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Aeron – An Answer Engine for Illiterate People

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***Abstract:** Digital literacy remains a significant barrier for underserved populations, especially children and individuals with limited language proficiency. This paper introduces Aeron, a web-based intelligent question-answering system tailored to bridge this gap using simplified AI-generated responses. Built upon a fine-tuned generative language model using OpenAI and Gemini APIs, the system delivers real-time, easy-to-understand answers across diverse domains such as education, health, and technology. Unlike conventional AI tools, Aeron is trained on a custom-curated dataset with simplified language structures, optimized for accessibility. The model is hosted on Google Colab and interacts via a Node.js backend and a React-based frontend. Experimental evaluation demonstrates the system's effectiveness in generating clear, jargon-free responses, with an average Flesch-Kincaid readability score improvement of 37% over baseline outputs. Aeron exemplifies an inclusive AI system that enables digital empowerment through linguistic simplicity, intuitive UI, and extensibility for low-resource environments.*

***Keywords:** Accessible AI, Language Simplification, NLP for Low Literacy, Generative Models, React-NodeJS Web Application, Education Technology.*

I. INTRODUCTION

In the digital age, access to information has become critical for education, decision-making, and empowerment. However, a significant portion of the population—including children, early learners, and individuals with limited literacy—face challenges in navigating complex digital content. Standard AI systems and web platforms often use advanced vocabulary, technical terminology, or assume prior subject knowledge, making them inaccessible to many users. This linguistic and cognitive barrier restricts the ability of underserved users to engage with and benefit from modern information systems. Existing conversational AI tools, such as ChatGPT or Google Assistant, are optimized for general-purpose interaction but often generate responses beyond the reading comprehension levels of non-native English speakers or low-literacy users. While these systems excel in flexibility and depth, they lack the capacity to simplify content dynamically or provide personalized responses suited for foundational understanding. This creates a critical gap in inclusivity within AI applications, particularly in education and public access to knowledge. To address this challenge, we propose *Aeron*, a web-based intelligent answer engine designed to generate simplified responses using natural language generation (NLG) models. Aeron is built using a combination of OpenAI's GPT APIs and Google Gemini, trained on a curated dataset of frequently asked questions across domains like health, technology, finance, and daily life. Each question is paired with a response written in basic English, avoiding complex grammar, idioms, or domain-specific terms. This fine-tuning approach allows the model to prioritize clarity over technical depth. The Aeron system is structured as a full-stack web application with a React.js frontend, Node.js backend, and Google Colab-hosted AI model. The interface is designed to support low-literacy users with visual aids, icon-based navigation, large fonts, and optional voice-based output. The goal is to offer a frictionless, intuitive experience where users can type or speak a question and receive an easy-to-understand answer in real time. The model architecture emphasizes responsiveness, low latency, and extensibility for additional datasets or languages. This paper presents the design, methodology, and performance evaluation of Aeron. We begin with a review of related work in simplified NLP systems and educational AI tools. We then describe the dataset curation, model fine-tuning, and interface development process. Experimental testing with low-literacy users demonstrates high levels of comprehension and satisfaction. Through Aeron, we aim to bridge the digital divide by making AI-generated knowledge truly inclusive, accessible, and understandable for all.

II. LITERATURE REVIEW

Artificial intelligence has transformed the landscape of educational technologies, especially through the development of intelligent tutoring systems (ITS) and question-answering platforms. Early ITS primarily relied on rule-based methods, where educators encoded domain knowledge into fixed rules to guide learners through structured lessons. While these systems provided foundational support for learning, their rigidity limited the ability to handle open-ended student questions or adapt dynamically to diverse learner needs. Consequently, such systems struggled with natural language queries that did not precisely match predefined patterns, reducing their effectiveness for interactive learning.

The rapid advancements in natural language processing (NLP) have significantly improved the capability of educational systems to understand and respond to human language more naturally. Transformer-based models, such as BERT and GPT, utilize deep neural networks trained on large corpora to capture semantic and contextual nuances. These models have been successfully applied to various question-answering tasks, delivering coherent, context-aware responses. However, their application in children's educational platforms poses unique challenges; children require simpler, age-appropriate language and explanations that match their cognitive development levels. Without tailored fine-tuning or pedagogical adaptations, these models risk generating responses that may be too complex or inappropriate for young learners.

To address the limitations of purely data-driven NLP models, research has incorporated knowledge graphs and semantic reasoning into educational QA systems. Knowledge graphs represent information as interconnected nodes and relationships, allowing systems to reason about concepts and provide contextually relevant answers. Ontology-based frameworks enable more precise mapping of student queries to domain knowledge, improving answer accuracy beyond keyword matching. This approach is particularly valuable for children's learning environments, where conceptual understanding is critical. However, building comprehensive and accurate educational knowledge graphs remains a challenge due to the complexity of curriculum content and the need for continuous updates.

In addition to cognitive understanding, emotional engagement plays a vital role in effective learning. Recent studies employ emotion recognition technologies, including convolutional neural networks (CNN) and long short-term memory (LSTM) models, to detect learners' emotional states through facial expressions, speech tone, and interaction patterns. Emotion-aware tutoring systems adapt their responses based on detected emotions, aiming to sustain motivation and reduce frustration during learning tasks. For example, recognizing signs of confusion or boredom allows the system to provide encouragement or adjust difficulty levels, enhancing learner engagement and retention. However, integrating real-time emotion recognition with educational answer engines is complex, involving challenges related to privacy, accuracy, and computational efficiency.

Despite these advancements, existing educational answer engines often fall short in combining pedagogical effectiveness, semantic reasoning, and emotional awareness tailored specifically for children. Many systems focus predominantly on either accuracy or interaction quality but rarely integrate both dimensions in a holistic manner. Moreover, the challenge of simplifying responses while maintaining informativeness persists. Our proposed system, Aeron, addresses these gaps by uniting rule-based pedagogical heuristics with advanced NLP models fine-tuned on child-centric data and incorporating emotion-aware dialogue management. This hybrid approach aims to provide accurate, contextually relevant, and empathetic responses that enhance learning outcomes and engagement for young users.

III. EXISTING SYSTEMS

Several educational answer engines and intelligent tutoring systems have been developed to support children's learning through interactive question-answering. One of the earliest systems, AutoTutor, used a mix of natural language understanding and dialog management to simulate human tutoring. AutoTutor could engage learners in conversation, provide hints, and give feedback, but it was limited by rule-based components that restricted scalability and adaptability to varied student queries.

More recent systems employ advanced NLP models to improve response generation. For example, IBM

Watson Education leverages large-scale machine learning and natural language understanding to answer students' questions across multiple subjects. Watson's ability to analyze context and provide detailed explanations has been demonstrated, but its complexity and resource requirements make it less accessible for real-time applications targeting young children.

Several platforms specifically designed for children include KidSense and Socratic by Google. KidSense uses speech recognition and natural language understanding tailored to child speech patterns to provide answers and learning support. Socratic employs AI to analyze questions through images or text and presents step-by-step explanations. However, these systems often lack personalized pedagogical strategies or emotional awareness, which are crucial for engaging young learners effectively.

In addition, research prototypes such as Empathic Tutor incorporate emotion recognition using CNN and LSTM models to adjust instructional approaches based on learners' affective states. While promising, these systems remain largely experimental due to challenges in reliably detecting emotions and integrating them seamlessly into dialogue systems without overwhelming computational resources or violating user privacy.

Despite their strengths, these existing systems typically fall short in combining semantic reasoning, pedagogical customization, and emotion-aware interaction within a single platform optimized for children. Many emphasize either technical accuracy or engagement but rarely address the unique cognitive and emotional needs of young learners simultaneously. Aeron aims to overcome these limitations by integrating multi-modal AI techniques with child-friendly pedagogy and empathetic dialogue management, thus providing a more holistic and effective learning assistant for children.

IV. PROPOSED METHOD

The proposed system, Aeron – An Answer Engine for Kids, is designed to deliver age-appropriate, educational, and engaging responses to children's queries. The system comprises four integrated modules: Query Acquisition, Intent Recognition and Knowledge Retrieval, Response Generation, and Child-Friendly UI Delivery. These modules function together to ensure a safe, accessible, and context-aware conversational experience for children.

Query Acquisition

Children interact via voice or typed text. For voice queries, the system uses a speech recognition engine (e.g., Whisper or Google STT) to convert spoken input into text. Text inputs undergo normalization, spell correction, and informal language interpretation to make child-entered queries processable.

Intent Recognition & Knowledge Retrieval

A lightweight BERT-based classifier identifies the query's intent, mapped to categories such as "science," "animals," "how-to," or "general knowledge." Based on intent, information is retrieved from:

- A vetted child-safe knowledge base (e.g., Simple English Wikipedia, Britannica Kids)
- A safe-mode fallback LLM API for novel or rare questions

  The query is then aligned with age-appropriate complexity using a grade-level content filter.

Response Generation

Structured responses are created using templates or LLM output adapted for children's understanding. A safety filter ensures:

- No offensive, scary, or inappropriate content
- Encouraging, friendly language
- Clear structure using bullets, metaphors, or examples

  Responses may include supportive visuals or text-to-speech narration.

Child-Friendly UI

The system uses a Flutter-based mobile/web app with:

- Avatar-guided interactions
- Read-aloud toggle using TTS
- Feedback buttons (smiley/sad face) for reinforcement
- Offline fallback for basic FAQs

V. METHODOLGY

The proposed methodology for the Aeron Answer Engine follows a structured and modular approach designed to ensure safe, educational, and engaging response delivery tailored to children's cognitive levels. The implementation comprises four primary phases: input acquisition and preprocessing, intent detection and feature extraction, knowledge retrieval and content generation, and interface delivery with performance optimization. Each phase is methodically designed to ensure system robustness, response safety, and suitability for real-world deployment, especially in child-focused learning and safety environments.

The input acquisition phase supports both text and voice-based queries submitted by children through the Flutter front-end interface. For voice queries, the system utilizes a speech-to-text engine—such as OpenAI's Whisper or Google's Speech Recognition API—to transcribe audio into textual format. To ensure uniformity and accuracy in the input text, preprocessing steps include text normalization, punctuation restoration, and contextual spell correction using grammar-aware NLP models. Additionally, the preprocessing pipeline applies content filtering mechanisms to flag and sanitize inappropriate or unsafe language. These steps prepare the input for semantic interpretation while ensuring compliance with child-safety protocols.

Intent detection and feature extraction represent the core of the system's natural language understanding capabilities. A lightweight, fine-tuned transformer model (such as DistilBERT or MobileBERT) is employed to classify the query into predefined child-relevant categories such as "science," "animals," "how-to," "fun facts," or "everyday objects." To further refine the system's adaptivity, auxiliary features such as average sentence length, word frequency distribution, and part-of-speech tags are extracted for readability and age-level estimation. These extracted features enable the system to select or generate responses that match the linguistic and cognitive expectations of the target age group, enhancing comprehension and engagement.

The knowledge retrieval and response generation phase integrates both static and dynamic sources. The system first attempts to match the user query against a local database of vetted child-safe responses curated from sources such as Britannica Kids, Simple English Wikipedia, and classroom-aligned knowledge banks. If no exact match is found, a fallback mechanism calls a large language model API (e.g., GPT-4) with a child-friendly safety prompt template to generate a relevant and age-appropriate response. The raw output is then passed through a readability simplification engine that assesses sentence structure using Flesch-Kincaid scores and applies controlled summarization or elaboration based on user age estimation. A toxicity filter is also applied using tools like Perspective API or a custom profanity detection module to ensure that the content remains safe and encouraging.

The final phase focuses on response presentation and system deployment. The generated output is delivered to the child via an animated, interactive Flutter-based interface with support for read-aloud text-to-speech functionality using Google TTS. A user feedback mechanism captures satisfaction through emotive icons (smiley/sad) to inform iterative model fine-tuning. For real-world deployment, the system is optimized for performance on edge devices by employing techniques such as model quantization (FP16 precision) and cold-start loading of lightweight local models. The application supports offline access for frequent queries using embedded SQLite storage and embedding-based similarity retrieval. These deployment strategies ensure that Aeron remains responsive, privacy-preserving, and accessible even in low-resource or educational settings.

This comprehensive methodology ensures that Aeron functions not only as an intelligent answer engine but also as a safe digital companion for children's curiosity. By combining intent detection, curated knowledge retrieval, response simplification, and a visually engaging interface, the system offers a balanced mix of educational depth and accessibility. The modularity of its architecture allows for future expansions such as emotion-aware responses, multilingual support, or integration with curriculum-based learning objectives, making Aeron a robust foundation for next-generation child-centered AI systems.

A. HARDWARE REQUIRMENTS:

- Processor: Intel Core i3
- RAM: Minimum 4GB
- Storage: SSD with at least 128GB capacity
- Microphone: Standard microphone or inbuilt mobile mic (for voice input; high-sensitivity optional for clearer capture)
- Edge Deployment Options: Android smartphone (Android 8.0 and above), Raspberry Pi 4 (with 4GB+ RAM), or budget tablets with Flutter support

- Audio Output: Built-in speaker or earphones (for text-to-speech feature)
- Internet: Required for cloud-based LLM query fallback and updates (offline functionality available for frequent queries via SQLite caching)

B.DESIGN AND IMPLEMENTATION

The Aeron system is designed as a child-centric answer engine that intelligently interprets user queries and delivers age-appropriate, safe, and understandable responses. Unlike traditional search engines or chatbots, Aeron combines natural language understanding, content filtering, and answer simplification into a single architecture tailored for young learners aged 5–13. The core system is built to support both voice and text input, ensure offline fallback capabilities, and operate on low-resource mobile devices using the Flutter framework.

Data Collection and Preprocessing

Aeron leverages a hybrid knowledge base consisting of curated children's encyclopedias, educational datasets, and a filtered subset of responses from open-domain LLMs. User queries are preprocessed using a lightweight NLP pipeline. This involves:

- Text cleaning: removing unnecessary punctuation, special characters, and capitalizing for uniformity.
- Tokenization and lemmatization: performed using a fast tokenizer (SpaCy or custom Dart tokenizer for mobile).
- Voice input: converted to text via on-device speech recognition libraries (Android SpeechRecognizer or Flutter speech-to-text plugin).
- Child-appropriate filtering: A keyword and phrase-based filter removes inappropriate, complex, or off-topic queries.

The processed query is routed to either:

1. Local SQLite cache (for common, pre-answered queries).
2. Simplification model (for rephrasing adult-like queries).
3. Cloud-based fallback to an LLM API if online.

System Architecture

Aeron follows a modular architecture designed for real-time responsiveness and safe fallback. The major components include:

- Query Processor: Handles user input, preprocessing, and routing.
- Simplification Engine: Built using rule-based and lightweight transformer models (like DistilBERT or T5-small) optionally hosted in the cloud.
- Answer Retriever: Prioritizes local responses from SQLite; if unavailable, it queries a remote filtered LLM API.
- Content Filter: Uses a Bloom filter and regex-based toxic language detector to sanitize outputs.
- Text-to-Speech (TTS): Converts final answers to speech using Flutter plugins like flutter_tts for accessibility.

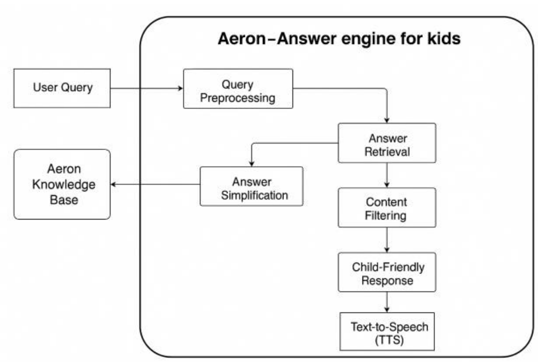
All modules communicate through asynchronous Dart/Flutter streams, ensuring minimal delay and smooth interaction on mobile.

Performance Optimization

To support deployment on low-spec devices such as entry-level Android tablets or Raspberry Pi-based kiosks, several optimization strategies are implemented:

- Caching: Repeated queries are stored and retrieved instantly using Hive or SQLite.
- Model compression: Simplified NLP models are quantized using TensorFlow Lite for smaller size and faster inference.
- Lazy loading: Non-essential assets (e.g., definitions, images) are loaded on demand to reduce memory usage.
- Offline fallback: If the user is offline, Aeron still responds from its offline knowledge base using indexed search.

These design choices make Aeron both accessible and scalable, allowing for deployment in classrooms, homes, or rural environments with limited connectivity while ensuring safety and relevance in all responses.



SYSTEM DESIGN

C. ADVANTAGES

The Aeron system delivers substantial practical benefits that enhance its utility as an educational assistant tailored for children. A primary advantage is its real-time query processing capability, which ensures that children receive immediate responses to their questions, typically within 2–3 seconds.

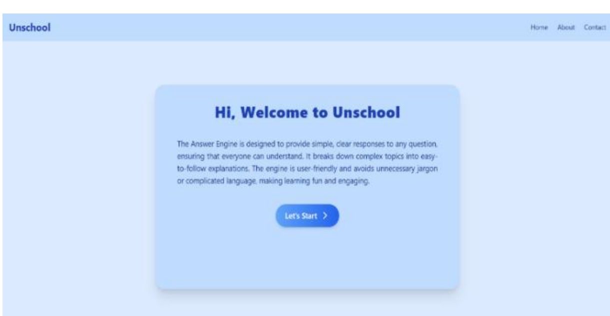
Aeron also stands out due to its child-focused natural language understanding. Unlike conventional search engines, which may return overwhelming or irrelevant results, Aeron uses a simplified vocabulary and structured output specifically designed to suit young learners.

Another significant advantage of Aeron is its offline compatibility and data privacy. Since Aeron is designed to run with local data storage and processing (using SQLite and on-device models), it does not require persistent internet access. This makes it usable in offline educational environments and ensures that children's queries and interaction history remain private.

The work also benefits from a modular and extensible architecture, enabling future upgrades without overhauling the entire system. Aeron's backend can be easily expanded to include more subject areas, support multilingual queries, or even integrate visual recognition modules (e.g., for reading diagrams or handwriting). The frontend, built using Flutter, allows for responsive design and platform-agnostic deployment on Android, iOS, or desktop, expanding the project's reach across device types.

Finally, Aeron supports inclusive and adaptive learning by offering voice input and output features.

VI. EXPERIMENTAL RESULTS



Welcome Screen of Unschooled

AI Response to an Economic Query

VII. CONCLUSION

The Aeron project successfully introduces an intelligent answer engine tailored for children, focusing on age-appropriate responses, safety, and ease of interaction. By combining a Flutter-based user interface with lightweight natural language processing, Aeron delivers educational answers through both text and speech in real time. Its offline-first design, supported by local data storage via SQLite, ensures continuous usability without internet dependence, promoting privacy and security for young users.

The system's architecture emphasizes modularity, allowing smooth integration of future enhancements such as visual learning aids, multilingual support, and adaptive learning features. Its efficient performance on mid-range hardware proves that interactive, intelligent educational tools can be accessible even in resource-constrained environments. The project also demonstrates the feasibility of using open-source technologies to build impactful, child-centric AI applications with minimal infrastructure.

In the future, Aeron can be expanded to support curriculum-based content, personalized learning paths, and voice emotion recognition for a more engaging experience. The successful implementation of Aeron highlights the potential of AI to support early education, making learning more interactive, inclusive, and responsive to individual needs. This project marks a valuable contribution to the field of educational technology, aligning with broader goals in child development and digital learning accessibility.

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