Empowering Private Tutoring by Chaining Large Language Models

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Abstract

Artificial intelligence has been applied in various aspects of online education to facilitate teaching and learning. However, few approaches has been made toward a complete AIpowered tutoring system. In this work, we explore the development of a full-fledged intelligent tutoring system powered by state-of-the-art large language models (LLMs), covering automatic course planning and adjusting, tailored instruction, and flexible quiz evaluation. To make the system robust to prolonged interaction and cater to individualized education, the system is decomposed into three inter-connected core processes-interaction, reflection, and reaction. Each process is implemented by chaining LLM-powered tools along with dynamically updated memory modules. Tools are LLMs prompted to execute one specific task at a time, while memories are data storage that gets updated during education process. Statistical results from learning logs demonstrate the effectiveness and mechanism of each tool usage. Subjective feedback from human users reveal the usability of each function, and comparison with ablation systems further testify the benefits of the designed processes in long-term interaction.

Introduction

Online education, along with artificial intelligence (AI) technology, brought the aspiration of personalized tutoring within reach (Bloom 1984). AI has been used to assist education in multiple aspects, ranging from adaptive content recommendation (Costello and Mundy 2009), automatic performance evaluation (McDonald et al. 2013; Grivokostopoulou, Perikos, and Hatzilygeroudis 2017), to personalized instruction and dynamic feedback (Bhutoria 2022; Tang et al. 2020; Gordon et al. 2016; Grawemeyer et al. 2016; Dzikovska et al. 2014). Although a few early approaches have been made towards a stand-alone dialoguebased intelligent tutoring system (Graesser et al. 2001; Rus et al. 2014), most of them are domain-specific and focus primarily on guiding the users to solve a pre-defined problem. Nevertheless, a more ultimate exploration lies in the pursuit of a fully-fledged AI-driven tutoring system with greater flexibility and generalizability.

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While previous works often employ diverse techniques jointly, including learner style classification (Grawemeyer et al. 2016; Nihad, Seghroucheni et al. 2017), data mining (Echeverria, Guamán, and Chiluiza 2015), Bayesian learning (Grawemeyer et al. 2016), etc, the recent emergence of large language models (LLMs) (Devlin et al. 2019; Raffel et al. 2019; Brown et al. 2020; Bommasani et al. 2021; Han et al. 2021), like ChatGPT (OpenAI 2022), has broadened our imagination on new designs of intelligent tutoring systems. LLMs impressed people firstly with the ability to generate and transform information following human instructions, then with the potential in task planning and tool usage. Given their extraordinary ability in providing detailed and accessible content and summarizing information, LLMs become great sources for consulting a wide range of knowledge. Additionally, LLMs have shown remarkable capabilities for interacting in a conversational, dialog-based manner, which makes them well-suited for tutoring applications where there is a back-and-forth exchange with a student. Although challenges like hallucination remain (Bang et al. 2023), LLMs can be adapted by further fine-tuning to have expertise in specific domains and pedagogical strategies tailored to different instructional needs. In this work, we explore the potential of employing generative large language models to build a full-fledged dialogue-based personalized tutoring system. The system carries out every stage in education systematically and dynamically, including instructing, question answering, exercise offering and evaluation. The system design has three core processes-interaction, reflection, and reaction, each composed of chained LLM-powered tools capable of performing specific tasks. The processes are connected to each other through various memory modules, which store the essential data describing the overall progress and support update and retrieval. The manipulation of these memory modules, coupled with the system's interactive feature, fosters a dynamic tutoring procedure that can adjust course plans and teaching styles accordingly.

Evaluation of the proposed system is conducted by statistics collection from learning logs and subjective survey feedback from human users. Results show that the system can satisfactorily handle various educational activities, including adaptive course plan design and updating, consistent instructing, impromptu question answering, and self-adaptive quiz designing and evaluation. Compared to ablation sys-

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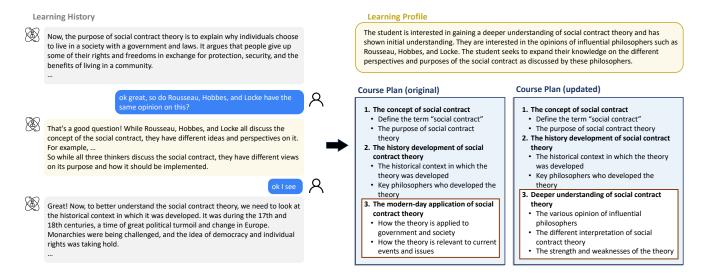


Figure 1: An example of the learning progress. Left side is the user interface directly controlled by interaction process. Right side is the backend memory changes brought by reflection and reaction processes.

tems with partial functions, the designed system proves more advantageous in long-term educational process in stability and consistency, further supporting the plausibility of the design principle.

System Overview

The system is essentially a dialogue-based tutoring system that aims to help learners acquire systematic knowledge on one given topic. As shown in Figure 1, the whole learning process is carried out in natural language conversations, with time-to-time backend reflection and updates in memories. Ideally, the system is expected to respond robustly to any kind of learner's input, and guide the learner through each piece of knowledge. This section gives a general picture of the system working flow. We start with explaining the design principles by introducing three underlying processes within the system. Then we briefly go over components employed to realize each process. Finally, we provide a complete introduction of how each process and components work together. Note that the proposed system mainly explores personalized tutoring and adaptive system reflection with chained LLMs, while we do acknowledge the potential of fallacious and biased output due to inherent flaws in LLMs.

Design Principles

The system design demonstrates the breakdown into three core system processes: *Interaction*, *Reflection*, and *Reaction*. They each has a modularized implementation and is connected to one another to form an execution loop that facilitates the whole education process.

Interaction. The interactive dialogue between the system and the user is the media for tutoring and learning, and therefore is the major process of the designed system. LLMs like ChatGPT can interact with users in a responsive and robust way in daily chit-chat. However, tasking them with long-term purposeful interaction is still tricky given restriction on

context length. As for educational purposes, it is especially important to keep the interaction on track, meanwhile ensuring its accessibility and informativeness.

Reflection. To facilitate interaction, we devise a reflection process to generate high-level insights on the learning progress, which serves as global information (Park et al. 2023). Meanwhile, it is expected to help adjust system response dynamically based on user preference and behavior to achieve personalized tutoring.

Reaction. Along with reflection, reaction refers to the automatically triggered system behavior afterwards, including adjustment of course plan and teaching style, and quiz generation. It differs from the interaction process in that *interaction* is always triggered directly by a new round of response, while *reaction* is performed at the backend from time to time, subsequent to reflection process.

Components

Tools. Under the principled design, each process is embodied by a set of tasks performed either sequentially or in parallel. For instance, there are diverse ways of engaging with the student, such as providing instructions, addressing questions, administering quizzes, and offering feedback. This variation in approaches complicates the development of a single unified solution. We therefore devise separate modules for each specific task to ensure performance. We term those modules as "tools", and that each tool is a task-specific prompted LLM responsible for generating system output or updating memories. As shown in Figure 2, they are categorized into three types, each corresponding to one system process. For example, interaction can be broken down into four types of response in terms of education function, each hosted by one well-prompted tool. At each round, only one tool is used to generate the response.

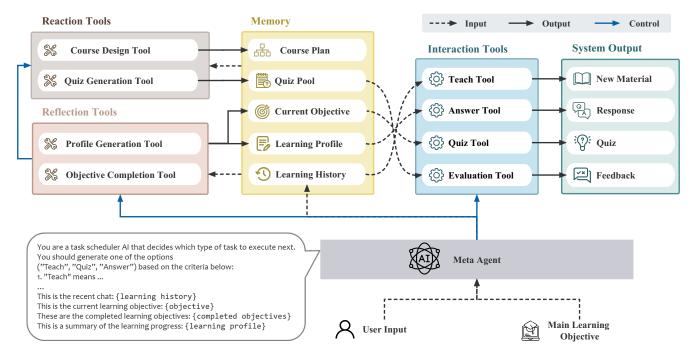


Figure 2: An overview of the system's modularized implementation and execution in a single round of conversation.

Memories. Apart from tools, data storage is required to host information generated by reflection and reaction processes, while also supporting querying and retrieving. We propose four types of memories to record the progress and current status of learning, each stored in distinct data format and supports different ways of querying and updating. Another critical feature of the memories is that they serve as a linkage between different sets of tools to pass on information to control tool output. The detailed description of each tool and memory can be found in the next section.

Meta Agent. Above all three processes, we introduce meta agent, the single access of the control flow. It is powered by LLM and prompted to decide what specific tasks to execute next. See Figure 2 for an example prompt for controlling the interaction process. The template contains helpful information retrieved from the memory and asks for an output deciding the type of interaction process. In our implementation, the meta agent only controls the interaction tools, while we set a fixed time interval for the execution of reflection process.

Overview of Control Flow

Above all, all designs serve for the ultimate goal of better interaction with the users. The system reflects from time to time to update cognition on the overall progress, and in turn refines the interaction production with new insights. At the frontend, the user first inputs what to learn with desired difficulty level. Then the system automatically calls the course design tool to generate the initial course plan, and starts the conversation accordingly. Upon receiving a new round of user input, the meta agent decides which interaction tool to use and the tool executes the task correspondingly to gener-

ate a new response with queried information from memories. At the backend, the reflection tools are triggered by the meta agent or at a hard-coded interval to reflect on the status quo and update the learning profile and current objective. If any updates, the reaction tools will be triggered immediately to generate new quiz questions and update course plan.

As shown in Figure 2, the right side represents the interaction process that is closest to user interface, while the left side demonstrates the backend processes that are responsible for generating and updating memory modules. Practically, throughout each dialogue session, the reflection and reaction processes run alternatively at the backend, where the output result is periodically utilized by the interaction process to produce the final response to the user in each round. The learning proceeds until all objectives in the course plan have been completed.

Tools and Memories

This section explains the components of the three main processes, tools and memories, in detail and illustrates how they close up the complete execution loop.

Memories

As mentioned above, it is often difficult to infer information from an exceedingly long conversation history. Memories are summarized information crucial to understanding the overall learning progress. Proper storage and update of memories help the system recap the big picture more effectively and more economically. We explain the management of each memory module below, including the data format, the retrieving methods, and the updating methods.

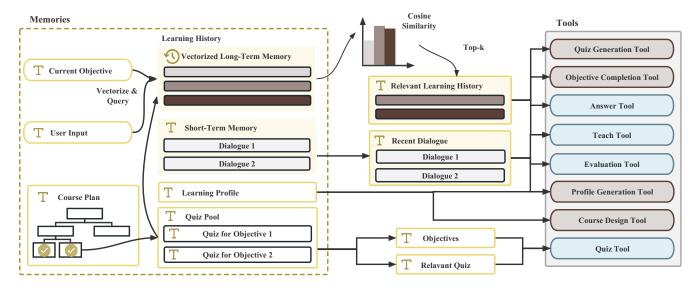


Figure 3: The details in memory storage and querying within a single round of conversation.

Process	Tool Name	Trigger Condition	Input	Output/Update
Interaction	Teach Tool Answer Tool Quiz Tool Evaluation Tool	Meta agent Meta agent Meta agent Quiz	Learning history, Current objective, Learning profile Learning history Quiz pool, Learning profile Learning history	System output System output System output System output
Reflection	Profile Generation	Each round	Learning history, Learning profile	Memory: Learning profile
	Objective Completion	Each round	Learning history, Current objective	Memory: Current objective
Reaction	Course Design	Profile generation	Course plan, Learning profile	Memory: Course plan
	Quiz Generation	Objective completion	Learning history, Current objective	Memory: Quiz pool

Table 1: A summary of the detailed tool usage. The "Input" means the prompt template contains the mentioned memories.

Course Plan. Course plan is the overall course syllabus that delineates the structure of the course. It is stored in a tree-like structure as in Figure 3. The tree has at most three layers and the main learning objective is to be split into fine-grained and coherent sub-objectives. Each objective is expressed in a concise phrase and is accompanied by a status attribute indicating whether it has been completed. The system is expected to instruct on the main topic by traveling through the course plan in a depth-first manner. The tree structure allows for easy operations to keep a record of the system progress, including querying for the next objective, and checking and updating the status of objectives.

Current Objective. Under this context, the current objective memory module is simply a pointer pointing to the next uncompleted objective. Keeping track of ongoing learning objectives is important for consistent instruction. It is presented in plain text upon retrieval.

Quiz Pool. Quiz pool stores the generated quiz beforehand. It is a mapping from one objective to a set of related quiz questions. When retrieving, it maps a given objective to a few quiz questions presented in plain text.

Learning Profile. As for learning profile, it is a short paragraph illustrating the learning progress of the student. It mainly summarizes the learned knowledge and provides

high-level insights into the user's preference and behavior to modulate the behavior of the course design tool. It is updated at a fixed time interval in our implementation.

Learning History. Learning history contains both short-term and long-term memories. The short-term learning history records the recent 5 rounds of conversation history in plain text. While the long-term memory is a vectorized storage that keeps track of all conversations. The short-term history is mainly used in tools whose output only requires only local attention and comprehension of recent conversation. While the long-term history is particularly valuable in offering pertinent but distant information. The cosine similarity of embeddings is used to search for the most relevant records when retrieving information.

Tools

This section elaborates on the specifics of each tool within every process, encompassing their inputs and outputs, as well as the conditions for utilization. Table 1 summarizes the main features of each tool.

Interaction Tools. Interaction tools handle different types of system output, and are controlled by the meta agent.

 Teach Tool executes the fundamental system function, instructing. It asks an LLM to provide new learning materials on the current objective. Specifically, the teach tool takes the current objective and the recent short-term conversation history as input to ensure both relevance and coherence. We also prompt the tool so that it produces more accessible instruction materials.

- Answer Tool is a specialized tool to generate instantaneous response to the student's request or question. It differs from teach tool in that it focuses on the recent query from the user. Additionally, the most relevant conversation histories are retrieved from long-term learning history to provide background information.
- Quiz Tool generates quiz questions to test user's understanding of the acquired knowledge. Whenever the meta agent decides it is proper time for a quiz, the tool is called to extract the most representative quiz questions from the pool. As shown in Figure 3, the completed learning objectives are taken from the course plan and mapped to their relevant quiz questions as part of input prompt.
- Evaluation Tool evaluates the user's performance on the quiz and gives feedback to enhance user's understanding of the topic. It is prompted to parse and judge the learner's answer automatically and give personalized feedback. To ensure validity, the prompt also contains the most relevant history queried by the quiz questions.

Reflection Tools. Reflection tools reflect on the learning process and update the memory modules. They are triggered each time a new user query comes in and run automatically at the backend.

- **Profile Generation Tool** gives high-level insights into the student's learning progress. The tool takes the short-term learning history and current learning profile as part of the prompt and outputs an updated profile.
- Objective Completion Tool checks recent conversation history and decides whether the current learning objective has been completed. It controls the pace of learning and initiates lectures on new topics when necessary. It also triggers quiz generation tool.

Reaction Tools. Reaction tools are invoked after the reflection tools to generate auxiliary memories.

- Course Design Tool is used to update the course plan when necessary. It is called every time after an update in the learning profile and instructed to infer valuable information to make necessary changes to the course plan.
- Quiz Generation Tool is used whenever the user has completed learning an objective. The tool generates representative multiple choice questions for the objective and stores them back into memories. The input includes the target objective and the most relevant history retriever by embedding similarity.

Experiments

To demonstrate and analyze the features of our tutoring system, the experiments are conducted in two folds. We invite a number of users to learn a series of pre-defined topics using the system. During interaction, we collect critical statistics

and record the conversation for future analysis. After learning completes, the users are required to answer a questionnaire to rate their experience with the system from multiple perspectives. We also develop ablation systems to better understand the effect of each process and module.

Experimental Design

System Setup. In addition to the main system, we implement two ablation systems with only partial functions. Specifically, we have one system without reflection process and another with both reflection and reaction processes removed. We collect 80 different topics as the main learning objectives for evaluation and randomly assign them with different difficulty levels. The topics cover a wide range of academic subjects and some daily life phenomena, varying in granularity and language format In evaluation, each topic is learned independently with three systems, making up altogether 240 courses. Further implementation details can be found in supplementary materials.

Participants. We invite 13 average adult users who are proficient in English to participate in learning. Every single course is randomly assigned to one user, while we make sure that each participant does not get repeated course topics.

Statistics Collection. The collected statistics from learning logs include (1) Complexity of course plan reflects the ability to design adaptive course plan; (2) Average length of system response and Average number of objectives per response are indicators of instruction informativeness; (3) Frequency of course plan update shows the reflective feature of the system; and (4) Frequency of in-course quiz explores the pattern of quiz offerings.

Survey Design. After completing the course, the learner is required to answer a survey composed of 9 questions targeting different aspects of the system. Each question is a statement to be rated on a $1\sim5$ scale, where higher scores mean better qualities. Table 2 presents the statements by category.

Course Plan

- 1. Relevance: The course plan is relevant to the main objective.
- 2. Coherence: The course plan is coherent and logical.
- 3. Compatibility: The course plan is compatible with difficulty level.

Instruction

- 4. No Repetition: There is no repeated instruction.
- 5. Accessibility: The language used is easy to understand.

Question Answering

- 6. Timeliness: The learner's questions always get immediate response.
- 7. Consistency: The response is consistent with learning material.

Quiz

- 8. Relevance: The quiz questions match what has been covered.
- 9. Judgment: The quiz evaluation is accurate in parsing and scoring.

Table 2: The complete survey questions. Learners are asked to rate the compatibility of each statement on a scale of $1\sim5$.

Results

Statistical Results. Figure 4 presents the statistical characteristics related to teach tool, including average length of

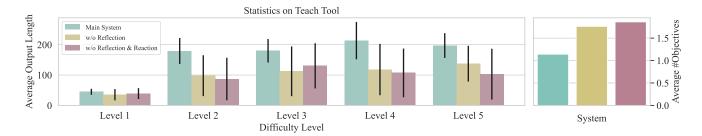


Figure 4: Average output length (calculated by the number of words) and the number of objectives covered in each output for different systems. Average number of objectives are manually annotated with 50 randomly sampled response from each system.

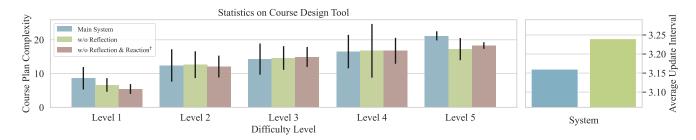


Figure 5: Average course plan complexity (calculated by the number of objectives) and update interval (calculated by the number of conversation rounds in between) by course design tool for different systems.† means this is the baseline statistics as the system without reflection or reaction processes has a fixed course plan throughout learning.

output and the average number of objectives covered in each generation. Overall all systems can generate tailored output according to difficulty level. Higher difficulty comes along with longer and more informative output. It means the teach tool is successfully aware of the dynamic prompting controlled by difficulty. What is worth noting is that the main system generates significantly longer output with the smallest variation. It demonstrates that the main system is able to consistently generate informative content on the given topic, which is further testified by the number of objectives covered in each output. This phenomenon shows the benefits of reflection process in judging objective completion. It operates on the status of each objective and thus allows the teach tool to focus on one atomic objective at a time.

Figure 5 showcases the behavior of course design tool. Note that all systems start with the same initial course plan. The system without reflection relies on learning history in future updates, while the main system takes advantage of the learning profile. Similarly, the tool can generate difficulty-aware course plans, seen in a positive correlation between complexity and difficulty. It is also observed that the future updates in course plan tend to do more addition than deletion, making the course plan more complex than the initial state. Nevertheless, the main system shows more stability in complexity control with longer course plans. In terms of frequency of updates, we observe that the main system seems more prone to making updates, meaning that it is easier to detect helpful information in a compressed learning profile compared to verbose learning history.

As for in-course quizzes, the average interval between

quizzes for the main system and ablation system are 6.91 and 10.20, respectively. Without the backend processes, the meta agent has little information available to suggest quiz generation. We also calculate the average number of objectives covered in each quiz for the main system, the result is reasonably 3.96 with good stability.

Survey Results. Table 3 and Table 4 present results on survey questions. Overall, with powerful ChatGPT, all systems demonstrate promising usability and quality. The designed reflection and reaction processes offer advantages in complex learning settings. For intricate course plan updates, the main system achieves better coherence and compatibility with difficulty levels. Through reflection and memory querying, the system maintains better control with fewer repetitive instructions during longer conversations. Additionally, with similarity-based querying over long-term history, the evaluation tool makes a more accurate judgment on the learner's answer. However, it should also be noted that although the main system performs satisfactorily on QA consistency, the timeliness in response is compromised by backend processes. It indicates that prompts with global information may interfere with the LLM's ability to focus locally and generate timely and coherent response.

Related Work

Ever since the development of artificial intelligence techniques, methods and tools have been proposed to assist in teaching and learning process. AutoTutor (Graesser et al. 2001) is the first conversation-based intelligent tutoring system, which inspires a number of works followed (McNa-

System	Course Plan		Instruction		Question Answering		Quiz		
System	Relevance	Coherence	Compatibility	No Repetition	Accessibility	Timeliness	Consistency	Relevance	Judgment
Main System	4.72	4.51	4.65	4.29	4.77*	4.41	4.82	4.88	4.24
w/o Reflection	4.71	4.62	4.77	4.42	4.66	4.64	4.85	4.75	4.65
w/o Reflection & Reaction	4.97 [†]	4.77^{\dagger}	4.78^{\dagger}	4.38	4.77	4.75	4.95	4.86	4.36

Table 3: Survey results for learning courses at difficulty level $1\sim3$. † means the score evaluates the initial course plan only, as no changes in course plan happen throughout the learning process. It could be viewed as the static quality evaluation of course plan generated from scratch. * means p-value < 0.1 using t-test.

Custom	Course Plan		Instruction		Question Answering		Quiz		
System	Relevance	Coherence	Compatibility	No Repetition	Accessibility	Timeliness	Consistency	Relevance	Judgment
Main System	4.87*	4.87**	4.73	4.27	4.53	3.67	5.00	4.87	4.20
w/o Reflection	4.67	4.60	4.67	3.87	4.87	4.80	4.67	4.40	4.13
w/o Reflection & Reaction	4.93 [†]	4.73^{\dagger}	4.80^{\dagger}	4.07	5.00	4.33	4.93	4.93	4.13

Table 4: Survey results for learning courses at difficulty level $4\sim5$. † means the score evaluates the initial course plan only, as no changes in course plan happen throughout the learning process. It could be viewed as the static quality evaluation of course plan generated from scratch. * and ** means p-value < 0.1 and 0.05 using t-test.

mara et al. 2006; D'mello and Graesser 2012; Graesser et al. 2003; Rus et al. 2013; VanLehn 2011; Dzikovska et al. 2014). In addition to AutoTutor's application to various fields, enhancement of specific aspects of education are also investigated, including adaptive feedback (Dzikovska et al. 2014; Roscoe and McNamara 2013), learning material recommendation (S. 2014; Mohammed and Mohan 2015), and classifying learners (Grawemeyer et al. 2016; Nihad, Seghroucheni et al. 2017; J. 2014). Commonly adopted techniques include data mining (Echeverria, Guamán, and Chiluiza 2015), condition-action rule based (J. 2014; S. 2014), and bayesian based methods (Grawemeyer et al. 2016), and reinforcement learning (Malpani, Ravindran, and Murthy 2011; Gordon et al. 2016). NLP-specific techniques like semantic analysis (Graesser et al. 2001) and textual entailment (Rus and Graesser 2006; VanLehn, Jordan, and Litman 2007; McCarthy et al. 2008) are also adopted. In terms of application field, existing systems often rely on well-structured knowledge bases and therefore only target a single domain, most popular among which are health (Mc-Donald et al. 2013; El Saadawi et al. 2008), computer science (Grivokostopoulou, Perikos, and Hatzilygeroudis 2013; Mohammed and Mohan 2015), and language learning (S. 2014; Emran and Shaalan 2014).

As for applications with LLMs, with proper prompting and chaining, LLMs could be employed to complete a wide range of static tasks. A number of works have exploited LLMs in decomposing tasks (Wei et al. 2023), refining answers (Madaan et al. 2023; Shinn et al. 2023), and using external tools (Qin et al. 2023). While our work focuses on building an interactive tutoring system by chaining LLMs with a general-purpose of learning, featuring ever-changing fine-grained learning objectives and memory status.

Discussion

AI in education is an intriguing yet complicated topic, especially for a stand-alone AI-powered education system. This work is a pioneering exploration of an LLM-powered intelli-

gent tutoring system, with an emphasis on the possibility of employing LLMs to complete complex and dynamic tasks based on natural language conversation with users. Although our evaluation reveals mechanism of the adaptive behaviors and proves the advantage of memory mechanism and process design in long-term interaction, we acknowledge that comprehensively evaluating an intelligent tutoring system is far more tricky. In addition to the ongoing debate and discussion about what makes good education (Graesser, Person, and Magliano 1995; Cohen, Kulik, and Kulik 1982), AI techniques face their own special concerns such as the validity of generated education content and the potential bias from training data (Feng et al. 2023; Nozza, Bianchi, and Hovy 2022). Meanwhile, quantitatively assessing the learning outcome is also difficult, as our system teaches openended topics and devises quiz questions by itself.

Therefore, one important direction for future work is to incorporate more techniques to avoid hallucination and mitigate bias in LLMs, for instance, through domain-specific fine-tuning and search-engine-based fact-checking. As for evaluation, apart from potential falsehood and bias, we observe that properly evaluating multi-turn conversation is in itself a topic worth investigating. More standard metrics should be developed other than human evaluation which is rather subjective. Despite that, as a first approach in chaining LLMs to build a full-fledged intelligent tutoring system, this work demonstrates the promising application of a pure LLM-based purposeful interaction system based on reflection and memory mechanism, which might inspire future efforts in employing LLMs to build increasingly interactive and reflective systems.

Ethical Statement

The implemented system realizes a full-fledged intelligent education process, which can help achieve efficient online personalized tutoring and in turn, promote education equality. On the other hand, the experimental system faces the risk of generating inaccurate information given the hallucination problem in LLMs. The inherent bias may also mislead the users. It is important to address these issues before a practical application is launched. The participants in the evaluation process are all fairly paid with agreed salaries.

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Appendices

Ablation Systems

For the first ablation system (**w/o Reflection**), we remove the reflection process only. It means no learning profile is generated throughout the whole process, and the system does not explicitly judge the objective status. Only the course plan and learning history are available for retrieval. As a result, the reaction process is triggered at a fixed time interval with limited input. For example, the course design tool has only the recent learning history as input without the learning profile, and the teach tool has no access to the current ongoing objective but can only infer from the course plan and learning history implicitly. At the same time, to mitigate the loss of learning profile, we increase short-term learning history volume to up to 10 rounds of conversation. This, however, will exceed the maximum input length for ChatGPT in some extreme cases.

For the second ablation system (w/o Reflection & Reaction), both reflection and reaction processes are removed, and long-term learning history is also made unavailable. This means only short-term learning history and the initial course plan can be used in all educational activities. Figure 6 is an illustration of the differences between main system and ablation systems.

Topic Collection

We employ GPT-4 to generate the list of main learning objectives used in evaluation. We first ask GPT-4 to generate a set of general academic subject (e.g. Physics, Biology, Computer Science, etc.). Then we ask for generation of more fine-grained branches of discipline under each subject (e.g. "Developmental psychology" in psychology subject), and related classic concepts (e.g. "Newton's first law" in physics subject). Besides, we also include some daily phenomena that may inspire people's wondering. We encourage GPT-4 to generate a typical list of them in diverse language style. To demonstrate the system's robustness in dealing with various types of learning objectives, we randomly sample from course-grained subjects, atomic concepts, and daily wondering. To make the learning process more diverse and controllable, we also design 5 difficulty levels according to Bloom's taxonomy (Bloom and Krathwohl 2020). The course topics are randomly assigned to difficulty levels. Specifically, we have 15 courses at difficulty level 1, 25 at level 2, 25 at level 3, 10 at level 4, and 5 at level 5. Each course is learned and evaluated with all three systems, respectively. Table 9 is a completed list of all selected topics. In reference to Bloom's taxonomy, we manually design the difficultyspecific prompt for course design tool and teach tool for better adaptiveness and clarity. Table 6 and Table 7 present the prompts for course design tool and teach tool.

User Interface

We build a frontend interface to support interaction with the backend system. Figure 7 shows the frontend design used in real system evaluation. The main component is a chat window through which the user interacts with the system in natural language. On the right side is the current course plan,

Difficulty Level	Update Interval	Max. Dialogue Round	Avg. Time Spent (mins)
1	1	10	17
2	1	15	30
3	2	20	40
4	3	25	60
5	4	30	60

Table 5: Designed update interval of learning profile and the maximum round of dialogue in system evaluation.

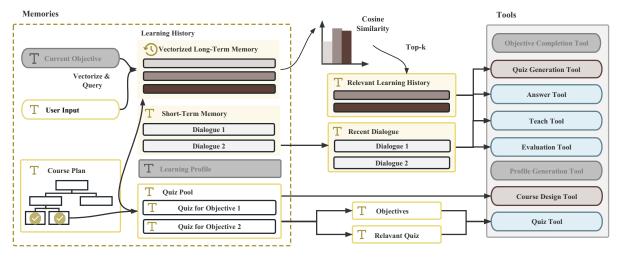
the completed objectives will be shown in blue (as shown in Figure 7b). Since both ablation systems do not conduct judgment on objective status. We change the next objective status to "completed" at each round of conversation on user interface to make them visually indiscriminate to the main system to avoid potential influence in evaluation.

Other Details

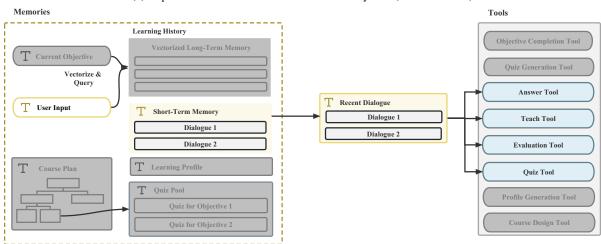
To ensure better usability and system stability, we also set different time intervals for learning profile update for each difficulty level, and control for the maximum round of conversation. Table 5 presents the detailed setting and the average time spent on courses at every difficulty level. Altogether, the evaluation for the three systems with 240 courses takes around 150 hours.

In addition to in-course quiz automatically triggered by meta agent, when all objectives have been completed or the pre-defined maximum round has been reached, the system explicitly calls for the quiz chain to generate a final quiz for the course. For final quiz generation, our system and ablation system without reflection process use similarity-based search for the most relevant 20 pieces of history as input context, while the ablation system with only interaction process uses the overall course plan.

As for long-term history storage and query, we use contriever model (Izacard et al. 2021) for embedding texts and cosine similarity score for most relevant record ranking and querying.



(a) Implementation details for the first ablation system (w/o Reflection).



(b) Implementation details for the second ablation system (w/o Reflection & Reaction).

Figure 6: Implementation details for ablation systems, in comparison to main system. Modules in gray means the modules are de-activated or non-existent in the system.

Course Design Prompt

Level 1: Remembering (Knowledge) At this level, the focus is on providing basic facts. Students are required to remember facts, definitions, and concepts. Design a **very** short course.

Level 2: Understanding (Comprehension) This level involves describing and interpreting facts, definitions, and concepts. Design a course as concise as possible.

Level 3: Applying (Application) At this level, students are expected to use acquired knowledge in new and practical situations. The focus is on applying concepts to solve problems and complete tasks. Try to make the course concise and well-structured.

Level 4: Analyzing (Analysis) In this level, the course should break down information into its components to understand the relationships between parts and the overall structure. Try to make the course concise and well-structured.

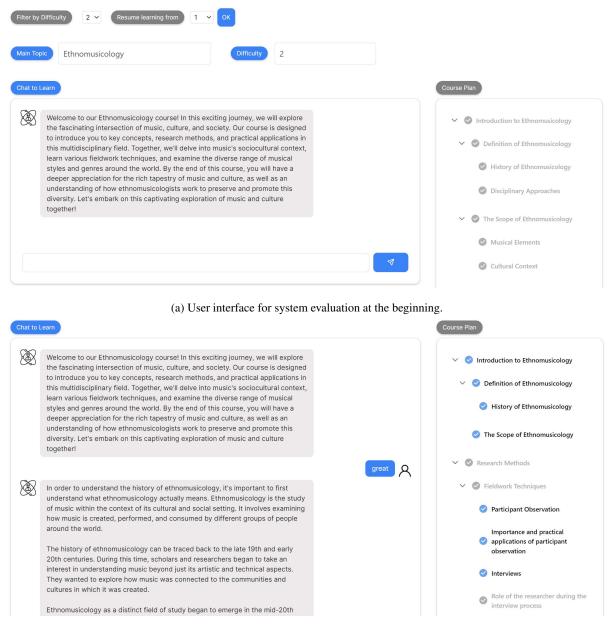
Level 5: Evaluating (Evaluation) The course should assess the quality, validity, and relevance of information and arguments. Try to make the course concise and well-structured.

Table 6: Prompts for course design tool at each difficulty level.

Teach Prompt

- Level 1: Teach in very simple and accessible language. Keep generated text short within a few sentences.
- Level 2: Teach in simple and accessible language. Keep language and wording easy to understand.
- Level 3: Teach in well-structured language and paragraph. Make information digestable. Try to use structured format to make it clearer, e.g. bullet point.
- Level 4 & 5:Use precise language to explain things in a systematic way. Try to use structured format to make it clearer, e.g. bullet point.

Table 7: Prompts for teach tool at each difficulty level.



(b) User interface for system evaluation in progress.

Figure 7: User interface for system evaluation. The users select which course to learn and start learning by chatting to the system. The right-hand side shows the real-time course plan.

Table 8: A complete list of course topics and difficulty level by category used for system evaluation.

Category	Main Learning Objective	Difficulty Leve
	Baroque architecture	2
Art	Installation art	2
	Impressionism	3
	Cognitive biases	2
Psychology	Obedience and conformity	3
	Operant conditioning	1
	Developmental psychology	5
	Paleontology	2
	Earth's mantle	2
	Igneous rocks	2
Geology	Mineralogy	2
Geology	Volcanoes	2
	Geologic formations	3
	Geothermal energy	3
	Erosion	1
	Sorting algorithms (e.g., bubble sort, merge sort)	2
Computer Science	Linked lists	3
Computer Science	Web development	4
	Computer architecture	4
Chamister	pH scale	2
Chemistry	Lewis dot structure	3
	How do bees communicate and find their way back to the hive?	2
	Biological Circadian Rhythms (sleep-wake cycles)	2
	Gravity Waves (not to be confused with gravitational waves)	2
	Volcanic Eruptions	2
	Predator-prey relationships	2
	Formation of Coral Reefs	2
	How do magnets work, and what makes some materials magnetic?	2
	Change of Seasons	3
	Boom-and-bust cycles	3
Daily Wondering	Reflection and Refraction of Light	3
Duny Wondering	Formation of Crystals	3
	How does our brain store and retrieve memories?	3
	Hibernation	3
	Bioluminescence in Deep-Sea Creatures	3
	How do plants "know" which way to grow toward light?	3
	Why do some people have allergies, and how do they develop?	3
	Formation of Rainbows	3
	Cyberbullying	3
	How do rainbows form and why do they have different colors?	3
	Bioluminescence (e.g., glowing organisms in the ocean)	1
	Entanglement Aurora Borealis (Northern Lights)	1
	How do airplanes stay up in the air and maintain flight?	1
	Formation of Rain and Snow	1
	Why do some people have left-handed dominance while others are right-handed?	1
	Creation and Dissipation of Fog	1
	The uncertainty principle	4
	Hurricane formation	4
	Personalized ads	4
	Umami taste	4
	Jet lag	5
	Fight-or-flight response	5

Category	Main Learning Objective	Difficulty Level
	Ethnomusicology	2
Music	Rhythm and meter	2
Music	Baroque composers (e.g., Johann Sebastian Bach, Antonio Vivaldi)	2
	Polyphony	1
	Quantum physics	2
Physics	Newton's second law of motion	1
rilysics	Newton's first law of motion	1
	Snell's law of refraction	5
	Medieval history	2
History	Mongol Empire	3
THStory	Ancient Egyptian civilization	3
	American history	4
	Aesthetics	2
Philosophy	Pragmatism	1
	Syllogism	5
	Permutations and combinations	2
Mathematics	Mathematical modeling	4
	Differential equations	4
	Food chains and food webs	2
Biology	Nitrogen fixation	3
	Plant biology	3
C = = : = 1 = = = :	Deviance and social control	3
Sociology	Social networks	3
	Postcolonial literature and writers	3
T 14	Literary theory	1
Literature	Stream of consciousness	1
	Symbolism in poetry	4

Table 9: An example of dialogue and corresponding real-time course plan.

Dialogue



Welcome to our Ethnomusicology course! In this exciting journey, we will explore the fascinating intersection of music, culture, and society. Our course is designed to introduce you to key concepts, research methods, and practical applications in this multidisciplinary field. Together, we'll delve into music's sociocultural context, learn various fieldwork techniques, and examine the diverse range of musical styles and genres around the world. By the end of this course, you will have a deeper appreciation for the rich tapestry of music and culture, as well as an understanding of how ethnomusicologists work to preserve and promote this diversity. Let's embark on this captivating exploration of music and culture



In order to understand the history of ethnomusicology, it's important to first understand what ethnomusicology actually means. Ethnomusicology is the study of music within the context of its cultural and social setting. It involves examining how music is created, performed, and consumed by different groups of people around the world.

The history of ethnomusicology can be traced back to the late 19th and early 20th centuries. During this time, scholars and researchers began to take an interest in understanding music beyond just its artistic and technical aspects. They wanted to explore how music was connected to the communities and cultures in which it was

Ethnomusicology as a distinct field of study began to emerge in the mid-20th century. It was influenced by various disciplines such as anthropology, folklore studies, and musicology. Ethnomusicologists started conducting field research, traveling to different parts of the world to study and document traditional music practices

This approach differed from the traditional Western musicology, which largely focused on the study of classical music. Ethnomusicologists sought to understand and appreciate the diversity of musical traditions found globally. They recognized that music was not just a universal language, but also a reflection of the values, beliefs, and identities of the communities that created it.

Ethnomusicologists use a wide range of research methods to study music in its cultural context. They may conduct interviews with musicians and community members, observe musical performances, and analyze the historical and social factors that shape musical practices. Through their work, ethnomusicologists aim to preserve and promote the rich tapestry of musical traditions from around the world.

By studying the history of ethnomusicology, we gain a deeper understanding of how our appreciation and understanding of music has evolved over time. It helps us recognize the importance of cultural diversity and the role music plays in shaping our collective human



Now that we have a better understanding of the history of ethnomusicology, let's explore the scope of this fascinating field. Ethnomusicology encompasses a wide range of topics and approaches, allowing us to delve into various aspects of music and culture

One important aspect of ethnomusicology is the study of musical instruments. Different cultures have unique instruments, each with its own distinct sounds, techniques, and meanings. Ethnomusicologists examine how these instruments are made, how they are played, and how they contribute to the overall musical experience.

Another area of interest in ethnomusicology is the study of musical genres. Just as different cultures have their own instruments, they also have their own musical styles and genres. From traditional folk songs to contemporary pop music, ethnomusicologists analyze the characteristics, cultural significance, and historical development of these

Ethnomusicology also involves studying the role of music in different social contexts. Music has the power to bring people together, express emotions, and communicate cultural identities. Ethnomusicologists explore how music is used in rituals, celebrations, ceremonies, and everyday life, shedding light on the social functions and meanings

In addition to studying music within specific cultures, ethnomusicology also examines the interactions between different cultures and musical traditions. With globalization and migration, musical styles and practices often intersect and blend. Ethnomusicologists investigate these cross-cultural exchanges, exploring how music travels and adapts to new environments while retaining its original cultural and artistic elements.

Lastly, ethnomusicology explores the significance of music in identity formation and cultural preservation. Music plays a crucial role in shaping individual and collective identities, reflecting the values, beliefs, and aspirations of communities. Ethnomusicologists study how music is used as a form of cultural expression and as a means of preserving heritage and traditions

By exploring the diverse scope of ethnomusicology, we can gain a deeper appreciation for the richness and complexity of music and its connection to culture. This multidimensional approach allows us to understand how music serves as a bridge between different societies and as a powerful tool for social change and understanding.

Course Plan

- 1. Introduction to Ethnomusicology
- a. Definition of Ethnomusicology
- i. History of Ethnomusicology
- ii. Disciplinary Approaches
- b. The Scope of Ethnomusicology
- i. Musical Elements
- ii. Cultural Context
- 2. Research Methods
- a. Fieldwork Techniques
- i. Participant Observation
- ii. Interviewing
- b. Analysis and Interpretation
- i. Transcription
- ii. Contextual Analysis
- 3. Key Concepts
- a. Musical Diversity
- i. Cultural Differences
- ii. Music Styles and Genres
- b. Music, Identity, and Representation
- i. Social Identity
- ii. Music as Cultural Expression
- 4. Ethnomusicology in Practice
- a. Applied Ethnomusicology
- i. Community-based Projects
- ii. Advocacy and Activism
- b. Teaching and Dissemination
- i. Academic Institutions
- ii. Public Outreach





A

Dialogue

Got it







Now, let's discuss another important aspect of ethnomusicology: fieldwork techniques or research methods. Ethnomusicologists often engage in fieldwork, which involves immersing themselves in a particular culture or community to observe and document musical practices firsthand. Through fieldwork, ethnomusicologists are able to gather valuable information and insights about the music and its cultural context.

One fieldwork technique commonly used in ethnomusicology is participant observation. This method involves actively participating in the musical activities and events of a particular community while also observing and taking notes. By being a part of the musical experience, ethnomusicologists can gain a deeper understanding of the music's cultural significance and how it is performed within its social context.

In addition to participant observation, ethnomusicologists also conduct interviews as part of their fieldwork. They engage in dialogue with musicians, community members, and experts to gather information about the music, its origins, and its role in society. These interviews provide valuable insights into the cultural meanings and practices associated with the music, as well as the personal experiences and perspectives of those

Ethnomusicologists may also employ audio and video recording techniques during their fieldwork. Recording performances, rituals, or everyday musical encounters allows for a more detailed analysis and documentation of the music. These recordings capture the nuances of the music, including its melodies, rhythms, and vocal expressions, which can be analyzed later in the research process.

In addition to these techniques, ethnomusicologists often utilize archival research. This involves studying historical records, manuscripts, recordings, and other existing materials related to the music and culture of interest. Archival research helps ethnomusicologists establish historical context, trace the evolution of musical practices, and understand how music has been shaped by social, political, and cultural forces over time

Another important tool in ethnomusicological fieldwork is ethnographic writing. Ethnography involves writing detailed descriptions and narratives based on the researcher's observations and interactions in the field. Ethnomusicologists use ethnographic writing to convey the rich sensory experiences of music and to provide cultural context for their findings. This form of writing allows ethnomusicologists to share their research with others and contribute to the broader understanding of music and culture.

By utilizing these fieldwork techniques and research methods, ethnomusicologists are able to explore the complexities and intricacies of music in its cultural context. Through nt observation, interviews, recordings, archival research, and ethnographic writing, they gain a comprehensive understanding of the music's meaning, function, and impact on society. Fieldwork techniques are integral to ethnomusicology as they enable researchers to engage with music and culture in a holistic and immersive manner.





That's a great question! Ethnomusicology is an important subject because it allows us to go beyond simply appreciating music and understand it in a deeper and more meaningful way. Here are a few reasons why studying ethnomusicology is important:

- 1. Cultural Understanding: Ethnomusicology helps us understand how music is connected to a culture's history, values, beliefs, and social practices. By studying different musical traditions, we gain insight into the diverse ways in which people express themselves artistically and culturally. This understanding promotes cultural appreciation and fosters empathy and respect for different societies and their musical traditions
- 2. Preservation of Cultural Heritage: Ethnomusicology plays a crucial role in preserving and documenting musical traditions that may be endangered or at risk of being lost. By studying and documenting these traditions, ethnomusicologists contribute to the preservation of cultural heritage and history. This ensures that future generations can learn from and appreciate these rich musical traditions
- 3. Cross-Cultural Dialogue: Music has the power to bridge gaps and foster understanding between different cultures. Studying ethnomusicology allows us to explore the similarities and differences in musical practices across cultures. By engaging in cross cultural dialogue and understanding, we promote global awareness and create opportunities for collaboration and exchange.
- 4. Shedding Light on Social Issues: Music often reflects the social, political, and cultural realities of a society. Ethnomusicology allows us to analyze and understand how music can be used to express and address social issues such as identity, inequality, and resistance. By examining the ways in which music is used as a form of cultural expression and activism, we can gain insight into the experiences and struggles of different
- 5. Personal Growth and Enrichment: Studying ethnomusicology can also be personally enriching. It deepens our appreciation for the diversity of human creativity and expression, and allows us to develop a broader perspective on music and its cultural significance. It enhances our ability to critically analyze and interpret different musical traditions, and can also inspire creativity and innovation within our own musical pursuits.

Overall, studying ethnomusicology is important because it provides us with a deeper understanding and appreciation of music's role in shaping our world. It helps us recognize the power of music as a cultural and social force, and allows us to engage with diverse musical traditions in a meaningful and respectful manner.

Course Plan

- 1. Introduction to Ethnomusicology
- a. Definition of Ethnomusicology
- i. History of Ethnomusicology
- b. The Scope of Ethnomusicology
- 2. Research Methods
- a. Fieldwork Techniques
- b. Analysis and Interpretation
- 3. Key Concepts
- a. Musical Diversity
- b. Music, Identity, and Representation
- 4. Ethnomusicology in Practice
- a. Applied Ethnomusicology
- b. Teaching and Dissemination

Dialogue Course Plan

alright talk about some practical application then





Surel Let's talk about a research method called participant observation, which is commonly used in ethnomusicology fieldwork.

Participant observation is a qualitative research technique that involves immersing oneself in a specific musical community or cultural context. Ethnomusicologists who use this method actively participate in the musical activities and events of the community they are studying, while also observing and taking notes on their experiences.

By actively participating in the musical practices of a community, researchers gain a firsthand understanding of the cultural and social significance of music within that particular context. This method allows ethnomusicologists to not only observe but also experience the music in its intended cultural and social setting.

Through participant observation, researchers can develop close relationships with community members, which can provide valuable insights into their perspectives, beliefs, and experiences. By engaging with the community as a participant, researchers are able to build trust and rapport, which leads to more authentic and meaningful data collection.

In addition to observing and participating, ethnomusicologists also document their experiences through fieldnotes. These fieldnotes capture their observations, thoughts, and reflections on the musical practices, performances, and interactions within the community. Fieldnotes provide a detailed record of the researcher's experiences, which can be analyzed and interpreted to gain a deeper understanding of the music and its cultural significance.

Participant observation allows researchers to uncover the nuances and intricacies of a musical tradition. It provides rich and detailed data that goes beyond mere descriptions, allowing for a more holistic analysis of the music and its cultural context.

This method also enables researchers to gain a more nuanced understanding of how music is learned, transmitted, and practiced within a specific community. By actively participating, researchers can witness firsthand the teaching methods, learning processes, and social dynamics that shape the musical practices of the community.

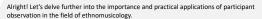
Overall, participant observation is a valuable research method in ethnomusicology because it allows researchers to immerse themselves in a musical community, experience the music firsthand, build connections with community members, and gain a deep understanding of the music's cultural and social significance.

Dialogue

good







One of the key benefits of participant observation is its ability to capture the dynamic nature of music within a cultural context. By actively immersing themselves in the musical community, ethnomusicologists can witness the evolving nature of music and how it adapts to changes in society. This method allows researchers to identify and understand the cultural and historical factors that influence the development and transformation of musical traditions.

Another practical application of participant observation is its role in debunking stereotypes and misconceptions surrounding different musical communities, by directly engaging with the community as a participant, researchers can challenge preconceived notions and stereotypes, gaining a more accurate and nuanced understanding of the musical practices and their social significance. This can help in breaking down cultural barriers and fostering cross-cultural understanding and appreciation.

Participant observation also enables researchers to explore the social dynamics and power structures within a musical community. By immersing themselves in the community, ethnomusicologists can observe how music is used as a means of social interaction, communication, and identity formation. This method allows researchers to uncover the hierarchical relationships, gender dynamics, and other social dimensions that shape the musical practices and their broader cultural context.

Furthermore, participating in musical events and activities provides researchers with valuable opportunities for data collection and analysis. By actively engaging in the music-making process, researchers can gather detailed information about musical techniques, performance styles, and the underlying meanings behind the music. This firsthand experience enhances the authenticity and depth of research findings.

Participant observation can also contribute to the preservation and documentation of musical traditions. By actively participating in the community's musical activities, researchers can help to safeguard cultural heritage by documenting and recording performances, rituals, and traditions that might otherwise be lost or forgotten. This documentation serves as a valuable resource for future generations, ensuring the continuity and appreciation of diverse musical practices.

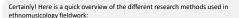
Lastly, participant observation can be a catalyst for meaningful collaborations and partnerships between researchers and community members. By immersing themselves in the community, ethonousicologists can foster trust and mutual respect, leading to collaborative research projects that address the concerns and interests of the community. This participatory approach allows for a more ethical and inclusive research process, where the voices and perspectives of the community are represented and respected.

In conclusion, participant observation is a vital research method in ethnomusicology that provides researchers with a unique and in-depth understanding of musical traditions and their cultural significance. Through active participation, observation, and documentation, this method allows for a holistic analysis of music within its cultural context, while also promoting cross-cultural understanding, breaking down stereotypes, and ensuring the preservation of diverse musical practices.

thx for your information, now maybe just give a quick







- Participant observation: Involves actively participating in the musical activities and events of a community while also observing and taking notes. Provides a firsthand understanding of the cultural and social significance of music within a specific context.
- 2. Interviews: Engages in dialogue with musicians, community members, and experts to gather information about the music, its origins, and its role in society. Provides valuable insights into cultural meanings and practices.
- Audio and video recording: Utilizes recording techniques to capture performances, rituals, and everyday musical encounters. Allows for detailed analysis and documentation of the music's nuances and characteristics.
- 4. Archival research: Involves studying historical records, manuscripts, recordings, and other existing materials related to the music and culture of interest. Establishes historical context and traces the evolution of musical practices.
- 5. Ethnographic writing: Involves writing detailed descriptions and narratives based on the researcher's observations and interactions in the field. Conveys the richness and cultural context of the music.

These methods, when used in combination, provide a comprehensive understanding of the music's meaning, function, and impact on society. They allow for an immersive and holistic exploration of music and its cultural context within ethnomusicology research.

Course Plan

- 1. Introduction to Ethnomusicology
- a. Definition of Ethnomusicology
- i. History of Ethnomusicology
- b. The Scope of Ethnomusicology
- 2. Research Methods
- a. Fieldwork Techniques
- i. Participant Observation
- ii. Importance and practical applications
- of participant observation
 - iii. Interviews
- iv. Importance and practical applications of interviews
 - v. Audio and Video Recording Techniques
- vi. Importance and practical applications
- of audio and video recording techniques
 - vii. Archival Research
- viii. Importance and practical applications of archival research
 - ix. Ethnographic Writing
- x. Importance and practical applications
- of ethnographic writing
- b. Analysis and Interpretation
- 3. Key Concepts
- a. Musical Diversity
- b. Music, Identity, and Representation
- 4. Ethnomusicology in Practice
- a. Applied Ethnomusicology
- i. Practical applications of ethnomusicology in cultural understanding, preservation of cultural heritage, cross-cultural dialogue, shedding light on social issues, and personal growth and enrichment
- b. Teaching and Dissemination