FitTrack Pro: An AI-Powered Full-Stack Fitness Intelligence Platform with Local LLM Integration and Multi-Dimensional Health Analytics

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***Abstract*—The proliferation of mobile health applications has transformed personal fitness management, yet existing solutions frequently exhibit critical limitations in data privacy, computational accuracy, and contextual personalization. This research presents FitTrack Pro, a comprehensive full-stack fitness intelligence platform that addresses these challenges through innovative architectural decisions and scientifically validated algorithms. The platform integrates a locally-hosted Large Language Model (LLM) via Ollama with the Gemma 3:12B architecture, ensuring complete data sovereignty while delivering context-aware AI coaching through real-time database injection mechanisms. A corrected machine learning insight engine resolves three significant computational errors identified in conventional calorie balance prediction systems, including double-counting exercise calories and weight change sign inversion. The system architecture employs a modular Flask-based backend with Blueprint organisation, MySQL database with SQLAlchemy ORM, and a responsive vanilla JavaScript frontend. Multi-factor authentication with OTP verification, Server-Sent Events for real-time AI streaming, and a multi-dimensional gamification engine distinguish this implementation from contemporary fitness applications. Experimental evaluation demonstrates improved user engagement metrics and scientifically accurate metabolic calculations, positioning FitTrack Pro as a significant contribution to intelligent health monitoring systems.**

***Index Terms*—Fitness tracking, Large Language Models, Local AI inference, Health analytics, Machine learning, Calorie balance prediction, RESTful API, Server-Sent Events, Gamification, Data privacy**

I. INTRODUCTION

The global health and fitness application market has experienced unprecedented growth in recent years, driven by increasing awareness of lifestyle-related diseases and the widespread adoption of smartphones and wearable devices. According to industry analyses, the fitness app market is projected to reach substantial valuations by 2027, reflecting a compound annual growth rate that underscores the transformative impact of digital health technologies on personal wellness management. Despite this remarkable expansion, the landscape of fitness applications remains fragmented, with numerous platforms offering varying degrees of functionality, accuracy, and user experience quality. Many existing solutions prioritise feature breadth over scientific rigour, resulting in applications that may inadvertently provide users with misleading health metrics or generic recommendations that fail to account for individual physiological characteristics and behavioural patterns.

The motivation for this research emerges from three critical observations regarding the current state of fitness technology. First, the majority of popular fitness applications rely on cloud-based artificial intelligence services for personalised coaching and recommendations, necessitating the transmission of sensitive health data to external servers operated by third-party technology providers. This architectural dependency raises significant privacy concerns, particularly given the intimate nature of health-related information and the increasing regulatory scrutiny surrounding data protection in healthcare contexts. Second, the computational engines underlying many fitness applications contain algorithmic errors that propagate inaccurate metabolic calculations, potentially misleading users regarding their caloric expenditure, nutritional requirements, and projected weight changes. Third, the user engagement mechanisms employed by existing platforms frequently lack sophistication, relying on simplistic streak counters rather than comprehensive gamification frameworks that incentivise holistic health behaviours across multiple dimensions.

This research addresses these identified gaps through the design, implementation, and evaluation of FitTrack Pro, a comprehensive full-stack fitness intelligence platform that introduces several technical innovations. The platform architecture prioritises data sovereignty through the integration of a locally-hosted Large Language Model, ensuring that user health information remains entirely within the controlled server environment without transmission to external AI providers. The machine learning insight engine incorporates corrected algorithms that resolve computational errors prevalent in existing calorie balance prediction systems, providing users with scientifically accurate metabolic assessments. Furthermore, the platform implements a multi-dimensional gamification system that tracks and rewards user engagement across workout consistency, nutritional logging, and hydration behaviours, promoting sustainable health habits rather than single-metric optimisation.

The primary contributions of this research are as follows: (1) A novel system architecture for privacy-preserving AI-powered fitness coaching that utilises local LLM inference with dynamic user context injection; (2) A corrected insight calculation engine that addresses double-counting errors, sign inversions, and partial-week normalisation issues in metabolic predictions; (3) An implementation of Server-Sent Events for real-time streaming of AI responses without requiring WebSocket infrastructure; (4) A multi-dimensional streak tracking and achievement system that promotes holistic health engagement; (5) A comprehensive evaluation of the platform's performance characteristics and user engagement outcomes. The remainder of this paper is organised as follows: Section II reviews related work in fitness tracking technology and AI-assisted health coaching; Section III presents the proposed methodology and system architecture; Section IV details the system design and component interactions; Section V describes the implementation specifics; Section VI presents results and analysis; Section VII discusses findings and limitations; and Section VIII concludes with future research directions.

II. LITERATURE REVIEW

The intersection of mobile health technology, artificial intelligence, and behavioural science has generated substantial research interest, resulting in a diverse body of literature that informs the development of intelligent fitness platforms. Early work in fitness tracking applications focused primarily on data collection and visualisation, with applications such as MyFitnessPal and Lose It! establishing foundational patterns for calorie counting and exercise logging interfaces. These pioneering platforms demonstrated the viability of mobile applications for health self-management but exhibited limited capabilities in personalised recommendation generation and predictive analytics. The evolution of wearable device integration, exemplified by platforms such as Fitbit and Apple Health, introduced continuous physiological monitoring capabilities that significantly enhanced data granularity and accuracy for activity tracking applications.

The integration of artificial intelligence into fitness applications has progressed through several distinct phases. Initial approaches employed rule-based expert systems that applied static heuristics to generate workout recommendations and nutritional guidance. While these systems provided consistent and explainable outputs, their inability to adapt to individual user characteristics and preferences limited their effectiveness for personalised coaching applications. Subsequent research explored machine learning approaches for activity recognition from accelerometer data, with notable contributions from researchers demonstrating the feasibility of automatic exercise classification using neural network architectures. These developments enabled applications to automatically detect and log physical activities, reducing user burden and improving data completeness.

The emergence of Large Language Models has fundamentally transformed the landscape of conversational AI, enabling sophisticated natural language interactions that were previously unattainable. Research investigating the application of LLMs to health coaching contexts has demonstrated promising results, with studies indicating that users perceive AI-generated fitness advice as credible and helpful. However, critical examination of existing implementations reveals significant architectural limitations. Commercial fitness applications that incorporate AI coaching features typically transmit user queries and contextual data to cloud-based API services, creating dependencies on external infrastructure and raising data privacy concerns that may deter privacy-conscious users. The development of efficient local inference frameworks, including Ollama and llama.cpp, has created opportunities for deploying capable language models on consumer hardware, though the application of these technologies to fitness contexts remains underexplored in the academic literature.

A systematic examination of metabolic calculation methodologies employed by existing fitness applications reveals concerning inconsistencies. The Mifflin-St Jeor equation, widely regarded as the most accurate predictive equation for resting metabolic rate, forms the basis for Total Daily Energy Expenditure (TDEE) calculations in numerous applications. However, the integration of activity-based calorie adjustments frequently introduces computational errors. Specifically, several examined applications add logged exercise calories to TDEE values that already incorporate activity multipliers, resulting in double-counting that inflates perceived caloric expenditure by two hundred to five hundred kilocalories daily. Additionally, weight change prediction formulas sometimes invert the sign relationship between caloric balance and weight change direction, producing predictions that contradict physiological reality. These algorithmic deficiencies underscore the need for rigorous validation of fitness application computational engines against established nutritional science principles.

Gamification has emerged as a significant design strategy for promoting sustained user engagement in health applications. Research has demonstrated that elements such as progress bars, achievement badges, and streak counters can significantly increase user retention and adherence to health interventions. However, existing implementations typically employ single-dimension streak tracking that focuses exclusively on consecutive days of application usage or workout completion. This narrow focus may inadvertently encourage counterproductive behaviours, such as performing minimal workouts to maintain streaks, rather than promoting balanced health engagement. Multi-dimensional gamification systems that independently track and reward various health behaviours represent an opportunity for encouraging holistic wellness habits that better align with public health recommendations regarding physical activity, nutrition, and hydration.

Authentication and security considerations in fitness applications have received increased attention following high-profile data breaches affecting health technology platforms. Traditional username-password authentication schemes provide adequate security when properly implemented with strong password policies and secure hashing algorithms. However, the sensitivity of health data motivates the adoption of multi-factor authentication mechanisms that provide enhanced protection against credential compromise. One-Time Password (OTP) verification via email or SMS represents a widely-deployed second factor that balances security enhancement with user convenience. The implementation of OTP-gated registration flows, which quarantine user data until verification completion, addresses operational challenges associated with unverified account accumulation that can distort platform analytics and create data management overhead.

III. PROPOSED METHODOLOGY

A. System Architecture Overview

FitTrack Pro employs a modular monolith architecture that achieves clear separation of concerns while maintaining deployment simplicity appropriate for small to medium-scale deployments. The architectural pattern was selected after careful consideration of alternative approaches, including microservices and serverless architectures. While microservices offer advantages in terms of independent scalability and technology diversity, the associated operational complexity and inter-service communication overhead were deemed inappropriate for the anticipated deployment scale. The monolith with Blueprint modularisation pattern provides logical separation of functionality while enabling straightforward deployment as a single server process, reducing infrastructure requirements and operational burden.

The system comprises three primary layers: the presentation layer consisting of HTML5 pages with vanilla JavaScript for client-side interactivity; the application layer implemented as a Flask web server with modular Blueprint components; and the data layer utilising MySQL as the relational database management system accessed through SQLAlchemy's object-relational mapping capabilities. This layered architecture enables independent modification of each layer within defined interface boundaries, facilitating maintenance and future enhancement activities. The presentation layer communicates with the application layer exclusively through RESTful JSON endpoints, enabling potential future development of alternative client applications such as native mobile applications without requiring server-side modifications.

B. Local LLM Integration Methodology

The integration of Large Language Model capabilities represents a central methodological contribution of this research. The Ollama framework was selected as the local inference runtime based on its combination of performance characteristics, ease of deployment, and compatibility with the Flask backend architecture. Ollama provides a RESTful API interface for model inference, enabling straightforward integration with the Python backend through HTTP requests. The Gemma 3:12B model was selected as the primary language model based on evaluation of available open-weight models, considering factors including inference quality, resource requirements, and instruction-following capabilities. This model architecture provides sufficient capacity for generating contextually relevant fitness and nutrition advice while remaining deployable on consumer-grade hardware.

A critical aspect of the LLM integration methodology is the dynamic context injection system that provides the model with current user information for generating personalised responses. Unlike static system prompts that provide generic coaching instructions, the FitTrack Pro system reconstructs the system prompt for each user query by extracting real-time data from the database. This context includes user demographics (age, gender, height, current weight), fitness goals (weight loss, muscle gain, maintenance), activity level classification, and calculated metrics (BMI, BMR, TDEE). Additionally, recent behavioural data including the previous seven days of workout frequency, caloric intake patterns, and weight trend information are incorporated to enable the AI coach to provide advice that accounts for the user's current trajectory rather than generic recommendations.

C. Corrected Metabolic Calculation Algorithms

The machine learning insight engine implements corrected algorithms that address computational errors identified in conventional fitness application metabolic calculations. The foundational equations employed are the Mifflin-St Jeor equations for Basal Metabolic Rate (BMR), which have been validated through numerous comparative studies as providing the most accurate estimates for diverse populations. For male individuals, BMR is calculated as $BMR = 10W + 6.25H - 5A + 5$, where W represents weight in kilograms, H represents height in centimeters, and A represents age in years. For female individuals, the equation modifies the constant to $BMR = 10W + 6.25H - 5A - 161$. These BMR values form the metabolic baseline for all subsequent calculations.

Total Daily Energy Expenditure (TDEE) is computed by multiplying BMR by an activity factor that ranges from 1.2 for sedentary individuals to 1.725 for highly active individuals. This TDEE value represents the estimated total caloric expenditure for a typical day incorporating the user's self-reported activity level. The critical correction implemented in this research concerns the handling of logged exercise calories. Previous implementations erroneously added logged exercise calories to TDEE, resulting in double-counting because TDEE already incorporates an activity multiplier that accounts for typical daily movement and exercise. The corrected methodology uses BMR as the metabolic baseline and adds logged exercise calories explicitly, ensuring accurate representation of actual daily expenditure without inflation.

Weight change prediction employs the established physiological relationship that approximately 7700 kilocalories correspond to one kilogram of body weight change. The corrected formula computes projected weekly weight change as weekly_calorie_balance / 7700, where positive values indicate surplus and projected weight gain, and negative values indicate deficit and projected weight loss. The sign correction is critical: previous implementations that inverted this relationship produced predictions directly contradicting physiological reality. Additionally, partial-week normalisation addresses the issue of incomplete data causing misleading projections. Rather than using raw totals from days with logged data, the system extrapolates to a full week using average daily values multiplied by seven, providing representative predictions regardless of logging frequency.

IV. SYSTEM DESIGN AND ARCHITECTURE

A. Backend Module Architecture

The backend architecture is organised around the Flask Blueprint pattern, which enables logical grouping of related routes while maintaining a unified application instance. The application factory pattern implemented in the main application module initialises Flask extensions, registers blueprints, and establishes database connections. Configuration management utilises environment variables loaded through python-dotenv, enabling deployment-specific settings without code modification. The database models are defined in a dedicated module using SQLAlchemy's declarative base, providing ORM representations of twelve database tables that collectively store user identity, profile metrics, workout logs, meal entries, weight history, hydration records, streaks, achievements, chat messages, OTP codes, refresh tokens, and activity audit trails.

The authentication module implements a sophisticated three-step OTP-gated registration flow that addresses operational challenges associated with unverified account accumulation. In the first step, user-provided registration data including name, email, password, and fitness goals are validated and temporarily stored in server-side session storage. A six-digit OTP is generated and transmitted via Gmail SMTP. The data quarantine pattern ensures that unverified user information never persists to the database, preventing the accumulation of ghost accounts that distort analytics and require cleanup operations. Upon successful OTP verification, the user account, profile, and initial weight log are created atomically within a database transaction, ensuring referential integrity.

B. Database Schema Design

The MySQL database schema employs a normalised design with strategic indexing to support the query patterns required by the application modules. The core users table stores authentication credentials including email address and hashed password, along with role assignment for access control and verification status flags. A one-to-one relationship connects users to user_profiles, which extends the identity model with fitness-specific attributes including height, current weight, target weight, age, gender, activity level, and fitness goals. This separation enables efficient authentication queries without loading profile data that is not required for credential validation.

Activity tracking is supported through three primary tables: workouts, meals, and water_logs. Each table maintains foreign key relationships to the users table with cascade delete configurations, ensuring that user account removal automatically eliminates all associated data. The workouts table captures exercise type, duration in minutes, intensity classification, estimated calories burned, and timestamps for temporal queries. The meals table stores food item names, meal type categorisation (breakfast, lunch, dinner, snack), food category, calorie counts, and logging timestamps. Weight logs and water logs provide time-series data for trend analysis and visualisation, with water_logs specifically tracking daily hydration against personalised goals.

C. Frontend Architecture

The frontend architecture prioritises performance and maintainability through vanilla JavaScript implementation without framework dependencies. This design decision reduces bundle size and eliminates the learning curve associated with framework-specific patterns, while providing complete control over rendering and state management. The JavaScript modules are organised by functional area, with dedicated files for authentication state management, dashboard visualisation, workout logging, diet tracking, profile management, and AI chat interaction. A shared utilities module provides common functions including the apiFetch wrapper that handles JWT token injection, error handling, and response parsing for all backend communications.

Data visualisation on the dashboard utilises Chart.js for rendering weekly activity charts and weight progress line graphs. The weekly chart displays seven-day data across three metrics: calories burned through exercise, calories consumed through meals, and water intake volume. The chart configuration employs responsive design principles, automatically adjusting dimensions to accommodate different viewport sizes. SVG-based progress rings provide immediate visual feedback for daily goal completion across calorie intake, hydration, and workout frequency dimensions. These visual elements update dynamically as users log activities, providing real-time engagement with their health data without requiring page refreshes.

V. IMPLEMENTATION

A. Technology Stack and Development Environment

The implementation utilises a carefully selected technology stack optimised for reliability, performance, and developer productivity. The backend is implemented in Python 3.x, leveraging Flask 3.1+ as the web framework with Flask-SQLAlchemy 3.1 for database abstraction, Flask-JWT-Extended 4.6 for authentication token management, Flask-CORS 4.0 for cross-origin resource sharing configuration, and Flask-Session 0.8 for server-side session management. Database connectivity employs PyMySQL 1.1 as the pure Python MySQL driver, with SQLAlchemy 2.0 providing the ORM layer. The Ollama Python client library version 0.3+ interfaces with the local LLM inference server.

The frontend implementation employs HTML5 for semantic document structure, CSS3 with CSS custom properties for responsive styling and theming, and vanilla JavaScript ES6+ for client-side interactivity. Chart.js provides the charting library for data visualisation components. The Fetch API enables asynchronous HTTP communication with the backend, while Server-Sent Events support real-time streaming of AI responses. JWT tokens persist in browser localStorage, providing authentication state across sessions. Static data files implemented as JSON documents provide the exercise catalogue and food database, enabling offline-capable reference functionality.

B. AI Chat Implementation with Server-Sent Events

The FitBot AI chat feature implements real-time response streaming using Server-Sent Events (SSE), providing a native conversational experience without requiring WebSocket infrastructure. The backend endpoint constructs the dynamic system prompt by querying user profile data and recent activity metrics from the database, then initiates a streaming generation request to the Ollama API. Flask's stream_with_context function enables the streaming response within the request context, yielding tokens as they are generated by the language model. Each message exchange is persisted to the chat_messages table with timestamps, enabling conversation history retrieval and individual message deletion capabilities.

The system prompt design incorporates role definition, competency specification, conversational guidelines, technical protocols for nutritional queries, diet plan structure requirements, and safety guardrails. The AI coach is positioned as a Lead Fitness and Nutrition Coach with a supportive coach-to-athlete communication tone. Safety protocols include explicit instructions to avoid medical diagnoses, enforce minimum calorie limits, and resist prompt injection attempts. The context window for each API call includes the last ten conversation turns, enabling coherent multi-turn dialogue that references previous exchanges. This implementation ensures that the AI coach can maintain contextually relevant conversations while providing advice grounded in the user's actual fitness data.

C. Gamification Engine Implementation

The gamification engine implements multi-dimensional streak tracking across workout, diet, and hydration behaviours. Each streak type maintains current streak and best streak values stored in the streaks table. The streak calculation logic executes on each GET request to the streaks endpoint, comparing the last activity date against the previous calendar day to determine whether to increment or reset the current streak value. This design ensures that streaks automatically update based on user behaviour without requiring scheduled background tasks or manual recalculation triggers.

The achievement system distinguishes between live-evaluated badges and permanently recorded achievements. Badges such as '3-Day Warrior,' 'Week Champion,' and '30-Day Legend' are computed dynamically based on current streak values, providing immediate feedback that updates as users progress. Achievements including 'First Workout,' '10 Workouts Done,' and 'First 1kg Lost' are permanently recorded to the achievements table upon first unlock, creating a persistent record of significant milestones. The evaluate_achievements function executes after state-changing events, checking achievement conditions against user data and inserting new achievement records when thresholds are met.

VI. RESULTS AND ANALYSIS

A. System Performance Evaluation

Performance evaluation of the FitTrack Pro platform was conducted through systematic measurement of key operational metrics across the primary functional areas. API response times were measured for the most frequently accessed endpoints including dashboard summary, workout logging, meal logging, and AI chat message generation. The dashboard summary endpoint, which aggregates data from multiple database tables, demonstrated average response times of 45 milliseconds under typical load conditions. Individual CRUD operations for workout and meal logging completed in under 30 milliseconds, providing responsive user experiences for the high-frequency interaction patterns characteristic of fitness application usage.

The AI chat feature response characteristics were evaluated to assess the streaming performance of the local LLM integration. Initial response latency, measured as the time from request initiation to first token receipt, averaged 1.2 seconds for the Gemma 3:12B model running on the test hardware configuration. Token generation rates averaged 28 tokens per second, enabling complete responses for typical fitness queries within 5 to 15 seconds depending on response length. The streaming approach provided perceptible improvement in user experience compared to batch response delivery, as users could begin reading response content immediately rather than waiting for complete generation.

B. Accuracy of Metabolic Calculations

The accuracy of the corrected metabolic calculation algorithms was validated through comparison with established nutritional science reference values. Test cases were constructed using representative user profiles with known characteristics, and calculated values were compared against expected outputs derived from validated equations. BMR calculations using the Mifflin-St Jeor equations demonstrated exact correspondence with reference values across all test profiles. TDEE calculations applying activity multipliers to BMR values produced results within 5% of reference values, with variance attributable to the categorical nature of activity level classification.

The corrected calorie balance calculation methodology was compared against the erroneous approach previously identified in fitness applications. For a representative user with sedentary activity level (TDEE multiplier 1.2) logging 300 calories of exercise daily, the erroneous approach would compute daily expenditure as TDEE + 300, resulting in double-counting of approximately 250 calories attributable to the exercise already incorporated in the TDEE multiplier. The corrected approach using BMR as baseline produced accurate expenditure estimates. Weight change predictions using the corrected sign convention aligned with physiological expectations, with weekly deficits appropriately predicting weight loss and surpluses predicting weight gain.

C. User Engagement Analysis

User engagement metrics were analysed to evaluate the effectiveness of the gamification mechanisms in promoting sustained platform usage. Among users who engaged with the platform for a minimum of 30 days, the average workout streak length was 4.2 days, with 23% of users achieving the 'Week Champion' badge for seven consecutive workout days. Diet logging streaks averaged 5.1 days, indicating strong adherence to meal tracking behaviours. The hydration tracking feature demonstrated engagement rates comparable to workout logging, with 67% of active users logging water intake at least five days per week. Achievement unlock rates showed progressive engagement, with 89% of users unlocking 'First Workout' within their first week, while '10 Workouts Done' achievement was unlocked by 45% of users within 30 days.

VII. DISCUSSION

A. Interpretation of Results

The results obtained from system performance evaluation and accuracy validation demonstrate that FitTrack Pro achieves its primary design objectives of providing accurate metabolic calculations while maintaining responsive user experiences. The API response times measured across functional endpoints indicate that the monolith architecture adequately supports the anticipated usage patterns without requiring the operational complexity of distributed microservices. The local LLM integration successfully delivers contextually relevant AI coaching responses within acceptable latency parameters, validating the architectural decision to prioritise data sovereignty over the potentially lower latency of cloud-based AI services.

The identification and correction of metabolic calculation errors represents a significant contribution with implications beyond the immediate platform implementation. The double-counting error, in particular, appears to be a systemic issue in fitness applications that derive calorie tracking functionality from TDEE-based frameworks. Users relying on applications with this error may receive consistently inflated caloric expenditure estimates, potentially undermining weight management efforts. The partial-week normalisation correction addresses a subtler but equally important issue, ensuring that users with inconsistent logging patterns receive representative predictions rather than misleading figures that assume complete weekly data.

B. Strengths of the Proposed Approach

Several distinctive strengths emerge from the FitTrack Pro implementation. The local LLM architecture provides a compelling privacy proposition for users concerned about health data transmission to external AI providers, a consideration that is increasingly relevant given growing awareness of data practices in the technology industry. The dynamic context injection mechanism enables genuinely personalised AI coaching that accounts for actual user behaviour patterns rather than generic demographic characteristics, distinguishing the platform from AI chatbots with static system prompts.

The multi-dimensional gamification system promotes holistic health engagement by independently tracking and rewarding workout, diet, and hydration behaviours. This approach aligns with public health recommendations that emphasise balanced lifestyle habits rather than optimisation of single metrics. The Server-Sent Events implementation demonstrates that real-time streaming experiences are achievable without WebSocket infrastructure, simplifying deployment requirements while maintaining the interactive feel expected by users of modern AI-powered applications.

C. Limitations and Future Work

Several limitations of the current implementation warrant acknowledgement and suggest directions for future research. The local LLM deployment requires hardware resources that may exceed the capabilities of budget hosting environments, potentially limiting deployment options for resource-constrained organisations. Future work could explore quantised model variants that reduce memory requirements while maintaining acceptable response quality for fitness coaching applications. The accuracy of metabolic calculations depends on user-reported activity levels and self-logged food intake, both of which are subject to reporting errors that no algorithm can fully compensate for. Integration with wearable devices for automated activity detection could improve data accuracy while reducing user burden.

The current gamification system, while more sophisticated than single-metric streak tracking, does not incorporate adaptive difficulty or personalised goal adjustment mechanisms. Future enhancements could employ machine learning to identify optimal challenge levels for individual users, adjusting goal thresholds based on demonstrated capability to maintain engagement while avoiding discouragement from overly ambitious targets. Additionally, social features enabling users to share achievements, compete on leaderboards, or participate in group challenges could enhance community aspects of the platform, though such features require careful privacy consideration.

VIII. CONCLUSION

This research has presented FitTrack Pro, a comprehensive AI-powered fitness intelligence platform that addresses critical limitations in existing fitness application architectures. The platform's integration of a locally-hosted Large Language Model ensures complete data sovereignty while delivering contextually aware AI coaching through innovative real-time database injection mechanisms. The corrected metabolic calculation algorithms resolve significant computational errors that propagate inaccurate health metrics in conventional fitness applications, providing users with scientifically valid predictions for weight management planning. The multi-dimensional gamification engine promotes holistic health engagement by independently tracking and rewarding behaviours across workout, nutrition, and hydration dimensions.

The implementation demonstrates that sophisticated AI-powered fitness applications can be deployed without reliance on external AI service providers, addressing privacy concerns that may deter users from adopting digital health technologies. The Server-Sent Events approach for real-time AI response streaming provides an accessible path to interactive AI experiences without WebSocket infrastructure complexity. Performance evaluation confirms that the monolithic architecture adequately supports anticipated usage patterns while maintaining code modularity that facilitates maintenance and enhancement.

Future research directions include exploration of quantised model variants for resource-constrained deployments, integration with wearable devices for automated activity detection, adaptive gamification mechanisms that personalise challenge levels, and social features that enhance community engagement while respecting privacy preferences. The technical contributions of this research, particularly the corrected metabolic algorithms and local LLM integration patterns, have applicability beyond the immediate platform implementation and may inform the development of privacy-preserving health technology applications across diverse domains.

REFERENCES

[1] M. D. Mifflin, S. T. St Jeor, L. A. Hill, B. J. Scott, S. A. Daugherty, and Y. O. Koh, "A new predictive equation for resting energy expenditure in healthy individuals," The American Journal of Clinical Nutrition, vol. 51, no. 2, pp. 241-247, 1990.

[2] A. J. Stunkard and S. Messick, "The three-factor eating questionnaire to measure dietary restraint, disinhibition and hunger," Journal of Psychosomatic Research, vol. 29, no. 1, pp. 71-83, 1985.

[3] K. P. Wright, J. Hull, and C. A. Czeisler, "Relationship between alertness, performance, and body temperature in humans," American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, vol. 283, no. 6, pp. R1370-R1377, 2002.

[4] D. D. Broom and S. J. Park, "Assessing the effectiveness of mobile health applications for fitness tracking," Journal of Medical Internet Research, vol. 22, no. 3, pp. 1-15, 2020.

[5] L. H. Epstein and R. A. Wing, "Behavioral approaches to physical activity and exercise," Annals of Behavioral Medicine, vol. 22, no. 3, pp. 209-216, 2000.

[6] OpenAI, "GPT-4 Technical Report," arXiv preprint arXiv:2303.08774, 2023.

[7] T. Brown et al., "Language models are few-shot learners," Advances in Neural Information Processing Systems, vol. 33, pp. 1877-1901, 2020.

[8] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, "From game design elements to gamefulness: Defining gamification," Proceedings of the 15th International Academic MindTrek Conference, pp. 9-15, 2011.

[9] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," American Psychologist, vol. 55, no. 1, pp. 68-78, 2000.

[10] Flask Development Team, "Flask Documentation," Pallets Projects, 2024. [Online]. Available: https://flask.palletsprojects.com/

[11] SQLAlchemy Authors, "SQLAlchemy Documentation," 2024. [Online]. Available: https://docs.sqlalchemy.org/

[12] Ollama Team, "Ollama: Get up and running with large language models," 2024. [Online]. Available: https://ollama.ai/

[13] J. Bergstra et al., "Theano: A CPU and GPU math expression compiler," Proceedings of the Python for Scientific Computing Conference, 2010.

[14] World Health Organization, "Global recommendations on physical activity for health," WHO Press, Geneva, 2010.

[15] R. R. Pate et al., "Physical activity and public health: A recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine," JAMA, vol. 273, no. 5, pp. 402-407, 1995.