical product. How does that sort of sound as an approach?
(label1:ChapterConclusion,SectionSolution)
... ch? Does this idea sort of make sense, tying the ... h, I think it sounds good. Perfect.
... rviewquestion)
... icipant)
... question in my mind is regarding constraints. Do we ... aints? Considering Amazon, I don't think we will have some cost constraints, right?

4 *The red labels turn to black*

Chapter Allocation Manager

Chapter Allocation Data | Add Rows | Save Data

focused on weight loss. This ensures that the marketing strategy is both effective and sensitive to users' mental health..	tionGo-to-Market Plan	tionGo-to-Market Plan	×
Hi Aish, how are you? I'm doing good. How are you? Doing well, thank you.	ChapterIntroduction,SectionParticipant	ChapterIntroduction,SectionParticipant	×
Doing well, thank you. I'm excited to get a product sense interview question today and excited to be doing this mock with you. Sure, sounds good. You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids.	ChapterIntroduction,SectionParticipant	ChapterIntroduction,SectionParticipant	×
You can assume we are Amazon and you are a PM at Amazon, and your task is to basically design a smart product that uses AI for kids. So, as in my understanding, the mission of Amazon is to be Earth's most customer-centric company. We want to make it easy for customers to buy everything on amazon. com.	ChapterIntroduction,SectionInterviewquestion	ChapterIntroduction,SectionInterviewquestion	×

5 *The modified lables have been added to the chapter allocation database*

Figure 8: Chapter allocation modification procedure. Participants are notified with the unauthentic labels by a red "[Not Sure]" sign. By modifying these unauthenntic labels and clicking the "Upload Writing Modification" button, the modified labels turn black and been added to the chapter allocation database.

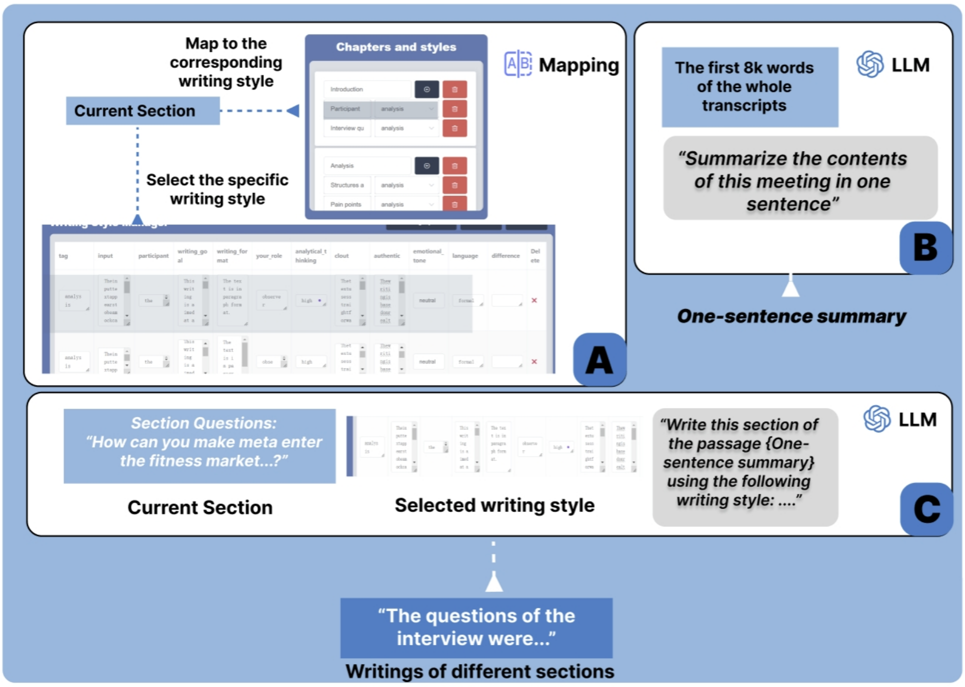
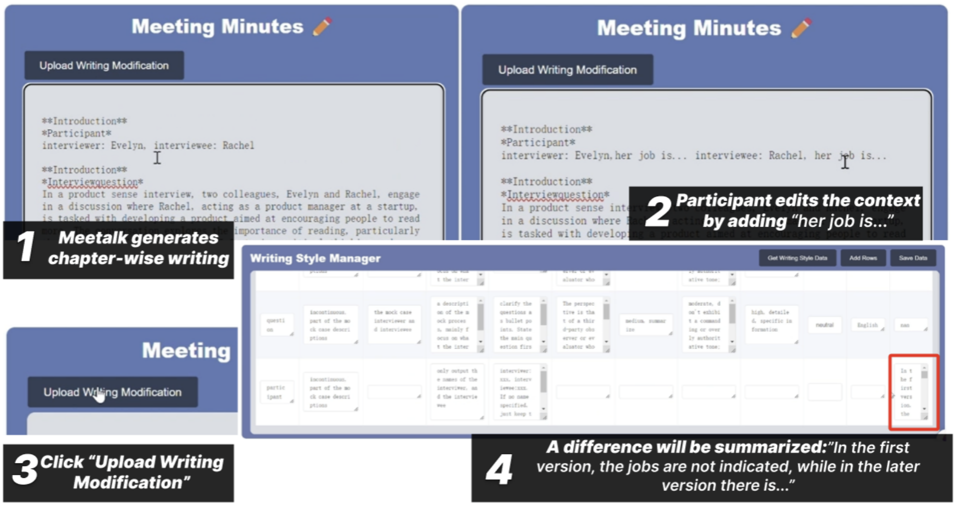

Map to the corresponding writing style
Current Section
Select the specific writing style
Chapters and styles
Introduction
Participant
analysis
Interview qu
analysis
Analysis
Structures a
analysis
Pain points
analysis
Mapping
tag
input
participant
writing_goal
writing_format
your_role
analytical_thinking
clout
authentic
emotional_tone
language
difference
Delete
neutral
formal
high
A
The first 8k words of the whole transcripts
LLM
"Summarize the contents of this meeting in one sentence"
B
One-sentence summary
Section Questions: "How can you make meta enter the fitness market...?"
Current Section
Selected writing style
"Write this section of the passage {One-sentence summary} using the following writing style: ...."
LLM
C
"The questions of the interview were..."
Writings of different sections

Figure 9: Chapter-wise Writing Procedure. **Step A**: Map the writing style with current section. **Step B**. Summarize the first 8k words (compatibility of the LLMs) of the whole transcripts with one sentence. **Step C**. Prompt current section and the writing style to an LLM for writing this section.



```
**Introduction**
*Participant*
interviewer: Evelyn, interviewee: Rachel

**Introduction**
*Interviewquestion*
In a product sense interview, two colleagues, Evelyn and Rachel, engage
in a discussion where Rachel, acting as a product manager at a startup,
is tasked with developing a product aimed at encouraging people to read
more. The conversation explores the importance of reading, particularly
```

```
**Introduction**
*Participant*
interviewer: Evelyn,her job is... interviewee: Rachel, her job is...

**Introduction**
*Interviewquestion*
In a product sense inte
in a discussion where R
is tasked with develop
```

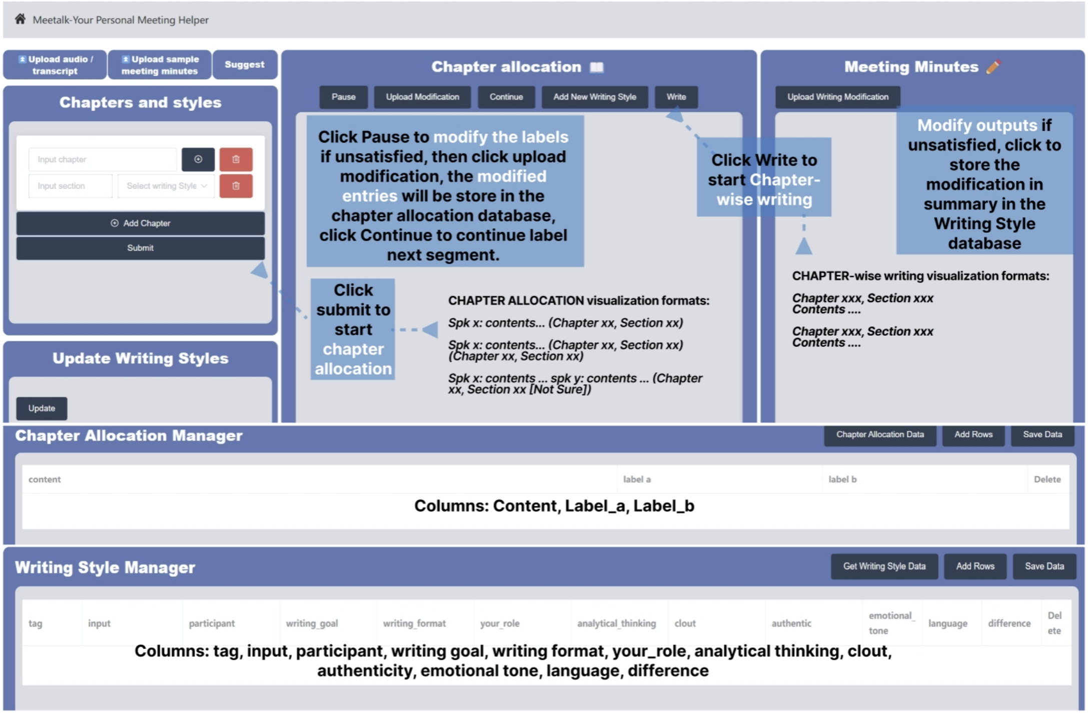
1 Meetalk generates chapter-wise writing

2 Participant edits the context by adding "her job is..."

3 Click "Upload Writing Modification"

4 A difference will be summarized:"In the first version, the jobs are not indicated, while in the later version there is..."

Figure 10: Chapter-wise writing revision procedure



Click Pause to modify the labels if unsatisfied, then click upload modification, the modified entries will be store in the chapter allocation database, click Continue to continue label next segment.

Click submit to start chapter allocation

CHAPTER ALLOCATION visualization formats:

Spk x: contents... (Chapter xx, Section xx)

Spk x: contents... (Chapter xx, Section xx) (Chapter xx, Section xx)

Spk x: contents ... spk y: contents ... (Chapter xx, Section xx [Not Sure])

Click Write to start Chapter-wise writing

Modify outputs if unsatisfied, click to store the modification in summary in the Writing Style database

CHAPTER-wise writing visualization formats:

Chapter xxx, Section xxx
Contents ....

Chapter xxx, Section xxx
Contents ....

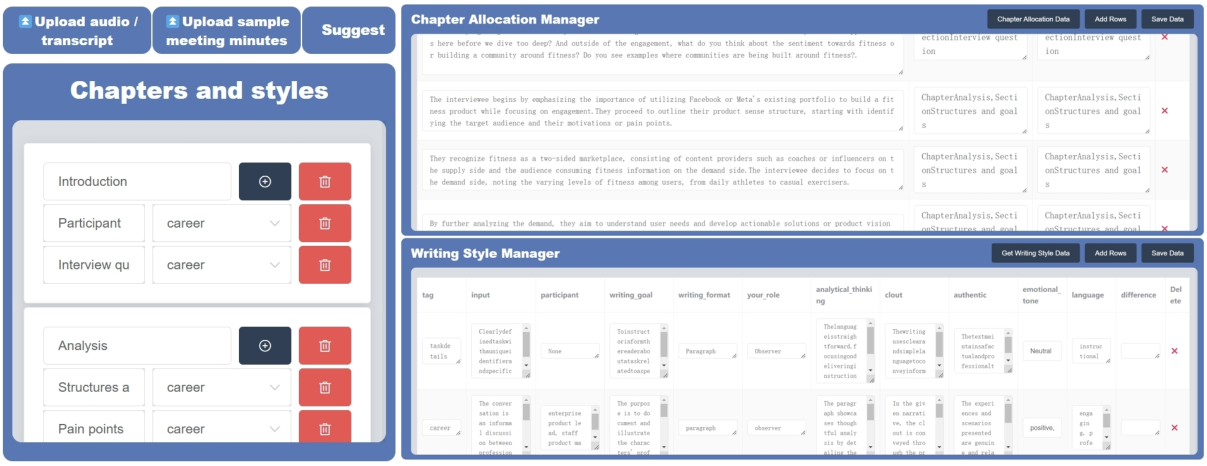
Columns: Content, Label_a, Label_b

Columns: tag, input, participant, writing goal, writing format, your_role, analytical thinking, clout, authenticity, emotional tone, language, difference

Figure 11: Meetalk, an adaptively personalized meeting minutes generation system. As illustrated in the Meetalk User Interface, after uploading meeting audio and a sample meeting file, Meetalk suggests a table of contents, chapter allocation data, and writing style data based on the sample file to personalize the meeting minutes. After that, Meetalk starts chapter allocation to label each segment according to the table of contents. Finally, meetalk write for each section to form a final meeting minutes. For both the chapter allocation and chapter-wise writing procedure, users could modify the outputs and Meetalk will learn the modifications to better adapt to user preferences.

Table 2: demographics, meeting frequency, and LLM usage of study participants

Scenario	ID	Age	Gender	Degree	Occupation	Meeting Freq.	LLM Usage
Legal consultations	P1	18-24	M	Bachelor	Lawyer trainee	Daily	Daily
	P2	18-24	F	Undergrad.	Law student	Weekly	Daily
	P3	25-34	M	Bachelor	Junior lawyer	Daily	Daily
Study abroad counseling	P4	25-34	F	Bachelor	Consultant	Weekly	Weekly
	P5	25-34	F	Master	Teacher	Weekly	Weekly
	P6	25-34	F	Bachelor	Teacher	Weekly	Weekly
	P7	25-34	M	Postgrad.	Senior postgraduate	Weekly	Daily
	P8	18-24	F	Postgrad.	Senior postgraduate	Monthly	Weekly
Academic discussions	P9	18-24	M	Undergrad.	Music major	Monthly	Daily
	P10	35-44	M	Ph.D.	Lecture tutor	Weekly	Daily
Mock Interviews	P11	25-34	M	Bachelor	HR intern	Weekly	Daily
	P12	25-34	M	Bachelor	HR intern	Weekly	Daily
	P13	25-34	F	Undergrad.	HR intern	Weekly	Daily
Company pitches	P14	35-44	M	Master	Sales manager	Weekly	Daily
	P15	24-34	M	Bachelor	Sales agent	Daily	Daily
	P16	35-44	F	Bachelor	Sales agent	Daily	Daily
	P17	35-44	F	Master	Venture Capital	Daily	Daily
	P18	35-44	M	Master	Venture Capital	Daily	Daily



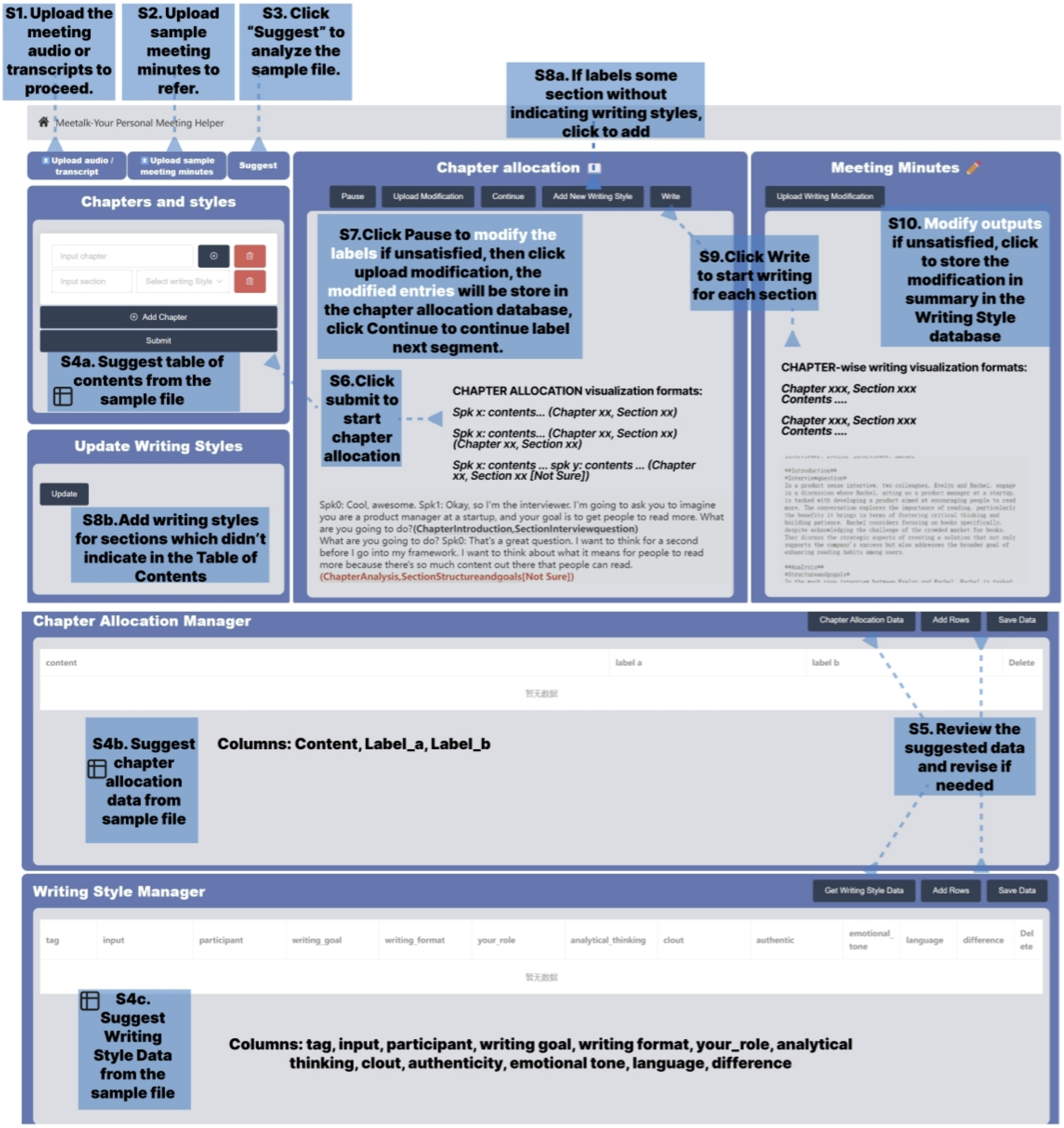
Introduction
Participant — career
Interview qu — career

Analysis
Structures a — career
Pain points — career

s here before we dive too deep? And outside of the engagement, what do you think about the sentiment towards fitness or building a community around fitness? Do you see examples where communities are being built around fitness?.	ectionInterview question	ectionInterview question	×
The interviewee begins by emphasizing the importance of utilizing Facebook or Meta's existing portfolio to build a fitness product while focusing on engagement.They proceed to outline their product sense structure, starting with identifying the target audience and their motivations or pain points.	ChapterAnalysis,SectionStructures and goals	ChapterAnalysis,SectionStructures and goals	×
They recognize fitness as a two-sided marketplace, consisting of content providers such as coaches or influencers on the supply side and the audience consuming fitness information on the demand side.The interviewee decides to focus on the demand side, noting the varying levels of fitness among users, from daily athletes to casual exercisers.	ChapterAnalysis,SectionStructures and goals	ChapterAnalysis,SectionStructures and goals	×
By further analyzing the demand, they aim to understand user needs and develop actionable solutions or product vision	ChapterAnalysis,SectionStructures and goal	ChapterAnalysis,SectionStructures and goal	×

tag	input	participant	writing_goal	writing_format	your_role	analytical_thinking	clout	authentic	emotional_tone	language	difference	Delete
taskdetails	Clearlydefinedtaskwithauniqueidentifierandspecific	None	Toinstructorinformthereaderaboutataskrelatedtoaspe	Paragraph	Observer	Thelanguageisstraightforward,focusingondeliveringinstruction	Thewritingusesclearandsimplelanguagetoconveyinform	Thetextmaintainsafactualandprofessionalt	Neutral	instructional		×
career	The conversation is an informal discussion between profession	enterprise product lead, staff product ma	The purpose is to document and illustrate the characters' prof	paragraph	observer	The paragraph showcases thoughtful analysis by detailing the	In the given narrative, the clout is conveyed through the pr	The experiences and scenarios presented are genuine and rela	positive,	engaging, profe		×

Figure 12: **Meetalk's Databases UI**: This comprehensive view showcases Meetalk's suggestions following document parsing in the databases' UI. The left panel displays a suggested Table of Contents, while the right side presents a Chapter Allocation Database (top) and Writing Style Database (bottom). These AI-generated recommendations offer a strategic starting point, with full user customization available to tailor the content structure and style to specific needs.



S1. Upload the meeting audio or transcripts to proceed.

S2. Upload sample meeting minutes to refer.

S3. Click "Suggest" to analyze the sample file.

S8a. If labels some section without indicating writing styles, click to add

S4a. Suggest table of contents from the sample file

S8b. Add writing styles for sections which didn't indicate in the Table of Contents

S7. Click Pause to modify the labels if unsatisfied, then click upload modification, the modified entries will be store in the chapter allocation database, click Continue to continue label next segment.

S6. Click submit to start chapter allocation

CHAPTER ALLOCATION visualization formats:

Spk x: contents... (Chapter xx, Section xx)

Spk x: contents... (Chapter xx, Section xx) (Chapter xx, Section xx)

Spk x: contents ... spk y: contents ... (Chapter xx, Section xx [Not Sure])

Spk0: Cool, awesome. Spk1: Okay, so I'm the interviewer. I'm going to ask you to imagine you are a product manager at a startup, and your goal is to get people to read more. What are you going to do?**(ChapterIntroduction,SectionInterviewquestion)**
What are you going to do? Spk0: That's a great question. I want to think for a second before I go into my framework. I want to think about what it means for people to read more because there's so much content out there that people can read.
(ChapterAnalysis,SectionStructureandgoals[Not Sure])

S9. Click Write to start writing for each section

S10. Modify outputs if unsatisfied, click to store the modification in summary in the Writing Style database

CHAPTER-wise writing visualization formats:

Chapter xxx, Section xxx
Contents ....

Chapter xxx, Section xxx
Contents ....

```
**Introduction**
*Interviewquestion*
In a product sense interview, two colleagues, Evelyn and Rachel, engage
in a discussion where Rachel, acting as a product manager at a startup,
is tasked with developing a product aimed at encouraging people to read
more. The conversation explores the importance of reading, particularly
the benefits it brings in terms of fostering critical thinking and
building patience. Rachel considers focusing on books specifically,
despite acknowledging the challenge of the crowded market for books.
They discuss the strategic aspects of creating a solution that not only
supports the company's success but also addresses the broader goal of
enhancing reading habits among users.

**Analysis**
*Structureandgoals*
In the mock case interview between Evelyn and Rachel, Rachel is tasked
```

S4b. Suggest chapter allocation data from sample file

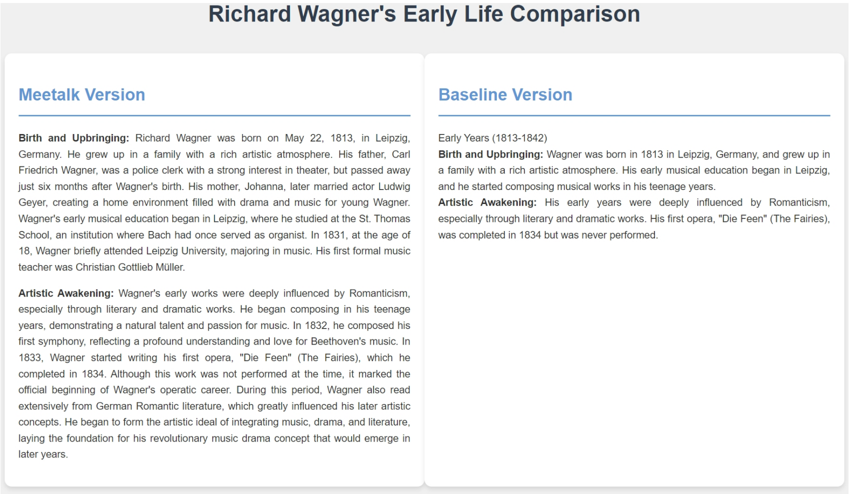
Columns: Content, Label_a, Label_b

S5. Review the suggested data and revise if needed

S4c. Suggest Writing Style Data from the sample file

Columns: tag, input, participant, writing goal, writing format, your_role, analytical thinking, clout, authenticity, emotional tone, language, difference

Figure 13: **Meetalk's Full UI illustration**: S1-2, upload meeting audios or transcripts to proceed, and upload sampe meeting minutes file to be referred by the system. After clicking on the suggest button in S3, Meetalk analyzes the uploaded files to suggest Table of Contents, chapter allocation data, and writing style data, as shown in S4. In S5, three buttons in each database are provided to reveiw and revise the suggested data if needed. In S6, while submitting the data to start chapter allocation, and could pause to modify the labels and store the modifications in the chapter allocation database. In S8, users could add writing styles if they are not specified in the table of contents. In S9, click write to start chapter-wise writing, and again in S10, if users are not satisfied with the outputs, modification is allowed and will be summarized in high level to store in the writing style database.



Richard Wagner's Early Life Comparison

Meetalk Version

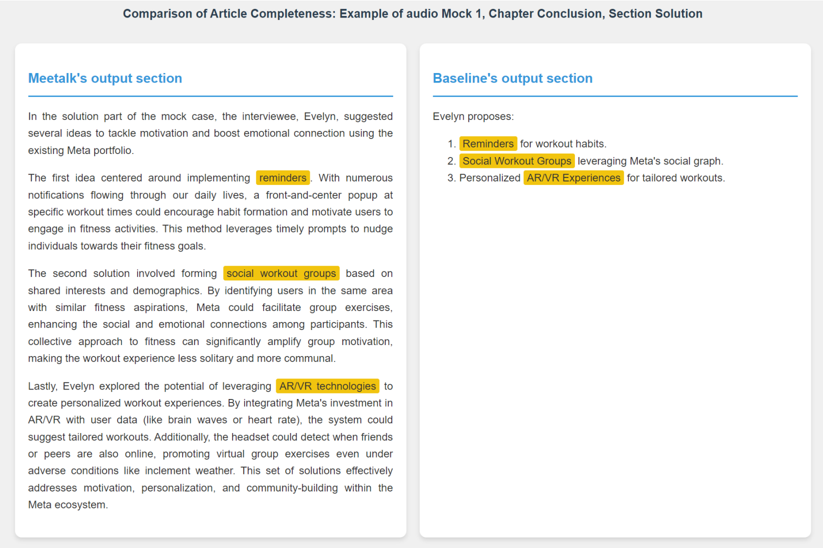
Birth and Upbringing: Richard Wagner was born on May 22, 1813, in Leipzig, Germany. He grew up in a family with a rich artistic atmosphere. His father, Carl Friedrich Wagner, was a police clerk with a strong interest in theater, but passed away just six months after Wagner's birth. His mother, Johanna, later married actor Ludwig Geyer, creating a home environment filled with drama and music for young Wagner. Wagner's early musical education began in Leipzig, where he studied at the St. Thomas School, an institution where Bach had once served as organist. In 1831, at the age of 18, Wagner briefly attended Leipzig University, majoring in music. His first formal music teacher was Christian Gottlieb Müller.

Artistic Awakening: Wagner's early works were deeply influenced by Romanticism, especially through literary and dramatic works. He began composing in his teenage years, demonstrating a natural talent and passion for music. In 1832, he composed his first symphony, reflecting a profound understanding and love for Beethoven's music. In 1833, Wagner started writing his first opera, "Die Feen" (The Fairies), which he completed in 1834. Although this work was not performed at the time, it marked the official beginning of Wagner's operatic career. During this period, Wagner also read extensively from German Romantic literature, which greatly influenced his later artistic concepts. He began to form the artistic ideal of integrating music, drama, and literature, laying the foundation for his revolutionary music drama concept that would emerge in later years.

Baseline Version

Early Years (1813-1842)
Birth and Upbringing: Wagner was born in 1813 in Leipzig, Germany, and grew up in a family with a rich artistic atmosphere. His early musical education began in Leipzig, and he started composing musical works in his teenage years.
Artistic Awakening: His early years were deeply influenced by Romanticism, especially through literary and dramatic works. His first opera, "Die Feen" (The Fairies), was completed in 1834 but was never performed.

Figure 14: High Readability Example: Audio Musician3



Comparison of Article Completeness: Example of audio Mock 1, Chapter Conclusion, Section Solution

Meetalk's output section

In the solution part of the mock case, the interviewee, Evelyn, suggested several ideas to tackle motivation and boost emotional connection using the existing Meta portfolio.

The first idea centered around implementing reminders. With numerous notifications flowing through our daily lives, a front-and-center popup at specific workout times could encourage habit formation and motivate users to engage in fitness activities. This method leverages timely prompts to nudge individuals towards their fitness goals.

The second solution involved forming social workout groups based on shared interests and demographics. By identifying users in the same area with similar fitness aspirations, Meta could facilitate group exercises, enhancing the social and emotional connections among participants. This collective approach to fitness can significantly amplify group motivation, making the workout experience less solitary and more communal.

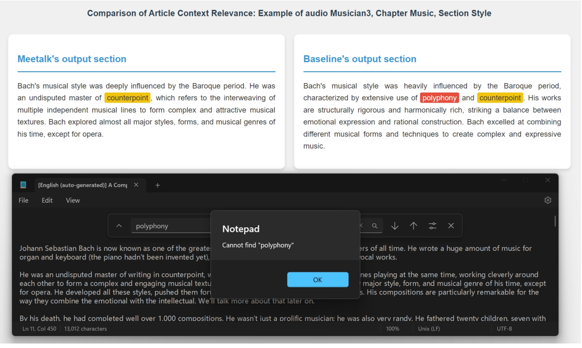
Lastly, Evelyn explored the potential of leveraging AR/VR technologies to create personalized workout experiences. By integrating Meta's investment in AR/VR with user data (like brain waves or heart rate), the system could suggest tailored workouts. Additionally, the headset could detect when friends or peers are also online, promoting virtual group exercises even under adverse conditions like inclement weather. This set of solutions effectively addresses motivation, personalization, and community-building within the Meta ecosystem.

Baseline's output section

Evelyn proposes:

1. Reminders for workout habits.
2. Social Workout Groups leveraging Meta's social graph.
3. Personalized AR/VR Experiences for tailored workouts.

Figure 15: Comparison of **Article Completeness**: Example of audio Mock 1, Chapter Conclusion, Section Solution



Comparison of Article Context Relevance: Example of audio Musician3, Chapter Music, Section Style

Meetalk's output section

Bach's musical style was deeply influenced by the Baroque period. He was an undisputed master of counterpoint, which refers to the interweaving of multiple independent musical lines to form complex and attractive musical textures. Bach explored almost all major styles, forms, and musical genres of his time, except for opera.

Baseline's output section

Bach's musical style was heavily influenced by the Baroque period, characterized by extensive use of polyphony and counterpoint. His works are structurally rigorous and harmonically rich, striking a balance between emotional expression and rational construction. Bach excelled at combining different musical forms and techniques to create complex and expressive music.

Notepad

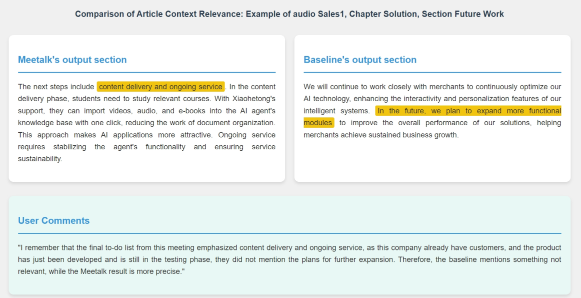
Cannot find "polyphony"

Johann Sebastian Bach is now known as one of the greate ers of all time. He wrote a huge amount of music for organ and keyboard (the piano hadn't been invented yet), ocal works.

He was an undisputed master of writing in counterpoint, w nes playing at the same time, working cleverly around each other to form a complex and engaging musical textu major style, form, and musical genre of his time, except for opera. He developed all these styles, pushed them for s. His compositions are particularly remarkable for the way they combine the emotional with the intellectual. We'll talk more about that later on.

By his death, he had completed well over 1,000 compositions. He wasn't just a prolific musician; he was also very randy. He fathered twenty children, seven with

Figure 16: The image above is the **Comparison of Context Relevance** for Example of audio Mock 3, Chapter Music, Section Style. The screenshot below shows **no results for 'polyphony' in the audio Mock 3 transcript**, confirming its absence in the original text.



Comparison of Article Context Relevance: Example of audio Sales1, Chapter Solution, Section Future Work

Meetalk's output section

The next steps include content delivery and ongoing service. In the content delivery phase, students need to study relevant courses. With Xiaohetong's support, they can import videos, audio, and e-books into the AI agent's knowledge base with one click, reducing the work of document organization. This approach makes AI applications more attractive. Ongoing service requires stabilizing the agent's functionality and ensuring service sustainability.

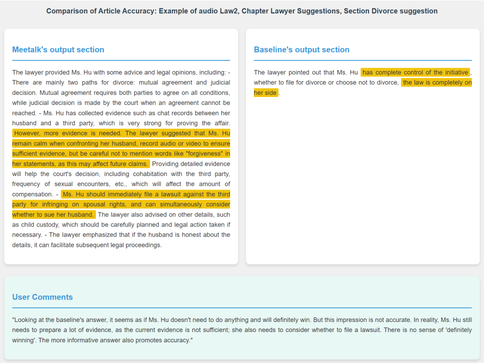
Baseline's output section

We will continue to work closely with merchants to continuously optimize our AI technology, enhancing the interactivity and personalization features of our intelligent systems. In the future, we plan to expand more functional modules to improve the overall performance of our solutions, helping merchants achieve sustained business growth.

User Comments

"I remember that the final to-do list from this meeting emphasized content delivery and ongoing service, as this company already have customers, and the product has just been developed and is still in the testing phase, they did not mention the plans for further expansion. Therefore, the baseline mentions something not relevant, while the Meetalk result is more precise."

Figure 17: The image above is the **Comparison of Context Relevance** for Example audio Sales 1, Chapter Solution, Section Future work. The screenshot below shows **user comments**, proving the baseline results contain irrelevant information.



Comparison of Article Accuracy: Example of audio Law2, Chapter Lawyer Suggestions, Section Divorce suggestion

Meetalk's output section

The lawyer provided Ms. Hu with some advice and legal opinions, including: - There are mainly two paths for divorce: mutual agreement and judicial decision. Mutual agreement requires both parties to agree on all conditions, while judicial decision is made by the court when an agreement cannot be reached. - Ms. Hu has collected evidence such as chat records between her husband and a third party, which is very strong for proving the affair. However, more evidence is needed. The lawyer suggested that Ms. Hu remain calm when confronting her husband, record audio or video to ensure sufficient evidence, but be careful not to mention words like "forgiveness" in her statements, as this may affect future claims. Providing detailed evidence will help the court's decision, including cohabitation with the third party, frequency of sexual encounters, etc., which will affect the amount of compensation. - Ms. Hu should immediately file a lawsuit against the third party for infringing on spousal rights, and can simultaneously consider whether to sue her husband. The lawyer also advised on other details, such as child custody, which should be carefully planned and legal action taken if necessary. - The lawyer emphasized that if the husband is honest about the details, it can facilitate subsequent legal proceedings.

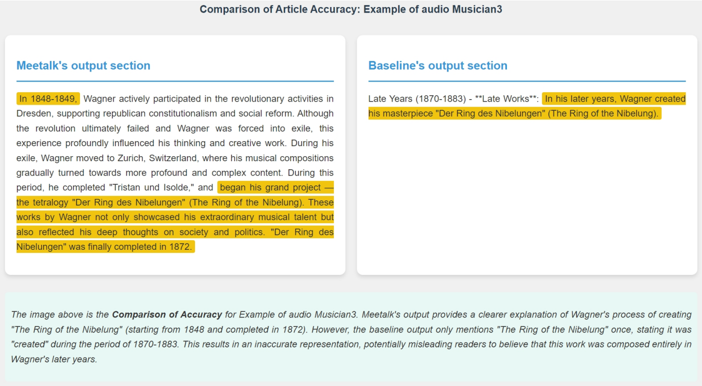
Baseline's output section

The lawyer pointed out that Ms. Hu has complete control of the initiative, whether to file for divorce or choose not to divorce, the law is completely on her side.

User Comments

"Looking at the baseline's answer, it seems as if Ms. Hu doesn't need to do anything and will definitely win. But this impression is not accurate. In reality, Ms. Hu still needs to prepare a lot of evidence, as the current evidence is not sufficient; she also needs to consider whether to file a lawsuit. There is no sense of 'definitely winning'. The more informative answer also promotes accuracy."

Figure 18: The image above is the **Comparison of Accuracy** for Example audio Law 2, Chapter Suggestion, Section Divorce suggestion. The screenshot below shows **user comments**, proving results of Meetalk are more accurate.



Comparison of Article Accuracy: Example of audio Musician3

Meetalk's output section

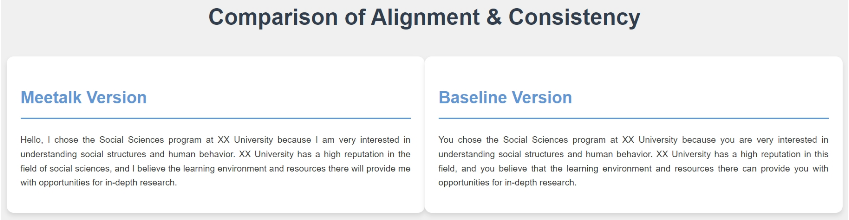
In 1848-1849, Wagner actively participated in the revolutionary activities in Dresden, supporting republican constitutionalism and social reform. Although the revolution ultimately failed and Wagner was forced into exile, this experience profoundly influenced his thinking and creative work. During his exile, Wagner moved to Zurich, Switzerland, where his musical compositions gradually turned towards more profound and complex content. During this period, he completed "Tristan und Isolde," and began his grand project — the tetralogy "Der Ring des Nibelungen" (The Ring of the Nibelung). These works by Wagner not only showcased his extraordinary musical talent but also reflected his deep thoughts on society and politics. "Der Ring des Nibelungen" was finally completed in 1872.

Baseline's output section

Late Years (1870-1883) - **Late Works**: In his later years, Wagner created his masterpiece "Der Ring des Nibelungen" (The Ring of the Nibelung).

*The image above is the **Comparison of Accuracy** for Example of audio Musician3. Meetalk's output provides a clearer explanation of Wagner's process of creating "The Ring of the Nibelung" (starting from 1848 and completed in 1872). However, the baseline output only mentions "The Ring of the Nibelung" once, stating it was "created" during the period of 1870-1883. This results in an inaccurate representation, potentially misleading readers to believe that this work was composed entirely in Wagner's later years.*

Figure 19: The image above is the **Comparison of Accuracy** for Example of audio Musician3.



Comparison of Alignment & Consistency

Meetalk Version

Hello, I chose the Social Sciences program at XX University because I am very interested in understanding social structures and human behavior. XX University has a high reputation in the field of social sciences, and I believe the learning environment and resources there will provide me with opportunities for in-depth research.

Baseline Version

You chose the Social Sciences program at XX University because you are very interested in understanding social structures and human behavior. XX University has a high reputation in this field, and you believe that the learning environment and resources there can provide you with opportunities for in-depth research.

Figure 20: Alignment and consistency comparison, with Meetalk got the correct narrative perspective but the baseline method does not.

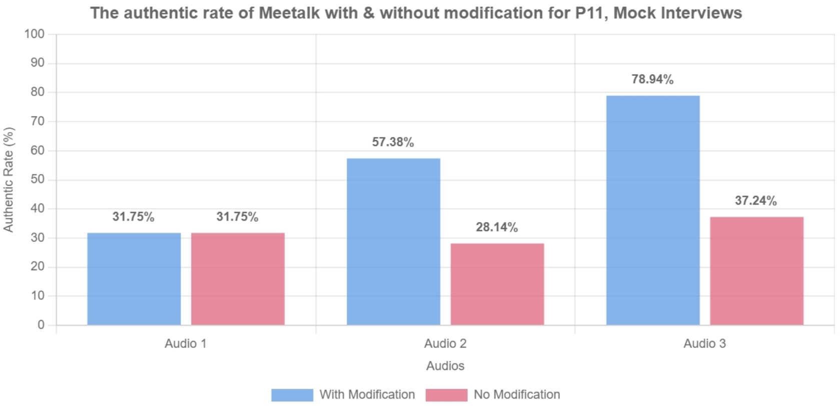


Figure 21: The authentic rate of Meetalk with & without modification for P11's mock interview audio tasks.