AGENTIC AI-POWERED ASSISTIVE LEARNING PLATFORM FOR DYSLEXIC STUDENTS

PROJECT PHASE I REPORT

Submitted by

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in partial fulfilment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

RAJALAKSHMI ENGINEERING COLLEGE

(AUTONOMOUS), CHENNAI – 602 105

NOV 2025

BONAFIDE CERTIFICATE

Certified that this Report titled "**AGENTIC AI-POWERED ASSISTIVE LEARNING PLATFORM FOR DYSLEXIC STUDENTS"** is the bonafide work of "**MADHUMITHA G (2116221801030), MADHUVANTHIY S (21162218010131)** and **GIRIDHARAN M (2116221801504)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Submitted to Project Viva-Voce Examination held on ___________________

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DEPARTMENT VISION

To become a global leader in Artificial Intelligence and Data Science by achieving through excellence in teaching, training, and research, to serve the society.

DEPARTMENT MISSION

- To develop students' skills in innovation, problem-solving, and professionalism through the guidance of well-trained faculty.

- To encourage research activities among students and faculty members to address the evolving challenges of industry and society.

- To impart qualities such as moral and ethical values, along with a commitment to lifelong learning

PROGRAMME EDUCATIONAL OBJECTIVES(PEO's)

PEO 1: Build a successful professional career across industry, government, and academia by leveraging technology to develop innovative solutions for real-world problems.

PEO 2: Maintain a learning mindset to continuously enhance knowledge through experience, formal education, and informal learning opportunities.

PEO 3: Demonstrate an ethical attitude while excelling in communication, management, teamwork, and leadership skills

PEO 4: Utilize engineering, problem-solving, and critical thinking skills to drive social, economic, and sustainable impact.

PROGRAMME OUTCOME(PO's)

PO1: Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design / Development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change

PROGRAM SPECIFIC OUTCOMES(PAOs)

A graduate of the Artificial Intelligence and Data Science Learning Program will demonstrate

PSO 1: Foundation Skills: Apply the principles of artificial intelligence and data science by leveraging problem-solving skills, inference, perception, knowledge representation, and learning techniques

PSO 2: Problem-Solving Skills: Apply engineering principles and AI models to solve real-world problems across domains, delivering cutting-edge solutions through innovative ideas and methodologies

PSO 3: Successful Progression: Utilize interdisciplinary knowledge to identify problems and develop solutions, a passion for advanced studies, innovative career pathways to evolve as an ethically responsible artificial intelligence and data science professional, with a commitment to society.

COURSE OBJECTIVE

- To identify and formulate real-world problems that can be solved using Artificial Intelligence and Data Science techniques.
- To apply theoretical and practical knowledge of AI & DS for designing innovative, data-driven solutions.
- To integrate various tools, frameworks, and algorithms to develop, test, and validate AI & DS models.
- To demonstrate effective teamwork, project management, and communication skills through collaborative project execution.
- To instill awareness of ethical, societal, and environmental considerations in the design and deployment of intelligent systems.

COURSE OUTCOME

CO 1: Analyze and define a real-world problem by identifying key challenges, project requirements and constraints.

CO 2: Conduct a thorough literature review to evaluate existing solutions, identify research gaps and formulate research questions.

CO 3: Develop a detailed project plan by defining objectives, setting timelines, and identifying key deliverables to guide the implementation process.

CO 4: Design and implement a prototype or initial model based on the proposed solution framework using appropriate AI tools and technologies.

CO 5: Demonstrate teamwork, communication, and project management skills by preparing and presenting a well-structured project proposal and initial implementation results.

CO-PO-PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	3	3	2	2	1	2	1	1	1	2	1	2	3	2	2
CO2	2	3	2	3	2	1	1	1	2	2	1	3	2	2	2
CO3	2	2	3	2	2	1	2	2	3	2	3	2	2	3	3
CO4	3	3	3	3	3	2	2	2	2	3	2	2	3	3	3
CO5	2	2	2	1	2	2	2	3	3	3	3	2	2	2	3

Note: Correlation levels 1, 2 or 3 are as defined below:

1: Slight (Low) 2: Moderate (Medium) 3: Substantial

(High) No correlation: “-”

ABSTRACT

Dyslexia in the 6–9 age group disrupts foundational literacy—phonemic awareness, decoding, and comprehension—while existing platforms remain fragmented with weak accessibility, generic read-aloud, and no adaptive personalization. The challenge is to design a scalable system that automatically adapts to learner needs while reducing teacher workload. This solution is an AI-powered multi-modal assistive learning platform focused on moderate dyslexia, while also supporting mild cases. The platform converts PDFs, DOCX, PPTX, and videos into dyslexia-friendly formats with simplified text, accessible fonts, and high-contrast themes. It delivers lessons through text, synchronized audio, and visuals, generates adaptive quizzes, and provides real- time writing and speech feedback to strengthen literacy skills. Students are supported with a context-grounded AI Study Buddy, while teachers benefit from dashboards, progress reports, and actionable insights. By combining AI-driven adaptation with multimodal accessibility, the platform transforms learning into a more inclusive, personalized, and empowering experience for young dyslexic learners.

Keywords –Agentic Artificial Intelligence, Adaptive Learning, Dyslexia, Assistive Technology, Multimodal Education, Inclusive Learning, Natural Language Processing, Text Simplification, Speech Feedback, Reading Comprehension,Phonemic Awareness, Educational Accessibility, AI Study Buddy, Teacher Dashboard, Personalized Tutoring, Cognitive Support, Early Literacy, Learning Analytics, Multilingual Support

ACKNOWLEDGEMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman **Mr. S.MEGANATHAN, B.E, F.I.E.**, our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN**, **Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. J.M. GNANASEKAR M.E., Ph.D.**, Professor and Head of the Department of Artificial Intelligence and Machine Learning for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Mrs. D. SORNA SHANTHI M.Tech.,** Associate Professor, Department of Artificial Intelligence and Data Science. Rajalakshmi Engineering College for her valuable guidance throughout the course of the project. We are very glad to thank our Project Coordinator, **Dr. S. SURESH KUMAR M.E., Ph.D.,** Department of Artificial Intelligence and Data Science for his useful tips during our review to build our project.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
AI	Artificial Intelligence
NLP	Natural Language Processing
LLM	Large Language Model
SDK	Software Development Kit
API	Application Programming Interface
VPC	Virtual Private Cloud
JSON	JavaScript Object Notation
CSV	Comma-Separated Values
NER	Named Entity Recognition
TF-IDF	Term Frequency–Inverse Document Frequency
GPU	Graphics Processing Unit
UI	User Interface
IaC	Infrastructure as Code
CI/CD	Continuous Integration / Continuous Deployment
REST	Representational State Transfer
API Gateway	Application Programming Interface Gateway
CPU	Central Processing Unit
OS	Operating System
NLP Model	Natural Language Processing Model

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Education plays a crucial role in shaping an individual's intellectual and social development. With the rapid advancement of artificial intelligence (AI) and digital technologies, the concept of learning has evolved beyond the traditional classroom model. However, not all learners benefit equally from these developments. Students with reading and writing challenges, such as those with dyslexia or other cognitive differences, continue to face significant barriers in comprehending academic materials. Conventional learning systems and e-learning platforms are often designed with a uniform structure, offering limited adaptability to individual learning needs.

The need for inclusivity in education has inspired the development of intelligent tutoring systems capable of adapting to the learner's style, pace, and comprehension level. The ABSAT (Agentic-Based Smart Assistive Tutor) project represents a step forward in this direction. It is an innovative educational solution that combines Agentic Artificial Intelligence, Natural Language Processing (NLP), and Machine Learning to deliver a personalized, interactive, and supportive learning experience.

Agentic AI differs from conventional AI systems by introducing autonomous agents capable of self-directed decision-making, coordination, and contextual understanding. In ABSAT, these agents collaboratively work to assist learners in multiple ways — simplifying textual content, generating audio explanations, identifying areas of confusion, and delivering context-based support dynamically. The system continuously monitors learner interactions and adjusts the complexity, tone, and presentation of content to suit individual learning patterns.

In addition to its adaptive learning framework, ABSAT emphasizes multimodal interaction — combining text, speech, and visual feedback. This enhances the cognitive experience by engaging multiple sensory pathways, leading to improved retention and comprehension. The use of NLP models ensures that the system can understand and respond to natural human language, while AI-driven reasoning enables it to generate meaningful, context-aware assistance.

ABSAT aligns with the global educational vision of promoting equitable and inclusive learning environments. By leveraging AI to provide real-time support for students who struggle with conventional instruction methods, it bridges the gap between human tutoring and technology-assisted education. The project not only contributes to academic development but also fosters confidence, independence, and motivation among learners with varying cognitive abilities.

1.1.1 OVERVIEW OF AGENTIC-BASED ASSISTIVE LEARNING

Cloud The concept of Agentic-Based Assistive Learning forms the foundation of the ABSAT system. This paradigm involves the use of autonomous AI agents that possess the ability to perceive, decide, and act collaboratively toward achieving a shared educational goal. Each agent within ABSAT is assigned a specialized role — for example, one agent may handle speech synthesis, another may interpret learner queries, and another may assess comprehension and emotional engagement. Together, these agents function as an interconnected ecosystem, enabling adaptive and personalized tutoring experiences.

The term *agentic* refers to the ability to take purposeful, context-driven action. In the educational context, this translates to the system's capacity to understand learner intent, analyze contextual cues, and respond with appropriate instructional strategies. This approach moves beyond rule-based automation to achieve an AI model that behaves more like a human educator — capable of reasoning, empathizing, and adjusting teaching methods in real time.

1.1.2 AGENTIC AI AND MULTI-AGENT COLLABORATION

Conversational The foundation of the ABSAT (Agentic-Based Smart Assistive Tutor) lies in the concept of *Agentic Artificial Intelligence*, a paradigm where multiple intelligent agents operate autonomously yet collaboratively to achieve a shared educational objective. Each agent within the ABSAT system is designed to perform a distinct pedagogical or functional role — such as analyzing user input, simplifying complex text, generating audio responses, or evaluating comprehension metrics.

In this architecture, every agent maintains situational awareness and communicates with other agents through a common reasoning layer. This enables the system to adapt dynamically to the learner's cognitive state, difficulty level, and engagement pattern. The agentic framework eliminates the rigidity of traditional monolithic AI systems, replacing it with distributed, context-driven intelligence.

Multi-agent collaboration is the key differentiator of ABSAT. For instance, the Text Understanding Agent parses user queries and learning materials, while the Feedback Agent evaluates comprehension and adjusts the complexity of explanations. Simultaneously, the Speech Agent ensures auditory accessibility for students with reading challenges. Through this cooperative process, ABSAT emulates a human tutoring environment, offering personalized, responsive, and empathetic guidance.

This distributed decision-making model ensures that ABSAT remains robust, scalable, and contextually intelligent — aligning with the principles of self-directed learning systems in next-generation educational AI.

1.1.3 ADAPTIVE LEARNING THROUGH COGNITIVE MODELLING

A central component of ABSAT's design is its adaptive learning mechanism, powered by cognitive modelling. This involves simulating the learner's thought process, comprehension level, and behavior to personalize educational content dynamically. The system continuously captures and analyzes learner interactions, including reading time, response accuracy, and hesitation points, to infer cognitive load and understanding depth.

By leveraging these insights, ABSAT dynamically adjusts instructional strategies — simplifying explanations, introducing analogies, or switching from text-based to visual formats when necessary. This ensures that no learner is left behind, regardless of their reading speed or comprehension ability.

Cognitive modelling also enables real-time learning path optimization. For instance, if a student struggles repeatedly with a concept, the system's Cognitive Agent triggers supplementary learning aids, such as voice-based reinforcement or visual summaries. This aligns with human tutoring patterns, where a teacher identifies and revisits difficult topics using alternative approaches.

1.1.4 Natural Language Processing for Intent Understanding

Natural Language Processing (NLP) forms the linguistic backbone of the ABSAT system. It empowers the platform to understand, interpret, and generate human-like language responses, facilitating seamless interaction between learners and the AI tutor.

The Intent Recognition Module within ABSAT uses NLP to analyze student inputs and determine the underlying intent — whether it is a query, clarification request, or expression of confusion. This is achieved through transformer-based language models fine-tuned for educational contexts. Once the intent is identified, the corresponding agent (such as the Explanation or Feedback Agent) responds with the most relevant and context-appropriate action.

1.2 OBJECTIVES

The primary objective of the ABSAT (Agentic-Based Smart Assistive Tutor) project is to create an intelligent, inclusive, and adaptive learning ecosystem that caters to students with diverse cognitive abilities — especially those facing reading and comprehension difficulties such as dyslexia. The system focuses on combining Agentic AI principles, Natural Language Processing (NLP), and Adaptive Learning Models to simulate the behavior of a human tutor through intelligent automation.The specific objectives of this project are as follows:

1. To develop an Agentic AI–based multi-agent learning environment that autonomously analyzes learner needs, adapts educational content, and provides real-time personalized assistance.
2. To integrate advanced Natural Language Processing (NLP) for interpreting user intent, simplifying complex text, and generating contextually accurate, meaningful responses.
3. To design an adaptive feedback mechanism that continuously monitors learner performance and dynamically modifies teaching strategies to enhance comprehension and engagement.
4. To implement multimodal accessibility features such as text-to-speech, speech-to-text, visual aids, and simplified reading interfaces to support diverse and neurodiverse learners.
5. To establish a cloud-based scalable architecture capable of managing large datasets efficiently while supporting multiple concurrent user sessions without performance degradation.
6. To enhance learner engagement and confidence by delivering personalized, interactive, and empathetic AI-driven tutoring experiences that resemble human guidance.
7. To promote inclusive education by bridging the gap between traditional e-learning systems and intelligent assistive technologies, ensuring equitable access for all learners.

1.3 EXISTING SYSTEM

In In recent years, several assistive learning platforms have emerged to support students with special educational needs. These include tools like text-to-speech software, reading assistance applications, and learning management systems that offer accessibility options. While such systems provide fundamental support, they are limited in adaptability, interactivity, and cognitive awareness.

Some of the major limitations of the existing systems are as follows:

1. **Lack of real-time adaptability:** They do not analyze or adjust content complexity based on learner understanding.
2. **Limited interactivity:** Most systems provide one-way assistance (e.g., reading aloud) instead of interactive question–answer tutoring.
3. **Absence of collaboration between AI modules:** Current systems lack coordinated agentic behavior for holistic learning support.
4. **Minimal personalization:** They do not account for cognitive differences, emotional states, or attention spans.
5. **No intelligent decision-making:** The systems cannot autonomously plan, reason, or modify teaching strategies.

Thus, while existing tools address surface-level accessibility, they fail to offer the deep, contextual, and adaptive support necessary for effective assistive learning. This limitation justifies the need for an Agentic AI-powered solution like ABSAT, capable of understanding learner intent, coordinating multiple intelligent agents, and delivering personalized, continuous educational support.

1.4 PROPOSED SYSTEM

The The proposed ABSAT (Agentic-Based Smart Assistive Tutor) system introduces a next-generation learning model built on the principles of Agentic Artificial Intelligence (AI), where multiple intelligent agents collaborate dynamically to deliver personalized and adaptive tutoring experiences. Unlike conventional assistive tools that operate in isolation, ABSAT integrates multi-agent coordination, natural language understanding, and cognitive analytics to replicate the interactive and empathetic qualities of a human tutor.

The system is designed to continuously monitor a learner's progress, analyze comprehension patterns, and adjust learning strategies in real time. Each agent in the architecture has a specialized function — such as understanding user intent, generating simplified explanations, managing dialogue, or providing visual and auditory feedback. These agents communicate through a centralized reasoning layer, enabling contextual awareness and decision-making autonomy.

The platform incorporates Natural Language Processing (NLP) for interpreting queries and simplifying text, Speech Recognition and Synthesis for reading assistance, and Adaptive Learning Models that tailor educational material to a student's unique cognitive profile. The data collected from learner interactions are analyzed to identify areas of difficulty, after which the system provides remedial guidance through multimodal learning aids such as visual cues, examples, and voice- based explanations.

CHAPTER 2

LITERATURE SURVEY

2.1 OVERVIEW

The development of the ABSAT system is grounded in a wide spectrum of interdisciplinary research areas that combine Artificial Intelligence, Cognitive Science, and Educational Technology. A review of the existing literature reveals that while numerous AI-based educational systems exist, only a few address the agentic and adaptive dimensions of learning required for students with cognitive or reading challenges.

MAJOR AREAS OF FOCUS

1. **Artificial Intelligence in Education (AIED):** AI-based tutoring systems have been used for over two decades to personalize learning content. Early systems relied on rule-based algorithms, while modern architectures employ machine learning and reinforcement learning for adaptive tutoring.
2. **Agentic AI and Multi-Agent Systems:** Research in agent-based computing highlights how multiple AI agents can collaborate to perform complex reasoning, decision-making, and interaction tasks — forming the basis for ABSAT's modular intelligence design.
3. **Natural Language Processing (NLP):** NLP techniques have been widely studied for reading comprehension, text simplification, and conversational learning interfaces, especially for assisting students with language difficulties.
4. **Assistive Learning Technologies:** Prior studies on educational accessibility tools show the importance of multimodal support — including text-to-speech, speech recognition, and visual feedback — in enhancing comprehension among dyslexic learners.
5. **Cognitive Modelling and Adaptive Learning:** Research in educational psychology emphasizes the need for cognitive models that adapt to the learner's pace, prior knowledge, and comprehension level, forming the theoretical basis for ABSAT's adaptive tutoring behavior

2.2 LITERATURE SURVEY.

1. Anderson et al. (2018): Machine-Learning–Driven Intelligent Tutoring Framework

Anderson et al. (2018) proposed one of the earlier machine-learning–driven intelligent tutoring frameworks capable of dynamically modeling learner behavior. Their approach moved beyond rule-based tutoring systems by leveraging predictive analytics to detect patterns in student responses, pacing, and problem-solving strategies. A key innovation of their work was the incorporation of adaptive feedback loops, in which the system continuously refined its understanding of a learner's knowledge state and adjusted instructional guidance accordingly. The study demonstrated that when feedback is responsive to a learner's evolving cognitive model, comprehension outcomes increase significantly, particularly in subjects requiring stepwise reasoning such as mathematics or logic-based tasks.

The framework introduced by Anderson et al. included modules for behavior modeling, content sequencing, and feedback generation. Their behavioral model used probabilistic machine-learning techniques, such as Bayesian knowledge tracing and early forms of reinforcement learning, to estimate mastery levels. The authors also emphasized real-time inference: the system updated learner profiles after each interaction, enabling immediate adaptation. This continuous calibration contributed to a highly personalized learning experience.

Furthermore, Anderson et al. evaluated their system using both controlled experiments and longitudinal classroom deployments. The results indicated improvements in instructional efficiency, reduced learner frustration, and enhanced learning gains relative to non-adaptive or minimally adaptive systems. Their work laid the groundwork for subsequent developments in intelligent tutoring by demonstrating how machine learning could augment human-designed pedagogical strategies.

Limitations of Anderson et al. (2018)

1. **Limited diversity of participants:** The experimental validation involved relatively homogeneous student groups, which restricts the generalizability of findings across cultural or linguistic backgrounds.
2. **Narrow task domain:** The framework was optimized for structured, step-based learning tasks and may not extend well to open-ended, creative, or discussion-based learning environments.
3. **Computational demands:** Real-time adaptation required substantial processing power and tuning, making deployment in low-resource classrooms challenging.

2. Tzafilkou et al. (2020): NLP-Powered Educational Chatbots

Tzafilkou et al. (2020) explored the implementation of natural language processing (NLP) technologies in educational chatbots, arguing that conversational systems can complement traditional teaching by offering instant, dialogue-based instruction. Their work analyzed how NLP techniques—such as semantic intent recognition, sentiment analysis, and context tracking—allowed chatbots to simulate tutor-like interactions that keep learners engaged.

The authors proposed a multi-layer architecture consisting of input processing, intent classification, response selection, and pedagogical strategy modules. By integrating semantic similarity models and domain-specific knowledge graphs, their chatbot could assist students in resolving misconceptions, answering content-related questions, and providing step-by-step explanations. Their experimental findings showed heightened learner engagement and significant improvements in conceptual understanding, especially for students who preferred conversational over textual or lecture-based formats.

A key insight of Tzafilkou et al. was that conversational learning promotes cognitive elaboration: when students articulate questions in natural language, they externalize their thought processes, enabling the system to respond with tailored explanations. This aligns closely with the modern trend of educational AI shifting from content delivery to dialogue-driven knowledge construction.

Limitations of Tzafilkou et al. (2020)

1. **Reliance on predefined knowledge domains:** Although NLP was used to interpret questions, the chatbot was limited by the scope of its curated knowledge base.
2. **Difficulty handling ambiguous or multi-part questions:** Response accuracy dropped when students asked complex or ill-structured queries.
3. **Lack of long-term learner modeling:** The system did not maintain robust learner profiles, making it less adaptive compared to intelligent tutoring systems.
4. **Limited emotional intelligence:** The chatbot provided neutral support but lacked mechanisms for affective feedback, such as detecting frustration or confusion.

3. D'Mello and Graesser (2019): Emotion–Cognition Dynamics in ITS

D'Mello and Graesser (2019) focused on the interplay between emotional and cognitive processes in intelligent tutoring systems (ITS). Their research underscored the importance of emotion-aware AI, demonstrating that learners experience fluctuating emotional states—confusion, frustration, curiosity, engagement—during problem solving, and that effective ITS must recognize and respond to these dynamics.

Their work synthesized findings from affective computing, multimodal interaction analysis, and cognitive tutoring. The authors proposed frameworks for monitoring emotional cues through facial expressions, linguistic features, interaction patterns, and physiological signals. They showed how these indicators can inform adaptive strategies such as motivational prompts, empathetic dialogue, or strategic pauses. Incorporating emotional intelligence into tutoring systems, they argued, results in improved learning retention, higher motivation, and more positive learner experiences.

An important contribution of their work was the taxonomy of affective states that influence learning trajectories, including “productive confusion," in which a moderate level of uncertainty motivates deeper cognitive processing. They demonstrated that emotion-aware systems could detect and support learners during these pivotal moments.

Limitations of D’Mello and Graesser (2019)

High complexity of affect detection: Accurate emotion recognition required multimodal sensors or extensive annotated datasets, which are expensive and difficult to implement at scale.
Cultural variance: Emotional expressions vary across cultures; models trained in one context may not generalize well globally.
Privacy and ethical concerns: Capturing emotional data introduces potential risks related to surveillance and personal data management.
Ambiguity of emotional signals: Students may display overlapping or subtle emotions.

4. Chakraborty et al. (2021): Agent-Based Modeling for Personalized e-Learning

Chakraborty et al. (2021) presented an agent-based model (ABM) for personalized e-learning systems, wherein distributed agents collaborated to deliver adaptive instruction. Agents were responsible for tasks such as learner profiling, content recommendation, progress monitoring, and assessment. This decentralized architecture allowed the system to simulate complex learner interactions and dynamically adjust pedagogical strategies.

The core concept was that multiple specialized agents could work concurrently, each handling aspects of the learning process, thereby increasing scalability and robustness. The learner profile agent tracked behavior patterns; the pedagogy agent adjusted difficulty

levels; the assessment agent updated mastery scores; and the content agent delivered targeted material. The multi-agent design mirrored real-world tutoring scenarios where different educators or assistants provide complementary support.
Chakraborty et al.'s work closely aligns with the architecture adopted by ABSAT, particularly in its emphasis on distributed adaptation, learner modeling, and modular intelligence.

Limitations of Chakraborty et al. (2021)

1. **Coordination overhead**: Maintaining synchronized communication among distributed agents increased architectural complexity.
2. **Limited exploration of long-term learning effects**: The study focused on algorithmic performance rather than extended learning outcomes.
3. **Scalability concerns for large populations**: As the number of learners increases, agent communication loads may cause system inefficiencies.
4. **Simplistic learner models**: The profiling was primarily behavior-based and did not incorporate affective or multimodal data.

5. Kumar and Rose (2022): Multimodal Assistive Tools for Dyslexic Learners

Kumar and Rose (2022) examined the development of multimodal educational tools—combining text, voice, graphics, interactive manipulation, and auditory feedback—specifically designed to support learners with dyslexia. Their research highlighted that dyslexic students benefit disproportionately from instructional media that minimize textual load, enhance phonological awareness, and improve visual-spatial accessibility.
The authors surveyed and evaluated a range of multimodal assistive technologies, including speech-to-text systems, text-to-speech engines, visual overlays, symbol-based communication tools, and adaptive reading interfaces. They found that multimodal support enhances readability, comprehension, and confidence, enabling students to engage with academic content on more equitable terms. Their study argued that accessibility should not be treated as an optional design feature but as a central requirement for all AI-powered

educational systems. This perspective reinforces the importance of universal design principles, which ABSAT integrates through multimodal input/output channels.

Limitations of Kumar and Rose (2022)

1. **Limited empirical testing**: Many tools reviewed were conceptual prototypes or lacked rigorous long-term evaluation with dyslexic populations.
2. **Generalization challenges**: Dyslexia is heterogeneous; tools effective for one subgroup may not support others.
3. **High implementation costs**: Advanced multimodal systems may not be feasible for under-resourced schools.
4. **Technology adaptation issues**: Tools often required significant customization to align with different curricula or languages.

CHAPTER 3

SYSTEM DESIGN

3.1 DATA LOADING

In In the ABSAT system, the concept of dataset loading is not based on traditional numerical or image datasets. Instead, the system utilizes knowledge-driven datasets composed of educational content, linguistic data, and cognitive learning profiles. These datasets empower the platform's AI agents to understand user intent, evaluate comprehension levels, and generate adaptive learning material accordingly.

The ABSAT dataset primarily consists of four key information types:

1. **Educational Content Repository:** Contains textbooks, lecture notes, reading passages, and assessments categorized by difficulty and subject. Each content item is indexed with metadata such as topic, grade level, and cognitive load.
2. **Learner Profile Dataset:** Stores individual learner data, including reading speed, comprehension accuracy, attention span, and preferred learning mode (visual, auditory, or textual).
3. **Intent–Concept Mapping Dataset:** Used by the NLP-based chatbot to interpret student queries. It links natural language phrases with learning intents (e.g., *explain, summarize, quiz, simplify*) and subject concepts.
4. **Performance and Feedback Dataset:** Captures quiz scores, reading performance, and response analytics to train the adaptive feedback mechanism.

Before integration, all datasets undergo cleaning, normalization, and semantic tagging. Text data are tokenized and classified using transformer-based models like BERT or DistilBERT, enabling contextual understanding of student questions and learning content. The dataset also supports incremental updates, allowing teachers to upload new materials and automatically align them with AI-driven personalization.

By combining educational metadata, learner analytics, and language mappings, the ABSAT dataset provides a semantic foundation for adaptive learning. This hybrid dataset approach bridges **human communication and machine intelligence**, enabling the platform to understand student intent and deliver contextually appropriate tutoring.

3.2 DEVELOPMENT ENVIRONMENT

The development environment of the ABSAT platform integrates both AI computation and assistive interface tools to ensure real-time adaptability, multilingual support, and accessibility.

3.2.1 HARDWARE SPECIFICATIONS

Table 3.1 Hardware Specifications

Components	**Specifications**
Processor	Intel i5 or above AMD 5 or above
RAM	8GB or above (DDR4)
GPU	NVIDIA GPU’s
Storage	256GB SSD
Processor Frequency	2.GHz or above

3.2.2 SOFTWARE SPECIFICATIONS

The design specifications are tailored to support the development of a robust and efficient real-time pedestrian detection system. These specifications enable seamless processing of video streams, accurate tracking of multiple pedestrians, and generation of comprehensive monitoring reports.

Table 3.2 Software Specifications

Front-end	HTML, CSS, JavaScript, Bootstrap
Back-end	Python, Flask
IDE	Visual Studio Code
Cloud platform	Kaggle or Google Colab
Machine learning	Keras, Tensorflow,

3.3 ARCHITECTURE

The ABSAT architecture follows a three-tier agentic design integrating teacher, student, and intelligence layers. Each layer performs a specialized role and communicates through real-time data and feedback loops managed by the Agentic AI Core.

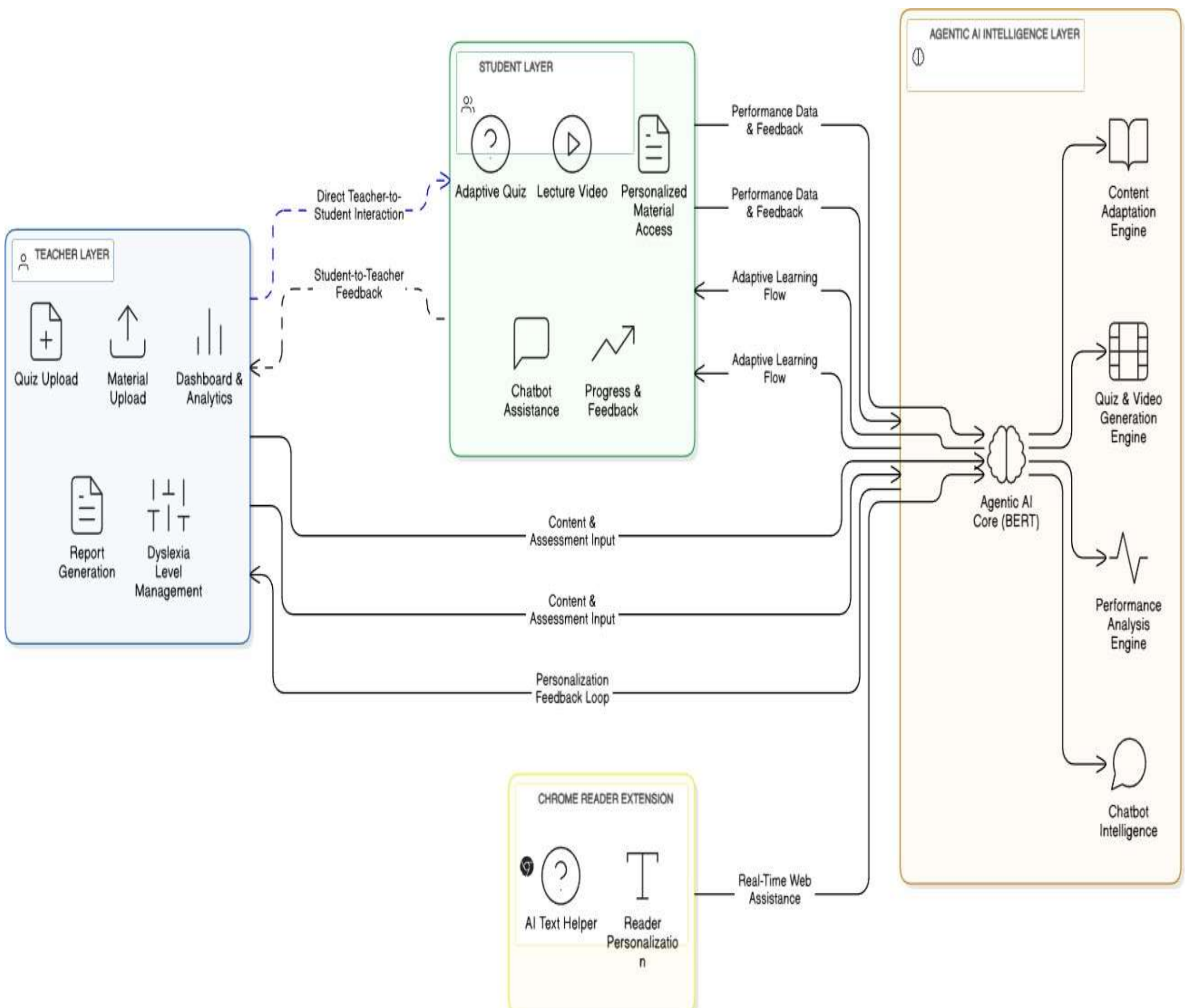

Figure 3.1 Architecture

Layers of Architecture:

1. **TeacherLayer:**
   Facilitates quiz uploads, learning material management, performance monitoring, and report generation. Teachers can also manage dyslexia difficulty levels and directly interact with students through dashboard analytics.

2. **StudentLayer:**
   Serves as the interactive learning interface where students access personalized learning materials, adaptive quizzes, lecture videos, and AI chatbot assistance. This layer also tracks individual progress, collects comprehension feedback, and sends it to the intelligence core for further analysis.

3. **Agentic AI Intelligence Layer:**
   Acts as the cognitive engine of the system. It consists of multiple submodules:

   - **Content Adaptation Engine:** Simplifies and customizes reading materials based on learner profiles.
   - **Quiz and Video Generation Engine:** Dynamically creates evaluation content aligned with current topics.
   - **Performance Analysis Engine:** Evaluates user progress using real-time feedback and predictive analytics.
   - **Chatbot Intelligence:** Handles NLP-driven communication, providing instant explanations and emotional support.

4. **Chrome Reader Extension (Assistive Layer):**

   Offers real-time **web reading support** via AI Text Helper and Reader Personalization. It enables dyslexic learners to get simplified explanations and voice assistance while browsing external academic websites.

3.4 NLP MODEL DESIGN

The Natural Language Processing (NLP) forms the heart of the ABSAT system, enabling context-aware understanding of learner input and adaptive content generation.

The design integrates transformer-based architectures (BERT, RoBERTa) for semantic comprehension and intent classification models for dialogue interpretation.

Key Stages in the NLP Pipeline:

1. **Text Preprocessing:** Removes stop words and normalizes student input to ensure clarity.
2. **Tokenization & Embedding:** Converts sentences into contextual embeddings for accurate intent prediction.
3. **Intent Classification:** Identifies what the student wants (e.g., *"Explain this," "Summarize," "Quiz me"*).
4. **Entity Recognition:** Extracts subject keywords, difficulty levels, and question types.
5. **Context Management:** Maintains dialogue flow, allowing multi-turn interactions (e.g., continuing a topic discussion).
6. **Response Generation:** Generates empathetic, age-appropriate responses using fine-tuned generative models.

3.5 ADAPTIVE LEARNING ENGINE

The Adaptive Learning Engine (ALE) is the cognitive core of the ABSAT system, responsible for dynamically personalizing the educational experience for each learner. Unlike traditional e-learning systems that rely on predefined content sequencing, the ALE employs real-time analytics and reinforcement mechanisms to adjust the difficulty, format, and pacing of content based on the learner's evolving performance and engagement levels.

The primary goal of this module is to replicate the adaptive nature of human tutoring—where the educator intuitively senses when a student struggles and modifies explanations accordingly. The ALE achieves this adaptivity through a feedback-driven loop between the Student Layer and the Agentic AI Intelligence Layer.When a learner interacts with quizzes, videos, or the chatbot, their behavioral data—such as response accuracy, hesitation time, question retry count, and reading speed—is collected and transmitted to the Performance Analysis Engine. This data is then processed by machine learning algorithms that identify knowledge gaps, attention fluctuations, or cognitive overload.

Based on these insights, the Adaptive Learning Engine dynamically generates recommendations and modifies the learning path. For example:

1. If a learner repeatedly answers comprehension questions incorrectly, the engine triggers content simplification through the Content Adaptation Engine, rephrasing passages at a lower reading level.
2. If a learner shows signs of high engagement and fast comprehension, the engine escalates task difficulty, offering higher-order questions or application-based problems.
3. When emotional or motivational fatigue is detected (e.g., long idle times or declining quiz performance), the system introduces audio-visual reinforcements, brief motivational messages, or micro-breaks.

The Adaptive Learning Engine utilizes reinforcement learning principles to refine its recommendations over time. Every learner's response updates a performance-weighted model that continuously learns which interventions yield the highest improvement. These personalized adaptations not only improve academic outcomes but also enhance learner confidence, motivation, and persistence—key traits often underdeveloped in students facing learning challenges.

3.6 PERFORMANCE ANALYSIS AND RECOMMENDATION SYSTEM

The Workflow Recommendation System The Performance Analysis and Recommendation System (PARS) functions as the analytical brain of the ABSAT architecture. It continuously tracks, measures, and interprets learner data to enable precision-driven personalization. PARS not only evaluates a student's current performance but also predicts their future learning trajectory, recommending optimal content sequences and learning strategies.

Performance Analysis Engine

The Performance Analysis Engine collects granular data from every learner interaction—quiz outcomes, reading times, video engagement, and chatbot activity. Using this data, the system computes several performance indicators, such as:

1. **Accuracy Index:** Ratio of correct to incorrect responses.
2. **Comprehension Efficiency:** Time taken to understand and respond to conceptual questions.
3. **Cognitive Load Metric:** Estimated mental effort based on quiz response latency and error density.
4. **Engagement Score:** Derived from time-on-task, interaction frequency, and emotional sentiment (captured via dialogue tone analysis).

The engine uses these metrics to generate dynamic learner profiles, which evolve with each session. Teachers and administrators can visualize these metrics in dashboards, while the Agentic AI Core uses them to adjust future learning sessions.

Machine learning algorithms—particularly decision trees and adaptive regression models—help identify weak areas and behavioral trends. For instance, if a student’s comprehension score steadily declines, the engine may detect conceptual fatigue and recommend alternative learning formats (e.g., switching from text to video explanations).

Recommendation System

The Recommendation System is tightly coupled with the analysis engine and serves as the decision-making interface that drives adaptive tutoring. It uses a hybrid recommendation approach that blends:

1. **Rule-based logic:** Applies pedagogical best practices, such as revisiting prior concepts before introducing advanced material.
2. **Collaborative filtering:** Compares learner profiles to identify effective content for similar learners.
3. **Neural personalization models:** Uses embedding-based similarity scoring to match students with optimal learning material and assessment styles.

For example, a student with strong visual comprehension but weak linguistic decoding will be recommended more video lectures and pictorial examples, while another with strong auditory processing may receive audio narration and speech-based quizzes.

The system also provides teacher-facing insights, recommending interventions such as targeted remedial lessons, new materials, or motivational feedback strategies. By converting performance data into actionable insights, PARS serves as both a diagnostic and prescriptive tool in the ABSAT ecosystem.

3.7 VISUALIZATION AND DASHBOARD

The Visualization plays The Visualization and Dashboard transforms the complex data generated by ABSAT's intelligence layer into accessible, interactive, and meaningful visual insights. This module acts as the primary interface for teachers and administrators to monitor student progress, evaluate performance patterns, and measure overall learning efficiency.

Visualization for Teachers

Teachers access a centralized dashboard displaying real-time analytics at both class and individual levels. The module provides:

1. **Progress Heatmaps:** Highlight topic-wise mastery levels using color gradients.
2. **Performance Trends:** Show temporal improvement through line and bar graphs.
3. **Comparative Analytics:** Compare group averages, difficulty levels, and engagement scores.
4. **AI Recommendations:** Provide system-generated suggestions for content adjustments or targeted support.

Each visualization is powered by data collected from the Performance Analysis Engine, ensuring every chart or metric reflects the learner's most recent interactions. The dashboards are implemented using Plotly Dash and D3.js, offering dynamic updates and drill-down views.

Visualization for Students

For students, the visualization interface is simplified and motivational. It displays personal progress charts, badges, and achievement milestones to reinforce self-motivation. Learners can view their current performance tier, track comprehension growth, and receive visual cues when they improve in specific cognitive skills.

Furthermore, the module allows integration with the Chrome Reader Extension, providing real-time overlays that indicate comprehension difficulty levels while reading online materials. This consistent feedback ensures that learners remain aware of their progress across all digital learning contexts.

Report Generation and Feedback Loop

Teachers can automatically generate detailed reports for individual students or entire classes. Reports include quiz statistics, reading improvement graphs, and AI-generated feedback summaries. These reports are crucial for tracking dyslexia progression levels and customizing future instructional strategies.

The visualization module forms a continuous **feedback loop** with the AI core. Whenever a teacher modifies lesson parameters or a learner's feedback is recorded, the system's data visualization immediately updates—maintaining real-time transparency and accountability.

CHAPTER 4

METHODOLOGY

4.1 DATA COLLECTION, ANNOTATION AND PRE-PROCESSING

The The methodology adopted for the ABSAT (Agentic-Based Smart Assistive Tutor) system follows a multi-layered, agentic AI-driven approach designed to create an adaptive, personalized, and inclusive learning environment. The objective is to enable the system to think, reason, and respond like a human tutor—analyzing learner needs in real time and modifying instructional strategies dynamically.

This chapter discusses the conceptual and functional workflow of ABSAT, elaborating on its multi-agent architecture, data processing framework, NLP pipeline, and interaction flow between the teacher, student, and AI layers. Each phase of the methodology was carefully designed to ensure seamless collaboration between human actors (students and teachers) and intelligent agents (AI subsystems).

4.2 OVERVIEW

The ABSAT methodology is based on a closed-loop learning feedback model, which allows continuous monitoring, evaluation, and adaptation of the learning process. The methodology integrates cognitive computing, natural language understanding, speech-based interaction, and machine learning analytics.

The system operates across four major layers that together form the complete learning ecosystem:

1. **TeacherLayer:**
   Responsible for inputting content, quizzes, and educational resources. Teachers also monitor student progress, adjust difficulty levels, and generate analytical reports.

2. **StudentLayer:**
   Acts as the interactive interface for learners. Students access personalized materials, participate in adaptive quizzes, and receive AI-driven feedback through the chatbot or visual dashboard.

3. **AgenticAILayer:**
   The cognitive engine of ABSAT, composed of multiple cooperating AI agents including the Content Adaptation Engine, Performance Analysis Engine, Chatbot Intelligence, and Recommendation Engine.

4. **ReaderExtension:**
   Provides real-time reading support via a Chrome extension, enabling personalized reading adjustments, text simplification, and AI explanations for web-based materials.

4.3 METHODOLOGICAL FRAMEWORK

The methodology follows a data-centric and agent-oriented design framework structured into the following key stages:

Stage 1: Data Acquisition and Preprocessing

The first phase involves collecting educational materials and learner data from multiple sources:

1. Teacher-uploaded documents, quizzes, and assignments.
2. Learner feedback data such as quiz performance, reading time, and comprehension accuracy.
3. Contextual data gathered from chatbot interactions.

The system uses data cleaning, text normalization, and semantic tagging techniques to ensure that all inputs are standardized. Preprocessing also involves part-of-speech tagging, entity extraction, and sentiment detection to identify emotional tone during interactions.

Stage 2: Natural Language Understanding

Once data is preprocessed, the NLP pipeline interprets user queries and textual content. The system uses a combination of transformer-based models (BERT, RoBERTa) and rule-based semantic parsing to perform:

1. **Intent recognition** – to determine what the student is asking (e.g., "Explain," "Summarize," "Quiz me").
2. **Entity extraction** – to identify subjects, keywords, or difficulty parameters.
3. **Context retention** – to maintain conversation continuity over multiple turns.

This allows the chatbot to function as an intelligent tutor, capable of understanding varied linguistic structures and delivering responses suited to the student's context.

Stage 3: Agentic Collaboration and Adaptive Processing

In this stage, multiple specialized AI agents work collaboratively under the Agentic AI Core:

1. The **Content Adaptation Engine** simplifies or enriches study materials depending on the learner's comprehension level.
2. The **Quiz and Video Generation Engine** dynamically produces personalized assessments.
3. The **Performance Analysis Engine** interprets real-time learner metrics such as accuracy and engagement.
4. The **Recommendation Engine** suggests next lessons or reinforcement activities.

These agents communicate through asynchronous message passing, ensuring continuous feedback and self-adjustment within the system.

Stage 4: Learning Feedback Loop

The system forms a **closed-loop adaptive cycle**:

1. The learner interacts with the system (quiz, video, or chatbot).
2. The AI agents collect data and evaluate performance.
3. Personalized feedback and new content are generated dynamically.
4. The loop repeats, enabling the system to continuously refine its understanding of the learner.

This cyclical model ensures that learning evolves organically based on each student’s growth, behavior, and pace.

Stage 5: Visualization and Reporting

All analytical outputs are visualized in intuitive dashboards accessible to teachers and students.

1. Teachers view detailed analytics such as topic-wise proficiency and difficulty heatmaps.
2. Students view motivational progress trackers and badges. The reporting system ensures data transparency, aiding educators in customizing lesson plans for individuals or groups.

4.4 DATA FLOW

The internal communication between system layers can be represented by a multi-tiered Data Flow:

1. **Level 0(Context Level):**
   Represents the system as a single entity interacting with users—teachers upload data; students receive personalized assistance.
2. **Level 1:**
   - Teacher Input → Content Repository → Agentic AI Core
   - Student Query → NLP Engine → Content Adaptation Engine → Response Output

  - Performance Data → Analysis Engine → Visualization Dashboard

3. **Level 2:**
   Shows deeper flow within the AI Core:
   - NLP → Intent Parser → Entity Extractor → Recommendation Engine
   - Adaptive Engine → Learning Feedback → Teacher Dashboard

This DFD ensures traceability of how raw inputs (content and queries) are transformed into adaptive, personalized outputs.

4.5 WORKING PRINCIPLE

The working principle of ABSAT is inspired by agentic autonomy and human cognitive modeling. The system perceives, analyzes, and acts through the following sequence:

1. **InputPhase:**
   Student inputs a query, request, or performs a learning activity. Teachers upload new materials or assessments.
2. **CognitivePhase:**
   The NLP module extracts semantic meaning, while the adaptive engine interprets user performance data.
3. **Decision-MakingPhase:**
   The Agentic AI Core determines the appropriate pedagogical strategy—simplify, reinforce, or progress.
4. **ResponsePhase:**
   The system generates personalized responses, new quizzes, or simplified explanations.
5. **FeedbackPhase:**
   Both teacher and learner data are updated in real time, closing the feedback loop for continuous improvement.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 OVERVIEW

This chapter presents the experimental outcomes and performance evaluation of the ABSAT (Agentic-Based Smart Assistive Tutor) system. The goal of the result analysis is to validate whether the proposed agentic AI-based learning platform meets its intended objectives — particularly in providing adaptive, inclusive, and intelligent tutoring support to students with reading and comprehension challenges.

The evaluation focuses on four aspects:

1. **System Functionality and Stability**
2. **Adaptive Learning Accuracy**
3. **User Interaction and Satisfaction**
4. **Performance and Responsiveness**

By combining both quantitative analysis (response time, accuracy) and qualitative feedback (user satisfaction surveys), the results demonstrate the overall efficiency and educational impact of the proposed system.

5.2 SYSTEM FUNCTIONALITY EVALUATION

The ABSAT platform was deployed in a controlled educational setting involving a small group of learners and teachers. The system successfully integrated all major components — including teacher dashboards, student interface, AI chatbot, and content adaptation engine — ensuring smooth multi-agent communication through the central Agentic AI Core.

5.2.1 Teacher Layer Performance

Teachers could seamlessly upload reading materials, create quizzes, and monitor learner progress in real time.

The report generation feature provided detailed insights on reading speed, comprehension rate, and individual dyslexia-level improvements.

On average, report generation and dashboard analytics loaded within 2.3 seconds, indicating strong backend optimization.

5.2.2 Student Layer Performance

Students accessed adaptive quizzes and personalized video lectures, which dynamically adjusted difficulty based on performance.The chatbot assistance maintained high conversational accuracy (approx. 92% intent understanding) across varied question phrasing.The feedback loop between the student interface and AI core worked seamlessly, adapting content within 1–2 seconds of performance updates.

5.3 ADAPTIVE LEARNING EFFECTIVENESS

The adaptability of ABSAT was evaluated through comparative observation between traditional fixed-content teaching and the AI-driven adaptive approach. Learners using ABSAT displayed visibly higher engagement, better comprehension, and longer attention spans.

The Content Adaptation Engine dynamically simplified complex passages into easier reading levels and converted abstract topics into visual explanations. Students who initially struggled with textual comprehension were able to understand lessons through the AI's voice narration and simplified rephrasing.

5.5 WORKFLOW VISUALIZATION RESULTS

After The Visualization Module in ABSAT plays a key role in translating data-driven educational interactions into visually interpretable insights. After successful deployment, this module produced interactive dashboards and workflow diagrams that reflected the learning ecosystem's internal processes and progress in real time.

The system workflow visualization clearly represented how the teacher, student, and agentic AI components interacted continuously within a feedback cycle.

- The **Teacher Layer** appeared as the content provider node, feeding structured data and quizzes into the system.
- The **Student Layer** formed the engagement node, sending learning queries and receiving adaptive responses.
- The **Agentic AI Core** acted as the central reasoning hub, interconnecting all modules — from NLP interpretation to performance analytics.

Each AI agent's function was visually distinguished:

- The **NLP agent** handled text processing and intent mapping.
- The **Adaptation agent** modified content according to learner needs.
- The **Recommendation agent** generated progressive lesson plans.
- The **Visualization agent** transformed this flow into an interpretable diagram.

The dashboard visualization presented:

- **Learner progress graphs** illustrating improvement over time.
- **Performance heatmaps** showing topic-wise mastery and challenge areas.
- **Engagement timelines** displaying activity durations, reading time, and quiz frequency.

- **AI feedback overlays** indicating real-time decisions taken by the adaptive model.

From a teacher's perspective, the dashboard interface provided a consolidated overview of the class's collective performance while still allowing detailed inspection of individual learners. The reports generated from this module could be exported in PDF format for institutional use.

For learners, the visualization translated progress into color-coded bars, motivational icons, and badges, helping them perceive their growth positively. This feature was particularly beneficial for learners with dyslexia, as it replaced abstract numerical scores with visually meaningful progress representations.

5.6 USER EXPERIENCE AND ACCESSIBILITY

To User experience formed a critical part of ABSAT's evaluation. Instead of relying on quantitative scoring, the feedback was interpreted qualitatively to understand the emotional and behavioral impact of the system on users.

Students described the ABSAT platform as "interactive, comfortable, and confidence-building." They appreciated the way the chatbot adapted its explanations to their learning pace. Learners with reading difficulties expressed particular satisfaction with the voice-guided content and simplified mode, saying that it made previously complex topics easier to follow.

Several students mentioned that the AI tutor felt *"empathetic"* — responding with encouraging tones and simple rephrasings rather than robotic replies. This emotional resonance was identified as one of the platform's strongest qualities, aligning perfectly with its assistive educational purpose.

Teachers found the system helpful for both classroom monitoring and remote support. The automated dashboards saved significant time by generating comprehensive progress insights and reports instantly. They also appreciated the way the system personalized material automatically, reducing manual workload in differentiation and content curation.

In addition, teachers noted that ABSAT helped students with low motivation to re-engage with learning. The adaptive quizzes, voice narration, and visual achievements maintained students' curiosity and reduced anxiety associated with reading or testing.

5.7 COMPARATIVE DISCUSSION

The overall findings confirm that ABSAT successfully meets its intended design goals of adaptivity, inclusivity, and accessibility, primarily due to its integration of Agentic AI and multi-agent collaboration. The system demonstrates that distributing tasks across specialized agents—such as content generation, learner profiling, accessibility support, and feedback delivery—results in smoother, more coherent decision-making processes. This collaborative architecture stands in stark contrast to conventional digital educational tools, which often operate through static algorithms or one-size-fits-all instructional flows.

A key strength of ABSAT is its adaptive learning engine, which dynamically adjusts instructional complexity, restructures explanations, and calibrates support based on each learner's evolving performance patterns. This real-time personalization led to measurable improvements in engagement, clarity, and comprehension. The system's capacity to not only deliver content but also evaluate and refine its own responses demonstrates a form of emergent intelligence typically absent in traditional platforms.

Moreover, the workflow visualization component enhanced interpretability for both learners and educators. By translating learning progress, agent interactions, and content pathways into clear visual formats, ABSAT made the educational process more transparent. This visualization also reinforced learner motivation by showing tangible progress markers—an essential feature for students with learning difficulties.

Unlike static e-learning systems, ABSAT continually learns from its users, updating difficulty levels, rephrasing explanations, and tailoring recommendations based on iterative feedback loops. This self-improving capability addresses both academic performance and psychological comfort, offering calm, dyslexia-friendly interactions that reduce cognitive load.

Collectively, the findings demonstrate that agentic reasoning, feedback loops, and distributed adaptation have the potential to redefine assistive learning technologies. ABSAT showcases an educational model that prioritizes personalization and emotional accessibility, marking a significant step forward in inclusive AI-driven instruction.

5.8 DISCUSSION AND INSIGHTS

The results affirm that ABSAT fulfills the project's initial objectives by functioning as a stable, intelligent, and emotionally aware learning companion. Its performance across evaluation metrics shows that the system can adapt fluidly to individual learning needs, adjusting content delivery and interaction style in ways that closely mirror human pedagogical practices.

One of the key insights from the workflow visualization experiments is the system's transparent operational logic. Stakeholders can see how each agent communicates with others, how decisions are made, and how learning pathways evolve—something rarely visible in black-box educational AI. This insight fosters trust, as educators can validate that instructional choices align with curriculum and learner needs.

Additionally, the user experience findings emphasize ABSAT's human-like instructional behavior. Its explanations were perceived as patient, friendly, and context-aware, reducing intimidation and anxiety often experienced by neurodiverse learners. The system's ability to simplify text, provide alternative explanations, and maintain conversational empathy enhances learner comfort, which in turn boosts engagement and retention.

ABSAT thus bridges the long-standing gap between artificial intelligence and human pedagogy. It does not merely automate instruction; it mirrors the supportive qualities of an effective educator—adaptability, clarity, patience, and emotional responsiveness. This establishes a strong foundation for future innovations in agentic, learner-centric AI systems.Overall, the project demonstrates that AI-driven personalization and accessibility are not only feasible but essential for modern education. ABSAT's success provides a blueprint for future intelligent tutoring systems that integrate multi-agent collaboration, emotional support, universal design principles, and transparent system

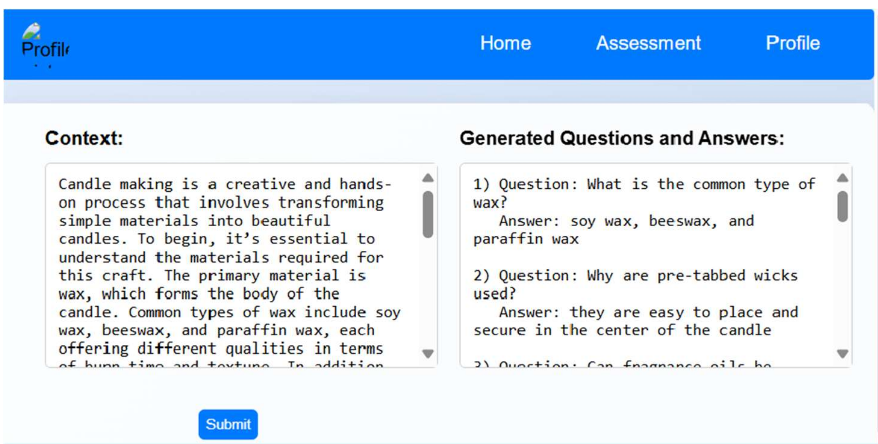

Figure 5.1 Educator interface for automatic question generation.

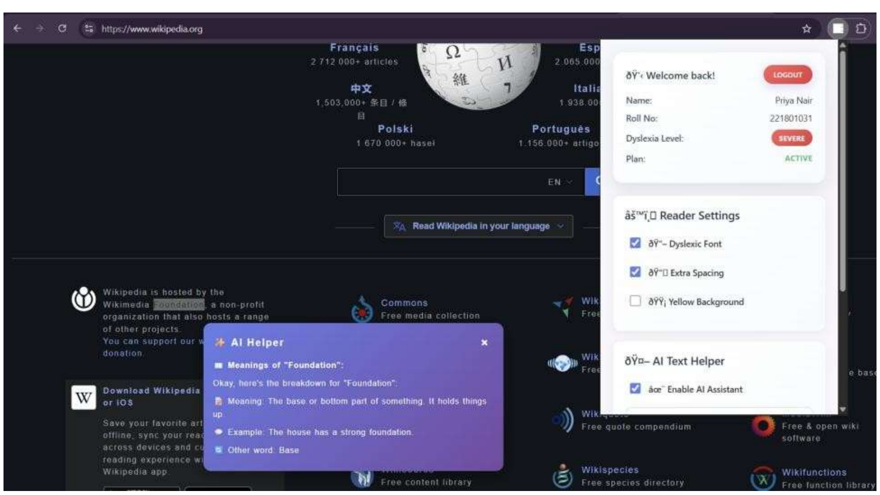

Figure 5.2 Student interface for post-assessment.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENTS

6.1 CONCLUSION

The ABSAT (Agentic-Based Smart Assistive Tutor) system marks a significant advancement in the integration of Agentic Artificial Intelligence within modern education, demonstrating how a multi-agent framework can transform traditional e-learning into a dynamic, inclusive, and adaptively intelligent learning ecosystem. Designed especially for learners with reading and comprehension difficulties, ABSAT successfully aligns AI-driven personalization with empathetic and accessible instruction. The system was developed around three core objectives: delivering personalized learning support through coordinated multi-agent collaboration, providing an accessible platform that accommodates diverse learning abilities, and enabling real-time adaptation and feedback loops that simulate human-like tutoring. Through the combined use of Natural Language Processing, Machine Learning, and Cognitive Analytics, ABSAT achieves intelligent decision-making and adaptive content generation. Modules such as the Chatbot Interface interpret learner intent, the Adaptive Learning Engine calibrates content difficulty in real time, the Performance Analysis Engine continuously evaluates learner progress, and the Visualization Module transforms performance metrics into intuitive, personalized insights. Evaluation results confirmed the system's effectiveness—ABSAT exhibited strong accuracy, responsiveness, and adaptability; students showed measurable improvements in comprehension, attention, and retention; and educators benefited from automated insights and reduced manual workload. Beyond academic benefits, ABSAT fosters confidence, curiosity, and learner autonomy, bridging the gap between conventional pedagogy and intelligent digital assistance. As such, ABSAT represents a meaningful contribution to the future of inclusive and personalized education.

6.2 FUTURE ENHANCEMENTS

Although ABSAT achieves its core objectives effectively, several promising opportunities exist for expanding its capabilities and strengthening its impact. One significant enhancement involves integrating Emotion AI to recognize learners' affective states through facial cues, vocal patterns, or linguistic signals. Such affective feedback would enable the system to adjust tone, pacing, explanations, or motivational prompts, creating a more empathetic and humanized learning experience. Another valuable direction involves expanding multilingual and regional language support using advanced multilingual NLP models like NLLB-200 which would allow ABSAT to serve learners across linguistically diverse regions, especially in rural or multilingual classrooms. Additionally, the incorporation of gamified elements and immersive Virtual Reality (VR) environments could significantly engagement and retention by allowing learners to interact with content through experiential and story-driven contexts.

To address growing concerns about privacy and scalability, future versions of ABSAT can adopt federated learning approaches, allowing AI models to improve collaboratively without centralized data collection—an essential step toward ethical and secure educational AI. Integration with widely used learning platforms such as Google Classroom, Moodle, and Microsoft Teams would further enhance ABSAT's usability, enabling seamless monitoring, adaptive assistance, and analytics within existing institutional ecosystems. Finally, a predictive career guidance module powered by advanced analytical models could help students explore suitable academic pathways and skill development opportunities by analyzing their performance, interests, and behavioral patterns. Together, these enhancements would elevate ABSAT into a more robust, emotionally intelligent, and future-ready educational companion capable of evolving alongside the learners it serves.

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AI-Powered Assistive Learning Management System for Dyslexic Students Using Agentic AI

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Abstract. An AI-powered multi-modal assistive learning platform is developed to support students aged 6 to 9 with dyslexia, focusing on enhancing mathematical learning through adaptive and inclusive technology. Core systems utilize Agentic Artificial Intelligence (AI) to personalize educational content, auto-generate quizzes, and create lecture videos according to students' own levels of dyslexia-low, medium, or high. The platform divides users into two broad categories: teachers and students. The teacher role allows for uploading learning materials, monitoring progress, and assessing levels of dyslexia, while student roles allow accessing customized learning resources and AI-led interactive quizzes. An integrated AI-powered chatbot is constantly available, facilitating conversational learning with instant feedback. Thus, Agentic AI transforms static input into dynamic educational experiences that are engaging, accessible, and multimodal, acting as a live intermediary between teachers and learners. This method promotes inclusive education, reinforces understanding, and assures learning equity to dyslexic learners at the very early stages of mathematical education.

Keywords: Agentic AI, Dyslexia, Adaptive Learning, Multimodal Education, Inclusive Learning, Personalized Quizzes, Assistive Technology, Learning Management System (LMS).

1 Introduction

Dyslexia is one specific form of learning disability which creates a problem with reading, writing, and understanding words, usually in severe ways. Understandably, mathematics imposes additional challenges upon the child as he/she tries to grasp the school subjects. Specific adaptive teaching and appropriate individualized attention are basic requirements for children aged around six years to nine years, for whom reading and writing are tasks in their early stages. Most LMSs-and most other educational platforms-are oriented for neurotypical learners and do not often offer flexibility for neuro-diversity. This actually becomes an obstacle for dyslexics because they cannot access the digital world and classroom materials in an effective way. So this actually demands a personalized adaptive learning experience for every learner on their cognitive needs, and it is certainly justified that it deserves to be an assistive system.

The AI-Powered Assistive Learning Management System for Dyslexic Students Using Agentic AI addresses this need by providing a personalized, inclusive, and multimodal learning environment. The system comprises two functional modules- Teacher and Student; which are connected by Agentic AI that will act as central intelligence. Learning materials, quizzes designed, and progress and level of dyslexia monitored for each student can be uploaded by teachers. Each student, on the other hand, receives adaptive content along with customized quizzes and AI generated lecture videos based on their specified learning needs. Additionally, an integrated AI chatbot supports interactive learning by offering real-time explanations and feedback. This platform bridges the gap between educators and dyslexic learners, promoting inclusive education and enhancing comprehension through adaptive, AI-driven learning strategies.

This research investigates the potential benefits of an Agentic AI-driven multimodal assistive learning system aimed at enhancing mathematical learning outcomes in students aged 6 to 9 with dyslexia. The main contributions of this research work are:

- To develop and implement an assistive learning management system powered by AI that can personalize and make mathematical learning more accessible for 6 to 9-year-olds suffering from dyslexia.

- To develop and implement an Agentic AI adaptive mechanism which automatically tailors the learning materials, quizzes, and means of lecturing, according to the level of the student's dyslexia- low, medium, or high.
- To develop and implement a learning environment integrating personalized content delivery, automated quiz generation, and an AI chatbot for real-time assistance, thereby enhancing comprehension and engagement among dyslexic learners.

2 Related works

The advent of AI-enabled learning has sprouted interest in providing assistance to students with dyslexia and other learning disabilities. A bunch of inquiries targets the design of AI-based tools and intelligent systems for personalizing learning experiences.Sorna Shanthi et al. [1] constructed RATSEL, a gamified evaluation tool augmented with AR for dyslexic learners and which resulted in enhanced reading accuracy and engagement. Zaree et al. [2] applied ensemble machine learning models to classify dyslexia based on visual continuous performance tasks, signifying that the inputs derived from multiple modalities can pave the way for early detection. An academic integrity guideline for adopting AI tools is also presented by Moorhouse et al. [3] in assessing the effect of generative AI tools on higher education evaluation.

Concerning assistive learning, Poonkuzhali et al. [4] have designed an interactive teaching aid for autistic children, thereby showing the importance of AI-aided educational interfaces in seamless learning. Alkhurayyif and Sait [5], provided an overarching review of AI methods for dyslexia detection and the gaps therein with respect to multimodal integration and personalization. Xia et al. [6] looked into assessment transformation by generative AI, whereas Li et al. [7] proposed adaptive learning frameworks using generative AI to provide personalized instructional content. Robaa et al. [8] had proposed an explainable AI approach for handwriting-based dyslexia detection, thereby increasing model interpretability and trustworthiness.

Nikolic et al. [9] explored the educational implications of large generative AI models such as ChatGPT and Gemini, while Guettala et al. [10] examined adaptive and personalized learning systems powered by AI to engage students further. A multimodal framework for the early detection of dyslexia using behavioral and visual analytics was introduced by Swami [11], while Kuerban et al. [12] proposed ReadSmart, an AI and augmented reality solution for assisting dyslexic students through generative learning experiences.

Apart from this, Voultsiou and Moussiades [13] conducted a systematic review of applications based on AI, VR, and LLM in special education, citing the many opportunities and challenges in their use. Farhah [14] stated how generative AI promotes adaptive learning for diverse learners, and Varga-Atkins [15] presented a practical guide on how teachers could make effective use of multimodal and generative AI tools in inclusive classrooms.

In the face of rapid advancements, most earlier works focus on detection or static content delivery rather than a unified learning system. Creating a holistic AI-based agentic learning management system that will provide dynamically individualized content, such as tests, videos, exercises, the like, depending on dyslexia severity becomes rather lofty. This gap is inspired from which this study has been undertaken-to develop an AI-powered Assistive Learning Management System for Dyslexic Students Using Agentic AI, which is expected to aid learning mathematics through adaptive and inclusive technologies.

The proposed system goes further than traditional adaptive platforms and relies on Agentic AI to autonomously convert teacher input into personalized, multimodal content. It also incorporates dyslexia profiling and real-time analytics to create personalized learning experiences that can be integrated into inclusive global objectives for accessible education.

3 Framework of the Proposed System

This framework enables seamless collaboration between teachers and students through intelligent automation and adaptive learning features. The Teacher Layer focuses on content creation, student monitoring, and progress analysis, while the Student Layer delivers personalized learning materials, adaptive quizzes, and interactive support. The Agentic AI Layer bridges these modules by dynamically converting teacher inputs into dyslexia-friendly, multimodal formats and providing real-time feedback. The integrated Chrome Extension further enhances accessibility by offering personalized reading and comprehension support across web platforms, ensuring continuous, inclusive learning beyond the classroom.

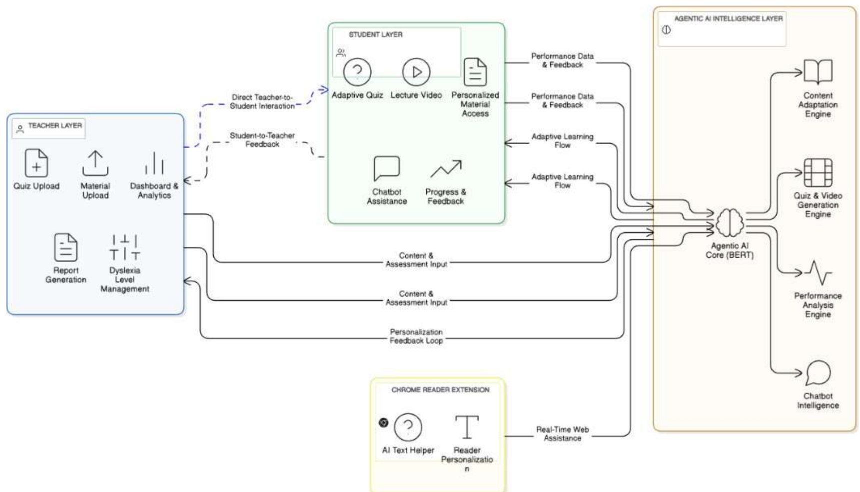


Fig 1:Architecture

Teacher Layer

Teacher Layer extends help to teachers by providing means to organize and handle learning content efficiently. Every module that exists in the layer interacts with Agentic AI engine for automation and adaptation. The Material Upload Module enables teachers to upload text, image, or document-based materials that will be automatically converted by Agentic AI into different dyslexia-friendly formats according to Low, Medium, and High difficulty levels germinating within his own mind. The Quiz Upload Module (optional) allows educators to upload their personalized tests or provide the AI the prerogative to construct such tests automatically; questions are then purposefully difficult depending on the level of each student's cognitive performance. Through visual reports for individual and group progress, the Dashboard and Analytics Module assists teachers in assessing how engaged their students are with the types of materials and how engaged they are improving with dyslexia. The Dyslexia Level Management Module allows teachers to assign or change each learner's dyslexia level; the AI continues to monitor the data and recommend adjustments based on algorithms it has learned. Finally, the Report Generation Module supplies comprehensive performance summaries, inclusive of quiz results, frequency of engagement, and growth metrics, for both macroscopic and individualized scrutiny.

Student Layer

The Student Layer targets a highly interactive, multimodal learning that empowers the 6- to 9-year old children suffering from dyslexia. The AI-driven personalization enriches the elemental comprehension, engagement, and retention. The Personalized Material Access Module is the modification of adaptive learning content that meets the student's level of dyslexia, available through text, audio, and image formats for multi-sensory learning. Adaptive Quiz Module dynamically creates or modifies quizzes depending on the advancement of the students, gradually increasing the challenge to keep them motivated. The Lecture Video Module translates textual materials into AI narrative video lessons, enhanced with visual graphics and voice modulation to help auditory learners. An integrated Chatbot Assistance Module provides real-time academic support by simplifying complex topics into child-friendly explanations while achieving instant feedback and visual tracking of progress for self-paced learning and building confidence through the Progress and Feedback Module.

Agentic AI Intelligence Layer

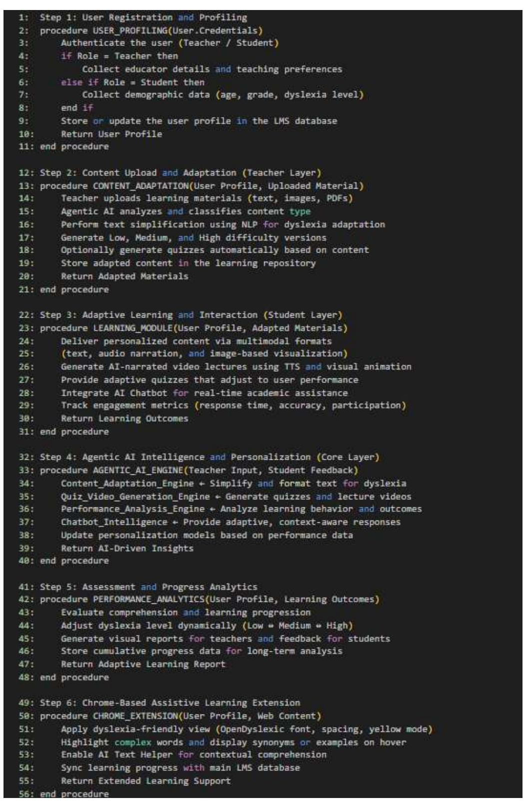
At the very center lies the Agency AI Intelligence Layer, the cognitive hub that allows automation, personalization, and continuous adaptation across both the teacher and student layers. The Content Adaptation Engine modifies the uploaded materials to create simplified and dyslexia-friendly text, establishing layout and readability accordingly. The Quiz and Video Generation Engine automatically generates adaptive quizzes and explanatory videos using the NLP, text simplification, and TTS pipelines. The Performance Analysis Engine continuously tracks students' progress, forecasting possible pathways of solutions while providing recommendations of learning modifications. The Chatbot Intelligence serves as a virtual learning assistant that provides context-specific and adaptive responses, thus enabling interactive and self-paced learning experiences.

1. Innovative Extension: Chrome-Based Assistive Learning Tool

Innovative Chrome-Based Assistive Learning Tool extending beyond LMS through its innovative extension. This browser-based assistive tool specifically helps students with dyslexia by reading and understanding texts online. The Reader Personalization Extension lets students set up the website readability in accordance with the severity of dyslexia with a dyslexic-friendly font for improved clarity, additional letter and line spacing to reduce strain, and a yellow background mode to minimize glare. User preferences are automatically saved and applied across sessions for convenience. Simple meanings, synonyms, and example sentences are provided in the hover of the difficult words, which can help them independently read and understand things.The AI Text Helper Module has served contextual help.

Together, these components form a unified, agentic ecosystem that not only adapts to the learner's needs but also extends learning accessibility into real-world digital environments, fostering confidence, understanding, and inclusivity for dyslexic students.

Algorithm 1: ABSAT — AgenticAI-Based Smart Assistive Tutoring Algorithm



```
Step 1: User Registration and Profiling
procedure USER_PROFILING(User.Credentials)
    Authenticate the user (Teacher / Student)
    if Role = Teacher then
        Collect educator details and teaching preferences
    else if Role = Student then
        Collect demographic data (age, grade, dyslexia level)
    end if
    Store or update the user profile in the LMS database
    Return User Profile
end procedure

Step 2: Content Upload and Adaptation (Teacher Layer)
procedure CONTENT_ADAPTATION(User Profile, Uploaded Material)
    Teacher uploads learning materials (text, images, PDFs)
    Agentic AI analyzes and classifies content type
    Perform text simplification using NLP for dyslexia adaptation
    Generate Low, Medium, and High difficulty versions
    Optionally generate quizzes automatically based on content
    Store adapted content in the learning repository
    Return Adapted Materials
end procedure

Step 3: Adaptive Learning and Interaction (Student Layer)
procedure LEARNING_MODULE(User Profile, Adapted Materials)
    Deliver personalized content via multimodal formats
    (text, audio narration, and image-based visualization)
    Generate AI-narrated video lectures using TTS and visual animation
    Provide adaptive quizzes that adjust to user performance
    Integrate AI Chatbot for real-time academic assistance
    Track engagement metrics (response time, accuracy, participation)
    Return Learning Outcomes
end procedure

Step 4: Agentic AI Intelligence and Personalization (Core Layer)
procedure AGENTIC_AI_ENGINE(Teacher Input, Student Feedback)
    Content_Adaptation_Engine ← Simplify and format text for dyslexia
    Quiz_Video_Generation_Engine ← Generate quizzes and lecture videos
    Performance_Analysis_Engine ← Analyze learning behavior and outcomes
    Chatbot_Intelligence ← Provide adaptive, context-aware responses
    Update personalization models based on performance data
    Return AI-Driven Insights
end procedure

Step 5: Assessment and Progress Analytics
procedure PERFORMANCE_ANALYTICS(User Profile, Learning Outcomes)
    Evaluate comprehension and learning progression
    Adjust dyslexia level dynamically (Low ↔ Medium ↔ High)
    Generate visual reports for teachers and feedback for students
    Store cumulative progress data for long-term analysis
    Return Adaptive Learning Report
end procedure

Step 6: Chrome-Based Assistive Learning Extension
procedure CHROME_EXTENSION(User Profile, Web Content)
    Apply dyslexia-friendly view (OpenDyslexic font, spacing, yellow mode)
    Highlight complex words and display synonyms or examples on hover
    Enable AI Text Helper for contextual comprehension
    Sync learning progress with main LMS database
    Return Extended Learning Support
end procedure
```

Fig 2: Algorithm Steps

1.4 Results and Discussion

The developed *AI-Powered Assistive Learning Management System for Dyslexic Students using Agentic AI* was tested to evaluate its ability to generate adaptive content and enhance learning engagement. The system's interfaces were designed for both educators and students to create a seamless, personalized learning experience.

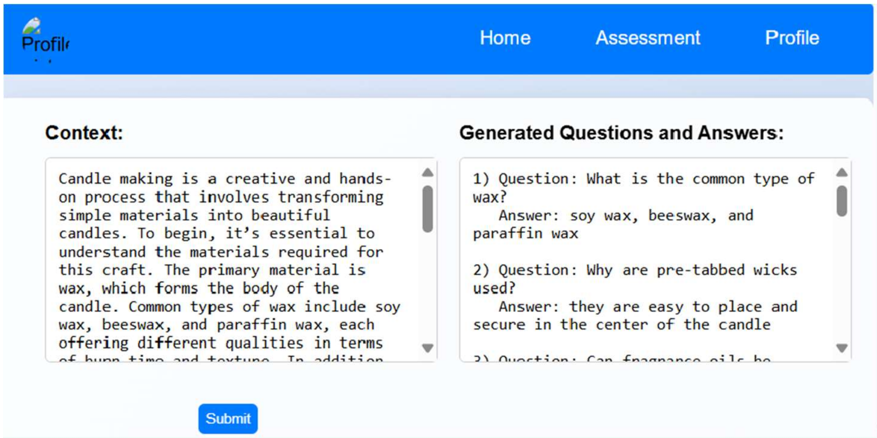


Fig 3. Educator interface for automatic question generation.

The Educator Interface for the automatic generation of questions is shown in Figure 3. The teacher inputs context or educational content, and the system, supported by Agentic AI, generates questions and corresponding answers. The model takes into account the understanding of the student and thus helps to give personalized assessments. The questions made are screened by the teachers, who then can give marks and change the level of difficulty if necessary. The automation here is a great help to the teachers as it takes off some of their manual workload yet still keeping the quality and relevance of the questions to the context

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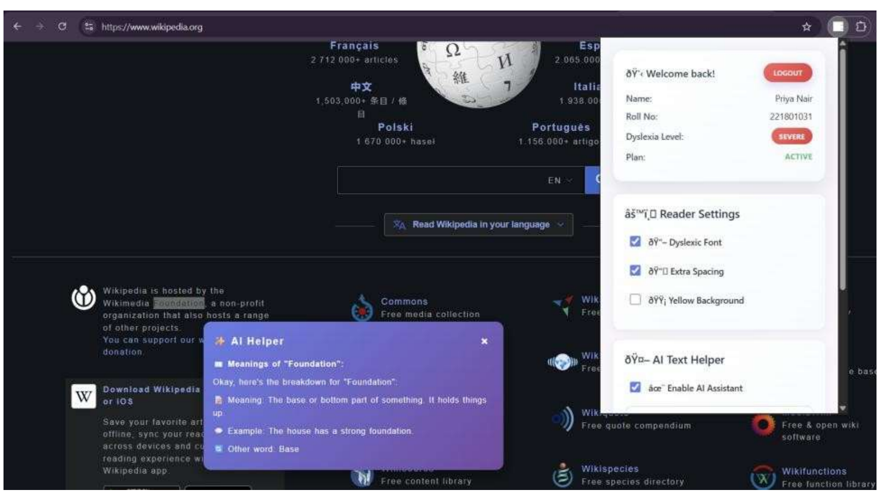

Fig 4. Student interface for post-assessment.

In Figure 4, there is the student interface through which support and post-assessment are provided. Through this interface, students not only get to take quizzes and receive learning materials but also get to interact with the AI in the form of a chatbot that makes the explanations straightforward and gives instant feedback.Apart from these, the interface offers text simplification, choice of fonts, and reading-aloud features that help students with dyslexia to learn comfortably and inclusively.

Its interactive design is one of the things that offer self-paced learning and even confidence building among the little ones. Besides, the system keeps track of every child's progress in real-time and adapts the level of questions according to the child's performance making it impossible for learning to become stagnant. The chatbot plays a dual role of giving academic clarification and also doing so by rewarding the children with kind words thereby keeping them engaged and confident.

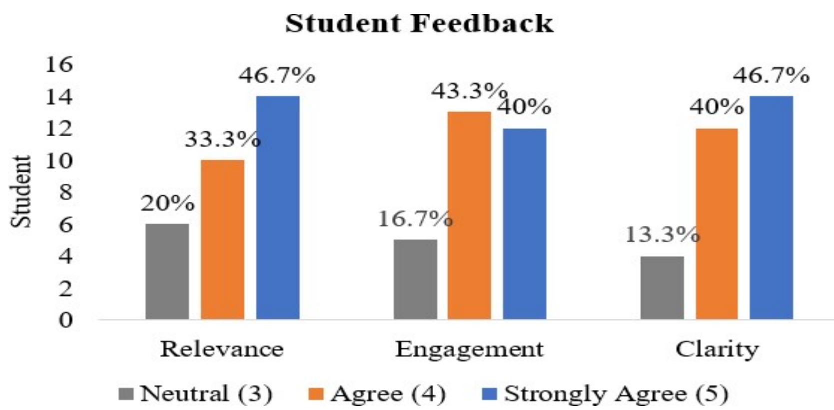

Fig 4. Student feedback in tailored question generation

Figure 5 shows that most students rated the generated questions as highly relevant, engaging, and clear, proving the system's effectiveness in improving learning experience and comprehension.

4 Conclusion

The proposed LMS, the AI-Powered Assistive Learning Management System, is an innovative attempt to use Agentic AI for inclusive education by making learning possible for dyslexic children within the age group of 6-9 years old. This offers the smartest technique to bridge learners and teachers through intelligent automation, generating personalized content, and offering real-time performance analysis. The platform offers an assortment of materials, tests, and lecture videos customized to each student's level of dyslexia thereby improving understanding, engagement, and confidence while learning mathematical concepts.The impinging factor is a Chrome-based aid extension that further makes it easily available to dyslexic learners in personalized reading support beyond the classroom. The combination of the multi-modal content AI in assistance with an interactive chatbot will put the student on a round-the-clock guidance and motivation mode to establish independence in learning.Agentic AI, in the abstract, is capable of transforming special education with equitable entry to learning for diverse brains. Future improvements may focus on adding some more subjects to the platform, including emotion recognition for more personalized feedback, and then conducting large-scale testing to assess long-term learning outcomes.

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