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FitnityAI: Personalized Fitness Goal Tracking Assistant with AI

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ABSTRACT

Abstract: With growing interest in health and wellness, there is a rising demand for intelligent tools that support personalized fitness routines. That's what inspired FitnityAI, a fresh approach to mobile fitness tracking that uses generative AI to deliver customized guidance tailored to each user's needs and progress. The application integrates key technologies, including the Gemini AI engine, a robust Spring Boot backend, and a user-friendly Android interface, to build a dynamic and adaptive fitness experience. Its standout feature is an AI-powered conversational assistant capable of interpreting user goals, activity patterns, and preferences to provide actionable, real-time fitness recommendations. FitnityAI was developed to support users in building sustainable fitness habits and to raise the bar for how mobile apps can use large language models to transform personal health management.

Keywords: *fitness tracking, AI recommendations, mobile application, health technology, personalized fitness*

Code metadata

Current code version	v1.0
Permanent link to code/repository	`https://github.com/BoktayaAmine/FitnityAI_AI_Fitness`
Legal Code License	MIT License
Code versioning system used	Git
Software code languages, tools, and services used	Java (Spring Boot), Kotlin (Android), Python (Flask), JavaScript, MySQL
Compilation requirements, operating environments & dependencies	JDK 17+, Android Studio, Python 3.8+, Node.js 14+
Link to developer documentation/manual	`https://github.com/BoktayaAmine/FitnityAI_AI_Fitness/blob/master/README.md`
Support email for questions	`soukaina.d623@ucd.ac.ma`

I. INTRODUCTION

The rise of mobile health technologies has transformed the way individuals engage with personal fitness and well-being. Over the past decade, fitness applications have proliferated across platforms, offering users tools for tracking workouts, setting goals, and monitoring nutrition [1]. However, most existing systems follow a one-size-fits-all model, providing static programs and generic recommendations that fail to account for user-specific variables such as personal fitness levels, health history, behavioral patterns, and long-term goals [2]. As a result, these tools often struggle to maintain user engagement and fail to deliver meaningful, sustained improvements in health outcomes.

Recent advances in artificial intelligence (AI), particularly in natural language processing (NLP) and machine learning (ML), present new opportunities to create intelligent fitness assistants capable of delivering personalized, context-aware guidance [3]. By leveraging AI to dynamically analyze user data, adapt recommendations over time, and communicate through conversational interfaces, modern fitness systems can shift from passive trackers to active digital coaches.

This paper introduces FitnityAI, an AI-powered mobile application designed to bridge the gap between static fitness tracking and intelligent, adaptive coaching. FitnityAI integrates the Gemini API for real-time, natural language interaction, enabling users to engage with the system through personalized, human-like conversations. It also incorporates dynamic goal adaptation and progress monitoring through a Spring Boot–based backend architecture and an intuitive Android user interface. The result is a comprehensive fitness assistant capable of delivering meaningful, actionable, and evolving support to users throughout their health journey.

This work investigates whether a large-language model-based mobile assistant can improve user personalization and engagement in fitness routines compared to conventional rule-based applications.

This paper is structured as follows. Section II provides a review of existing research on AI-driven fitness applications and highlights challenges related to personalization and engagement. Section III outlines the methodology and architectural design of the proposed solution. Section A details the system components and core functionalities. Section V presents illustrative examples demonstrating how FitnityAI adapts to individual user goals. Section VII discusses the broader technological and public health implications. Section VIII summarizes quality assurance results. Section IX reflects on limitations and ethical considerations. Finally, Section X concludes the paper and identifies future development opportunities.

II. RELATED WORK

Delivering personalized health and fitness solutions remains a significant challenge in the modern digital landscape. Traditional fitness applications frequently provide generic recommendations that fail to account for individual differences in fitness levels, health conditions, and personal goals [4, 5]. This limitation often leads to reduced user engagement and suboptimal health outcomes. The increasing demand for personalized digital health interventions has thus highlighted the necessity for intelligent systems capable of adapting dynamically to user needs [6].

Recent years have seen a considerable rise in the application of artificial intelligence (AI) to fitness and health monitoring. AI-based technologies, including machine learning and large language models, have demonstrated significant potential in enhancing user engagement, delivering tailored recommendations, and adapting continuously to evolving user profiles [7–10].

Reviews of AI-driven physical activity interventions have emphasized the use of machine learning (ML), deep learning (DL), and reinforcement learning (RL) for behavior prediction, personalized program design, and real-time activity tracking. Nevertheless, challenges persist in integrating multimodal data streams and ensuring model generalization across diverse user populations.

In parallel, context-aware recommender systems have emerged as a promising strategy to deliver timely and relevant fitness guidance. By leveraging contextual information such as time, location, and behavioral patterns, these systems aim to increase recommendation relevance and improve user adherence [11, 12]. However, issues related to the accurate collection and interpretation of contextual data, especially under conditions of sensor sparsity or privacy restrictions, remain substantial barriers to their effectiveness.

Behavior change support mechanisms have also become an essential feature in digital fitness platforms. Applications such as Freeletics integrate behavior change techniques (BCTs), including goal setting, self-monitoring, and feedback to promote sustained engagement [13]. Despite their utility, these platforms largely rely on static, rule-based systems that limit their ability to offer dynamic, personalized adaptations as users' goals and behaviors evolve.Recent studies have also explored the role of conversational agents in promoting health behavior change. For instance, Fadhil et al. emphasized the role of intelligent dialogue systems in coaching users toward sustainable health goals through natural interaction [14]. Similarly, Consolvo et al. demonstrated how mobile applications using behavioral cues and feedback loops can significantly enhance user engagement and long-term adherence [15].

FitnityAI addresses these limitations through an AI-driven, adaptive architecture designed to deliver intelligent fitness coaching. By leveraging the advanced natural language processing capabilities of the Gemini API, FitnityAI enables dynamic, conversational interactions that evolve alongside the user's behavior, goals, and progress history. Its backend, developed with Spring Boot, ensures scalable and efficient data processing, while the Android-based frontend offers an intuitive, interactive experience.

Furthermore, FitnityAI synthesizes and extends key functionalities observed across leading fitness platforms, introducing deeper personalization and real-time adaptive feedback mechanisms. Table 1 presents a comparative analysis of functionalities across popular fitness applications, highlighting the unique positioning of FitnityAI within the digital health ecosystem.

III. METHODS

FitnityAI has been developed as a personalized fitness tracking assistant powered by a large language model (LLM). The system design combines user profiling, AI-

[1] https://www.freeletics.com
[2] https://www.vi.ai
[3] https://www.myfitnesspal.com
[4] https://www.fitbod.me

Table 1: Comparative analysis of fitness applications with AI-driven features.

Feature	FitnityAI (Proposed)	Fitbod[2]	MyFitnessPal[1]	Freeletics[3]	Vi Trainer[4]
AI-Driven Recommendations	Yes	Limited	No	Yes	Yes
Natural Language Interaction	Yes	No	No	No	Limited
Goal Adaptation Over Time	Yes	Limited	No	Moderate	Moderate
Nutrition Tracking	Moderate	No	Yes	No	No
Custom Workout Generation	Yes	Yes	No	Yes	Yes
Real-Time Feedback	Yes	Limited	No	Limited	Yes
Voice or Audio Coaching	No	No	No	Yes	Yes
Integration with Wearables	Planned	Yes	Yes	Yes	Yes
Interface Customizability	High	Moderate	Moderate	High	High
Target Audience	General users	Strength athletes	General health	HIIT/Bodyweight users	Runners/Cyclists

based recommendation generation, and real-time interaction via a conversational agent.

The core technical architecture is based on a client-server model integrating Android, Spring Boot, and Gemini API. The methodology involves capturing user inputs (e.g., goals, physical profile, preferences), preprocessing them in the backend, and using the Gemini LLM to provide tailored responses.

Gemini API was selected due to its advanced language understanding capabilities, high-quality output generation, and ease of integration with Android-based systems compared to alternatives such as OpenAI's GPT or Meta's LLaMA. Evaluation was conducted through illustrative user scenarios, feature benchmarking, and a qualitative comparison with existing AI fitness applications.

This methods section provides the basis for assessing FitnityAI's value in enhancing user experience and adaptability through AI-based personalization.

IV. SOFTWARE ARCHITECTURE

A. *Software Description*

The FitnityAI application is built on a modern, scalable, and modular software architecture that integrates mobile development best practices with robust backend technologies. This section outlines the architectural decisions and their relevance to delivering intelligent, adaptive fitness coaching (see Fig. 1).

1. **Overview of the Architecture**

   FitnityAI employs a layered client-server architecture with distinct responsibilities split between the mobile Android client and a Spring Boot–based backend. The Android app follows the MVVM pattern (Model-View-ViewModel), allowing clear separation of UI, business logic, and data persistence. It communicates with the backend using Retrofit through secure HTTP requests. The backend exposes RESTful APIs and manages data persistence, user management, and business logic.

2. **Backend Infrastructure**
   The backend is designed to be scalable and maintainable, using Spring Boot to facilitate rapid development of RESTful services with dependency injection and modular configuration. It also integrates Spring Data JPA and MySQL to manage persistent fitness data through a repository-service-model structure, offering robust support for query abstraction and schema mapping. Additionally, a Flask-based API is employed as a microservice to handle specialized machine learning or analytics tasks, connected via REST communication.

3. **Frontend Composition (Android)**
   The Android client is developed using Kotlin and follows the MVVM architectural pattern. Key technologies include LiveData and ViewModel for reactive UI updates linked to underlying data changes, Room (SQLite) to provide a local storage layer for offline capabilities, and Retrofit to manage secure HTTP communication with the backend server.

4. **Database Management**
   MySQL is used as the main persistent storage system, connected via JPA and Hibernate , offering a scalable, efficient, and maintainable data access layer.

5. **Communication and Data Flow**
   Communication between the mobile client and the backend is managed through Retrofit and RESTful APIs. Requests are processed by Spring controllers, passed to service layers for business logic, and persisted or retrieved from the MySQL database.

6. **Deployment and Quality Assurance**
   Backend services and microservices are containerized using Docker to ensure consistent environment

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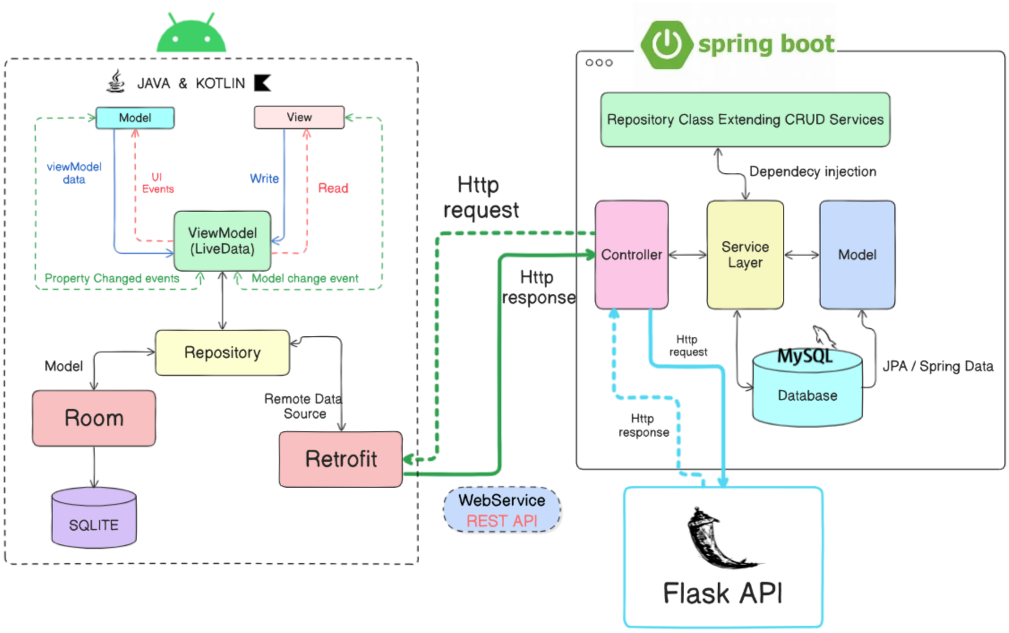


Figure 1: FitnityAI System Architecture.

configuration. CI/CD pipelines automate testing and deployment, while tools such as Postman and JUnit are used for integration and unit testing.

7. **Innovative Components**
FitnityAI integrates the Gemini API to offer conversational AI-based fitness guidance. This enables users to interact with the assistant in natural language, receive personalized recommendations, and dynamically update their goals based on context-aware understanding.

B. *Software functionalities*

FitnityAI delivers a comprehensive suite of features designed to support users throughout their fitness journey. At its core, the application provides sophisticated user management capabilities, including profile creation, goal setting, and progress tracking. Users begin by creating an account and providing essential information such as height, weight, health status, and current fitness level. This data forms the foundation for personalized recommendations and progress tracking.

The application's dashboard presents real-time tracking of various fitness metrics, including steps taken, calories burned, and overall progress toward fitness goals. A distinguished feature is the AI-powered chatbot that serves as a personal fitness assistant, providing immediate responses to user queries and offering contextualized guidance based on the user's profile and progress.

The workout tracking system includes detailed exercise logging capabilities, complete with video tutorials through YouTube integration to ensure proper form and technique. The application's recommendation system continuously analyzes user data, progress, and goals to generate personalized workout plans and necessary adjustments, ensuring optimal progression and reducing the risk of injury or burnout.

Nutrition tracking and guidance are integrated seamlessly into the application, with the AI system providing personalized dietary recommendations based on the user's fitness goals and activity levels. The BMI calculator offers insights into the user's health status, while the progress tracking features provide detailed analytics and visualizations of the user's fitness journey.

The BPMN diagram Fig. 2 illustrates the core business processes within FitnityAI, demonstrating the flow of data and interactions between different system components. The diagram shows how user inputs are processed through various services to generate personalized recommendations and track progress.

V. Illustrative Examples

To better understand how FitnityAI supports users in achieving their fitness goals, we present a series of illustrative examples showcasing its practical application. These scenarios demonstrate how the platform delivers personalized recommendations, adaptive fitness tracking, and user-friendly insights to enhance engagement and health outcomes. Furthermore, FitnityAI integrates complementary features such as real-time analytics, chatbot interactions, and progress monitoring to facilitate a

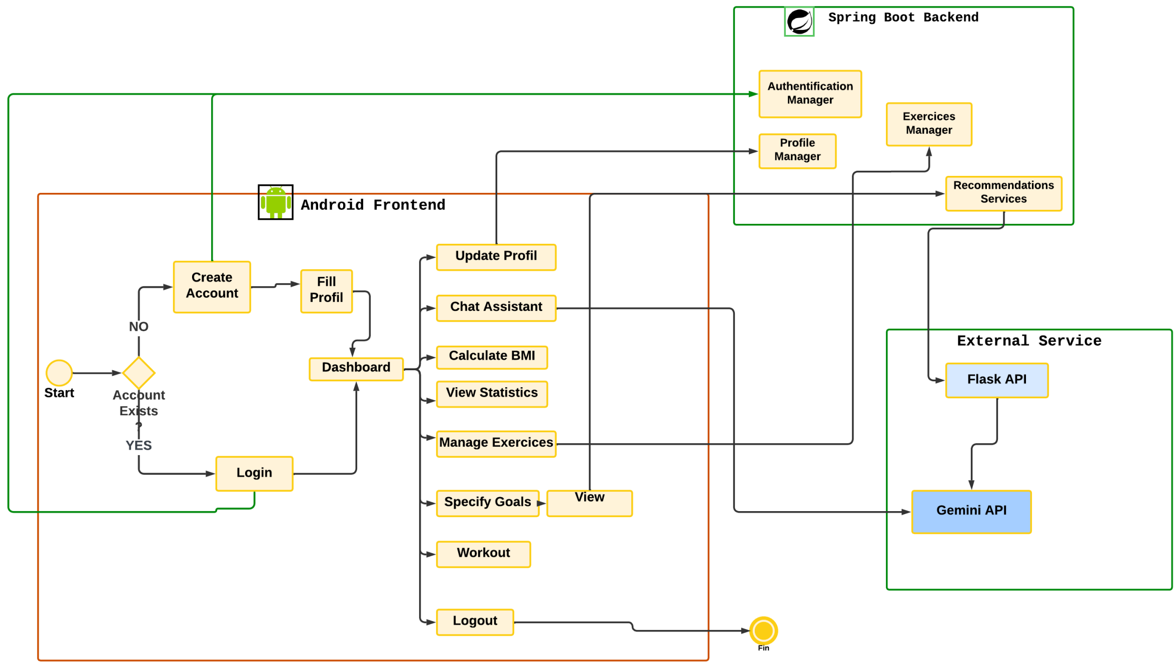


Figure 2: FitnityAI BPMN Workflow Diagram.

holistic fitness experience.

A. *Personalized Fitness Journey for a Beginner User*

Physical activity engagement can be challenging for beginners who lack structured guidance or personalized support. FitnityAI addresses these barriers by providing adaptive fitness coaching powered by AI analysis of user profiles and behaviors.

1. *Scenario 1: Salwa's Personalized Fitness Journey*

Salwa, a 28-year-old beginner, aims to lose 10 kilograms and improve his overall fitness. Upon registering, he inputs essential details, including height (180 cm), weight (85 kg), fitness level (beginner), and goal (weight loss). The FitnityAI dashboard welcomes her with an overview of daily metrics such as step counts and calories burned, along with calculated BMI indicators (see Fig. 3a).

Using the integrated AI chatbot powered by the Gemini API, Salwa queries the system about appropriate workouts for beginners. Based on his fitness profile and goals, FitnityAI suggests a personalized routine that includes light running, push-ups, and squats, complemented with links to exercise tutorials for correct form (see Fig. 3b). Progress in completed workouts is monitored through an intuitive tracking interface (see Fig. 3c).

During the following weeks, the application dynamically adjusts exercise intensity and nutrition advice based on his logged activities and progress, ensuring a gradual, sustainable path toward his goal.

B. *Administrator Dashboard for User Analytics*

In addition to the mobile user experience, FitnityAI offers an administration dashboard designed to monitor system usage, track user analytics, and manage platform health indicators. The web dashboard enables administrators to visualize distributions such as user weight categories, health conditions, and fitness levels (see Fig. 4).

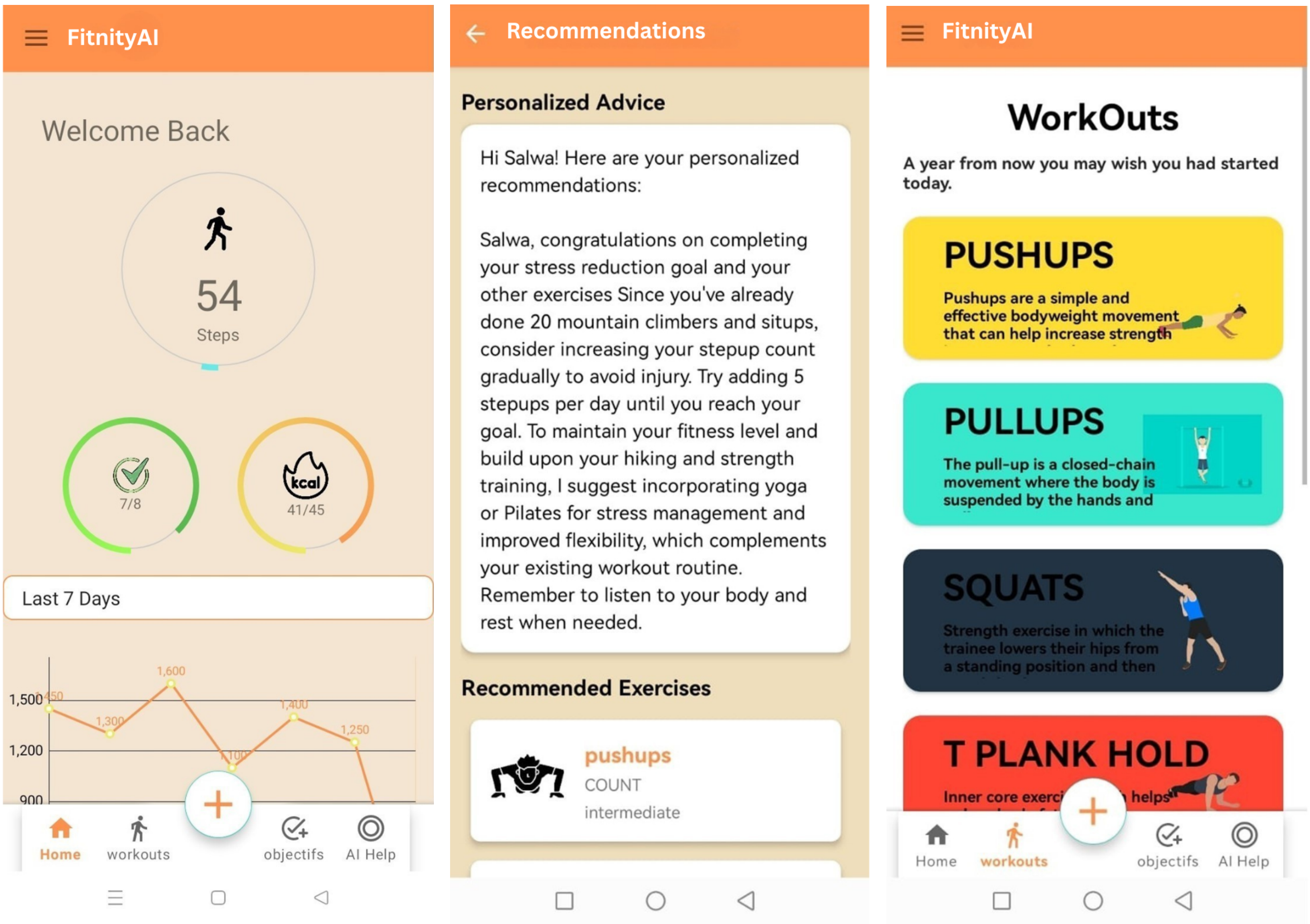
The analytics insights help platform managers identify trends, detect potential issues, and support the continuous improvement of FitnityAI's services, contributing to a better personalized experience across the user base.

VI. RESULTS

The results of the FitnityAI implementation were assessed through two complementary approaches: a comparative feature analysis and illustrative use-case scenarios.

The benchmarking table (Table 1) shows that FitnityAI outperforms several leading fitness applications in terms of AI-driven personalization, dynamic goal adaptation, and conversational capabilities. In contrast to traditional systems that rely on predefined rule sets, FitnityAI dynamically updates its recommendations based on real-time user feedback and activity logs.

In the illustrated use case, the application successfully delivered personalized workout plans, adjusted recommendations over time, and provided context-aware re-



(a) Mobile Dashboard Overview. (b) AI-Driven Recommendations. (c) Workout Tracking Interface.

Figure 3: Screenshots of the FitnityAI Mobile Application.

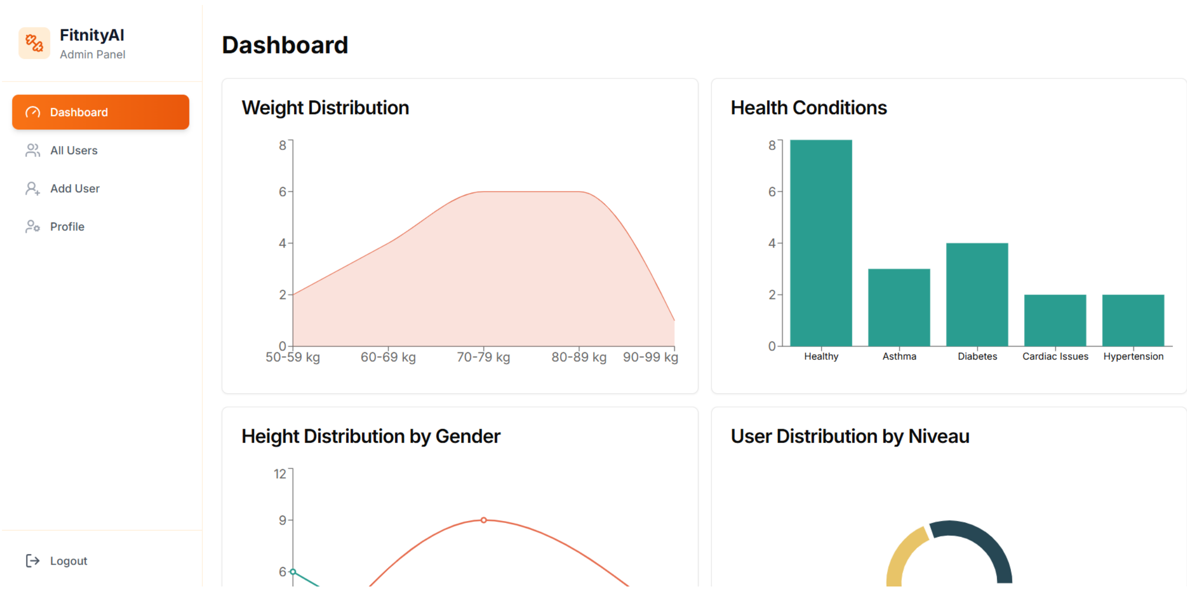


Figure 4: Web Administration Dashboard Displaying User Analytics and System Metrics.

sponses via the Gemini-powered chatbot. These results demonstrate FitnityAI's ability to act as an intelligent, adaptive assistant, guiding users through evolving fitness routines.

While no large-scale deployment was conducted, the scenarios confirm the platform's functional readiness and its potential impact on improving personalization and engagement in mobile health tracking.

VII. IMPACT

FitnityAI addresses critical challenges in personal fitness tracking by integrating real-time monitoring, AI-driven personalization, and dynamic goal adaptation. Leveraging advanced natural language processing through the Gemini API, FitnityAI enhances the personalization and adaptability of fitness programs, overcoming the limitations of traditional static applications. This architecture allows researchers and developers in digital health technologies to explore new frameworks for precision fitness interventions, behavioral modeling, and adaptive health coaching [6, 8].

Beyond its research contributions, FitnityAI transforms how individuals plan, execute, and adjust their fitness journeys. Through real-time feedback, personalized workout generation, and adaptive recommendations based on user performance, FitnityAI empowers users to maintain consistent engagement with their fitness goals. The application's proactive strategy—providing dynamic goal adjustments and human-like interaction—enables users to overcome motivational barriers, optimize their exercise routines, and adopt healthier long-term behaviors [5, 12].

Furthermore, FitnityAI's conversational AI assistant enhances accessibility by offering expert fitness advice through natural language interaction. Users can inquire about workout modifications, nutrition advice, or recovery strategies directly within the app, reducing reliance on costly personal training services. This democratization of fitness expertise ensures that even users with limited access to professional support can benefit from personalized, evidence-based guidance tailored to their individual needs.Prior reviews of AI-powered health chatbots have identified similar benefits, particularly in contexts where access to in-person coaching is limited [9]. However, ethical and reliability concerns remain a key consideration in the design and deployment of such systems [10].

On a broader scale, FitnityAI contributes to public health objectives by promoting sustainable exercise habits, reducing physical inactivity, and supporting preventive health strategies. By integrating behavior change techniques (BCTs) and maintaining real-time user engagement, FitnityAI aligns with initiatives targeting the reduction of non-communicable diseases linked to sedentary lifestyles [6, 8]. Moreover, anonymized, aggregated user data could serve future public health research initiatives and guide evidence-based policy development in digital health promotion.

Several fitness applications offer activity tracking or basic personalized guidance; however, FitnityAI differentiates itself by providing continuous adaptation and intelligent feedback throughout the user's fitness journey. As shown in Table 1, while applications like MyFitnessPal and Fitbod offer functionalities such as nutrition tracking or custom workout planning, they lack the real-time adaptability and conversational personalization capabilities implemented in FitnityAI.

Currently in its prototype deployment phase, FitnityAI is available on Android platforms, with plans for expansion to iOS and web-based environments. By combining scalable backend architecture with advanced AI-driven interaction, FitnityAI establishes a new benchmark for personalized, adaptive digital health solutions, promoting enhanced fitness engagement and sustainable long-term health improvement.

VIII. QUALITY ASSURANCE

A detailed quality assurance (QA) assessment was conducted across the Android client, Flask-based microservices, and Spring Boot backend of FitnityAI using SonarQube. The evaluation focused on key software quality metrics, including Reliability, Security, *Maintainability*, Code Duplication, and *Code Coverage*. The summary of the results is presented in Table 2.

The overall quality assessment yielded positive results, with all three components successfully passing the SonarQube Quality Gate criteria. Reliability analysis confirmed an A rating across the Android client, Flask microservice, and Spring Boot backend, indicating the absence of critical runtime issues.

Security evaluations demonstrated excellent results for the Flask API and the Spring Boot backend, both achieving an A rating with no vulnerabilities detected. However, the Android application reported a minor security issue, resulting in an E rating that should be promptly addressed to ensure full compliance with security best practices.

Maintainability ratings were consistently high, with A ratings across all components. The Android client showed a higher number of minor maintainability issues (78), while the Flask API and Spring Boot backend had only 1 and 41 minor issues respectively. Addressing these maintainability concerns will further optimize the codebase and reduce technical debt over time.

Code duplication metrics were outstanding, with a 0.0% duplication rate across all components, reflecting a clean and non-redundant code structure. However, a significant shortcoming was observed in code coverage, with all three components reporting 0.0%. This highlights a lack of automated tests, increasing the risk of undetected

Table 2: Quality assurance results for FitnityAI components.

Metric	Android Client	Flask API	Spring Boot Backend
Quality Gate Status	Passed	Passed	Passed
Reliability Rating	A (0 issues)	A (0 issues)	A (0 issues)
Security Rating	E (1 issue)	A (0 issues)	A (0 issues)
Maintainability Rating	A (78 issues)	A (1 issue)	A (41 issues)
Code Duplication	0.0%	0.0%	0.0%
Security Hotspots Reviewed	E(0.0%)	E(0.0%)	A
Coverage	0.0%	0.0%	0.0%

defects. To ensure future robustness and maintainability, it is recommended to implement a comprehensive testing strategy targeting at least 80% coverage across all modules.

Despite these challenges, the successful passing of the SonarQube Quality Gate for each component validates FitnityAI's commitment to maintaining high baseline software quality standards. Future improvements should prioritize resolving the security issue in the Android client and introducing systematic unit and integration testing to strengthen overall project reliability and scalability.

IX. DISCUSSION

FitnityAI introduces a novel approach to fitness tracking by integrating conversational AI and adaptive recommendations. Compared to existing applications that often rely on static logic or user-initialized inputs, FitnityAI dynamically interprets context and user data to provide relevant, real-time coaching. This aligns with findings from Cowan et al., who observed that many fitness apps present unrealistic or overly generic plans, underscoring the need for intelligent personalization [16].

However, several limitations remain. The current evaluation is qualitative and based on hypothetical usage scenarios. No longitudinal user studies or performance metrics have yet been conducted. Additionally, the recommendation engine could benefit from multimodal data (e.g., wearable integration) to improve contextual accuracy.

From an ethical standpoint, the system processes potentially sensitive user data. Although data is stored securely and locally in the prototype, broader deployment would require strict adherence to data protection laws and the implementation of transparent consent mechanisms.

Future iterations should focus on large-scale user testing, integrating biometric sensors, and refining privacy-preserving data practices.

X. CONCLUSIONS

FitnityAI represents a significant advancement in the domain of personalized fitness tracking, effectively merging AI-driven intelligence with practical health monitoring features. The current implementation leverages sophisticated AI algorithms and real-time data analysis to deliver highly personalized fitness guidance, offering users a uniquely tailored and engaging fitness experience.

While the application has demonstrated positive impacts on user engagement and health outcomes, further enhancements are anticipated. Key areas for future development include expanding AI capabilities to enable deeper personalization, integrating additional health and wearable platforms to create a more holistic user profile, and incorporating advanced analytics to refine the precision of fitness recommendations.

In an era where personalized health interventions are increasingly critical, tools like FitnityAI have the potential to contribute significantly to the broader digital health ecosystem. The modular and scalable architecture of the application lays a strong foundation for future enhancements, community-driven extensions, and wider adoption across diverse fitness and wellness contexts. This study highlights the promise of integrating large language models into health-focused mobile applications, offering new pathways for user engagement, dynamic feedback, and personalized behavior change at scale.

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