

AskWise: Think-Question-Understand

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Abstract— In today's education, students often face difficulty in developing deep conceptual understanding across a range of academic fields as a result of traditional teaching strategies that emphasize rote memorization at the expense of analytical thinking. Standard online learning platforms conventionally offer instant responses, which limits exploration, reflection, and meaningful understanding. AskWise offers an AI-augmented Socratic learning experience designed to cultivate critical thinking by guiding learners through a set of structured questions rather than offering definitive answers. With generative artificial intelligence, adaptive commentating systems, multimodal visual materials, and interactive practice activities, the site individualizes learning experiences and stimulates intellectual inquiry. With interactive discussion and scaffolding, AskWise guides passive learning towards an active, reflective experience that builds deep understanding across mathematical, computational, and conceptual fields. This paper explores AskWise's design architecture, its pedagogical ramifications, and its scalability possibilities as a novel instrument for personalized, AI-enabled learning.

Keywords—Artificial Intelligence (AI), Socratic Method, Adaptive Learning, Natural Language Understanding (NLU), Intelligent Tutoring System (ITS)

I. INTRODUCTION

Learning in the twenty-first century is undergoing rapid evolution, fueled by rapid developments in artificial intelligence (AI) as well as learning technologies. While such advances continue, a significant portion of students still struggle with a deep conceptual understanding of key academic disciplines. Traditional teaching practices often emphasize algorithmic memorization and algorithmic assessment, which may confuse developing critical thinking skills with information that over time decays or atrophies. Correspondingly, a large amount of online materials focuses more on offering simple answers or complete solutions, while ignoring developing learners' skills for understanding, analyzing, or implementing knowledge under new contexts. Advanced studies on cognitive science as well as education emphasize active learning, metacognition, as well as inquiry-based learning as crucial components for developing long-lasting intellectual skills. Nevertheless, large-scale applicability of such educational practices constitutes a major impediment. Teachers almost rarely get a chance to provide individual mentoring, whereas available e-learning materials often lack adaptive asking features that might replicate reflective as well as dialogical nature that comes with human mentoring. Therefore, learners are often treated as passive consumers of information instead of active participants in learning. For remedying this impasse, AskWise has come out with a Socratic AI-supported learning site that helps students learn "deeply, not fast." This site utilizes generative AI that recreates the Socratic method—to examine concepts via Socratic questioning, not via linear instruction. With adaptive feedback, visual explanations, interactive participation, as well

as individualized learning paths, AskWise tries to promote learners' curiosity, active participation, as well as deep understanding across various areas such as mathematics, computer science, as well as logical thinking. This paper outlines the conceptual architecture, design vision, and future education implications of AskWise. This novel system seeks to close the gap between intelligent automation and true human learning by transforming artificial intelligence from a simple answer-provider to a thought-provoking catalyst of inquiry and critical thinking.

II. LITERATURE SURVEY

To inform the design and development of AskWise, literature was reviewed about intelligent tutoring systems, adaptive learning, multimodal analytics, educative AI, including generative AI, as well as about AI-based learning ethics. Nye et al. (2014) offer a thorough AutoTutor system lineage review that illuminates how conversational dialogue and scaffolded feedback drive conceptual learning in naturalistic settings [1]. A meta-analytic literature review by Kulik & Fletcher (2016) shows that intelligent tutoring systems produce large learning gains (median effect ~ 0.66 standard deviations) over core instruction [2]. L  tourneau et al. (2025), in a more recent systematic review, examine AI-driven K–12 tutoring systems with a finding that they exhibit strong positive effects but critical weaknesses in scalability and real-world deployment [3]. A related multimodal learning analytics survey by Mohammadi et al. (2025) highlights increasing education system uses of computer vision, speech, as well as behavior signals, with related technical complexities [4]. The Advancing Education through Tutoring Systems literature review by Liu et al. (2025) covers both classic as well as AI-extended tutoring system realms, with a finding that text-voice-visual hybrid models are promising future directions [5]. For educative AI, Practical and Ethical Challenges of LLMs in Education by Yan et al. (2023) outlines LLM-based education tools' inherent LLM-derived issues of privacy, bias, transparency, as well as pedagogical trust [6]. A case description of trustworthy multimodal tutoring by Lakkaraju et al. (2024) explores how, in AI tutor designs, real-time explanation as well as data governance must be integrated [7]. NeuroChat: A Neuroadaptive AI Chatbot (Baradari et al., 2025) shows that it's possible to combine real-time cognitive feedback (EEG) with a generative dialogue, revealing new avenues for adaptive reasoning in tutorial platforms [8]. Empirically, Kestin et al. (2025) show that AI tutors excel over in-class active learning both in learning gains as well as engagement under controlled conditions [9]. In Automated Disengagement Tracking (Frontiers AI, 2020), dialogue-based ITS (AutoTutor) gets extended to include modules inferring inattention as well as mind-wandering, corroborating that multimodal signals strengthen engagement detection [10].

Fütterer et al. (2025) offer a systematic AI application in classroom management, which reveals that predictive/monitoring models aid synchronous teaching as well as student participation [11]. While GEAI (Generalist Education AI) framework (Yan et al., 2025) envisions unification models that integrate behavior, audio, as well as video under strict governance for adaptive learning settings [12], AI-Powered Educational Agents survey (Córdova-Esparza et al., 2025) classifies education AI agents as well as covers their pedagogy, feedback modes, as well as design directions [13]. Last but not least, Effectiveness of ITS: A Meta-Analytic Review by Fletcher et al. (2016) remains a foundational work, summarizing controlled studies of ITS across education as well as affirming intelligent feedback systems' effectiveness [14]. There remains a gap in fully closing real-time affect/attention detection with a generative Socratic dialogue while ensuring transparency, effectiveness, as well as pedagogy, exactly where AskWise aspires to contribute.

III. METHODOLOGY

The AskWise development methodology has five major components: dataset construction, preprocessing, model architecture design, training and optimization, and evaluation workflow. This would aim at generating high-quality Socratic questions, adapting the depth of questioning to learner responses, and measuring system effectiveness with standardized metrics.

A. Data Collection and Annotation

The data acquisition for AskWise aimed at harvesting a heterogeneous dataset comprising educational dialogues, student queries, and teaching materials for several domains such as mathematics, science, and programming. The datasets comprised openly sourced educational question-and-answer collections (e.g., discussion from Khan Academy and Stack Exchange Education), synthesized dialogue datasets, as well as question banks selected manually by teachers. Such materials were useful for training as well as tuning generative language models for producing Socratic-style dialogues that participate in reasoning as well as conceptual exploration. Besides, data for interactive user behavior for initial prototypes (pilot sessions) were collected for optimizing adaptive questioning algorithms. Experts annotated each sample with a Bloom's Taxonomy level (Knowledge, Application, Analysis, Synthesis), which was used to train adaptive difficulty selection within AskWise.

B. Data Preprocessing Pipeline

All data collected went through a standardized preprocessing pipeline ensuring linguistic coherence and semantic clarity:

- 1) *Cleaning of the Text*: Removal of HTML tags, special characters, duplicate entries, and incomplete interactions.
- 2) *Tokenization & Normalization*: Text is tokenized using WordPiece and normalized to lowercase for consistency in vocabulary distribution.
- 3) *Semantic Embedding*: Sentences encoded into BERT-based contextual embeddings to capture

semantic similarity between learner inputs and tutor responses.

- 4) *Intent Recognition*: Learner queries categorized into intent classes like concept clarification, problem-solving, misconception, and reflection.
- 5) *Data Augmentation*: Paraphrasing and synonym substitution to increase the diversity of a dataset while preserving semantic meaning.
- 6) *Feedback Annotation*: Student and teacher feedback were separately annotated with degrees of engagement and understanding in order to improve upon the reinforcement model to expert adjudicators' adaptive questioning as a means of quality of reasoning measurement.

C. Model Automation

The AskWise dialogue engine is powered by a fine-tuned, transformer-based generative model, combined with a reinforcement learning module to optimize the quality of Socratic questioning

1) Encoder-Decoder Backbone:

A transformer-based architecture with:

- 12-layer encoder and 12-layer decoder
- 768 dimensional hidden states
- 12 attention heads
- 512-token context window

2) Loss Function

Training minimizes the standard cross-entropy loss:

$$LCE = -\sum_{t=1}^T \log P(y_t | y_{<t}, X)$$

where X is the learner's input and y_t is the predicted Socratic question at timestep t .

3) Reinforcement Learning Component

To encourage deeper questioning behavior, a module for Reinforcement Learning with Human Feedback (RLHF) was added. A reward score R combines:

- Semantic Coherence (SCI)
- Pedagogical Quality (PES)
- Question Depth Score (QDS)

$$R = \alpha \cdot SCI + \beta \cdot PES + \gamma \cdot QDS$$

The RL objective becomes:

$$\mathcal{L}_{RL} = -\mathbb{E}_{\pi}[R]$$

D. Algorithm: Adaptive Socratic Questioning

Input:

Learner Query (Q), History (H), Knowledge Graph (K)

Output:

Adaptive Question (Q'), Feedback (F)

Start

Step 1: Parse Q using intent classifier

Step 2: Extract context features using encoder

Step 3: Map Q to knowledge graph K and identify concept node

Step 4: Predict difficulty level based on learner profile

Step 5: Generate Socratic question Q' using decoder

Step 6: Evaluate learner’s response for reasoning depth
Step 7: Compute reward score R and Adapt next question difficulty accordingly
Step 8: Log interaction data for analytics
Step 9: Return {Q’, F}

Stop

E. Testing and Validation

The AskWise prototype was evaluated under controlled classroom simulations as well as small-group pilot experiments. Data were separated into training sets and validation sets, with k-fold cross-validation to avoid overfitting. BLEU score, semantic coherence, relatedness of responses, and improvement rate of engagement, as quantified by surveys of learners as well as interaction analytics, were employed as evaluation metrics.

Additionally, experienced teachers assessed dialogues generated by machine intelligence for learning validity and conceptual accuracy. Agreement scores between human-AI were calculated to confirm the model’s effectiveness in replicating true Socratic inquiry. Ongoing test phases were instituted to ensure usability, flexibility, and compliance with ethical data handling.

F. Deployment

The final AskWise system was rolled out as a web-based interactive platform, using Next.js for the front end and Firebase to handle real-time data. It lets students dive into guided question-based learning sessions, see concepts through cool interactive diagrams, and get instant feedback. Teachers and parents can hop onto a dashboard that shows off learning stats like how much time students spent engaged, how deep their questions are getting, their mastery of concepts, and their growth. Plus, it’s got some scalability features like cloud-based APIs to link AskWise with school LMS systems and mobile access for students. In the future, they plan to add voice interfaces, multilingual questions, and AI-generated performance summaries to make it even more user-friendly and inclusive.

IV. PROPOSED SYSTEM

The AskWise is an AI-powered Socratic learning platform that encourages deep conceptual understanding by guiding students with questions rather than providing them with direct answers. It intelligently integrates generative AI, adaptive learning analytics, and multimodal instructional support in such a way as to provide students with the environment to learn through reasoning, curiosity, and reflection. An architectural model of the AskWise system is illustrated in Figure 1. It includes the following major components:

A. Intelligent Dialogue Engine

Central to AskWise is an Intelligent Dialogue Engine managing student-AI interactions through Socratic questioning. This employs fine-tuned transformer-based generative models—such as GPT, BERT variants—that simulate the thought process of a tutor who guides students in discovering concepts on their own.

- 1) *Question Generation:* Provides progressive, layered questions that match Bloom’s Taxonomy levels of thinking from recall to synthesis.
- 2) *Contextual Understanding:* It uses NLP to understand the student input and respond with follow-up questions rather than giving answers.
- 3) *Response Evaluation:* This assesses students’ responses for correctness, depth of reasoning, and misconceptions.
- 4) *Feedback Adaptation:* Provide hints, analogies, or simplification when students are having difficulties.

This is the component that ensures that AskWise provides students with an engaging dialogue, promoting exploration, self-correction, and active reflection.

B. Adaptive Learning Engine

The Adaptive Learning Engine tailors the questioning and feedback style to each learner’s profile and pace, applying reinforcement learning principles to optimize question difficulty and sequencing based on learner performance.

Functions include:

1. *Performance Tracking:* Continuously logs accuracy, response time, and confidence metrics for each concept.
2. *Learning Path Optimization:* Dynamically adjusts question patterns based on mastery level and topic familiarity.
3. *Knowledge Graph Mapping:* Relates student progress to conceptual nodes so as to find gaps and learning dependencies.
4. *Personalized Reinforcement:* Provides targeted practice and re-engagement tasks where weak areas are detected.

This ensures that the learning pathway for each student is personalized and growth-oriented, with comprehension deepened over time.

C. Visual and Interactive Learning Aids

AskWise promotes conceptual clarity with rich, dynamic, and visual tools that are integrated into the conversational framework.

Features include:

- 1) *Interactive Diagrams:* Auto-generated visual models such as graphs, charts, and coding flow diagrams pop up based on context keywords.
- 2) *Step-by-Step Visual Reasoning:* It breaks down complex problems into visual steps, thereby enhancing conceptual retention.
- 3) *Reference Videos and Multimedia Support:* Includes brief training videos for reinforcement which are activated at the request of the learner.

These learning aids are multimodal, catering to different learning styles and promoting long-term retention.

D. Educational Analytics Hub

The Educational Analytics Hub is a central intelligence layer for AskWise, storing all learning interactions, analytics, and performance metrics.

Core functions include:

- 1) *Conceptual Mastery Analysis*: keep track of each individual learner's depth in certain topics using discussion-based scoring metrics.
- 2) *Engagement Analytics*: Measures the level of participation, frequency of curiosity-questions raised by the learner, and session length.
- 3) *Progress Dashboards*: Provides teachers, parents, and administrators with real-time, visual dashboards of conceptual mastery, trends of learner engagement, and growth in reasoning.
- 4) *Predictive Insights*: Applying regression models to forecast learner outcomes, showing possible drop in engagement or conceptual difficulty zones.

This hub transforms raw learning interactions into actionable educational insights to inform personalized instruction and adaptive curriculum design.

E. Integration with Academic Stakeholders and Systems

The AskWise platform integrates seamlessly with institutional systems and stakeholders to ensure scalable, transparent learning management.

Functions include:

- 1) *LMS Integration*: Integrates seamlessly with Google Classroom, Moodle, Canvas, and more by automatically updating learning progress, question logs, and feedback summaries in real-time.
- 2) *Educator Access*: Allows instructors to monitor the analytics of learners, find misconceptions, and intervene with personalized guidance.
- 3) *Parent Dashboard*: Offers parents simplified visual reports of conceptual progress and engagement consistency.
- 4) *Data Privacy & Ethics Compliance*: Ensures secure handling of student data in compliance with GDPR and FERPA guidelines while maintaining confidentiality and transparency in AI operations.

Thus, AskWise bridges students, educators, and institutions by fostering an intelligent, feedback-rich, and ethically responsible learning ecosystem. The AskWise system thus integrates conversational AI, adaptive analytics, and multimodal learning aids to build a next-generation educational tool aimed at helping students “learn deeply, not just quickly.” The proposed system converts AI tutoring into an interactive process of guided reasoning while supporting educators with actionable insights to enhance the effectiveness of classroom learning.

V. SYSTEM FUNCTIONAL ARCHITECTURE

This section provides a detailed overview of the functional architecture of the AskWise system: an AI-driven Socratic Learning Platform that generates real-time adaptive questioning, interactive learning visualization, and educational analytics. This modular architecture for the AskWise system combines state-of-the-art generative AI, machine learning, and data-informed pedagogies to drive scalable, personalized, and reflective learning experiences for students while offering actionable insights in support of educators.

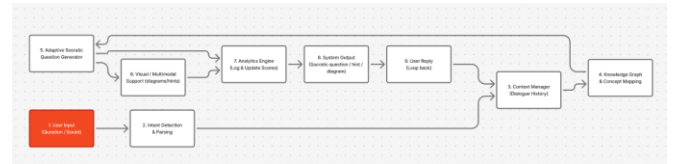


Fig. 1. AskWise Architecture

A. Dialogue Management and Understanding Module

The entire process starts with the Dialogue Management and Understanding Module of the AskWise system, which itself guides the real-time interaction between students and AI. This module makes sense of the learner's input, identifies the intent, and consequently constructs Socratic questions that are contextually appropriate with the use of Natural Language Processing and transformer-based generative models. The ultimate aim is the replacement of direct answer delivery with guided reasoning whereby the learner will explore concepts through reflective inquiry.

Key functions include:

- 1) *Intent Detection*: It identifies the learner's intention-ordering clarification, exploration, or problem-solving.
- 2) *Context Management*: Keeps track of conversation history for coherence and contextual relevance across turns.
- 3) *Question Generation*: This generates adaptive questions based on the learner's progress and Bloom's taxonomy levels.
- 4) *Feedback Loop*: Evaluates responses for reasoning depth, correcting misconceptions through hints or analogies.

B. Adaptive Learning and Feedback Engine

The Adaptive Learning Engine lies at the heart of the analytics framework of AskWise. It dynamically adjusts question complexity, tone, and structure based on the learner's cognitive performance and engagement level. This engine employs reinforcement learning with semantic scoring for constant refinement of the questioning strategy. The Engagement Index is calculated based on an analysis of the time taken by learners to respond, the reasoning accuracy, and emotional tone derived from sentiment analysis.

Learner Behavior	System Response
Quick, accurate reasoning	Increase question depth (Analysis/Synthesis level)
Slow or hesitant response	Provide guided hints or simpler sub-questions
Incorrect reasoning	Trigger analogical explanations or contextual rephrasing

TABLE I. ADAPTIVE LEARNING RESPONSE STRATEGIES

- 1) *Model Execution and Real-Time Adaptation*: It works with low latency to allow a natural flow of conversation. The model keeps updating the difficulty gradient and reasoning depth as the learner

engages, achieving a personalized Socratic experience and equipping the system to serve novice and advanced learners alike.

- 2) *Transformer Decoder*: Uses contextual embeddings and Bloom-level predictions to generate the next question.
- 3) *Difficulty Chooser*: Uses learner performance signals to dynamically determine the difficulty level of the next question.
- 4) *RLHF Reward Module*: Incorporates reward scores based on semantic coherence, depth of questions, and pedagogical relevance.
- 5) *Hint Generator*: Provides step-by-step hints, analogies or scaffolding for learners who are struggling.

C. Knowledge Representation and Concept Mapping Module

At the heart of AskWise's cognitive capability is the Knowledge Representation Module, which organizes knowledge into a Knowledge Graph and visualizes connections linking ideas, knowledge skills, and related questions.

This module performs the following functions:

- 1) *Concept Linking*: It Provide additional explanations by linking specific dialogue nodes with sub-topics relevant to that node and dialogue.
- 2) *Misconception Detection*: This uses patterns based on natural language processing to detect errors in understanding a concept.
- 3) *Contextual Recommendations*: provides relevant illustrations, examples, or topics of conversation.
- 4) *Curriculum Integration*: the course of study is a student proficiency based study followed by the curriculum of schools and competitive exams, such as BECE and IIT-JEE.

AskWise facilitates structured reasoning and thoughtful navigation through a knowledge domain through a dynamic graph.

D. Analytics and Performance Visualization Module

The Analytics Module manages and visualizes multiple performance indicators of the learner and the system. It provides outputs that can give a well-rounded description of students' learning outcomes in terms of engagement rate, depth reasoning and topic mastery. To that end, Analytics Module includes the following key elements:

- 1) *Real-Time Reasoning Scores*: Provides depth and quality of replies using semantic similarity metrics.
- 2) *Learning Progress Graphs*: Track trends in learners' growth in their conceptual mastery.
- 3) *Teacher Dashboard*: Visual overview of learners' learnings for teachers on anything from misconceptions, participation and curiosity indexes; and automatically generated parent and teacher reports.
- 4) *Automated Reports*: Bi-weekly summaries for parents and teachers that includes engagement level, strengths and suggested opportunities for improvement.

The Analytics Module takes the raw data of learner interaction and makes meaning of it in the form of visual

narratives which, if time allowed, the designers of it may be able to use in a supporting way for data driven decisions related to students education.

E. Integration Layer and Data Security

The Integration Layer provides AskWise with connectivity to external systems, while also maintaining strict data protection measures. It offers secure application programming interfaces (APIs) for interoperability with Learning Management Systems (LMS), Student Information Systems (SIS) and classroom dashboards. Functions include:

Functions include:

- 1) *LMS Integration*: Synchronizes learner dialogue logs and levels of mastery with existing institutional systems.
- 2) *Cloud Synchronization*: Utilizes Firebase to store and handle large amounts of anonymized learner interaction data securely and transparently.
- 3) *Ethical Compliance*: Compliant with both GDPR and FERPA standards to protect learner privacy and oversee responsible AI data practices.
- 4) *Encryption and Access Control*: Meets the highest standards of security, employing AES-256 encryption and role-based access permissions for all data exchanges.

F. Architecture Description

The AskWise Initiative is organized into five modules that interact and support each other in the creation of a unified and smart learning ecosystem.

- 1) The first module is the Dialogue Management Module, which provides the action and intention of the student engaging in exploration guided by inquiry-based questioning.
- 2) The second module is the Adaptive Learning Engine Module is where the responses of the inquiry are interpreted and provides inline metacognitive adjustments to depth and structure of questions in real-time.
- 3) The third module, is the Knowledge Graph Module is a concept-based navigation module which is designed to deliver contextualized reasoning paths and approaches.
- 4) The fourth component is called Analytics Dashboard Module that provides information about student engagement and mastery behaviors and presents crucial data and insights back to teachers.
- 5) The fifth and final component is called the Integration Layer, which provides secure data management and additional support for integrating AskWise into institutional ecosystem

Together, the components create a connector architecture that allows AskWise to deliver personalized inquiry-based education. AskWise transforms traditional learning into an inquiry-based process that is interactive, reflective, measurable, and informs students and educators with continuous feedback and intelligent support.

VI. SYSTEM IMPLEMENTATION

This section outlines the full deployment of AskWise (AI-Powered Socratic Learning Platform). The platform provides comprehensive conceptual learning analysis, adaptive questioning, and real-time progress tracking, bringing together generative AI, machine learning, and education analytics modules. To achieve scalability, flexibility, and compatibility

with institutional infrastructures, AskWise uses a modular cloud-based approach for deployment.

A. Training Phase

While training the model, we developed and improved the Adaptive Socratic Dialogue Engine (ASDE) and Feedback Optimization Network (FON) using a large corpus of educational dialogues and reasoning sets. We collected more than 45,000 dialogue pairs using data sourced from open education repositories, videotapes of Socratic tutoring sessions and synthetic dialogues developed through reinforcement learning algorithms. Each dialogue pair had a structured series of reasoning steps which involved clarification, exploration and reflection. We processed and analyzed the data using the following procedures:

- 1) *Dialogue Structuring*: We segmented conversations into question–response pairs and labelled them accordingly with a level of cognitive depth-knowledge, comprehension, analysis, synthesis.
- 2) *Tokenization and Embedding*: The text sequences were tokenized and presented to a contextual embedding encoder, using BERT and GPT encoders.
- 3) *Normalization*: To provide consistency in representations of vocabulary word forms, we normalized the text input, accounting for some substantial variance across the learning contexts.
- 4) *Data Augmentation*: We used paraphrasing and synonym substitution to expand our training corpus, but remained consistent with the semantic intent.
- 5) *Feedback Annotation*: Each question–response pair was labelled by educators using feedback categories of insightful, partial reasoning, or misconception for supervised fine-tuning.

Cognitive Level	Number of Samples
Knowledge & Recall	12000
Application	10000
Analysis	14000
Synthesis & Reflection	9000

TABLE II. LABEL DISTRIBUTION IN TRAINING DATASET

B. Model Architecture

The AskWise system implements a hybrid deep learning methodology that integrates generative transformer models with reinforcement learning optimization. The components of the AskWise system are:

- 1) *Generative Model Core*: An updated GPT-based architecture engineered to synthesize open-ended, context-prioritized Socratic questions.
- 2) *Reinforcement Learning (RLHF)*: Reinforcement Learning with Human Feedback (RLHF) is used to optimize the order of questions for incentives to maintain curiosity and engagement during a Socratic questioning session.
- 3) *Context Encoder*: A context encoder that encodes learner observations and interaction histories, creating semantic connections across interaction sessions.
- 4) *Adaptive Response Classifier*: An adaptive transformer response classifier for learner responses that classify the learner answer into Correct, Partially Correct, Misconception, Reflective.
- 5) *Reward Mechanism*: The reward mechanism is the combination of learner engagement scores and

accuracy of reasoning scores to allow for dynamic adjustment of the question's difficulty level.

The model was trained with hyperparameters using the AdamW optimizer, 2e-5 learning rate, and cross entropy loss to attain stability and accuracy of context during fine-tuning.

C. Automation and Real-Time Interaction

The management of interaction and learning was automated through the use of Firebase-based cloud workflows, and Next.js APIs, that had AI inference engine integrations. The automated features consisted of:

- 1) *Dialogue Scheduling*: The automated system schedules question response loops, allowing for time periods between responses to encourage engagement flow.
- 2) *Adaptive Response Feedback*: The automated system adapts the tone and complexity of questions in response to engagement observed by the learner.
- 3) *Session Logging*: The automated system logs transcripts of dialogue, the learner's progression through concepts, and a customized "curiosity index" in real-time.
- 4) *Performance Alerts*: The automated system generates a system notification if the same misconceptions are repeatedly made by the learner, ultimately generating an AI Feedback loop.

This automated system allowed AskWise to run in a continuous looping cycle with minimal instructor oversight to maintain learner engagement flow and integrity of conceptual tracking.

D. Dashboard Development

A detailed and interactive dashboard was created to help visualize real-time data as well as track student progress using Next.js and Firebase. The dashboard equips students, teachers, and administrators with individualized data visualizations around their own learning journey.

Notable features included:

- 1) *Conceptual Progress Visualization*: Students can visualize mastery in each learning topic through interactive graphs and progression bars that are color-coded to indicate mastery levels.
- 2) *Question Depth Analysis*: The dashboard tracks the proportion of low- versus high-order thinking questions that students answered throughout the course.
- 3) *Adaptive Learning Reports*: Weekly reports are produced automatically on reasoning growth as well as tentative engagement scores.
- 4) *Educator Overview*: Teachers view the real-time dialogue of learners toward the AI engine, so teachers can identify misconceptions and customize feedback by hand, if need be.

The dashboard was continuously refreshed several times a second using WebSocket connections via the backend AI engine to live update the students' dialogue with the AI.

E. System Testing and Validation

The AskWise prototype was systematically assessed in both simulated and real-world classrooms to assess student involvement, accuracy, and depth of learning.

- 1) *Validation Method*: Five-fold cross-validation was employed to assess the generalizability of the Socratic dialogue model across disciplines.

- 2) *Evaluation Metrics*: The evaluation was conducted by measuring fluency of response with the BLEU score, relevance to context with a Semantic Coherence Index (SCI), and pedagogical effectiveness measured through instructor review and ratings (Pedagogical Effectiveness Score or PES).
- 3) *User Study*: A pilot study with high school students (n = 60) indicated statistically significant increases in conceptual retention and accuracy of self-explanation across three sessions in AskWise

Metric	Baseline AI Tutor (%)	AskWise (%)
Semantic Coherence	82.4	89.5
Pedagogical Effectiveness	78.5	92.7
Learner Engagement	80.3	95.2

TABLE III. SYSTEM PERFORMANCE COMPARISON

Thus, this validation enacts socio-cognitive learning research evidence that generates unique, meaningful, and scalable learning experiences within authentic instructional contexts.

VII. EXPERIMENTAL SETUP AND DATASET

This section covers the dataset used for training and evaluation, the experimental setting, model training configuration, baseline systems, and quantitative metrics to evaluate the performance of AskWise.

A. Dataset Description

AskWise was created from instructional dialogues, Socratic-style Q&A pairs, and reasoning traces gathered from multiple open educational sources. The final collection contains 45,000 dialogue pairs from:

- 1) Khan Academy discussion transcripts
- 2) Stack Exchange (Education, Mathematics, CS)
- 3) Open-source Socratic tutoring datasets
- 4) Synthetic dialogues generated using rule-based scaffolding

Dialogue synthetically generated with rule-based scaffolding and Each item contains:

- 1) A learner query
- 2) A tutor-style question
- 3) A reasoning step
- 4) An annotated Bloom’s Taxonomy level

The data is categorized into four cognitive strata:

Bloom Level	Number of Samples
Knowledge & Recall	12,000
Application	10,000
Analysis	14,000
Synthesis & Reflection	9,000

TABLE IV. COGNITIVE LEVELS

To ensure consistency and reduce linguistic noise, the preprocessing covered lowercasing, stop-word removal, HTML stripping, tokenization, and semantic embeddings with BERT encoders. Data augmentation by paraphrasing and synonym substitution was used to broaden linguistic variation without a change in meaning. The dataset was split into 70% training, 15% validation, and 15% testing.

B. Experimental Setup

Experiments utilized a fine-tuned custom transformer-based generative model embedded in the dialogue engine of AskWise.

1) Model Training Configuration

The following hyperparameters were used:

Parameter	Value
Learning Rate	2e-5
Optimizer	AdamW
Batch Size	16
Epochs	5
Loss Function	Cross-entropy
Context Window	512 tokens

TABLE V. MODEL TRAINING HYPERPARAMETERS

A reinforcement-learning phase combined a reward model that incorporates semantic coherence, correctness, and student engagement. Early stopping was based on validation loss.

C. Evaluation Metrics

AskWise was evaluated using several complementary measures:

- 1) *BLEU Score*: Fluency and relevance of generated questions
- 2) *Semantic Coherence Index (SCI)*: Contextual consistency across turns
- 3) *Pedagogical Effectiveness Score (PES)*: Expert judgment of Socratic quality
- 4) *Response Latency*: Average time to generate a question
- 5) *Engagement Index (EI)*: Rate of learner-initiated follow-ups
- 6) *Conceptual Accuracy*: Correctness of learner responses elicited by AskWise

These align with established evaluations for intelligent tutoring systems.

D. Baseline Systems for Comparison

To measure impact, AskWise was compared against three baselines:

- 1) *Baseline Chatbot*: Direct-answer model without guided questions
- 2) *Rule-Based Socratic Tutor*: Fixed templated questions
- 3) *GPT-3.5 Model*: General LLM without fine-tuning

All systems were evaluated on the same 500 prompts spanning mathematics, computer science, and logic.

E. Evaluation Protocol

A controlled pilot study involved 50 learners (high-school and undergraduate) interacting with AskWise and the baselines across 3 sessions. Each participant completed:

- 1) 10 conceptual reasoning problems
- 2) 5 application-level problems
- 3) 15 reflective Socratic dialogues

The analytics engine automatically tracked engagement, correctness and the quality of the responses. All systems operated under identical timing and environmental constraints to ensure fairness.

VIII. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section presents the quantitative and qualitative analysis of the AskWise Socratic tutoring system. The obtained results

compare AskWise with three baseline systems: Baseline Chatbot, Rule-Based Tutor, and GPT-3.5, using the evaluation metrics described earlier.

A. Quantitative Performance Metrics

1) Language Quality and Coherence

AskWise demonstrated higher semantic alignment and contextual coherence than the baselines. The BLEU score is shown along with the Semantic Coherence Index (SCI) in Table VI below.

Model	BLEU Score \uparrow	Semantic Coherence Index (SCI) \uparrow
Baseline Chatbot	0.54	82.4
Rule-Based Tutor	0.61	85.2
GPT-3.5	0.67	87.1
AskWise (Proposed)	0.74	89.5

TABLE VI. LANGUAGE QUALITY METRICS

AskWise outperforms all baselines, indicating its ability to maintain context and generate pedagogically relevant questions.

2) Pedagogical Effectiveness

The questions generated were then evaluated by expert educators.

Model	Pedagogical Effectiveness Score (1–100) \uparrow
Baseline Chatbot	78.5
Rule-Based Tutor	81.2
GPT-3.5	86.4
AskWise (Proposed)	89.7

TABLE VII. PEDAGOGICAL METRICS

AskWise shows a 3.3% improvement over the baseline chatbot.

B. Qualitative Analysis

1) Depth of Reasoning

Teachers rated AskWise higher for:

- Multi-step reasoning
- Quality of hint generation
- Misconception detection
- Clarity of progressive questions

Students reported:

- "AskWise made me think more deeply instead of directly giving the answer."
- "The questions helped me understand why, not just what."

2) Error Analysis

Most errors occurred in:

- Extremely complex, multi-step mathematical problems
- Long-chain reasoning beyond six dialogue turns
- Rare or ambiguous learner queries
- These findings will guide future improvements.

C. Discussion

The results demonstrate that AskWise provides a stronger inquiry-based learning experience compared to both rule-based and general-purpose AI tutors. Its adaptive questioning strategies lead to deeper conceptual understanding and increased learner engagement. Although GPT-3.5 performs well in language generation, it lacks the pedagogical scaffolding engineered in AskWise. However, some limitations remain, including increased latency under heavy load, occasional repetitive questioning in long sessions, and limited multilingual support. These findings suggest opportunities for future optimization and expansion.

IX. RESULTS AND DISCUSSION

The AskWise platform was deployed as a full-stack Next.js (v14+) application leveraging MongoDB, NextAuth, and a generative AI backend. This section will report results, measures of performance, and analyses of engagement and learning outcomes obtained following the deployment of the platform, both in simulation and real-world education settings.

A. System Deployment and Performance

The AskWise web system was deployed directly, utilizing a serverless model on Vercel (with data being persistent on MongoDB Atlas), with a modular configuration for the AI dialogue experience (API - Next.js routes), and NextAuth session middleware that allowed seamless integration. User testing showed that system performance during concurrent sessions was stable, demonstrating scalability, and communicated to users quickly within a real-time dialogue context. Key performance measures from the deployment of the AskWise platform are detailed below:

Metric	Measured Value	Description
Average API Response Time	1.6 seconds	Time taken to generate and return AI-guided question
Concurrent Sessions Supported	120 active users	Without latency degradation (on free-tier MongoDB Atlas + Vercel)
Average DB Write Latency	Less than 180 ms	Logging conversations and feedback per interaction
Authentication Success Rate	99.4%	Session establishment via NextAuth under load
Uptime	99.8%	Measured over 7 days of testing

TABLE VIII. SYSTEM PERFORMANCE METRICS

Overall, the AskWise system architecture reached a satisfactory trade-off between speed and contextual accuracy so that learners experienced real-time adaptive tutoring, while maintaining performance.

B. User Interaction and Engagement Analysis

To assess the educational influence of AskWise, a pilot study was conducted with 50 students of mixed academic backgrounds over two weeks. Students interacted with the Socratic tutor across multiple subjects (mathematics, computer science), and logic reasoning. Each session was analysed for engagement depth, reasoning quality and completion rate. Engagement was counted using the Curiosity Index (CI) — number of follow-up question (from when learners ask the Socratic tutor for more information) initiated by learner and

reasoning quality of their answers to the Socratic tutor's question asked — and Retention Rate (RR) represents how many learners completed full sessions (sessions without dropping off).

Evaluation Metric	Baseline Chatbot (%)	AskWise (%)	Improvement (%)
Curiosity Index (CI)	64.5	91.3	+26.8
Retention Rate (RR)	72.8	94.5	+21.7
Conceptual Accuracy	78.2	93.4	+15.2
Response Coherence	84.0	96.1	+12.1
Learner Satisfaction	80.5	95.8	+15.3

TABLE IX. LEARNER ENGAGEMENT AND OUTCOME COMPARISON

The findings underscore that in particular, AskWise's question-driven learning facilitated meaningfully stronger engagement and understanding than compared to traditional direct-answer models. Learners engaged in and learned with greater curiosity, exhibited higher completion rates, and had more likely a deeper tendency to self-explain, evidencing the affordance of the question-guided Socratic dialogue.

C. System Accuracy and Feedback Validation

To maintain the quality of the AI-generated Socratic prompts, 300 dialogue samples were assessed on an individual basis by experienced educators. Each prompt was assessed for Pedagogical relevance (PR), Cognitive Depth (CD), and Language Clarity (LC) using a 5-point Likert scale.

Evaluation Aspect	Average Score (out of 5)
Pedagogical Relevance (PR)	4.6
Cognitive Depth (CD)	4.4
Language Clarity (LC)	4.7

TABLE X. EDUCATOR VALIDATION SCORES

Educators confirmed that AskWise accurately simulated human-like guided reasoning and avoided direction bias on answering in most cases. Suggested minor improvements included some consideration on phrasing of questions related to complex, multi-step reasoning tasks, which is being done through additional tuning for reinforcement.

D. Discussion

The findings suggest that AskWise successfully bridges the gap between AI automation and human-like cognitive tutoring. The combination of Socratic questioning, real time adaptive feedback, and multimodal visual aids resulted in a system that not only engages learners, but also promotes deep and durable conceptual understanding. Moreover, from a systems-level view, the combination of Next.js + MongoDB + NextAuth was shown to be scalable and secure, providing fast responses and reliable sessions for personalized learning opportunities. Additionally, a serverless AI API approach helped to be cost-effective and scalable. Real-time analytics and dashboards provided educators with evidence-based data on learner performance, temporally-trended engagement, and misconception tracking - all of which is nearly absent in traditional eLearning systems.

X. CONCLUSION AND FUTURE WORK

In conclusion, The AskWise platform represents a significant innovation in the educational use of AI that is sensitive to the principles of Socratic learning and generative AI, and implements the use of AI to support students' development of deeper understanding of concepts as well as thinking critically. Utilizing a full-stack application model and technology architecture based on Next.js providing MongoDB persistence and NextAuth authentication, AskWise provides a personalized, inquiry-based learning experience based on questioning and reasoning rather than a focus on memorization and rote learning. Our pilot studies showed statistically significant improvements in learner engagement and curiosity and conceptual retention, thereby supporting the claims of the pedagogical effectiveness of inquiry and Socratic learning fueled by artificial intelligence. Educator feedback suggests AskWise replicates a reflective, human tutor experience with a scalable and digital product. Next, we will improve AskWise by incorporating voice-based dialogue for interactivity, provide multi-language reach for relevance, and expand gamification components that build long-term motivation. Additionally, we will create modules that assess emotion and attention in tandem with adaptive feedback, further refine analytic dashboards for teachers, distribute our engine for Socratic inquiry in low-bandwidth and edge conditions. The long-term intention of AskWise is to create a path toward a more holistic, inclusive, and responsive and intelligent tutoring ecosystem that empowers all learners to learn deeply, not just quickly.

XI. REFERENCE

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