Development of an Integrated AI-Based Learning Disability Identification and Support Application

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ABSTRACT

This study presents the development of an Integrated AI-Based Learning Disability Identification and Support Application designed to assist teachers in the early detection and support of students with learning difficulties, particularly dyslexia, dysgraphia, and dyscalculia. Utilizing machine learning algorithms and AI APIs, the application analyzes student performance data including reading speed, writing samples, quiz performance, and task completion time to identify patterns indicative of learning disabilities. The system features an offline-capable AI analysis module, a performance dashboard, a chatbot-based assessment assistant (KUGI), and a local database. Developed using the Waterfall SDLC model, the application integrates React Native (Expo Go) for cross-platform mobile development and Node.js for backend processing. The study employed developmental research design to systematically create and evaluate the proposed system. Planned evaluation metrics include accuracy, precision, and recall of the AI detection module. Results indicate that the application can provide timely, data-driven insights to support inclusive education in resource-constrained environments, particularly within the Philippine educational context.

Keywords: Artificial Intelligence, Learning Disabilities, Dyslexia, Mobile Application, Inclusive Education

INTRODUCTION

In today's rapidly evolving educational environment, the early identification and support of students with learning difficulties have become increasingly important. Among these, dyslexia is one of the most common yet under-recognized learning disorders, affecting a student's ability to read, decode words, and process written language. In developing countries like the Philippines, dyslexia often goes undetected due to limited access to diagnostic tools, educational specialists, and structured screening methods. This lack of early identification delays intervention and may lead to persistent academic challenges, decreased confidence, and reduced overall learning outcomes.

In many public schools, teachers play a critical role in identifying students who may be experiencing reading difficulties. However, without adequate training and reliable assessment tools, identification is often based solely on classroom observations and general academic performance. This approach can be inconsistent and subjective, leading to cases where students with dyslexia are either misidentified or remain undiagnosed. As a result, appropriate interventions are delayed, making it more difficult for learners to catch up academically.

A local study by Cariño and Bailey (2024) titled "Knowledge, Attitudes and Interaction on Dyslexia among Selected Filipino Public School Teachers" revealed that many teachers have limited knowledge about the characteristics and appropriate interventions for dyslexic learners. The study emphasized the need for accessible and practical tools that can assist teachers in recognizing early signs of dyslexia and providing timely support, even without formal specialization in educational psychology.

Despite increasing awareness of inclusive education, there remains a lack of integrated, accessible systems that combine automated detection, teacher assistance, and continuous student progress monitoring, particularly those that can operate in both online and offline environments. Existing educational technologies often focus on content delivery rather than on the early identification of specific learning difficulties.

The development of an Integrated AI-Based Learning Disability Identification and Support Application aims to address this need. The proposed system collects and analyzes student data, including reading speed, writing samples, quiz performance, and task completion time. Using AI APIs and machine learning principles, the application identifies patterns that may indicate learning disabilities and generates data-driven insights to support timely, evidence-based intervention.

Statement of the Problem

In many Philippine schools, the early detection of learning disabilities remains a persistent challenge due to limited access to diagnostic tools and professional evaluators. Teachers often rely on manual observation or general performance trends to assess a child's learning ability. Specifically, this study seeks to address the following problems:

- **Limited availability of intelligent and data-driven tools for early detection of learning disabilities.** Many Philippine schools rely primarily on manual observation and general academic performance to identify students who may have learning disabilities, leading to inconsistent assessments and delayed identification.

- **Lack of accessible analytical support for teachers in interpreting student learning patterns.** Teachers often face difficulty in analyzing complex student performance data due to the absence of user-friendly tools that translate learning analytics into understandable insights.

- **Insufficient personalized and adaptive learning support for students with learning challenges.** Existing educational tools commonly used in schools do not provide individualized recommendations or adaptive strategies tailored to students' specific learning needs.

Objectives of the Study

The main goal of this study is to design and develop an Integrated AI-Based Learning Disability Identification and Support Application that assists teachers in the early detection and intervention of students with potential learning disabilities. Specifically, the objectives are:

- To develop an AI-driven module capable of analyzing student performance data to identify potential indicators of learning disabilities, providing teachers with a more objective and data-supported approach to early identification.

- To design and integrate a teacher-oriented dashboard that presents analyzed learning data in a clear and organized format, allowing educators to monitor student progress and make timely, evidence-based decisions even in offline environments.

- To develop a personalized support module that generates customized teaching strategies and intervention recommendations for students with identified learning challenges.

SCOPE AND LIMITATIONS

This study focuses on the development of an Integrated AI-Based Learning Disability Identification and Support Application targeting common learning disabilities such as dyslexia, dysgraphia, and dyscalculia. The application includes an AI-powered screening module, a student performance dashboard, a teacher recommendation assistant, and a chatbot-based assessment assistant (KUGI). The system is designed to function both online and offline, making it suitable for resource-limited Philippine school environments.

The application will not serve as a formal medical or psychological diagnostic tool. Its accuracy depends on the quality and quantity of training data. The system excludes integration with large-scale educational databases, focusing instead on a localized prototype suited for small to medium-sized schools. Ethical safeguards including data privacy, user consent, and transparent AI reporting are embedded in the system design.

Significance of the Study

Students. The application provides a safe and supportive digital environment that helps identify learning difficulties at an early stage, promoting a more inclusive learning atmosphere.

Teachers. Teachers benefit from the application's analytics, visualization, and recommendation features, enabling more informed and efficient instructional decisions.

Schools. The application serves as an innovative and scalable educational tool that strengthens advocacy for inclusive learning and promotes data-driven decision-making.

Future Researchers. This study provides a foundation for further exploration into the integration of artificial intelligence in education and inclusive learning systems.

Definition of Terms

Artificial Intelligence (AI). Technology that enables the application to simulate human-like reasoning and decision-making, used to interpret student performance data and generate smart recommendations.

Chatbot Assessment Assistant (KUGI). An interactive AI-powered owl mascot that communicates with students through short questions or learning activities, collecting data to detect potential learning challenges.

Dashboard. The digital interface designed for teachers that displays student performance metrics in a clear and visually informative format.

Dyscalculia. A learning difficulty affecting a student's ability to understand and manipulate numbers.

Dysgraphia. A writing-related learning difficulty characterized by poor handwriting, inconsistent spelling, or challenges in organizing written thoughts.

Dyslexia. A learning difficulty that impacts reading accuracy, fluency, and comprehension.

Inclusive Education. An educational approach ensuring all students have equal access to quality learning opportunities through adaptive support and early detection.

Machine Learning. The application's capability to automatically learn and improve from patterns in student data to identify possible indicators of learning disabilities.

Recommendation Module. The part of the application that generates personalized teaching strategies and adaptive learning plans based on identified learning patterns.

REVIEW OF RELATED LITERATURE AND STUDIES

This chapter presents a review of related literature and studies that provide theoretical and empirical foundations for the development of an Integrated AI-Based Learning Disability Identification and Support Application. It discusses relevant concepts, frameworks, and findings concerning the use of artificial intelligence (AI), machine learning (ML), and educational technologies in identifying and supporting students with learning disabilities.

Related Literature

Artificial Intelligence has become a transformative force in education, particularly in addressing diverse learning needs. Garzón et al. (2025) explained that AI systems can analyze large volumes of student data to identify behavioral and cognitive patterns indicative of individual learning needs. Zawacki-Richter et al. (2019) further noted that AI enhances inclusivity by providing intelligent tools that assist educators in identifying and supporting struggling students.

Machine learning plays an important role in early detection of learning disabilities. Bernardo et al. (2021) emphasized that ML algorithms can analyze student performance data to predict learning difficulties before they become evident through traditional assessments. Drotár et al. (2020) found that handwriting-based ML models can detect dysgraphia by analyzing writing pressure, speed, and consistency, demonstrating that machine learning offers a more objective approach compared to manual assessment.

Deep learning models have also shown promise for detecting specific learning difficulties. Aldehim (2024) demonstrated success using convolutional neural networks (CNNs) in processing images of handwriting and reading samples for dyslexia identification. Zaibi et al. (2024) highlighted recurrent neural networks (RNNs) for analyzing sequential data such as reading speed and eye movement patterns, which are critical indicators of dyslexia.

AI-powered chatbots have emerged as supportive learning tools. Okonkwo and Ade-Ibijola (2021) found that chatbots improve student engagement through interactive questioning and immediate feedback. Labadze et al. (2023) demonstrated that AI chatbots can simulate individualized tutoring experiences, making learning more accessible for students who struggle in traditional classroom settings.

Learning analytics and natural language processing further strengthen AI-driven education systems. Siemens and Baker (2019) emphasized that systematic collection and analysis of educational data optimizes learning processes, while Winkler and Söllner (2018) explained that NLP enables meaningful interpretation of human language patterns useful for identifying dyslexia-related difficulties. Holmes et al. (2019) highlighted assistive AI technologies such as text-to-speech and intelligent tutoring systems that help remove barriers for students with disabilities.

In the Philippine context, Dela Cruz and Santos (2021) found that AI-supported learning tools significantly improved student engagement. Reyes et al. (2023) developed a learning analytics system for Filipino classrooms showing that data-driven dashboards helped educators identify at-risk learners earlier than conventional observation. Garcia and Lopez (2022) found that digital learning applications significantly enhanced reading comprehension in public school environments, and Bautista et al. (2023) found that AI-powered chatbots improved student participation and reduced learning anxiety.

Related Studies

Recent empirical studies have explored AI in identifying learning disabilities. Khan et al. (2022) developed an ML-based diagnostic system that analyzed students' academic performance and behavioral data to detect signs of dyslexia with high prediction accuracy. Sharma and Gupta (2021) implemented a deep learning framework analyzing handwriting samples of elementary learners to identify patterns associated with learning disabilities, finding significant improvements over traditional assessment methods.

Studies on adaptive learning systems reveal consistent benefits of AI-driven content delivery. Chen et al. (2023) developed an intelligent tutoring system that dynamically adjusts lesson difficulty based on real-time student responses, finding significant improvements in engagement and comprehension. Alqahtani et al. (2022) found that continuous modification of instructional content through AI-driven platforms significantly improved reading comprehension among learners with varied learning profiles.

In the Philippine context, Cruz et al. (2024) found that integrating multiple sources of student data significantly improved assessment accuracy. Mendoza and Torres (2024) found that assistive AI technologies significantly improved participation among students with disabilities. Aquino (2022) found that visual dashboards improved instructional planning and classroom management, while Ramos (2023) highlighted data privacy as a major concern that must be addressed in Philippine educational AI systems.

Synthesis

The reviewed literature and studies collectively establish that artificial intelligence plays a significant role in transforming education through early identification, personalized instruction, and continuous support for learners with diverse needs. AI systems, including machine learning, deep learning, and natural language processing, are capable of analyzing large-scale learner data to detect patterns associated with learning difficulties. A common finding across both foreign and local studies is the effectiveness of integrating assessment and instructional support into a unified system. Ethical considerations such as transparency, explainability, data privacy, and fairness are consistently identified as essential requirements. This synthesis reveals a clear research gap addressed by the present study: a unified, accessible, context-aware AI system that simultaneously performs learning disability identification and provides adaptive learning support within the Philippine educational setting.

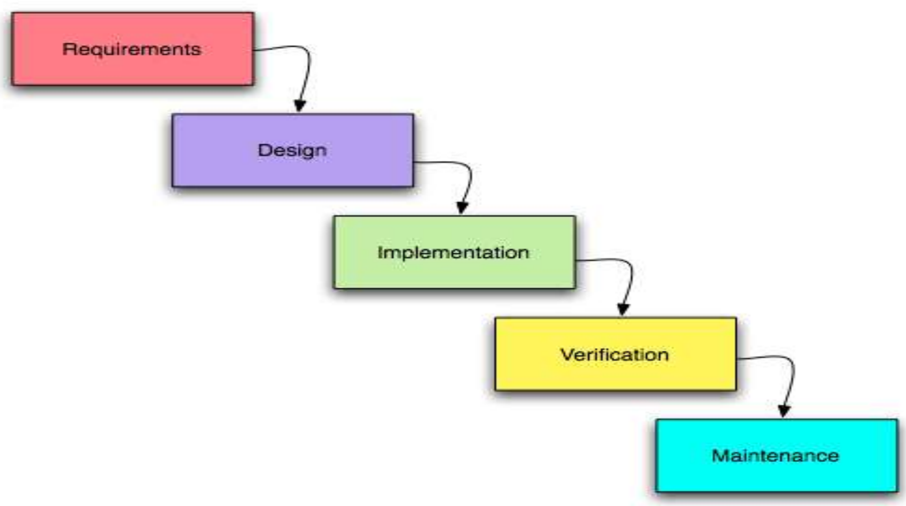
METHODOLOGY

This chapter presents the methodology used in the development of the Integrated AI-Based Learning Disability Identification and Support Application. It describes the research design, system architecture, hardware and software requirements, development tools, and ethical considerations embedded in the system design.

Research Design

This study employed a developmental research design to develop and evaluate the application. The proponents adopted the Waterfall Model as the Software Development Life Cycle (SDLC) framework, which follows a sequential development process in which each phase must be completed before proceeding to the next.

Figure 3.1 Waterfall Model Used in the Study



Requirement Phase

The Requirements Analysis Phase served as the foundation of the system development process. The proponents analyzed the educational problem, focusing on the difficulty of identifying learning disabilities early and the lack of accessible support tools. Literature and previous studies guided the identification of functional requirements, including the need for AI-based learning disability detection, interactive chatbot assistance, and performance monitoring dashboards.

Design Phase

The System Design Phase translated requirements into a technical blueprint. The proponents planned the overall architecture, database structure, and data flow. Interface design was developed, including prototypes for student and teacher dashboards, AI analysis outputs, and chatbot interaction screens.

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Development Phase

Program code was written, database structures were created, and AI API integrations for learning disability detection were implemented. Datasets were collected, organized, and preprocessed. The AI module was iteratively refined to ensure accurate detection of potential learning difficulties.

Testing Phase

Functional testing verified that all modules including the chatbot, dashboards, and AI analytics worked as intended. Usability testing assessed ease of navigation for both students and teachers. Performance metrics including accuracy, precision, and recall are planned for formal evaluation in subsequent phases. Errors detected were corrected to optimize system performance.

Deployment Phase

The Deployment Phase involved implementing the system in a controlled operational environment for demonstration and evaluation. Students and teachers interacted with the AI analysis, assessment modules, and analytics dashboards. Real-time observation ensured smooth operation and effective data flow across modules.

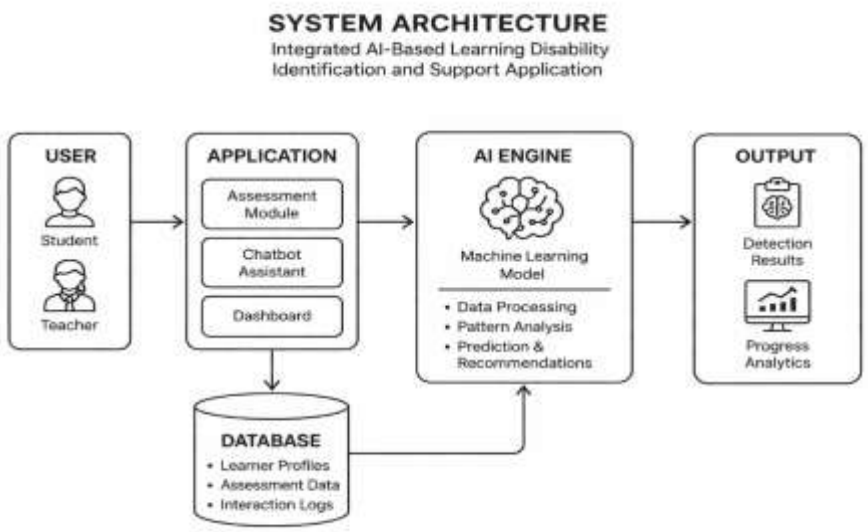
Maintenance Phase

Minor updates, debugging, and interface enhancements were conducted to ensure long-term system stability. AI outputs and predictive models were refined based on user interaction and testing feedback to improve accuracy and reliability.

System Architecture

The proposed application is designed using a layered system architecture that ensures efficient data processing, AI integration, and user interaction. The architecture is composed of multiple layers that work together to collect learner data, analyze performance, provide adaptive support, and present analytics to educators.

Figure 3.2 System Architecture



In the Input Stage, data is collected from both students and teachers, including assessment responses, activity completion records, and interaction data. The Process Stage involves transforming collected input through AI API analysis, including data preprocessing with cleaning, normalization, and feature selection. In the Output Stage, processed information is presented to users — students receive personalized feedback through the KUGI chatbot, while teachers access the analytics dashboard presenting visualizations such as graphs, charts, and progress summaries.

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AI Integration Approach

The application adopts an API-based AI integration approach rather than training models from scratch, making the system practical and deployable within resource-constrained environments. Pre-built AI APIs are integrated to process student response data, identify patterns associated with learning disabilities, and generate personalized recommendations.

The planned evaluation framework for the AI module includes the following performance metrics:

- **Accuracy:** The proportion of correctly identified learning difficulty cases out of all cases assessed.
- **Precision:** The proportion of true positive identifications among all positive predictions made by the system.
- **Recall (Sensitivity):** The proportion of actual learning difficulty cases correctly identified by the system.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of the system's detection performance.

Dataset preparation involves collecting anonymized student response data including quiz results, reading activity completion rates, and task interaction logs. Data preprocessing steps include cleaning incomplete records, normalizing numerical values, and extracting relevant features for AI analysis. Validation will be conducted using a hold-out dataset with cross-validation techniques to ensure the reliability and generalizability of AI-generated assessments.

SYSTEM REQUIREMENTS

Software Requirements

Category	Requirements	Description
Mobile Application Framework	React Native (Expo Go)	Cross-platform mobile application for Android and iOS
Frontend Development	React Native Components	Handles user interface including dashboards, chatbot, and navigation
Backend Framework	Node.js	Manages server-side logic, API requests, and database communication
Database Management System	MySQL / Firebase	Stores user accounts, student performance data, and analytics
AI Integration	Pre-built AI APIs	Processes student data to detect learning difficulties and generate recommendations
Authentication System	Firebase Authentication / JWT	Secures user login, registration, and role-based access control
Development Environment	Visual Studio Code (VS Code)	Primary code editor used for development and debugging
Mobile Testing Tool	Expo Go Application	Used to test the mobile application in real-time on physical devices

Hardware Requirements

Category	Component	Specification	Description

Server Hardware	Processor	Multi-core (Intel i5/i7 or AMD)	Handles backend processing and AI computations
Server Hardware	Memory (RAM)	16 GB or higher	Ensures smooth handling of concurrent users
Server Hardware	Storage	512 GB SSD or higher	Stores system database, user data, and AI outputs
Client Devices	Student Devices	Smartphone/tablet (4–8 GB RAM)	Access to React Native mobile application
Client Devices	Teacher/Admin Devices	Laptop/desktop (8 GB RAM+)	Used for dashboards, analytics, and monitoring
Network	Internet Connection	Stable broadband or mobile data	Required for API communication and data sync
Backup System	Storage Backup	Cloud or external backup drive	Protection against data loss

Methods and Tools

A. AI-Driven Student Performance Analysis Module

Figure 3.3 Development Process of the AI-Driven Student Performance Analysis Module

Figure A. *Process flow of AI-driven student performance analysis module*

The system collects data such as quiz results, activity completion, interaction logs, and behavioral patterns within the mobile application. Pre-built AI APIs are used to process and analyze this student data. Testing involves using sample student datasets to evaluate accuracy and consistency of AI-generated results. Planned metrics include accuracy rate, precision, recall, and F1-score to ensure reliable learning disability identification.

B. Teacher-Oriented Dashboard Module

Figure 3.4 Development Process of the Teacher-Oriented Dashboard Module

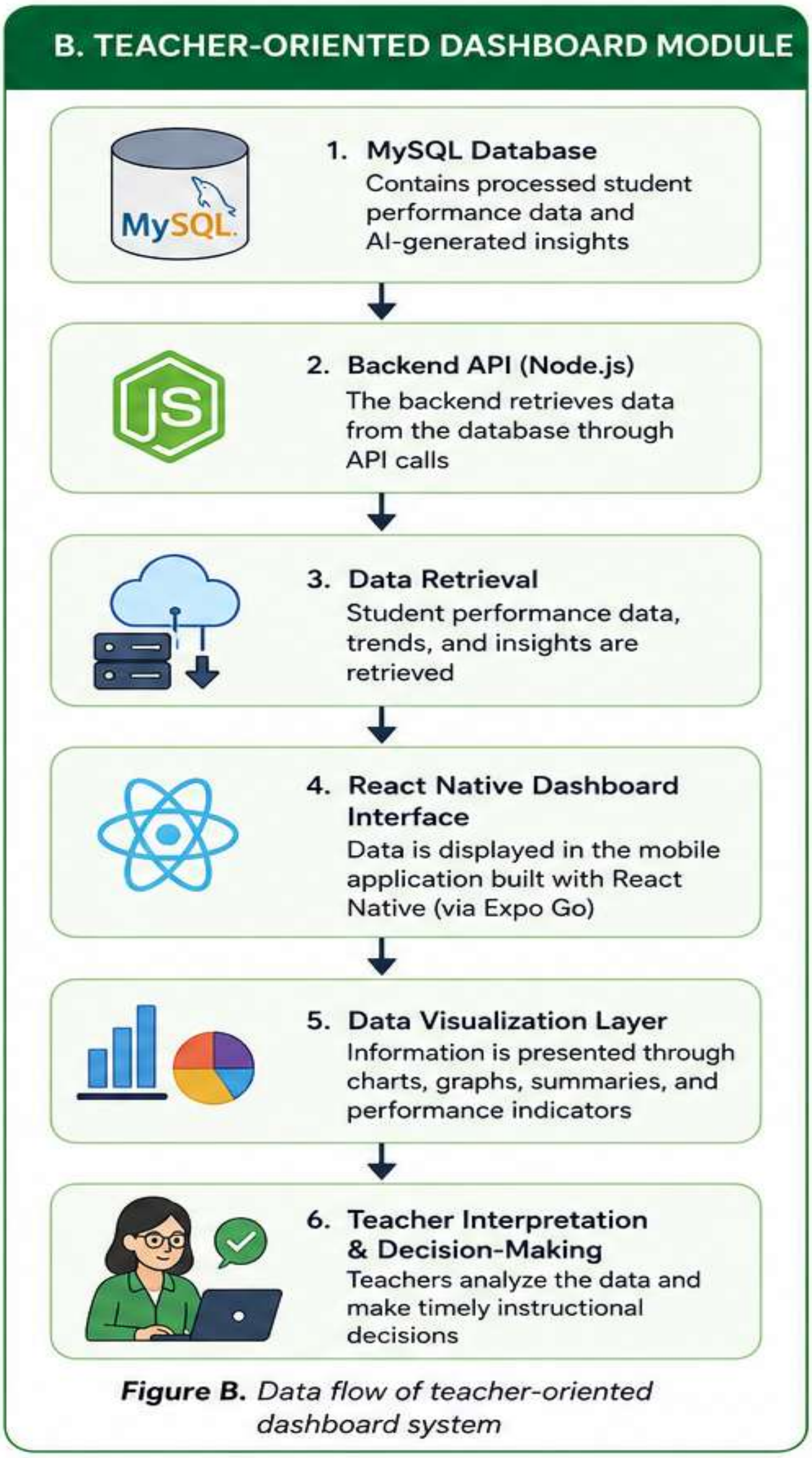
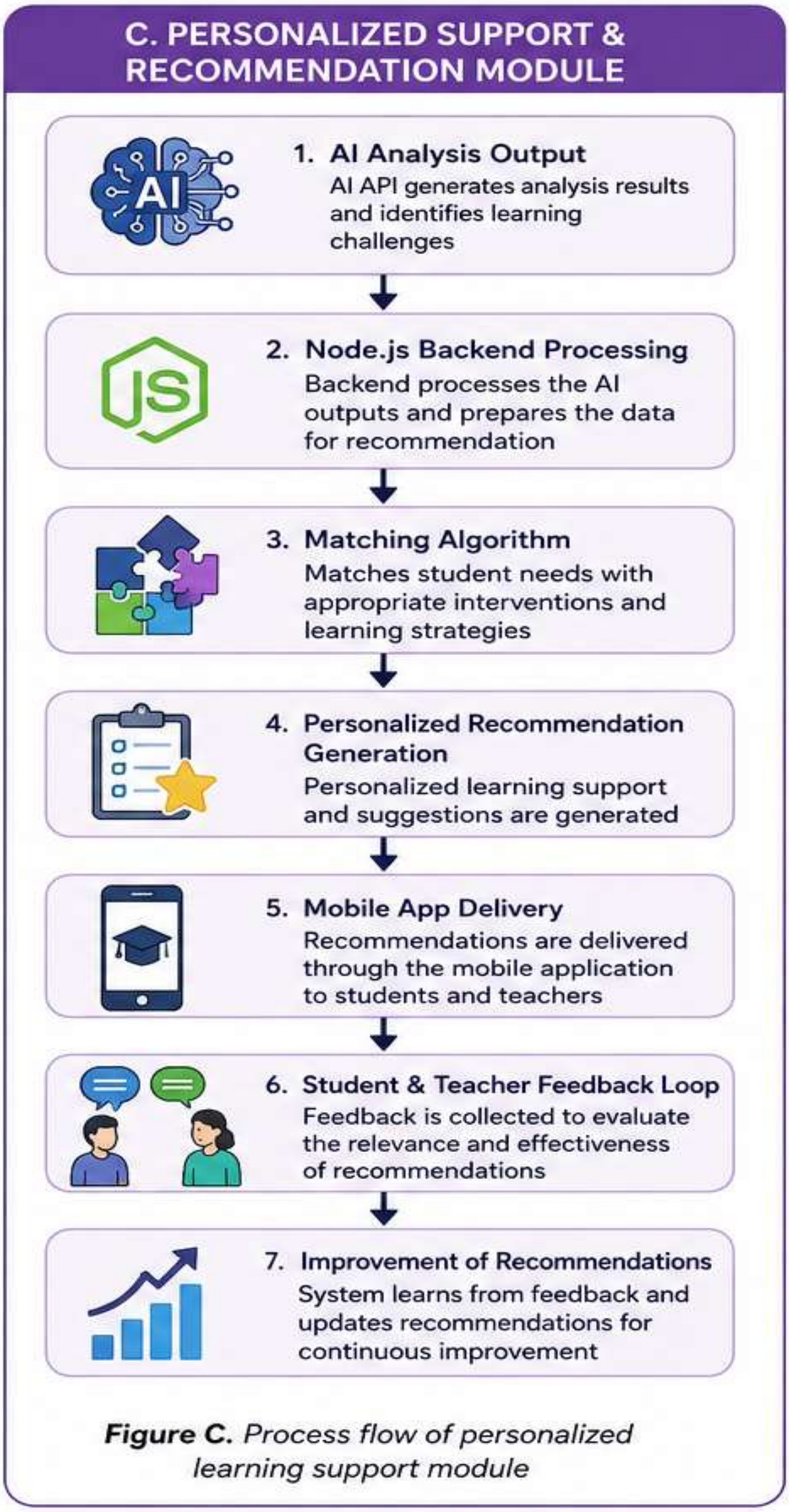


Figure B. *Data flow of teacher-oriented dashboard system*

The teacher-oriented dashboard is developed using React Native components. It displays student performance trends, learning progress, and AI-generated insights using visual elements such as charts, graphs, and summaries. Testing focuses on usability, responsiveness, and data accuracy.

C. Personalized Support and Recommendation Module

Figure 3.5 Development Process of the Personalized Support & Recommendation Module



The system generates personalized learning recommendations based on AI analysis of student performance data. The Node.js backend processes AI API outputs and matches them with appropriate intervention strategies. Testing evaluates the relevance, clarity, and effectiveness of generated recommendations.

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System Design Diagrams

Figure 3.6 Flowchart of the Proposed System

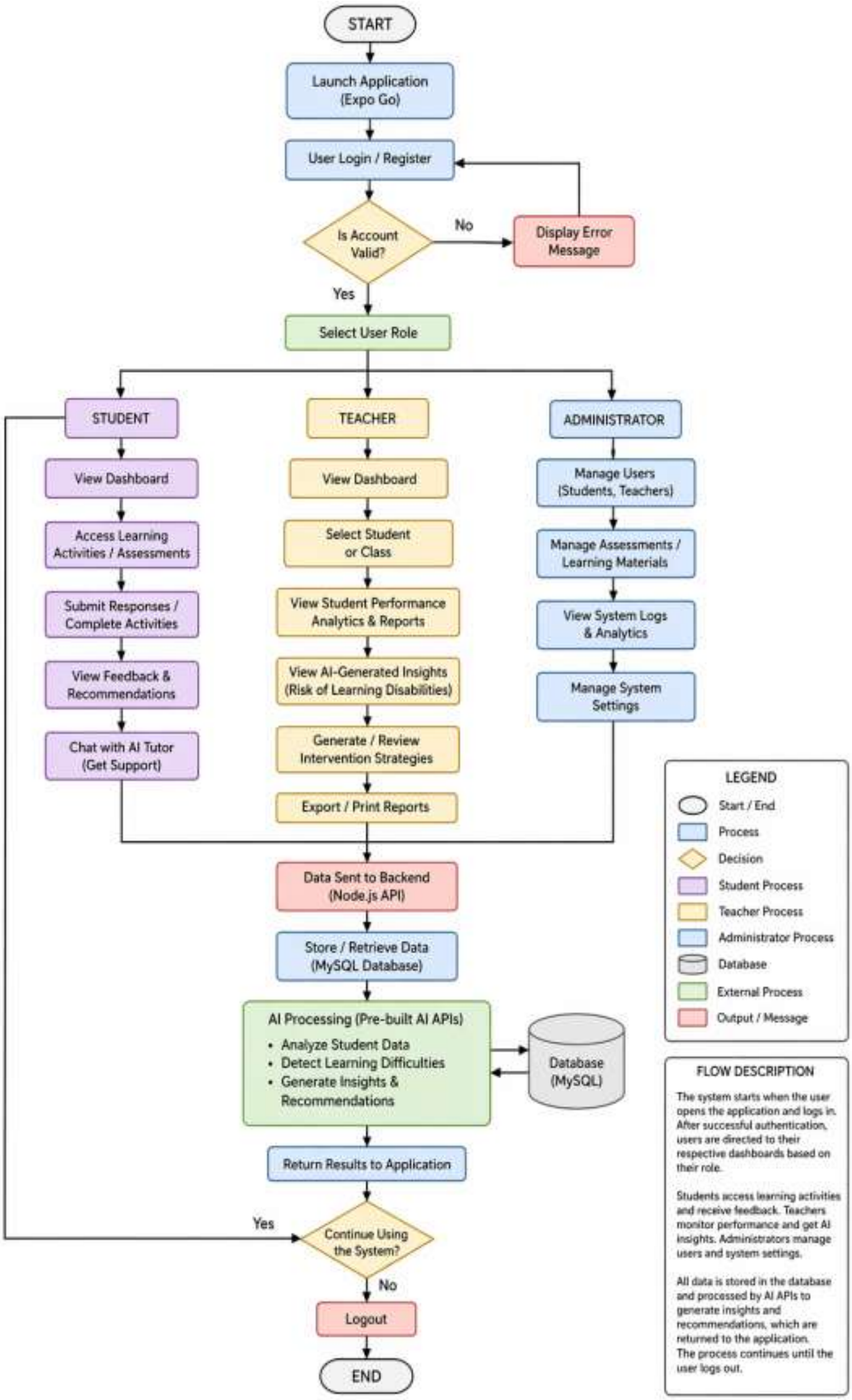

Figure 3.7 Data Flow Diagram of the Proposed System

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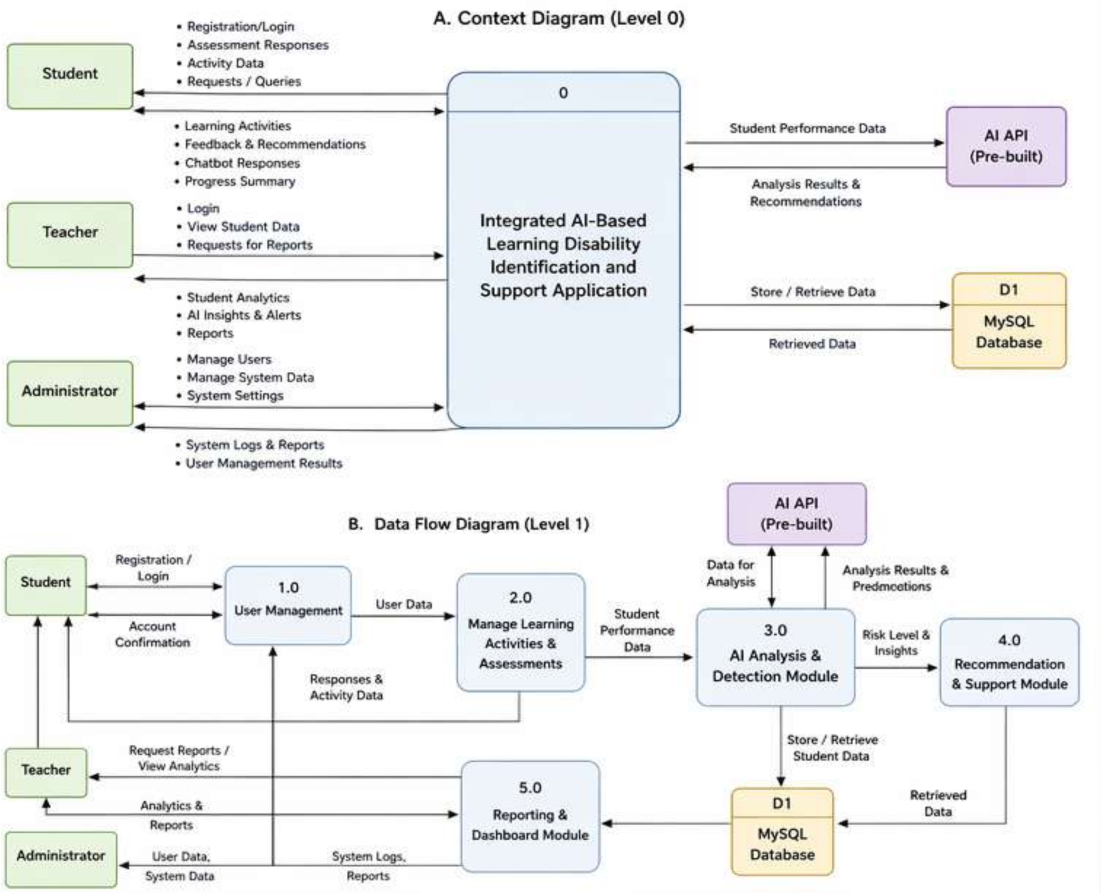


Figure 3.8 Entity-Relationship Diagram of the Proposed System

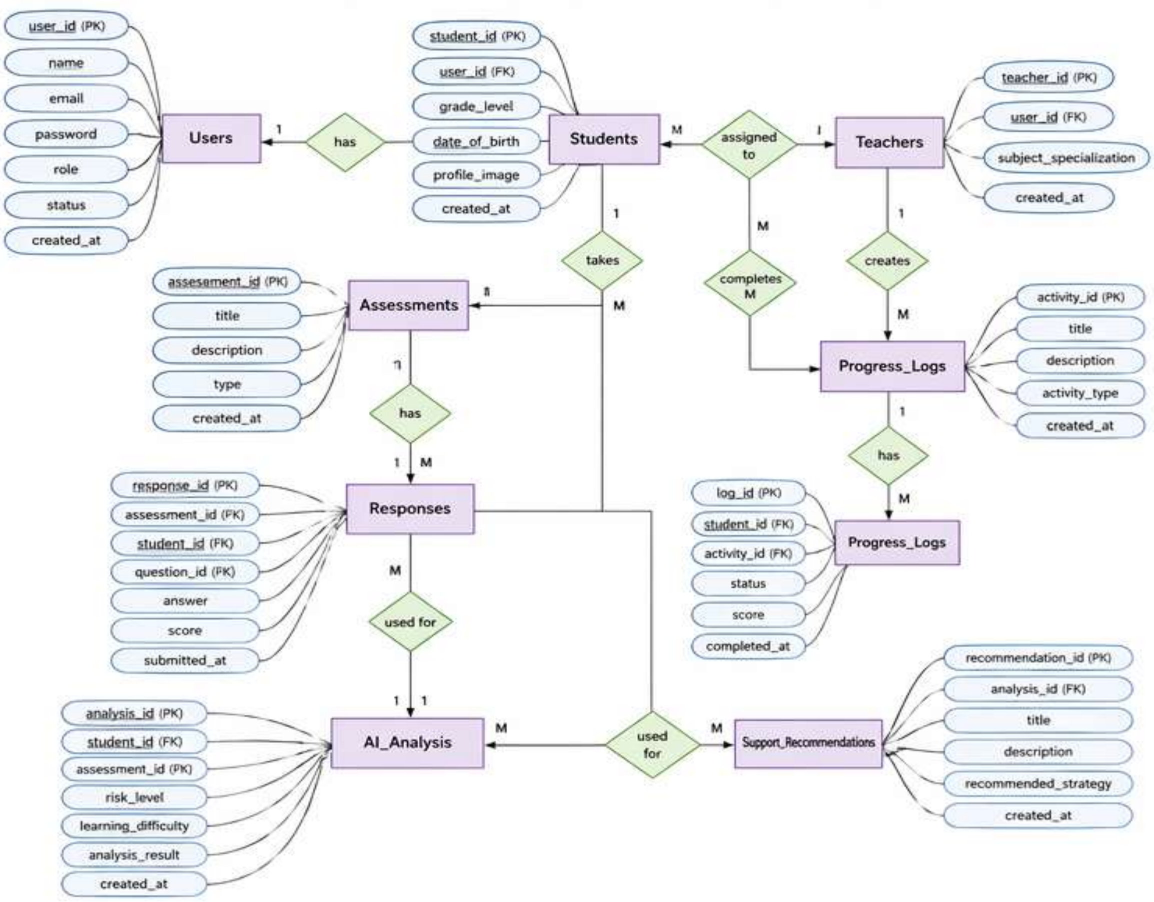
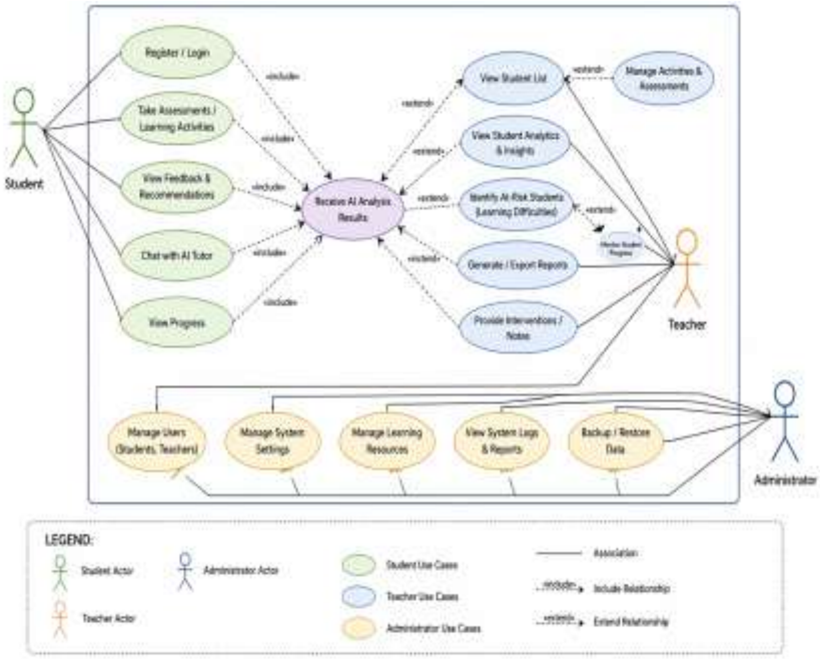


Figure 3.9 Use Case Diagram of the Proposed System



System Prototype

This section presents the actual interface screens of the developed prototype of the Integrated AI-Based Learning Disability Identification and Support Application, referred to as KUGI. The prototype demonstrates the key functional modules of the system and provides visual evidence of the application's design and usability.

Application Interface Screenshots

The following figures present the actual user interface screens captured from the KUGI mobile application prototype, developed using React Native with Expo Go. Each screen reflects a key functional component of the system.

Figure 4.1 Login Screen

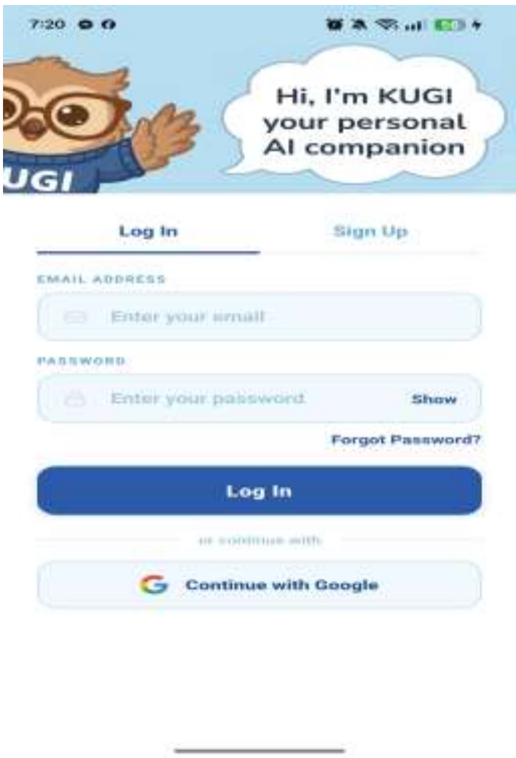


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Figure 4.1 shows the Login Screen of the KUGI application featuring the application mascot and branding. Users can log in using their email and password credentials or continue with Google authentication. The interface supports role-based access for students, teachers, and guardians.

Figure 4.2 Home Dashboard Screen

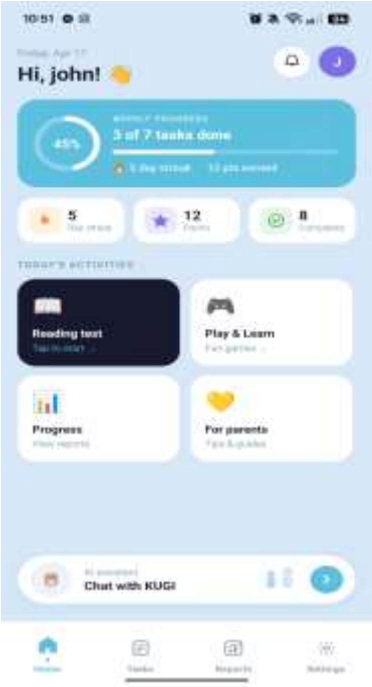

Figure 4.2 presents the Home Dashboard displaying the student's weekly progress summary, day streak, points earned, and completed tasks. It provides quick access to key features including the Reading Test, Play & Learn activities, Progress Reports, and the KUGI AI assistant chatbot, supporting the study's objective of providing comprehensive learning support.

Figure 4.3 Guardian Profile Screen

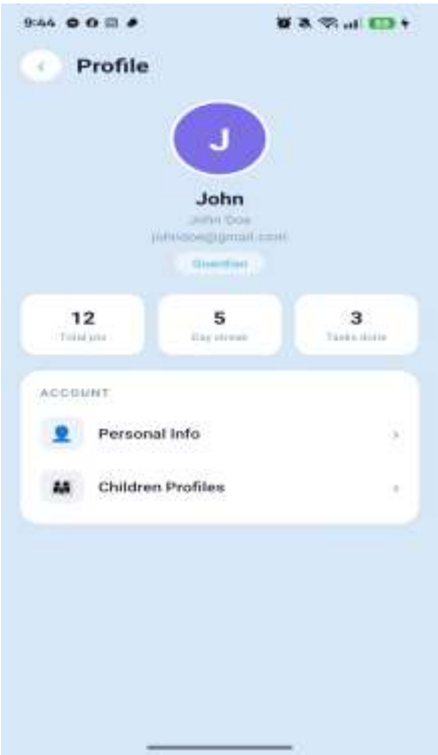

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Figure 4.3 shows the Guardian Profile Screen displaying user account information, performance statistics, and account management options including Personal Info and Children Profiles. This feature supports parental monitoring of student learning progress.

Figure 4.4 Settings Screen

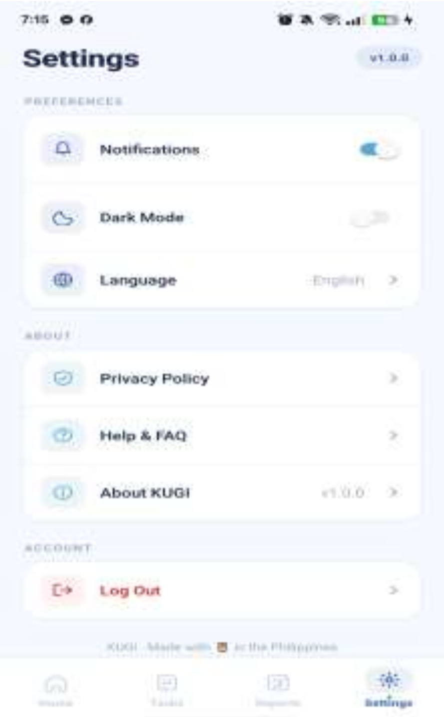

Figure 4.4 presents the Settings Screen offering user preference controls including notifications, dark mode, and language settings. The screen also includes About, Privacy Policy, and Help & FAQ sections, reflecting the application's commitment to user transparency and data privacy.

Ethical Considerations

The development of an AI-based application handling student data requires careful attention to ethical principles. This chapter discusses the ethical safeguards embedded in the design and implementation of the KUGI application, addressing data privacy, explainability, bias mitigation, and the limitations of automated predictions.

Data Privacy and Protection

The application strictly adheres to data privacy principles aligned with the Philippine Data Privacy Act of 2012 (Republic Act 10173). All student data collected by the system, including academic performance records, interaction logs, and assessment responses, are stored securely using encrypted local databases and Firebase Authentication with role-based access control.

Key data privacy safeguards include: (1) data minimization — only data necessary for learning disability identification is collected; (2) informed consent — users are informed of data collection practices through the Privacy Policy accessible within the application settings; (3) access control — only authorized users (students, teachers, and guardians) can access relevant data based on their assigned role; and (4) secure storage — all sensitive data is encrypted during transmission and at rest.

Explainable AI and Transparency

To address the concern that AI systems often act as 'black boxes,' the KUGI application is designed with transparency in mind. The AI analysis module provides clear, human-readable explanations for all generated assessments and recommendations. Rather than simply labeling a student as having a learning disability, the system presents specific performance indicators and behavioral patterns that led to the assessment, allowing teachers to make informed decisions rather than blindly relying on automated outputs.

Bias Mitigation in AI Predictions

Automated AI predictions carry the risk of bias, particularly in educational settings where cultural, linguistic, and socioeconomic factors may influence student performance. The KUGI system addresses this through: (1) diverse data collection ensuring that assessment content is culturally and linguistically appropriate for Filipino learners; (2) regular model review to identify and correct biased patterns in AI outputs; and (3) human-in-the-loop design where all AI-generated assessments serve as decision-support tools rather than final diagnoses, requiring teacher validation before any intervention is recommended.

Limitations of Automated Predictions

The application acknowledges that automated AI predictions have inherent limitations. The system is not intended to replace formal psychological or medical evaluation of learning disabilities. Its purpose is to serve as an early screening and support tool that flags students who may require further professional assessment. Teachers and guardians are explicitly informed through the application interface that AI-generated results are indicative only and should be supplemented with professional evaluation when necessary.

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