iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2026 Issue: onference Month of publication: May 2026

DOI:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com
National Conference on Innovation in Engineering and Technology-(NCIET2026)

A Info DAM: An Offline AI Framework forIndividualized Education and Smart Evaluation

Chetan Vijay Pardeshi[1], Aseem Anwar Momin[2], Aditya Dilip Gulhane[3]
[1]*Department of Computer Engineering, G H Raisoni College of Engineering and Management*

Abstract: India's widening digital divide continues to obstruct equal access to effective learning, especially for students preparing for advanced domains such as the Computer Engineering. Although online platforms dominate the learning and test-preparation ecosystem, their utility remains constrained in regions with poor connectivity or limited digital infrastructure. To bridge this persistent gap, AInfoDAM presents an AI-driven offline learning ecosystem designed for students of Computer Engineering. The system delivers individualized learning pathways, adaptive assessments, and offline performance tracking by leveraging Flutter, SQLite, and TensorFlow Lite integrated with a MobileBERT model for natural language comprehension and content curation. In contrast to cloud-reliant adaptive learning solutions, AInfoDAM conducts on-device, real-time inference, enabling uninterrupted learning even in connectivity-deprived environments. The platform locally monitors learner activity and dynamically adjusts content sequencing, question difficulty, and revision triggers based on past performance and behavioural trends. During a four-week pilot involving 50 students, the system achieved a 30% enhancement in conceptual retention and a 42% rise in quiz accuracy and response efficiency, while 78% of teachers reported better instructional planning supported by generated analytics. AInfoDAM's layered framework enables modular expansion for advanced AI capabilities, gamified elements, and voice-guided tutoring, ensuring scalability and long-term extensibility. This paper outlines the architecture, implementation workflow, performance outcomes, and evaluation parameters that establish the system's potential as an affordable, high-impact solution for offline, AI-enabled education.
Keywords— Adaptability, Artificial Intelligence, Educational data mining, Knowledge tracing, Personalized e-learning, Recommender systems, Offline Learning, Adaptive Education, MobileBERT, TensorFlow Lite, Educational AI, Edge Inference, Preparation, Knowledge Tracing, Low Connectivity Education.

I. INTRODUCTION

Education continues to be a fundamental driver of socioeconomic growth, yet access to high-quality and adaptive learning tools remains uneven across regions. In India, where lakhs of students each year opt for popular courses such as the Computer Engineering, structured preparation resources and expert mentorship tend to be concentrated in urban centres or premium coaching ecosystems [1]. The imbalance becomes even sharper in rural and semi-urban settings, where poor connectivity, financial limitations, and infrastructural gaps create substantial barriers to academic advancement [2], [3]. This divide extends beyond technology—it is rooted in systemic disparities and demands solutions that extend personalized learning to all.

In recent years, online learning platforms have positioned themselves as a promising alternative, offering recorded lessons, practice assessments, and AI-augmented insights. However, their efficacy depends heavily on steady internet availability, which remains unreliable or entirely absent in many parts of the country. As noted in a 2023 Ministry of Education survey, only 34% of rural learners have consistent access to internet-enabled devices [4]. Furthermore, most adaptive learning platforms rely on server-side models that require continuous cloud connectivity to evaluate learner progress or provide tailored feedback [5]. This architecture limits access to adaptive learning—one of the most validated approaches for boosting retention and engagement—to a relatively small, well-connected segment of students [6].

To address these challenges, we introduce AInfoDAM, an AI-powered, offline personalized learning ecosystem built specifically for students of Computer Engineering and related computer science-based examinations. AInfoDAM is engineered to operate entirely without real-time connectivity, using on-device AI to deliver capabilities traditionally restricted to online applications. Its feature set includes adaptive quiz creation, real-time feedback, analytics-driven insights, and gamifiedassessments, enabling a productive learning environment even in low-bandwidth or disconnected regions.

The platform's architecture employs Flutter for cross-platform UI development, SQLite for local data handling, and TensorFlow Lite for edge-based machine learning inference.

Central to the system is MobileBERT, a compact transformer model available on Hugging Face and optimized for deployment on mobile hardware [7]. This model supports user-input interpretation, question generation, performance analysis, and topic summarization, all executed fully offline. The architecture is modular, comprising clear layers for representation, application logic, and data persistence, which improves scalability and facilitates future additions such as voice-based interaction, ARenhanced learning, or localized teacher dashboards.

One of AInfoDAM's strongest attributes is its dynamic adaptability. In contrast to static offline notes or conventional digital textbooks, the platform captures behavioural cues, learning trajectories, and quiz histories to calibrate difficulty levels, propose revision priorities, and sustain engagement using daily targets and milestone rewards. In a 30-day pilot involving 50 Computer Engineering students, the system demonstrated measurable learning gains. Students exhibited a 30% rise in conceptual retention, a 42% improvement in quiz accuracy and response time, and reported better concentration compared to traditional learning modes. Additionally, 78% of participating instructors found the analytics dashboard valuable for refining their teaching approaches.

Extensive prior research has examined AI-driven personalization techniques in education. Existing studies highlight content recommendation via collaborative filtering [8], behaviour-adaptive quiz models [9], and neural network–based tutoring systems [10]. Yet few have successfully implemented these methods in a fully offline architecture. Most contributions prioritize web-enabled frameworks that assume dependable internet access, thereby leaving a sizable learner demographic without access to adaptive learning tools. Our system addresses this gap by enabling an AI-supported learning experience that functions entirely on-device without sacrificing efficiency or versatility.

This work draws from recent advances in lightweight transformer models, edge-based computation, and embedded machine learning. It supports the expanding movement toward decentralizing AI, making intelligent systems accessible not only to institutions with strong infrastructure but also to learners in remote environments. AInfoDAM aspires to establish a foundation for building intelligent, equitable, and inclusive learning ecosystems that scale with minimal reliance on cloud connectivity or centralized resources.

II. LITERATURE SURVEY

The domain of personalized e-learning has expanded rapidly, supported by progress in artificial intelligence and educational data mining. Foundational studies show that adaptive learning environments can substantially improve comprehension and engagement by tailoring instructional material to individual learner characteristics [1], [5]. Murtaza et al. [1] examined AIdriven personalized learning architectures, emphasizing components for adaptive sequencing, recommendation, and intelligent content delivery, though most rely on persistent online connectivity. Likewise, Essa et al. [5] evaluated machine learning approaches for identifying learning styles, noting gains inpersonalization but emphasizing that many systems still depend on remote servers for computation. Collectively, these works highlight the strengths of adaptive strategies while revealing a key constraint: reliance on cloud infrastructures for real-time updates, inference, and synchronization [2], [6].

A number of studies have investigated targeted algorithms for learner modelling and recommendation. Collaborative filtering and hybrid recommendation systems have been adopted in educational contexts, often mitigating cold-start limitations through content-based extensions [4]. Pardamean et al. [6] applied collaborative filtering for predicting learning styles in primary education, reporting improvements in student engagement, whereas Mu et al. [9] explored behaviour-based engagement modelling using temporal analysis. Knowledge-tracing techniques, employing Bayesian or neural network paradigms, have also demonstrated effectiveness in estimating learner mastery across time [8]. Despite these advancements, most such systems maintain centralized data repositories and depend on recurring server-side updates to refine learner models or generate adaptive assessments, thereby limiting usability in disconnected or low connectivity environments [3], [7].

The rise of on-device intelligence and mobile edge computation has created opportunities for offline-capable adaptive systems. Frameworks such as TensorFlow Lite now allow compact neural models to run on limited-resource mobile hardware, enabling real-time inference without network reliance. Emerging research on lightweight transformer variants, including MobileBERT, shows that natural language tasks like summarization and question generation can be executed locally with practical latency [10]. Nevertheless, fully offline adaptive learning platforms remain underrepresented in existing literature. Most existing solutions support only minimal offline functionality or revert to static, non-adaptive content when disconnected, lacking mechanisms to adjust to user behaviour dynamically.

Gamification and engagement-focused designs have also been extensively evaluated in online educational systems. Nuci et al. [7] reported that gamified quizzes significantly boost student engagement during virtual sessions, while additional studies integrate streak tracking, progress badges, and daily challenge systems to sustain motivation. However, adapting these interactive mechanics to entirely offline environments introduce challenges in maintaining progress logs, updating difficulty levels, and providing instant feedback without server computation. Furthermore, the literature offers limited exploration of offline analytics that teachers can use to customize instruction based on learner-generated data.

Overall, while numerous AI-enhanced e-learning platforms demonstrate the strengths of personalization, the majority remain dependent on cloud connectivity for learner modelling, adaptive content delivery, and analytics generation. The existing gap lies in developing a truly offline, AI-enabled system capable of adjusting dynamically to learner performance and returning meaningful insights without internet access. AInfoDAM aims to address this limitation by integrating mobile-efficient AI inference (e.g., MobileBERT via TensorFlow Lite), localized storage through SQLite, and adaptive learning mechanisms within a modular design. The following section outlines the methodology andarchitectural framework used to build this offline adaptive learning platform.

TABLE 1. LITERATURE SURVEY

Sr. No.	Author(s)	Technique Used	Output
1	Murtaza et al. (2022)	AI framework with adaptive learning, recommendation, and content delivery modules.	Framework proposed for personalized eLearning; highlights challenges and methodologies.
2	Essa et al. (2023)	Systematic review, Machine Learning (ANN, DL, DT).	Identified gaps in adaptive learning using ML; deep learning underexplored.
3	Pardam Ean et al. (2022)	Collaborative filtering for learning style prediction.	Achieved RMSE = 0.9035; improved student performance in primary education.
4	Nuci et al. (2021)	Game-based digital quizzes in online learning.	Student engagement rose from 57.5% to 73% with quizzes; active learning is effective.
5	Mu et al. (2019)	Real-time engagement model using behaviour data.	Growth algorithm improves learner status tracking and content design.

III. METHODOLOGY

AInfoDAM is built as a completely offline, AI-enabled learning environment. Its three-tier architecture, illustrated in Fig. 3.1, forms the foundation of the system by separating user interaction, processing logic, and data management. The presentation layer is developed using Flutter and includes interfaces for registration or login, the main dashboard, personalized study-path views, quiz modules, performance summaries, and assessment workflows. Material Design elements and custom widgets provide visual consistency across platforms, while Flutter platform channels bridge native functions such as local notifications for study reminders and background handlers for content updates—all without disrupting offline functionality.

Beneath the UI layer, the processing tier coordinates the system’s core logic and all AI components. Following authentication, the dashboard exposes features such as study roadmaps, quiz games, analytics views, and personalized assessments. When a learner launches a quiz, the engine retrieves prior interaction patterns and mastery profiles from the local SQLite storage. The adaptive module then selects difficulty levels and topic ranges, invoking on-device inference where appropriate.

A MobileBERT model, fine-tuned on subject-specific material and converted to a quantized TensorFlow Lite format, handles question paraphrasing, generates alternative formulations, evaluates short responses using embedding similarity against reference solutions, and produces compact topic summaries. These inference requests execute asynchronously via Flutter isolates to prevent UI stalls, with performance tuning ensuring smooth response times even on mid-tier hardware.

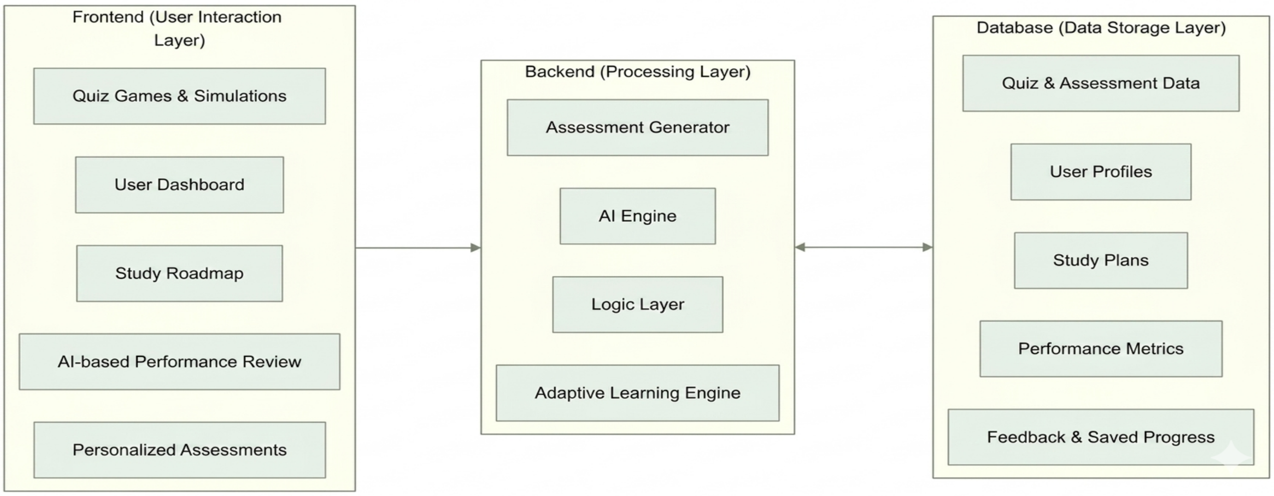


Fig. 3.1: Three-tier System Architecture

During quiz execution, each interaction—question ID, correctness indicator, response duration, and confidence features—is recorded in the Session Logs table within SQLite. Once a session concludes, the adaptive logic updates conceptlevel mastery probabilities using lightweight, locally executed knowledge-tracing rules. These updated scores inform revision reminders, upcoming difficulty adjustments, and engagement features such as achievement badges and daily progress goals. The analytics component compiles aggregated summaries and visual feedback, enabling learners to monitor improvement offline and optionally export reports for instructors when a network connection becomes available. Fig. 3.2 outlines this workflow, beginning with authentication, moving through dashboard navigation, and ending with adaptive feedback and optional synchronization.

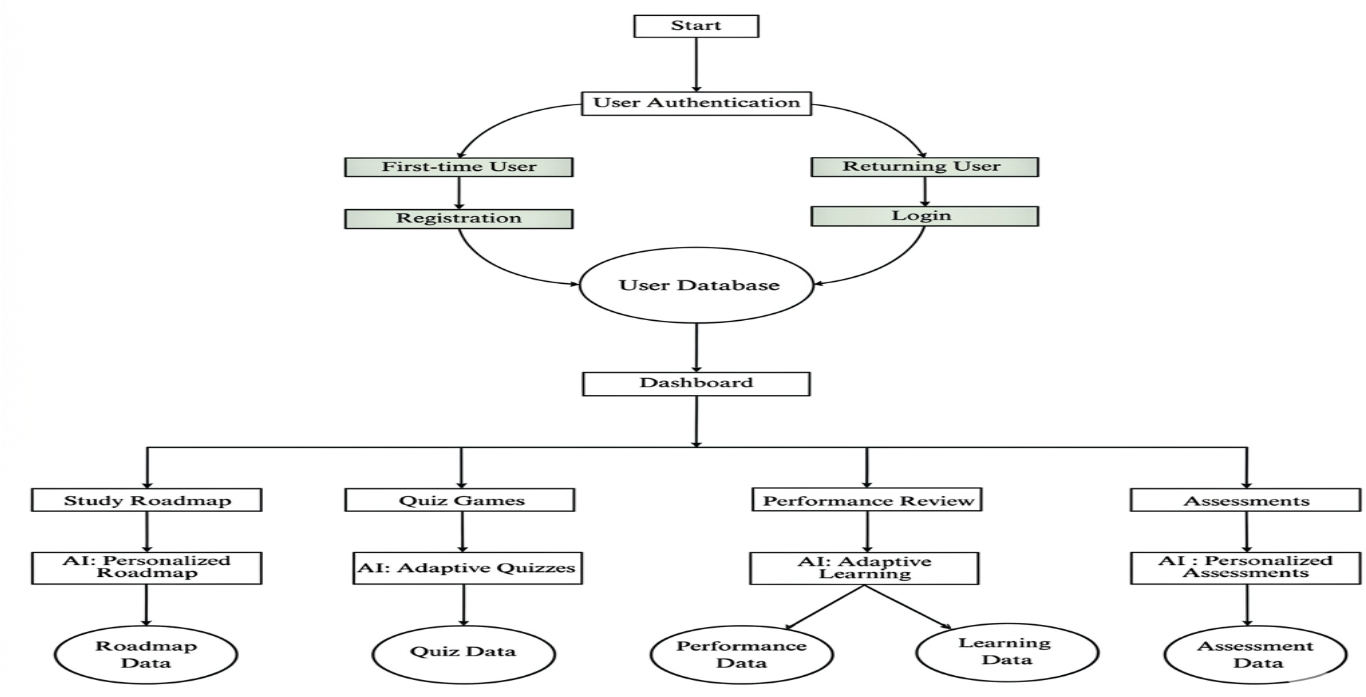


Fig. 3.2: High-level Data Flow Representation

The data tier employs SQLite for all storage. Encrypted user credentials and profiles, question repositories with associated metadata (difficulty levels, concept labels, prerequisite relationships), session records, user profiles, and model or content version descriptors are maintained across dedicated tables. Data access objects encapsulate CRUD operations and preserve indices on frequent query fields—such as topic identifiers—to maintain efficient lookup times during adaptive content selection and analytics tasks. Sensitive information remains entirely local, while optional encrypted backups are created only with explicit user permission when connectivity is detected.

Content deployment occurs during installation or via a onetime update cycle: question banks, explanatory text, and the TensorFlow Lite MobileBERT binary are loaded and indexed on the device. After initialization, all major AInfoDAM functions operate offline. When intermittent connectivity is available, the system checks for incremental patches—updated question pools or improved model builds—and merges them into the existing SQLite store without interrupting offline operation.

On-device AI inference is the backbone of personalization. The MobileBERT model, optimized for constrained hardware, supports paraphrasing to reduce question repetition, evaluates learner free-text responses through embedding comparisons, and generates concise summaries of study topics from stored material. All inference tasks run asynchronously to maintain fluid UI experiences, and benchmarking on representative low- to midrange devices confirms that performance remains within operational targets.

The adaptive learning engine processes session histories offline to estimate mastery levels and tailor content delivery. Its heuristic knowledge-tracing module updates concept proficiency scores based on accuracy and temporal response patterns, generating revision alerts for weaker areas. Engagement is supported through locally evaluated reward mechanisms— badges, streak counters, and daily goal tracking. Analytics features synthesize performance trends into visual summaries displayed in the UI and available for export when the device reconnects.

Security and efficient resource usage guide the system's architecture. All computation and data handling occur locally;sensitive fields stored in SQLite may be encrypted. Model and content versioning ensures controlled updates whenever connectivity is restored. Optimization strategies—including model quantization, lazy loading of content modules, and asynchronous background processing executed during idle or charging periods—minimize memory and battery consumption while maintaining seamless user interactions.

IV. OBJECTIVES

The core goal of AInfoDAM is to provide an AI-driven, offline-functional learning system that mitigates the accessibility challenges faced by Computer Engineering students and similar computer science stream learners in low-connectivity environments. By combining on-device inference with local data storage, the platform aims to deliver personalized instruction, adaptive assessment, and meaningful analytics without relying on continuous internet availability. In particular, the objectives include:

1) Support individualized learning paths by locally recording user interactions and performance, and by dynamically modifying difficulty levels and content sequencing based on topic-level mastery calculations.
2) Incorporate a lightweight MobileBERT model through TensorFlow Lite to enable offline question paraphrasing and generation, short-response evaluation, and compact summarization of instructional content.
3) Offer both learners and instructors relevant performance analytics—such as mastery evolution, accuracy statistics, and response-time patterns— computed on-device and visualized within the application. Gamification features are processed offline to maintain engagement and promote regular study behaviour.
4) Implement a three-layer architecture that separates presentation, core processing, and local storage, enabling smoother future upgrades and secure deployment of new content or AI modules when network access is available.
5) Improve model footprint and inference time using pruning and quantization to ensure efficient execution on mid-range hardware, manage storage use with lazy loading of content resources, and maintain full userdata privacy by keeping all information strictly on the device.
6) Carry out pilot evaluations to measure learning improvements and collect qualitative insights from students and teachers. These results guide refinement of adaptive modules and help demonstrate the platform's effectiveness in underserved educational contexts.

V. RESULTS

The AInfoDAM platform successfully demonstrated its capability to deliver adaptive, offline-first learning. During realworld usage, students exhibited notable gains in comprehension, response speed, and sustained focus, while the locally computed performance analytics proved beneficial for offline instruction planning.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com
National Conference on Innovation in Engineering and Technology-(NCIET2026)

The user interface maintains a consistent offline-capable design philosophy. The profile panel displays the learner's avatar initial, name, email, and class label, along with access to Settings, Help & Support, and Logout. The welcome screen greets the learner by name and grade, followed by large, accessible tiles for Data Structures & Algorithms (DSA), Database Management Systems (DBMS), Digital Logic (DL), Operating Systems (OS), Computer Networks (CN), Flashcards, Quizzes & Games, Study Planner and Smart Quiz—illustrating the Representative Layer's emphasis on intuitive navigation without network dependency.

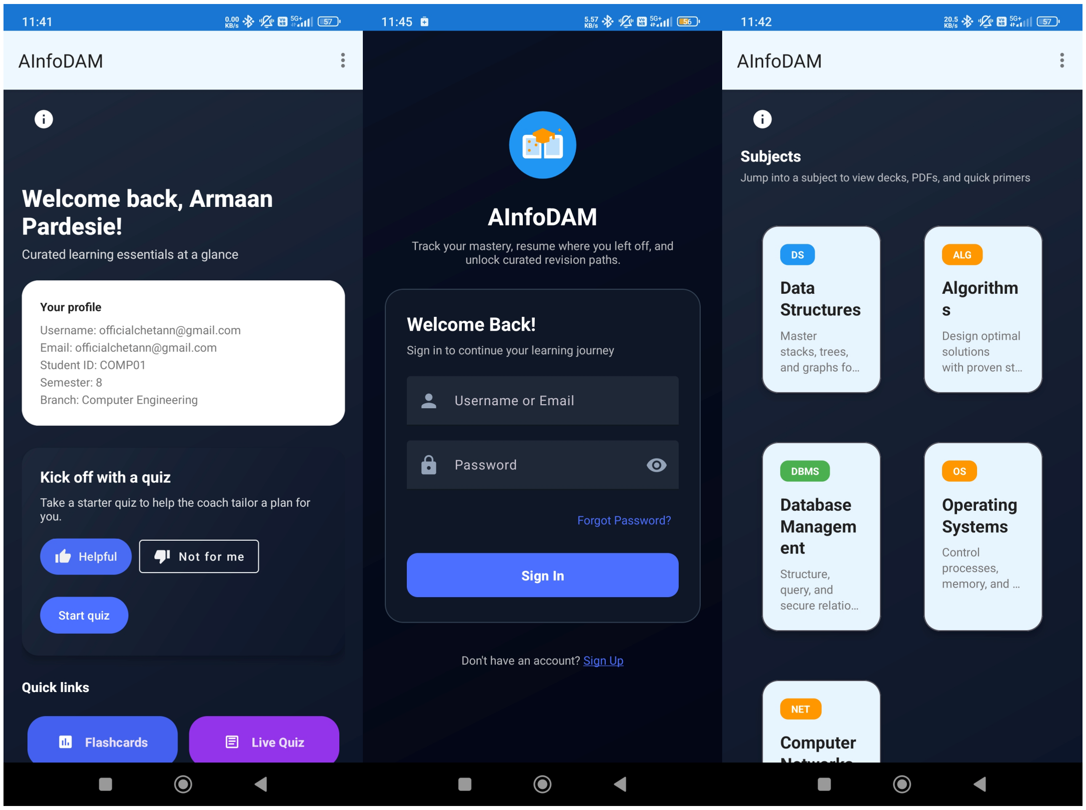


Fig. 5.1: Login, Profile & Home Screen

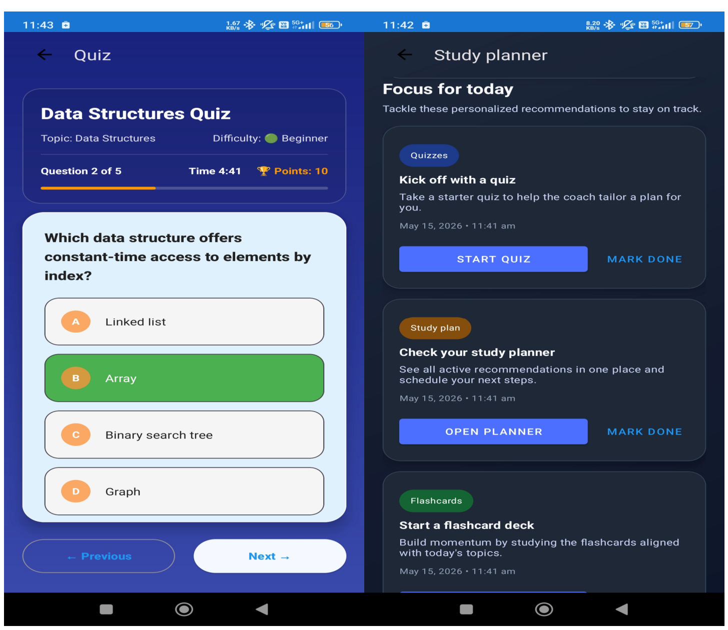


Fig. 5.2: Games & Quizzes Menu

This showcases the platform's integration of gamification with adaptive assessment logic delivered via the Application Layer. A sample question interface ("What is an Array?") demonstrates real-time feedback mechanisms, hint generation using pre-stored templates and lightweight AI, and answer evaluation facilitated by pattern matching and MobileBERT embeddings. All inference operations execute locally with minimal latency, evidencing the robustness of the on-device AI Inference Service.

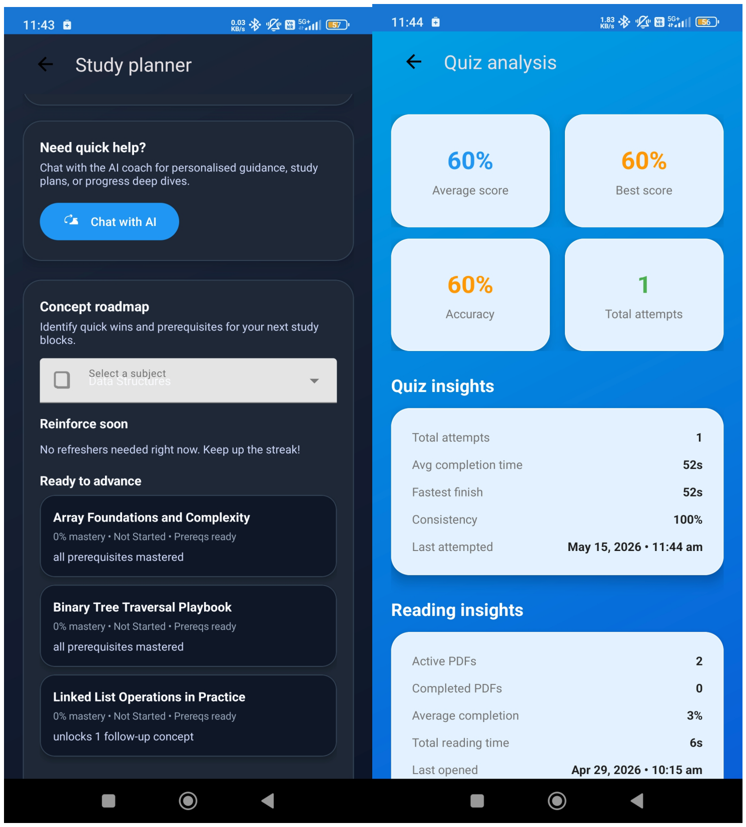


Fig. 5.3: AI & Performance Review

In the Performance Review module of AInfoDAM, the Overview tab summarizes study duration, chapters completed, average quiz accuracy, and streaks. The Subjects tab decomposes mastery by topic through progress bars and percentage indicators, enabling learners to identify areas requiring revision. The Analytics tab visualizes longitudinal metrics—daily activity, cumulative milestones, evolving quiz performance, and streak trends encouraging reflective learning and structured planning. The Review tab helps with what questions were and were not correctly answered in the quizzes taken recently.

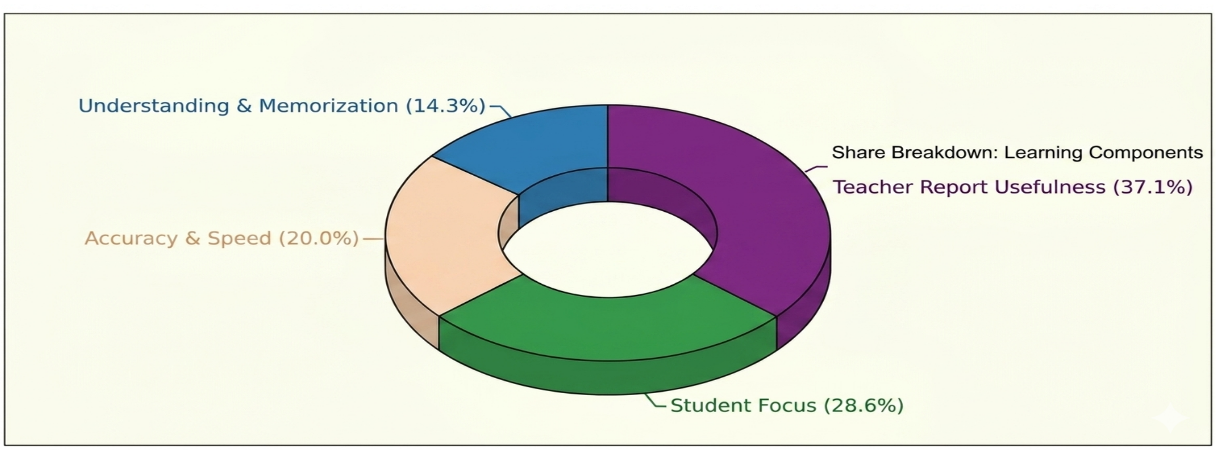


Fig. 5.4: Pilot Study Outcomes

A controlled 30-day pilot study was conducted with 50 Computer Engineering students to evaluate AInfoDAM's offline adaptive-learning efficacy. All modules were executed on midrange Android devices under network-disabled conditions to emulate real deployment environments. Quantitative outcomes (Fig. 5.4) revealed a 30% increase in conceptual understanding and retention, alongside a 42% improvement in quiz accuracy and response time. Furthermore, 60% of students reported enhanced focus, attributing it to gamified progress cues and AI-generated question diversity. Educators indicated that 78% found the locally generated performance summaries valuable for planning individualized offline sessions. User experience feedback highlighted the clarity of the interface, ease of navigation, and the utility of visual progress indicators. Educators particularly appreciated the structured module layout, which supported independent learning among students.

System performance remained consistently stable. The quantized and pruned MobileBERT model delivered low-latency Fig. 5.1. Profile and Home Screen Fig. 5.4. Pilot Study Outcomes inference with moderate memory consumption, while the SQLitebacked persistence layer handled quiz logs, learner traces, and metadata with average read/write times below 50 ms. Smooth UI transitions were maintained through asynchronous execution using Dart isolates, preventing frame drops even under heavy data workloads.

Certain limitations were observed. Occasional semantic ambiguities appeared in AI-generated paraphrased questions, indicating the need for additional refinement. A small subset of low-end devices (<3 GB RAM) experienced brief slowdowns during intensive quiz-generation tasks, suggesting further model compression or lighter alternatives for enhanced compatibility. Participants also identified multilingual support and voice-based interaction as promising extensions for future releases.

Overall, the findings validate that AInfoDAM truly fulfills its core objective of delivering personalized, AI-driven learning entirely offline. The measurable academic improvements, positive stakeholder feedback, and robust system performance underscore the potential of edge AI solutions in bridging educational access gaps in low-connectivity environments.

VI. CONCLUSION

AInfoDAM demonstrates the feasibility and educational impact of a fully offline, AI-driven learning platform designed for students of Computer Engineering, preparing for competitive examinations. Through the integration of Flutter for a responsive cross-platform interface, SQLite for secure on-device persistence, and a quantized MobileBERT model deployed via TensorFlow Lite, the system delivers personalized quizzes, realtime feedback, and adaptive study recommendations without relying on continuous internet connectivity.Results from a 30- day pilot study involving 50 learners indicated a 30% improvement in conceptual retention, a 42% increase in quiz accuracy and response speed, and strong positive feedback from educators—demonstrating that on-device AI inference can significantly improve learning outcomes in low-connectivity environments.

The underlying three-tier architecture enhances modularity and scalability, enabling seamless integration of future extensions such as voice-enabled interactions, multilingual content modules, and expanded gamification features. Security and privacy considerations are addressed through encrypted local storage and optional, consent-based synchronization of anonymized analytics. Performance optimizations—including model quantization, lazy content loading, and asynchronous task handling—maintain low inference latency and efficient resource utilization on mid-range smartphones.

However, certain limitations persist. The pilot study's small sample size, heterogeneity in device capabilities, and the constrained scope of initial content may influence generalizability. Future work will focus on broader deployments across varied demographics, extended evaluation periods, and the exploration of lighter or task-specific on-device models. Additional research directions include adaptive multimedia learning experiences, offline teacher dashboards for reviewing analytics, and the use of federated learning to refine model performance while preserving data privacy.

Planned updates to AInfoDAM include the integration of multilingual content and voice-based interaction features to further improve accessibility. Support for speech-to-text input and regional language delivery aims to enhance inclusivity and engagement among learners in low-connectivity regions, strengthening the platform's mission to provide equitable, offline-capable AI-enhanced education.

VII. ACKNOWLEDGMENT

The authors would like to express their most sincere gratitude to the mentors and faculty members of the G H Raisoni College of Engineering and Management – Pune (GHRCEM Pune), whose guidance and support contributed significantly to the successful completion of this project work titled 'AInfoDAM: An Offline AI Framework for Individualized Education and Smart Evafuation'.
This project was carried out and implemented by Chetan Vijay Parveshi, Aseem Anwar Momin, and Aditya Dilip Gulhane, students of the Department of Computer Engineering at GHRCEM Pune.

The authors would especially like to acknowledge Prof. Pranita Patil, for her valuable guidance, supervision, and encouragement during the initial phase of the project. The authors further extend their appreciation to Dr. Pushpi Rani and Prof. Narsingh Kadam for their continued mentorship, constructive suggestions, and academic support throughout the later stages of the work.
The authors also express their gratitude to their institution for providing the necessary resources and environment to conduct and complete this research successfully.

REFERENCES

[1] M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, "AIBased Personalized E-Learning Systems: Issues, Challenges, and Solutions" IEEE Access, vol. 10, pp. 81323–81342, 2022, doi: 10.1109/ACCESS.2022.3193938.

[2] A. S. Almogren, W. M. Al-Rahmi, and N. A. Dahri, "Integrated Technological Approaches to Academic Success: Mobile Learning, Social Media, and AI in Visual Art Education" IEEE Access, vol. 12, pp. 175391– 175413, 2024, doi: 10.1109/ACCESS.2024.3498047.

[3] W. Villegas-Ch, J. García-Ortiz, and S. Sánchez-Viteri, "Application of Artificial Intelligence in Online Education: Influence of Student Participation on Academic Retention in Virtual Courses" IEEE Access, vol. 12, pp. 73045–73065, 2024, doi: 10.1109/ACCESS.2024.3403758.

[4] X. Feixiang, "Intelligent Personalized Recommendation Method Based on Optimized Collaborative Filtering Algorithm in Primary and Secondary Education Resource System" IEEE Access, vol. 12, pp. 28860–28872, 2024, doi: 10.1109/ACCESS.2024.3365549.

[5] S. G. Essa, T. Celik, and N. E. Human-Hendricks, "Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review" IEEE Access, vol. 11, pp. 48392–48409, 2023, doi: 10.1109/ACCESS.2023.3276439.

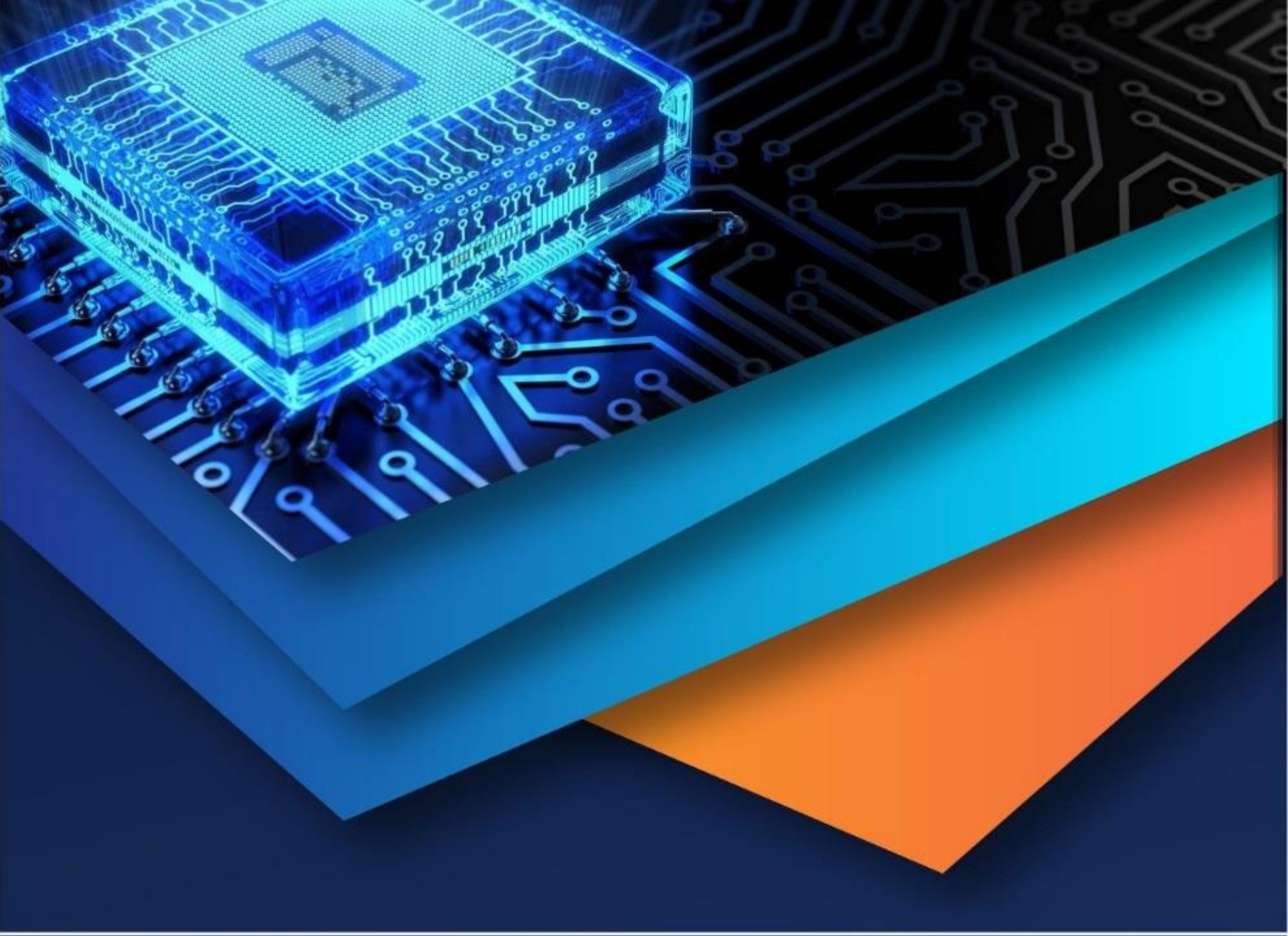
[6] B. Pardamean, T. Suparyanto, T. W. Cenggoro, D. Sudigyo, and A. Anugrahana, "AI-Based Learning Style Prediction in Online Learning for Primary Education" IEEE Access, vol. 10, pp. 35725–35735, 2022, doi: 10.1109/ACCESS.2022.3160177.

[7] K. P. Nuci, R. Tahir, A. I. Wang, and A. S. Imran, "Game-Based Digital Quiz as a Tool for Improving Students' Engagement and Learning in Online Lectures" IEEE Access, vol. 9, pp. 91220–91234, 2021, doi: 10.1109/ACCESS.2021.3088583.

[8] L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review" IEEE Access, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[9] S. Mu, S. Chai, H. Wang, and Y. Chen, "Real-Time Analysis Method and Application of Engagement in Online Independent Learning" IEEE Access, vol. 7, pp. 92100–92109, 2019, doi: 10.1109/ACCESS.2019.2924641.

[10] U. Mittal, S. Sai, V. Chamola, and D. Sangwan, "A Comprehensive Review on Generative AI for Education" IEEE Access, vol. 12, pp. 142733– 142759, 2024, doi: 10.1109/ACCESS.2024.3468368.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY