Sunno Fitness: A Fitness Coaching Platform Using Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring

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ABSTRACT

The integration of digital tools into fitness coaching has become increasingly important for delivering personalized and data-informed guidance. Despite this need, many practitioners continue to rely on manual tracking or costly body composition devices that lack seamless data integration. This study developed Sunno Fitness, a web-based coaching platform that combines a custom Bluetooth-enabled digital skinfold caliper with the Isolation Forest algorithm to support data-driven performance monitoring. The project employed a Developmental Research Design guided by Agile methodology. The hardware system incorporated an ESP32 microcontroller and an AS5047P magnetic rotary sensor to digitize skinfold measurements, while the software platform automated the Jackson–Pollock 3-site method and analyzed client progress. System validation was conducted through a two-phase testing procedure involving 31 participants. Results showed that the digital skinfold caliper achieved high precision, with a negligible mean difference of –0.01 mm and a percent error of 2.15% relative to a manual caliper. Automated body fat computation demonstrated strong agreement with manual calculations, reflected by a 0.01 percentage point mean difference and a 1.21% error rate. Higher variance observed when compared to Bioelectrical Impedance Analysis (21.87% error) was attributed to inherent methodological differences rather than hardware limitations. The machine learning component, validated using four health-related proxy datasets, effectively detected anomalies and distinguished long-term trends from data noise. Additionally, the web platform demonstrated reliable performance, achieving a 100% notification delivery rate with an average latency of under 1.5 seconds. Overall, Sunno Fitness offers a validated, cost-effective solution that integrates accurate body composition assessment with intelligent, real-time monitoring to enhance modern fitness coaching.

INTRODUCTION

Background of the Study

Over the past two decades, the fitness industry has transformed from a niche pursuit into a mainstream global phenomenon. Individuals increasingly prioritize physical activity not only for aesthetic goals but also for overall health improvement and the prevention of lifestyle-related diseases. This shift has been accelerated by the rise of fitness influencers, online training programs, and mobile applications that make health and wellness resources more accessible. As a result, the demand for personalized guidance and consistent support from qualified fitness professionals has grown significantly.

At the center of this movement are fitness coaches, who play a vital role in helping clients achieve goals such as weight loss, muscle gain, and general wellness. Gabay and Oravitan (2022) reported that structured support from a qualified trainer can improve program adherence by up to 30% compared to self-guided routines. However, the effectiveness of this support depends on accurate and timely tracking of client progress, which remains a challenge due to outdated monitoring methods. McGuigan et al. (2020) found that many coaches still rely on manual logs or basic spreadsheets, which are prone to errors and delays. Mason et al. (2020) emphasized that immediate, data-informed feedback enhances performance, highlighting the need for efficient digital tracking tools.

Among body composition assessment methods, skinfold calipers remain a practical and widely used option, particularly with the Jackson Pollock 3-site method, which offers a margin of error ranging from 3.4% to 3.9% (Escamilla et al., 2024). More advanced devices such as the InBody 770 provide detailed analyses but are often expensive and require complex software. In contrast, traditional analog calipers are more affordable but require manual calibration and can produce inconsistent results, especially when used by beginners who may generate errors of up to 7.5% (Cintra-Andrade et al., 2023). These limitations highlight the need for a solution that balances accuracy with accessibility.

Emerging technologies are beginning to address this gap. Internet of Things devices, including Bluetooth-enabled sensors, enable real-time collection and wireless transmission of health data (Rakshit et al., 2022). When combined with machine learning algorithms such as Isolation Forest, these data streams can be analyzed to detect irregular patterns and generate recommendations (Kareem and Muhammed, 2024). Web-based platforms support this ecosystem by offering visual tools such as dashboards and progress graphs that enhance engagement. Huang (2022) reported that clients are 40% more likely to stay consistent when they can visually track progress.

To address these challenges, this study introduces Sunno Fitness, a web-based coaching platform that integrates a custom Bluetooth-enabled digital skinfold caliper with data analytics. The device, powered by an ESP32 microcontroller and an AS5047P magnetic rotary sensor, measures skinfold thickness at three anatomical sites. For males, these include the chest, abdomen, and thigh, while for females, the triceps, suprailiac, and thigh are used in line with the Jackson Pollock method. Measurement data is transmitted wirelessly to a dashboard, where body fat percentage is automatically calculated and stored in each client profile.

The platform replaces manual tracking with features such as interactive progress graphs, in-app coach and client messaging, and shared goal setting, which support improved engagement (Huang, 2022). In addition, the system uses the Isolation Forest algorithm to detect anomalies in client data and provide coaches with insights without extensive manual review. By integrating accurate measurement hardware, real-time tracking, and analytics, Sunno Fitness aims to improve the efficiency of modern fitness coaching.

Statement of the Problem

The study addresses the absence of an integrated, data-driven fitness platform that connects a digital skinfold caliper with a web-based system to automate accurate body fat measurement and provide intelligent progress tracking for coaches and clients. Specifically, it seeks to answer the following questions:

1. How can a digital skinfold caliper be developed to deliver accurate and reliable body fat measurements that integrate seamlessly with a digital platform for real-time progress tracking?

2. How can machine learning algorithms be utilized to analyze client data and generate clear, personalized insights that support coaches in making informed decisions without requiring manual review of extensive client histories?

3. How can an effective web-based platform be designed for coaches and clients that enables seamless progress tracking, data visualization, and communication while maintaining usability and accessibility?

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Objective of the Study

General Objective

To develop a web-based fitness coaching platform that integrates a digital skinfold caliper and applies machine learning techniques to ensure accurate body composition tracking and generate data-driven, personalized fitness insights for coaches and clients.

Specific Objectives

1. To design and develop a prototype digital skinfold caliper that accurately measures body fat percentage and syncs with a web platform for real-time data integration, ensuring simplicity and reliability.
2. To integrate machine learning algorithms that analyze client data and generate clear, personalized insights on a web platform, enabling coaches to make effective and informed decisions for goals such as weight loss or muscle gain.
3. To design and develop a web-based platform that allows coaches and clients to track progress, visualize data from digital skinfold caliper measurements, and communicate effectively, ensuring efficiency and usability.

Significance of the Study

Sunno Fitness presents an innovative approach to fitness monitoring by integrating a digital skinfold caliper with a web-based coaching platform powered by machine learning. The system is designed to enhance accuracy, accessibility, and data-driven decision-making in the tracking of body composition and fitness progress. Its significance extends to the following stakeholders:

1. **Fitness Coaches**: The system streamlines the measurement and recording of body fat through an automated digital skinfold caliper, reducing manual errors and saving valuable time. It also provides coaches with data-driven insights, enabling them to design personalized fitness and nutrition programs grounded in objective client data rather than subjective assessment.
2. **Clients**: Sunno Fitness empowers clients to conveniently monitor their body composition and overall progress through the web platform. Interactive visualizations and goal-tracking features foster consistency, motivation, and a deeper understanding of personal fitness trends over time.
3. **Fitness Industry**: This study introduces an IoT- and machine learning–based solution that modernizes conventional fitness tracking methods. The integration of precise hardware components with intelligent data analysis enhances the efficiency and reliability of fitness monitoring, contributing to the ongoing digital transformation of the fitness sector.
4. **Researchers and Developers**: This study serves as a reference for future innovations in health and fitness technology. It demonstrates how hardware sensors, web-based systems, and machine learning algorithms can be effectively integrated to advance data-driven fitness applications and deepen the understanding of human performance analytics.

Scope and Limitations

Scope

This study encompasses the development of Sunno Fitness, a web-based fitness tracking and coaching system designed to support independent fitness coaches and their clients. The platform integrates workout tracking, nutrition logging, progress monitoring, and coach–client communication into a unified system that addresses the need for an accessible and organized digital coaching tool.

A central component of the system is the digital skinfold caliper, developed using an ESP32 microcontroller and the AS5047P magnetic rotary position sensor. This device enables coaches to measure body fat percentage with improved precision and reduced manual error using the Jackson–Pollock 3-site method. For male clients, the device captures skinfold readings from the chest, abdomen, and thigh; for female clients, measurements are taken from the triceps, suprailiac, and thigh. These data points are transmitted wirelessly from the caliper to the web application, where they are securely stored and integrated into each client's digital profile.

The system further incorporates the Isolation Forest algorithm to generate data-driven insights by evaluating client progress data for trends and irregularities. This enables coaches to make informed adjustments to training or nutrition programs based on objective evidence. An activity calendar and progress logging module complement these features by allowing users to track workouts, rest days, and key milestones such as scheduled body fat reassessments.

System validation was conducted through multiple procedures. The digital caliper's precision and accuracy were assessed by comparing its measurements against a standard manual caliper and a Bioelectrical Impedance Analysis (BIA) device. The machine learning module was evaluated using confusion matrices generated from health-related proxy datasets. The web platform's reliability was assessed through latency testing focused on notification delivery performance.

Limitations

Several limitations should be acknowledged in interpreting the findings of this study:

The digital skinfold caliper may exhibit reduced accuracy when used on obese individuals, as excessive subcutaneous fat can make it difficult to obtain consistent skinfold measurements (Sousa et al., 2025). Additionally, the Jackson–Pollock 3-site method is designed primarily for individuals within a general fitness range and may not yield equivalent accuracy for populations with extreme body compositions.

Due to the limited operational availability of the InBody BIA equipment, the comparative validation against this device was conducted on a reduced subset of participants (n = 10). However, this comparison served solely as a supplementary benchmark against a different class of technology. The primary validation — the comparison with the standard manual caliper — was conducted across the full participant cohort (n = 31).

Accurate skinfold measurement requires trained professionals who can precisely identify anatomical sites and apply consistent pressure. The caliper's hardware component is therefore intended as a supporting tool for fitness coaches, not for unsupervised client use. Without proper technique, data reliability may be compromised regardless of the device's precision.

The Isolation Forest algorithm requires approximately 12 to 14 days of accumulated client data before generating accurate and meaningful outputs. During this initial period, the quality and reliability of data-driven insights may be limited.

The system is designed exclusively as a fitness and progress-tracking platform. It does not provide diagnostic or therapeutic functions and should not be relied upon for medical decision-making.

Because live longitudinal client data was not yet available at the time of validation, the machine learning component was tested using publicly available proxy datasets that simulate realistic fitness and lifestyle patterns. While these datasets enabled a controlled assessment of the algorithm's capabilities, validation with real client data over extended periods would further strengthen the system's credibility and is recommended for future work.

Definition of Terms

To ensure a clear and common understanding of the concepts used in this study, the following terms are defined operationally and conceptually. These definitions provide specific context for the technical hardware, machine learning algorithms, and fitness metrics integrated into the Sunno Fitness system.

Anomaly Detection	The process of identifying data points that deviate significantly from the majority of the data. In this study, it refers to the capability of the machine

	learning algorithm to flag irregular patterns in a client's workout consistency, nutrition logs, or body composition trends.
AS5047P Sensor	A high-resolution magnetic rotary position sensor. In this project, it is the hardware component integrated into the digital caliper that detects the angle of the caliper jaws to precisely calculate the thickness of the skinfold in millimeters.
Bioelectrical Impedance Analysis (BIA)	A method for estimating body composition that works by sending a weak, imperceptible electrical current through the body to measure resistance. In this study, BIA (specifically the InBody device) serves as a secondary validation tool to benchmark the accuracy of the digital skinfold caliper.
Body Composition	The breakdown of the body's core components, specifically fat mass and fat-free mass (muscle, bone, and water). This study focuses on tracking changes in these components to assess fitness progress.
Confusion Matrix	A specific table layout that allows visualization of the performance of a machine learning algorithm. In this study, it is used to statistically evaluate how accurately the Isolation Forest algorithm classifies client progress trends (e.g., improving, plateauing, or regressing).
Data-Driven Insights	Actionable feedback and recommendations generated by the system based on the analysis of objective data. Unlike general advice, these insights are derived specifically from the client's logged activities and caliper measurements.
Digital Skinfold Caliper	The custom hardware device developed in this study. It is an electronic instrument powered by an ESP32 microcontroller that measures subcutaneous fat thickness and automatically transmits the data to the web platform via Bluetooth.
ESP32 Microcontroller	A low-cost, low-power system on a chip (SoC) with integrated Wi-Fi and dual-mode Bluetooth capabilities. It serves as the "brain" of the digital caliper, responsible for processing sensor data and managing wireless communication with the web application.
Internet of Things (IoT)	A network of physical objects embedded with sensors and software for the purpose of connecting and exchanging data. In this study, it refers to the ecosystem where the physical digital caliper communicates wirelessly with the web-based software platform.
Isolation Forest Algorithm	An unsupervised machine learning algorithm specifically designed for anomaly detection. It functions by isolating observations; in this system, it is used to analyze client data to detect outliers (anomalies) and identify meaningful trends in fitness progress.
Jackson-Pollock 3-Site Method	A standardized anthropometric formula used to estimate body density and body fat percentage. It requires skinfold measurements at three specific anatomical sites: the chest, abdomen, and thigh for males; and the triceps, suprailiac, and thigh for females.

REVIEW OF RELATED LITERATURE

This chapter presents a review of existing literature and studies that inform the development of the Sunno Fitness system. It explores key areas including body fat measurement using skinfold calipers, progress tracking and client engagement in digital fitness platforms, applications of machine learning for anomaly detection, and the integration of IoT technologies in health and fitness systems. The discussion identifies current practices, technological advancements, and research gaps that support the design rationale and overall relevance of the proposed system.

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Related Literature

Coaching Support, Progress Monitoring, and Feedback in Fitness

Long-term adherence to fitness programs depends not only on personal motivation but also on the quality and structure of available support systems. Gabay and Oravitan (2022) conducted a narrative review of 19 peer-reviewed studies and found that structured support from fitness professionals can boost adherence rates by up to 30% compared to self-guided routines. However, they also emphasized that the effectiveness of professional guidance relies heavily on accurate progress monitoring — without reliable data, even well-designed programs may fail to sustain client engagement.

Despite this recognized need for data accuracy, many coaches continue to rely on outdated tracking methods. McGuigan et al. (2020) reported that 65% of coaches still use pen-and-paper logs or basic spreadsheets, which are prone to human error and often delay feedback delivery. While tools such as heart rate monitors and sprint tests are commonly adopted for their convenience, more advanced biochemical tools remain confined to laboratory settings. This practical gap — where coaches favor ease of use over measurement precision — highlights the need for digital systems that offer both usability and accuracy.

The importance of timely, individualized feedback is further supported by Mason, Farrow, and Hattie (2020), who interviewed eight elite team sport coaches and identified feedback as serving multiple functions: enhancing performance, building athlete confidence, and facilitating progress tracking. Coaches emphasized the need to tailor feedback based on individual athlete responses and learning preferences, reinforcing the value of responsive, data-informed communication tools in modern coaching practice.

While the literature establishes that structured coaching support and timely feedback are critical for adherence, most practitioners still lack affordable digital tools that integrate accurate measurement with real-time, personalized communication. Sunno Fitness addresses this gap by combining automated body composition assessment with interactive dashboards and in-app messaging, enabling data-informed feedback loops between coaches and clients.

Body Fat Assessment Methods and Skinfold Caliper Technology

Accurate body composition assessment is foundational to effective fitness programming. Escamilla et al. (2024) compared four practical methods for estimating body fat percentage — Bioelectrical Impedance Analysis (BIA), Body Mass Index (BMI), abdominal and hip circumference (CIR), and skinfold measurements (SF) — across 180 healthy participants stratified by age and sex. Their findings revealed that accuracy varied significantly across demographic groups: skinfold calipers emerged as the most accurate method for young and middle-aged females, while CIR and BMI were more reliable for older males. Despite its simplicity and affordability, skinfold testing performed competitively, confirming its suitability for both fitness and clinical applications.

Table 2.1 Comparative Accuracy of Body Fat Assessment Methods by Age and Sex Group

Group	BIA (%BF)	BMI (%BF)	CIR (%BF)	Skinfold (%BF)	Most Accurate	Least Accurate
Young Males	15.7 ± 4.7	19.6 ± 3.2	17.3 ± 3.5	12.1 ± 4.1	CIR	BMI, SF
Middle – aged Males	18.3 ± 5.7	22.8 ± 3.6	19.6 ± 3.6	15.6 ± 4.5	CIR	BMI
Older Males	24.4 ± 6.5	25.8 ± 3.3	24.0 ± 4.5	20.0 ± 4.1	CIR, BMI	SF
Young Females	24.9 ± 6.9	28.9 ± 4.1	29.4 ± 4.6	22.4 ± 6.3	SF	BMI, CIR
Middle – aged Females	25.1 ± 7.0	31.4 ± 4.7	33.0 ± 4.5	25.0 ± 4.5	SF	BMI, CIR
Older Females	35.1 ± 6.3	35.5 ± 4.3	38.4 ± 4.8	26.4 ± 3.7	BMI	SF

The practical value of skinfold assessment depends heavily on instrument quality and operator technique. Cintra-Andrade et al. (2023) evaluated the structural, mechanical, and functional differences among the three most

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commonly used skinfold calipers — Harpenden, Lange, and Slim Guide — and found that these instruments are not interchangeable due to variations in jaw surface area, spring tension, and pressure characteristics. The authors proposed a new static downward calibration test and the first eligibility flowchart for skinfold calipers, highlighting the need for standardization in device selection and use.

Operator expertise further influences measurement reliability. Machado et al. (2024) compared skinfold measurements between an expert anthropometrist and a novice across eight anatomical sites on 25 male participants. While expert measurements maintained a technical error of measurement (TEM) below the acceptable 5% threshold, novice readings exceeded acceptable limits at several sites — in some cases producing body fat estimates over 55% higher than expert values. This finding underscores the critical role of training and standardization in body composition assessment.

Regarding measurement protocols, Elsey et al. (2021) compared the Jackson–Pollock 3-site and 7-site methods using a BodyMetrix™ A-mode ultrasound device on 40 NCAA Division II female athletes. The 3-site method yielded significantly lower body fat estimates (23.21 ± 3.61%) than the 7-site method (25.75 ± 4.39%, $p < 0.001$), while requiring approximately two minutes less per assessment. This finding supports the 3-site protocol as a time-efficient yet reliable alternative for regular body composition monitoring.

Table 2.2 Comparison of Jackson-Pollock 3-Site and 7-Site Methods

Parameter	**3-Site Method**	**7-Site Method**
Measurement Points	3 sites	7 sites
Average Body Fat % (Mean ± SD)	23.21 ± 3.61	25.80 ± 4.45
Statistical Difference (p)	$p < 0.001$ (vs 7-site)	Reference
Time Required	~2 min 15 sec	~4 min 0 sec

Existing literature confirms that skinfold calipers are accurate and cost-effective, but their reliability is compromised by instrument variability and operator skill. The Sunno Fitness digital caliper addresses both issues by integrating a high-resolution magnetic rotary sensor (AS5047P) for precise, automated measurement capture, and by digitizing the computation process to eliminate manual calculation errors — thereby reducing the operator dependency that Machado et al. (2024) identified as a key source of inconsistency.

IoT Technologies and Real-Time Health Monitoring

The integration of IoT technologies into health and fitness systems has enabled real-time data collection and remote monitoring capabilities that were previously limited to clinical settings. Rakshit et al. (2022) explored the application of IoT-enabled devices in personalized health and fitness monitoring, highlighting how connected sensors and wearables facilitate efficient metric tracking, automated feedback, and tailored interventions. Their conceptual analysis validated the potential of wireless data transmission technologies to foster data-driven, self-reliant monitoring systems.

Several studies have demonstrated the practical viability of ESP32-based systems for real-time data acquisition in health-related applications. Rao et al. (2021) developed an ESP32-based water quality monitoring system using the Blynk platform, achieving measurements closely aligned with World Health Organization standards. Chen et al. (2022) created an intelligent fitness system that combined ESP32 sensor data with monocular camera–based posture estimation to provide real-time corrective feedback during exercise. Wu, Zhai, and Zhou (2024) implemented an ESP32-based university sports testing system that measured athletic performance metrics — including heart rate, blood oxygen saturation, and endurance measures — with errors maintained within 5%. Pawar et al. (2024) further demonstrated the ESP32's suitability for remote health monitoring by developing a prototype that captured heart rate and oxygen saturation data using photoplethysmography sensors and transmitted results to the Blynk cloud platform.

Across these studies, the ESP32 microcontroller consistently demonstrated reliability, cost-effectiveness, and versatility for real-time sensor data acquisition and wireless transmission. However, none of these systems specifically addressed the domain of body composition measurement or integrated skinfold caliper technology with a web-based coaching platform.

While ESP32-based health monitoring systems have been validated across multiple domains, no existing implementation applies this technology to digitize skinfold caliper measurements for fitness coaching. Sunno Fitness extends the demonstrated capabilities of ESP32-based IoT systems into the body composition assessment domain, enabling wireless transmission of skinfold data to a centralized web platform for automated computation and longitudinal tracking.

Machine Learning for Anomaly Detection in Health and Fitness Data

With the increasing volume of continuous data generated in fitness and health environments, the ability to detect anomalies in real time has become essential for delivering meaningful and accurate insights. Several studies have evaluated the effectiveness of anomaly detection algorithms, with Isolation Forest consistently emerging as a strong candidate for health-related applications.

Kareem and Muhammed (2024) discussed the challenges of anomaly detection in streaming high-dimensional data and highlighted Isolation Forest as a robust method due to its minimal distributional assumptions, effectiveness in identifying rare patterns, and linear time complexity — properties that make it well-suited for real-time fitness tracking applications. Agyemang (2024) compared five unsupervised algorithms on a synthetic dataset and found that Isolation Forest achieved the best balance between precision and recall among all tested methods, including One-Class SVM and Local Outlier Factor.

Table 2.3 Model performance of the unsupervised anomaly detection algorithms.

Model	Accuracy	Precision (Outliers)	Recall (Outliers)	F1 score (Outliers)
One-Class SVM	90.91%	50.00%	100.00%	66.67%
One-Class SVM with SGD	91.36%	100.00%	5.00%	9.52%
Isolation Forest	90.45%	78.72%	95.00%	64.41%
Local Outlier Factor	82.73%	9.09%	10.00%	9.52%
Robust Covariance	90.91%	50.00%	100.00%	66.67%

The performance of Isolation Forest variants has been further investigated in the literature. Tabassum et al. (2024) tested several variants — including SVM-based, Decision Tree–based, and Random Forest–based Isolation Forests — for detecting anomalies in electronic health records. The SVM-based variant achieved the highest accuracy (99.21%), sensitivity (99.75%), and F1 score (98.72%), demonstrating the potential for enhanced performance through hybrid approaches.

Table 2.4 Comparison of Isolation Forest Variants for Anomaly Detection

Model Variant	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
Isolation Forest SVM	99.21	99.75	99.32	98.72

Isolation Forest Decision Tree	98.92	Not reported	Not reported	99.35
Isolation Forest Random Forest	Not reported	Not reported	72.84	Not reported

Hariri, Kind, and Brunner (2019) introduced the Extended Isolation Forest (EIF), which addresses biased anomaly scores caused by axis-aligned splits in the standard algorithm by allowing hyperplanes with random slopes during the tree-splitting process. Their evaluation demonstrated improved consistency without compromising computational efficiency. Monemizadeh and Kiani (2025) further advanced this line of research with the Rotated Isolation Forest (RIF), which applies random rotations to the dataset prior to isolation, resolving ghost cluster artifacts present in both standard and extended variants. Experiments on synthetic and real-world datasets confirmed that RIF produces higher anomaly detection accuracy and greater stability, particularly in complex or noisy data distributions.

Complementary analytical techniques have also been proposed for fitness-related time-series data. Zuo et al. (2020) developed the Running Slope Difference (RSD) t-test for detecting trend turning-points in time series with multiple shifts, offering an additional layer of analysis for identifying gradual improvements or regressions that might not trigger anomaly detection alone. Robinson et al. (2024) emphasized the importance of n-of-1 trial designs for separating true individual responses from within-participant variability, enabling more precise personalization of exercise prescriptions.

While Isolation Forest and its variants have been validated for anomaly detection in various health domains, no existing study has applied these algorithms specifically to fitness coaching data — including body fat percentage trends, workout volume, and nutrition logs — within an integrated web-based platform. Sunno Fitness fills this gap by combining Isolation Forest with rolling slope and variance analysis to detect both sudden anomalies and gradual trends, providing coaches with actionable, real-time insights.

Digital Platforms, Behavior Change, and Client Engagement

The design of effective digital fitness platforms must account for behavioral science principles that promote sustained user engagement. Alslaity et al. (2022) systematically reviewed 70 mobile health applications and found that the most commonly employed and effective strategies were self-monitoring, customization, personalization, and reminders. Their analysis revealed a positive correlation between an app's ranking and its Behavior Change Score (BCS), indicating that behavior change features directly influence user satisfaction and adoption.

Gibson (2022) investigated whether client-set goals are more effective than coach-set goals in health coaching interventions. While both approaches increased physical activity levels, no significant difference in effectiveness was observed. However, all participants preferred the client-set goal condition, suggesting that enabling client autonomy in goal setting enhances social validity and may improve long-term adherence through increased ownership.

The role of data visualization in sustaining engagement has also been documented. Huang (2022) examined how visual elements such as personalized graphs and dynamic dashboards influence motivation in self-tracking fitness applications. The study found that individuals who regularly interacted with visual tracking tools demonstrated up to 40% higher adherence to workout routines compared to those using text-based logs alone.

The feasibility of remote fitness delivery has been validated across multiple populations. English et al. (2024) conducted a pilot trial demonstrating the safety and feasibility of a telehealth-delivered physical activity intervention for secondary stroke prevention, with participants attending a median of 89% of supervised sessions. Kettunen (2021) examined digital sport coaching for university students with low physical activity levels and found that personalized programs and tailored feedback enhanced motivation and engagement, though the

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integration of more empathetic, human-centered communication elements was recommended for improving long-term adherence.

Current digital fitness platforms typically implement behavior change strategies in isolation — offering either self-monitoring, or visualization, or communication features. Sunno Fitness integrates all of these elements into a unified platform: visual dashboards for progress tracking, personalized insights powered by machine learning, client-driven goal setting, and in-app coach–client messaging — creating a comprehensive ecosystem designed to sustain long-term engagement.

Related Study

Digital Skinfold Caliper Development

Two studies provide direct precedent for the development of digital skinfold measurement tools. Leão et al. (2023) evaluated the Lipowise digital skinfold caliper for assessing muscle mass in 38 healthy young adults and found no significant differences between Lipowise and the Harpenden manual caliper ($p > 0.05$), with correlation coefficients ranging from 0.724 to 0.991. Both calipers demonstrated nearly perfect correlation with DXA (Harpenden $r = 0.955$; Lipowise $r = 0.954$), establishing a benchmark for digital caliper accuracy.

Table 2.5 Comparison of Harpenden and Lipowise Skinfold Calipers

Parameters	**Harpenden Caliper**	**Lipowise Caliper**
Measurement Type	Manual skinfold caliper	Digital skinfold caliper
Sample Size	38 participants (27 males, 11 females)	38 participants (27 males, 11 females)
Correlation with DXA	$r = 0.955$	$r = 0.954$
Correlation Range	0.724 – 0.991	0.724 – 0.991
Statistical Difference	$p > 0.05$ vs. Lipowise	$p > 0.05$ vs. Harpenden

Muntean et al. (2024) explored the adaptation of traditional skinfold-based formulas for use with ultrasound measurements of subcutaneous fat thickness. For women, the best adapted formula achieved a Lin's concordance correlation coefficient (CCC) of 0.85 with a standard error of 3.2% body fat; for men, CCC was 0.80 with SEE of 2.4%. These results demonstrate that anthropometric equations can be successfully recalibrated for modern digital measurement technologies.

These studies validate the feasibility and accuracy of digital alternatives to traditional manual calipers. The Sunno Fitness digital caliper builds on this foundation by combining digital measurement capture (via the AS5047P sensor) with automated computation and wireless platform integration — capabilities not present in either Lipowise or the ultrasound-adapted approaches.

Anomaly Detection Validation Studies

Neupane et al. (2024) conducted a comparative analysis of semi-supervised anomaly detection methods for machine fault detection, demonstrating that traditional approaches such as Isolation Forest and Local Outlier Factor performed comparably to or better than more complex deep learning methods while requiring substantially fewer computational resources. This finding supports the selection of Isolation Forest for resource-constrained applications such as web-based fitness platforms.

The demonstrated computational efficiency of Isolation Forest relative to deep learning alternatives validates its selection for the Sunno Fitness platform, where the algorithm must process client data in real time without requiring specialized hardware infrastructure.

Synthesis

The development of Sunno Fitness is informed by converging research across body composition measurement, digital coaching platforms, IoT-based health monitoring, and machine learning for anomaly detection.

In the domain of body composition assessment, studies by Escamilla et al. (2024) and Cintra-Andrade et al. (2023) confirm the reliability and cost-effectiveness of skinfold calipers, while Machado et al. (2024) highlight the critical influence of operator expertise on measurement accuracy. Digital caliper technologies — as demonstrated by Leão et al. (2023) with Lipowise and by Muntean et al. (2024) with adapted anthropometric formulas — have proven capable of matching or approaching the accuracy of manual instruments. These findings collectively support the development of a digitized caliper that reduces operator dependency while maintaining measurement precision.

Regarding IoT and hardware integration, multiple studies (Rao et al., 2021; Chen et al., 2022; Wu, Zhai, & Zhou, 2024; Pawar et al., 2024) have validated the ESP32 microcontroller as a reliable, cost-effective platform for real-time sensor data acquisition and wireless transmission in health-related applications. However, no existing implementation has applied ESP32 technology specifically to the digitization of skinfold caliper measurements within a coaching ecosystem.

In the area of data-driven analytics, Isolation Forest and its variants — including Extended Isolation Forest (Hariri, Kind, & Brunner, 2019) and Rotated Isolation Forest (Monemizadeh & Kiani, 2025) — have been consistently validated as robust methods for anomaly detection across diverse datasets (Kareem & Muhammed, 2024; Agyemang, 2024; Tabassum et al., 2024). Complementary techniques such as the Running Slope Difference t-test (Zuo et al., 2020) and individual response analysis (Robinson et al., 2024) further support the identification of both abrupt anomalies and gradual trends in longitudinal data.

Finally, research on digital platforms and behavior change (Alslaity et al., 2022; Gibson, 2022; Huang, 2022; English et al., 2024; Kettunen, 2021) demonstrates that self-monitoring, data visualization, personalized feedback, and client-driven goal setting are effective strategies for sustaining engagement and adherence.

Sunno Fitness synthesizes these four research streams into a single integrated platform — combining a digitized skinfold caliper for accurate body composition measurement, an ESP32-based IoT system for wireless data transmission, Isolation Forest–based analytics for intelligent progress monitoring, and a web-based interface incorporating evidence-based behavior change strategies. This integration addresses a gap in the current landscape where these capabilities exist in isolation but have not been unified into a cohesive fitness coaching ecosystem.

METHODOLOGY

This chapter outlines the research design, system architecture, development tools, and analytical methods employed in the design, development, and evaluation of the Sunno Fitness system. It details the Software Development Life Cycle (SDLC) adopted, the structural and logical design of the system, the hardware and software requirements, and the validated formulas and algorithms used to achieve each project objective.

Research Design

This study uses a Developmental Research Design, a method suited for iterative system development. It focuses on creating, testing, and refining solutions to real-world problems. This approach is effective in addressing practical challenges through continuous cycles of analysis, design, development, and implementation. In this

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study, it guides the creation of the Sunno Fitness system, integrating digital caliper-based body fat measurement, client progress tracking, and data-driven coaching insights.

Participants and Data Collection

A total of 31 participants (17 males and 14 females) were voluntarily recruited for system validation, with an average age of 26 years, a mean height of 170 cm, and a mean weight of 68.29 kg. The cohort represented a diverse range of fitness levels — Inactive/Sedentary, Lightly Active, Moderately Active, and Very Active — to ensure the digital caliper was evaluated across varying body compositions. Each participant underwent body composition testing using the Sunno Fitness digital caliper, a standard manual caliper, and a Bioelectrical Impedance Analysis (InBody) device. The data collected included skinfold thickness values across gender-specific anatomical sites (chest, abdomen, and thigh for males; triceps, suprailiac, and thigh for females) and their corresponding body fat percentage values.

In addition to participant data, quantitative fitness metrics including body composition, workout logs, and nutrition records were collected through the Sunno Fitness web application. To validate the Isolation Forest algorithm before sufficient client data was available, publicly available proxy datasets simulating realistic fitness patterns were used. This approach addressed the system's cold-start limitation, which requires 12 to 14 days of data to generate reliable insights. It also allowed controlled evaluation of the algorithm under known conditions, offering a stronger baseline than early client data. Combining real participant data for hardware validation and proxy data for algorithm testing provided a co ensive basis for assessing system accuracy, consistency, and reliability.

Software Development Methodology

The study employed the Agile Software Development Life Cycle (SDLC), which supports continuous feedback, rapid prototyping, and flexible refinement of system components. Each development phase is described below.

Figure 3.1 AGILE Framework

Source: https://medium.com/paramtech/agile-development-why-it-rocks-85146f688312

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Planning. The project goals, scope, and development schedule were established based on an assessment of real-world challenges faced by fitness professionals, including limited access to personalized tracking tools and the need for improved client monitoring capabilities.

Requirement Analysis. Specific system functionalities were identified through feedback gathered from fitness coaches and clients. Key requirements included digital skinfold caliper integration, access to customizable workout and nutrition programs, and the generation of machine learning–powered progress insights.

Design. System requirements were translated into structured design artifacts, including the system architecture, data flow diagrams (DFDs), entity–relationship diagrams (ERDs), and wireframes for both coach and client interfaces.

Building. System components were developed incrementally within short development sprints. HTML, CSS, and JavaScript were used for the frontend; PHP and Python powered the backend and analytics engine. The REST API was developed to bridge the web interface with external hardware, and the ESP32 microcontroller was programmed to handle sensor data acquisition and wireless transmission.

Testing. Unit testing, integration testing, and user acceptance testing were performed throughout each development cycle. Feedback from fitness coaches was collected to verify system accuracy, usability, and reliability, with identified issues addressed promptly to maintain stability.

Deployment. The web application was hosted, connected to the hardware interface, and made available for user onboarding. Documentation and initial training were provided to coaches and clients to support smooth adoption.

System Design and Architecture

This section presents the structural design of the *Sunno Fitness* system, illustrating how its components interact to deliver the intended functionalities. It includes the system architecture, system flowcharts, data flow diagrams, entity–relationship diagram, and wireframes.

System Architecture

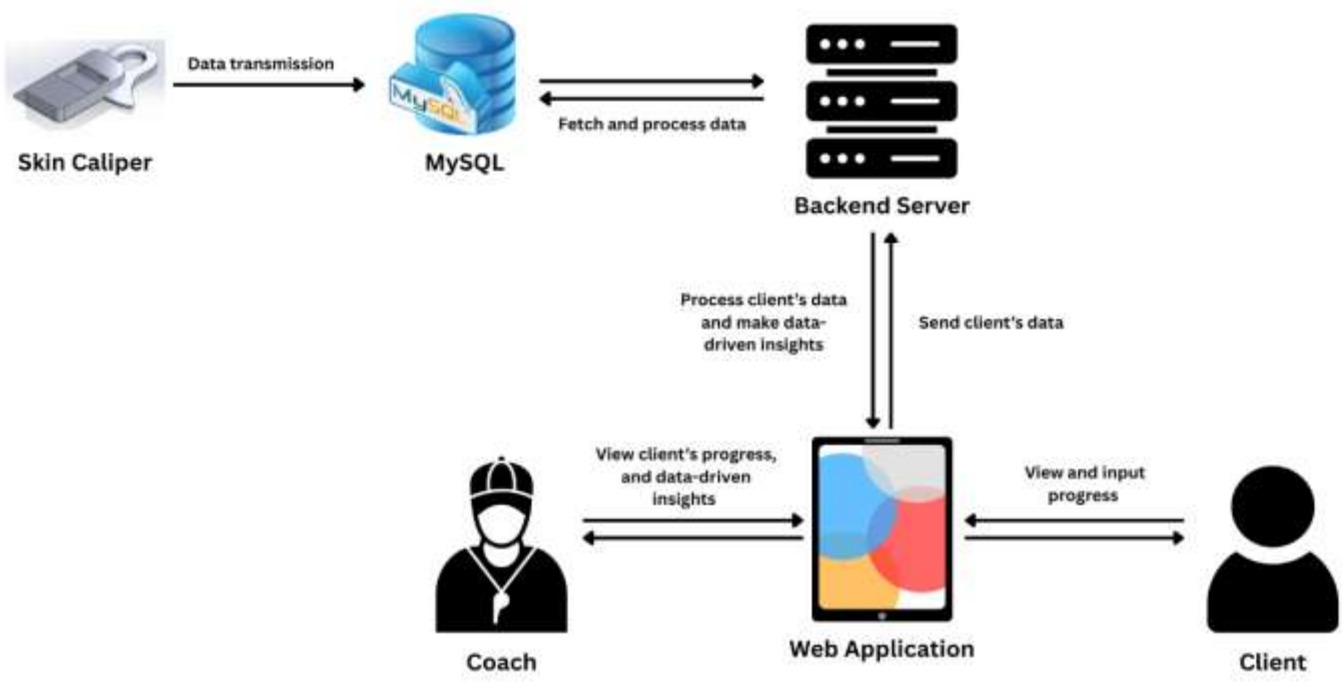

Figure 3.2 System Architecture

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Figure 3.2 illustrates the layered system architecture of Sunno Fitness. At the backend, a MySQL relational database stores structured data including client profiles, progress logs, nutrition and workout entries, and skinfold measurements captured by the digital caliper. The backend server manages database operations, data retrieval, processing, and synchronization, while also integrating the Isolation Forest algorithm for generating data-driven insights.

The processed information is delivered to the web application, which serves as the primary user interface. Both clients and coaches access the system through smartphones or tablets. Clients can log nutrition and workouts, view progress updates, and communicate with their coaches. Coaches can track client input, utilize the digital skinfold caliper for body composition measurements (which synchronize directly with the system), and access an analytics dashboard powered by the Isolation Forest algorithm. This architecture ensures a seamless flow of information between hardware components and the web platform, providing a responsive and interactive experience for all users.

System Flowchart

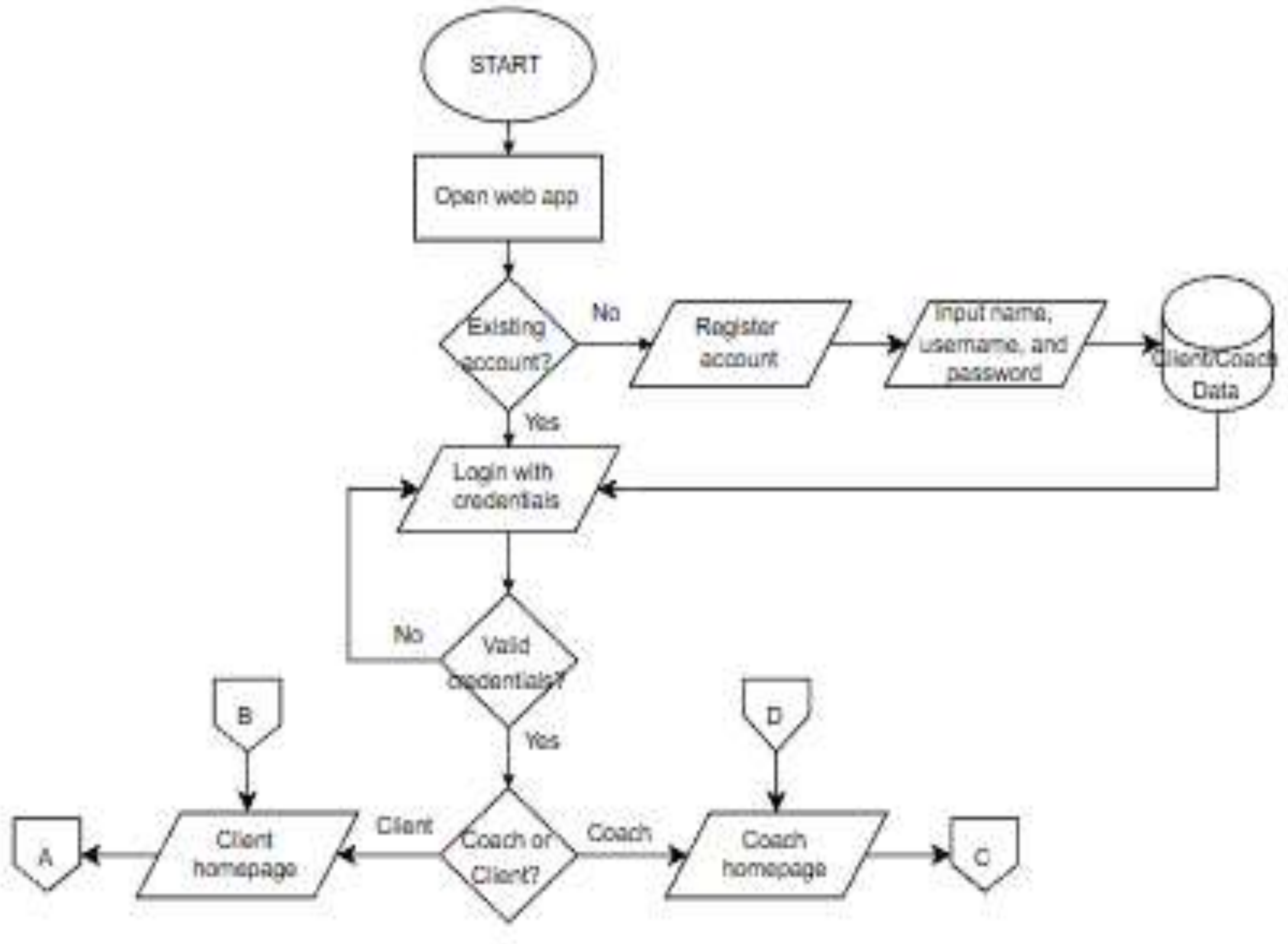

Figure 3.3 Overall System Flowchart 1

Figure 3.3 illustrates the authentication process, beginning when the user opens the web application. New users are prompted to register with their information stored in the appropriate database. Existing users are verified through login credentials, and the system directs them to their respective role-based homepages — clients to their personalized dashboard and coaches to the client management interface.

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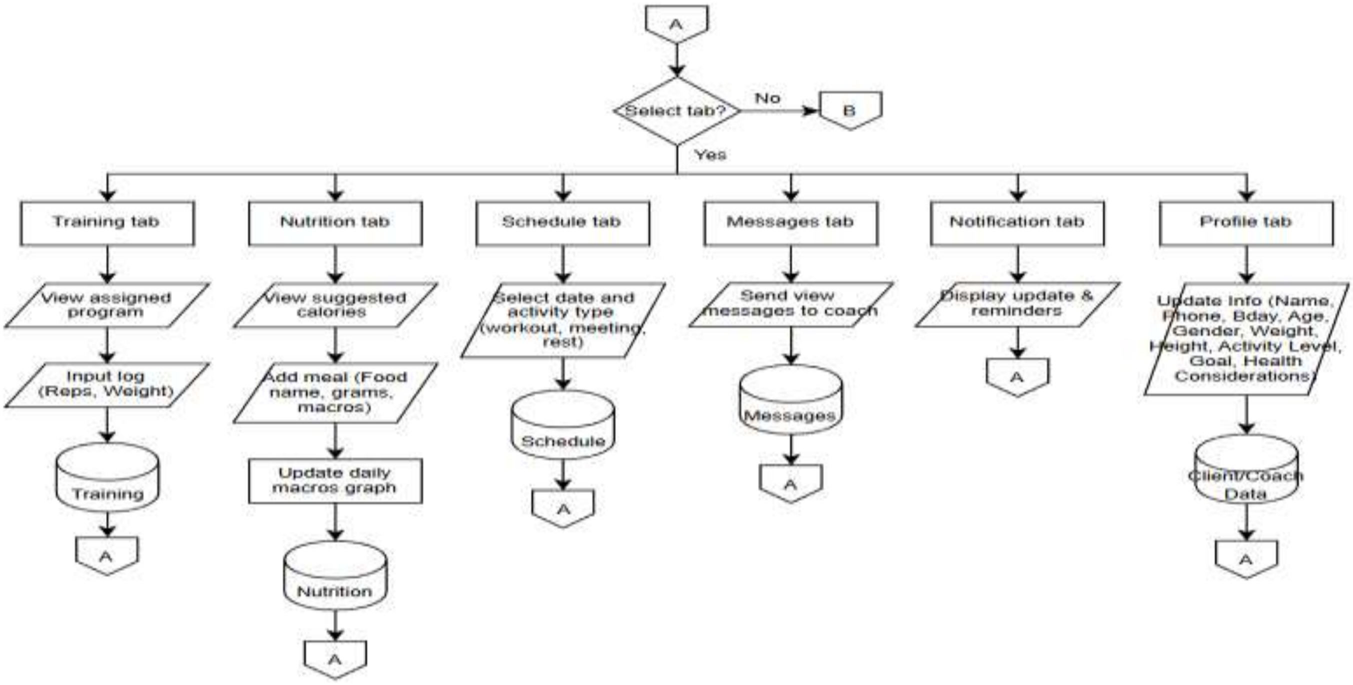

Figure 3.4 Overall System Flowchart 2

Figure 3.4 illustrates the client-side workflow following successful authentication. Clients can navigate features including profile management, messaging, activity calendar viewing, and the logging of nutrition or workout data. All inputs are timestamped and stored to maintain accurate progress records.

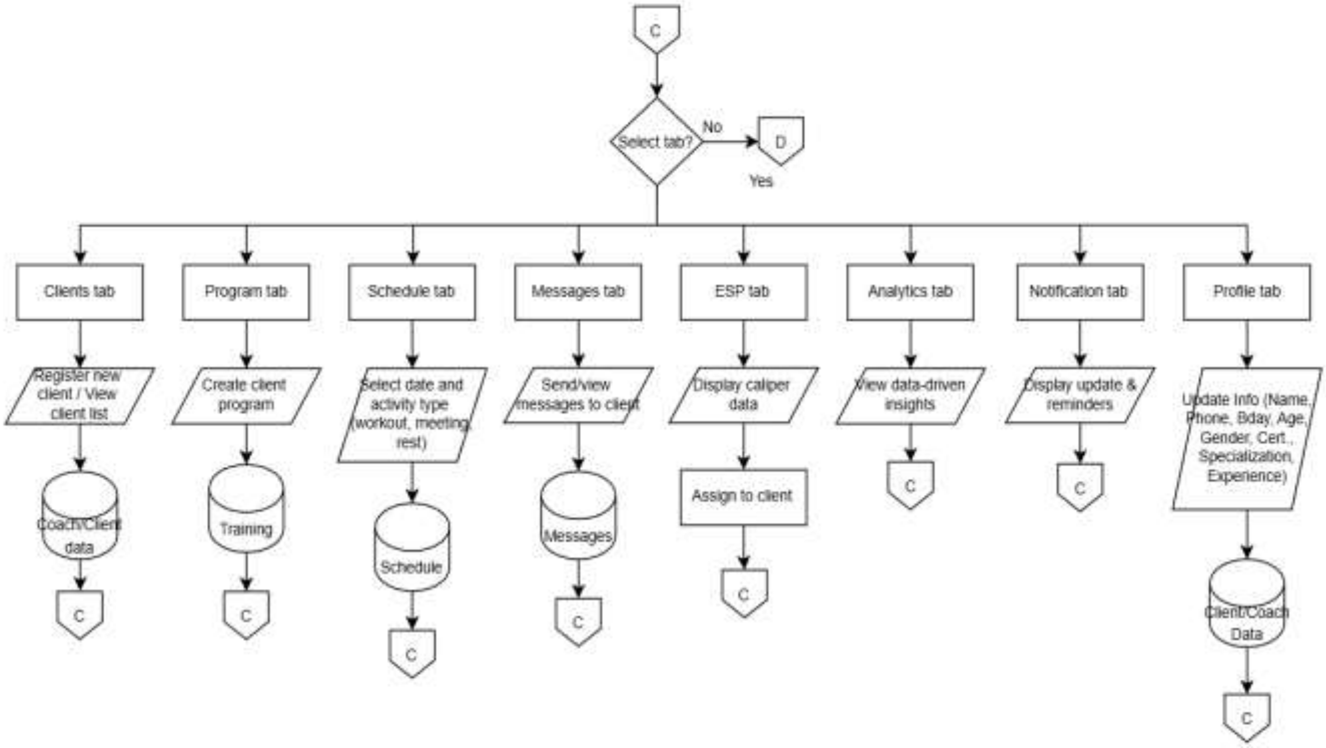

Figure 3.5 Overall System Flowchart 3

Figure 3.5 illustrates the coach-side workflow, including client list viewing, individual client dashboard access, calendar management, messaging, personal information updates, and execution of the Isolation Forest algorithm for generating data-driven insights. All interactions are recorded in the database for accurate tracking.

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Data Flow Diagram (DFD)

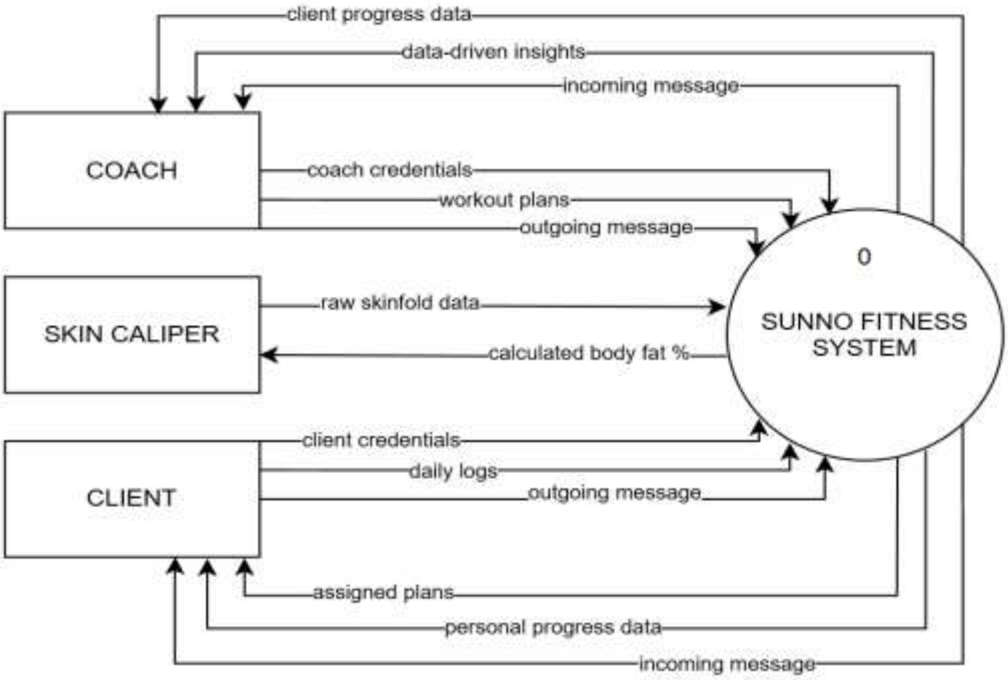

Figure 3.6 Overall Level 0 Data Flow Diagram

Figure 3.6 illustrates data flow between the central platform and its three external entities: the Coach, the Client, and the Digital Skinfold Caliper. Following secure authentication, the system collects raw skinfold measurements and daily activity logs, processes them to generate data-driven insights, and delivers personalized workout and nutrition plans along with progress reports and messages back to the appropriate users.

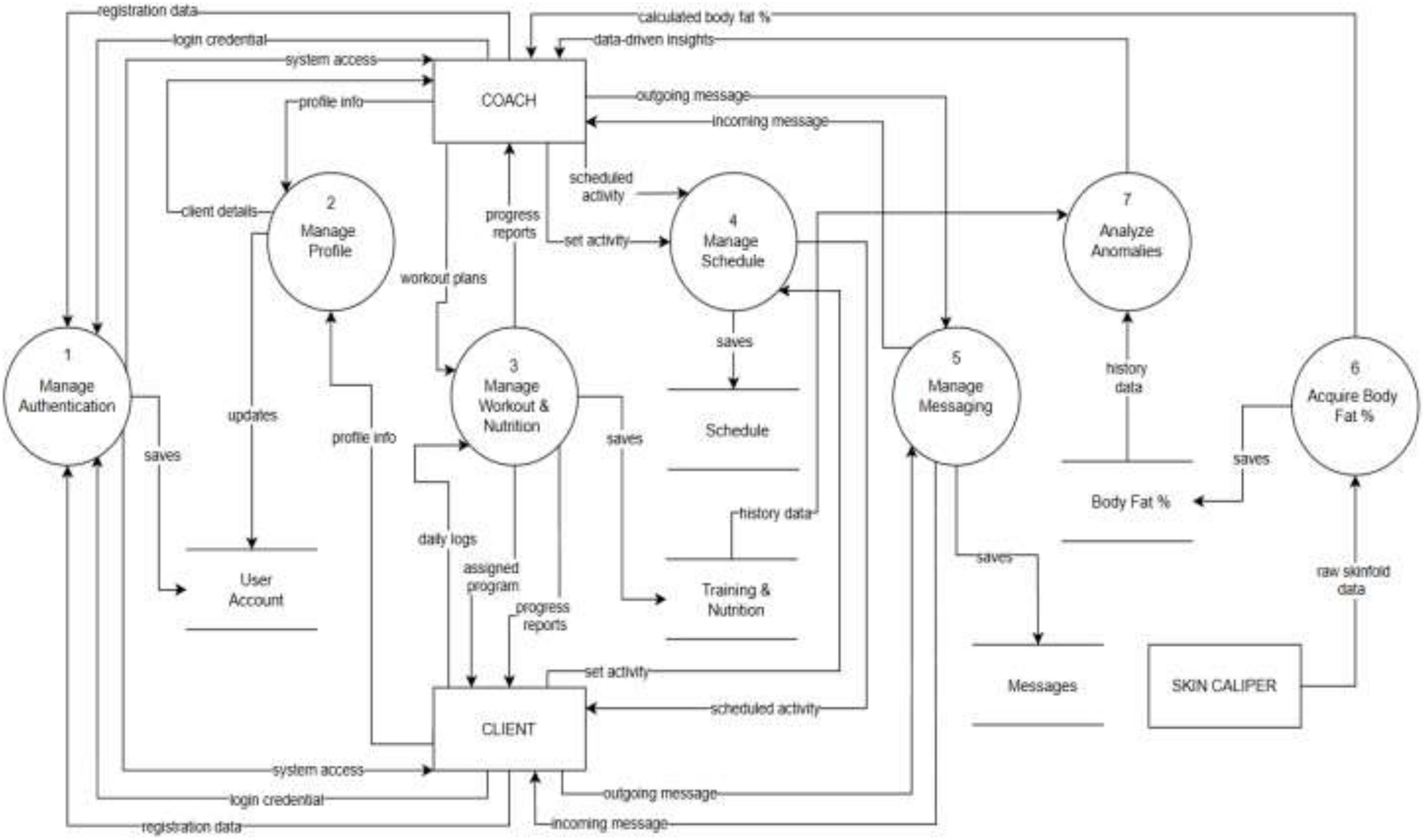

Figure 3.7 Overall Level 1 Data Flow Diagram

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Figure 3.7 decomposes the system into seven functional processes: Manage Authentication (1.0), Manage Profile (2.0), Manage Workout & Nutrition (3.0), Manage Schedule (4.0), Manage Messaging (5.0), Acquire Body Fat % (6.0), and Analyze Anomalies (7.0). Each process handles specific data transformations between external entities and internal data stores.

Entity Relationship Diagram (ERD)

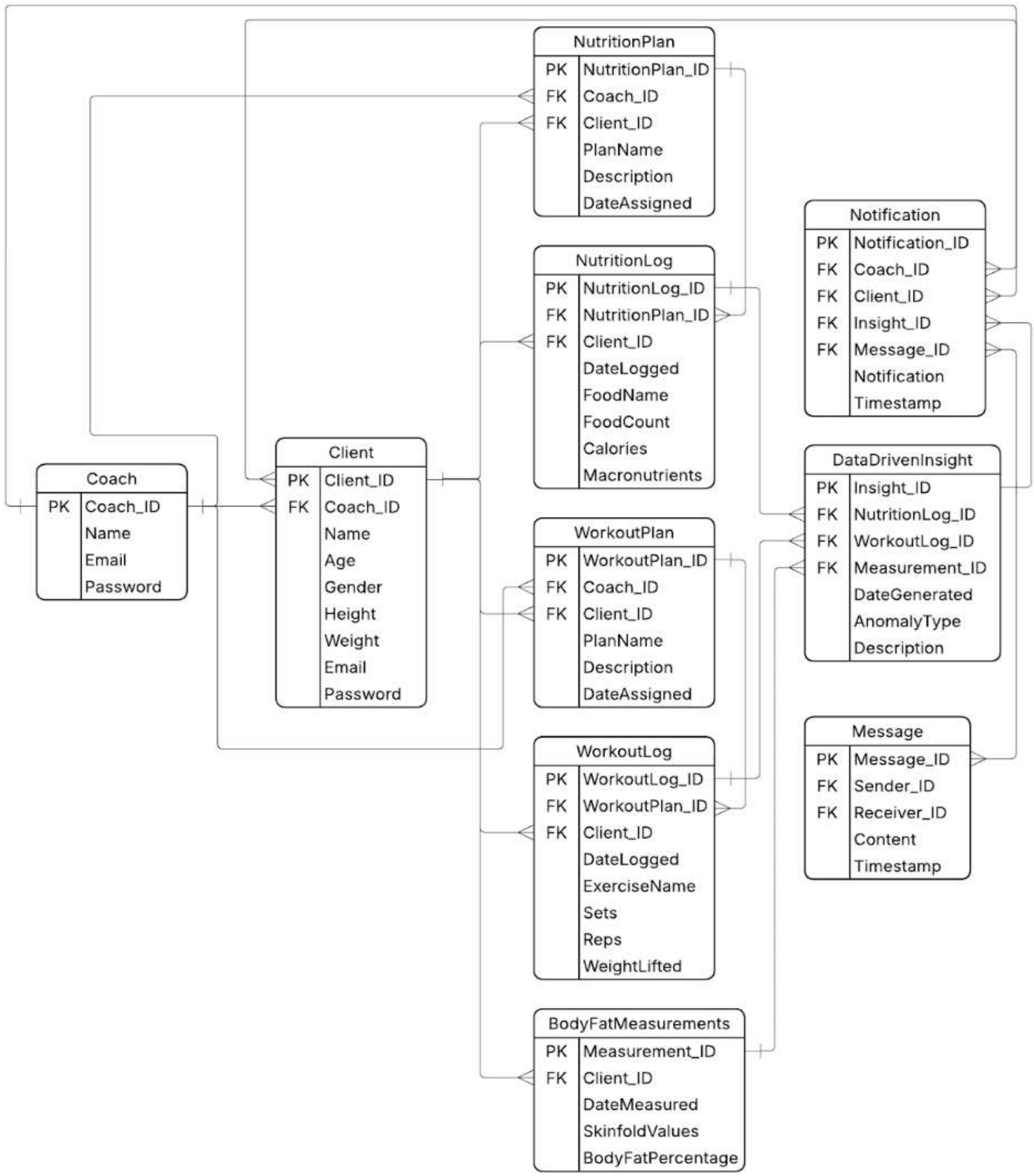

Figure 3.8 Overall Entity Relationship Diagram

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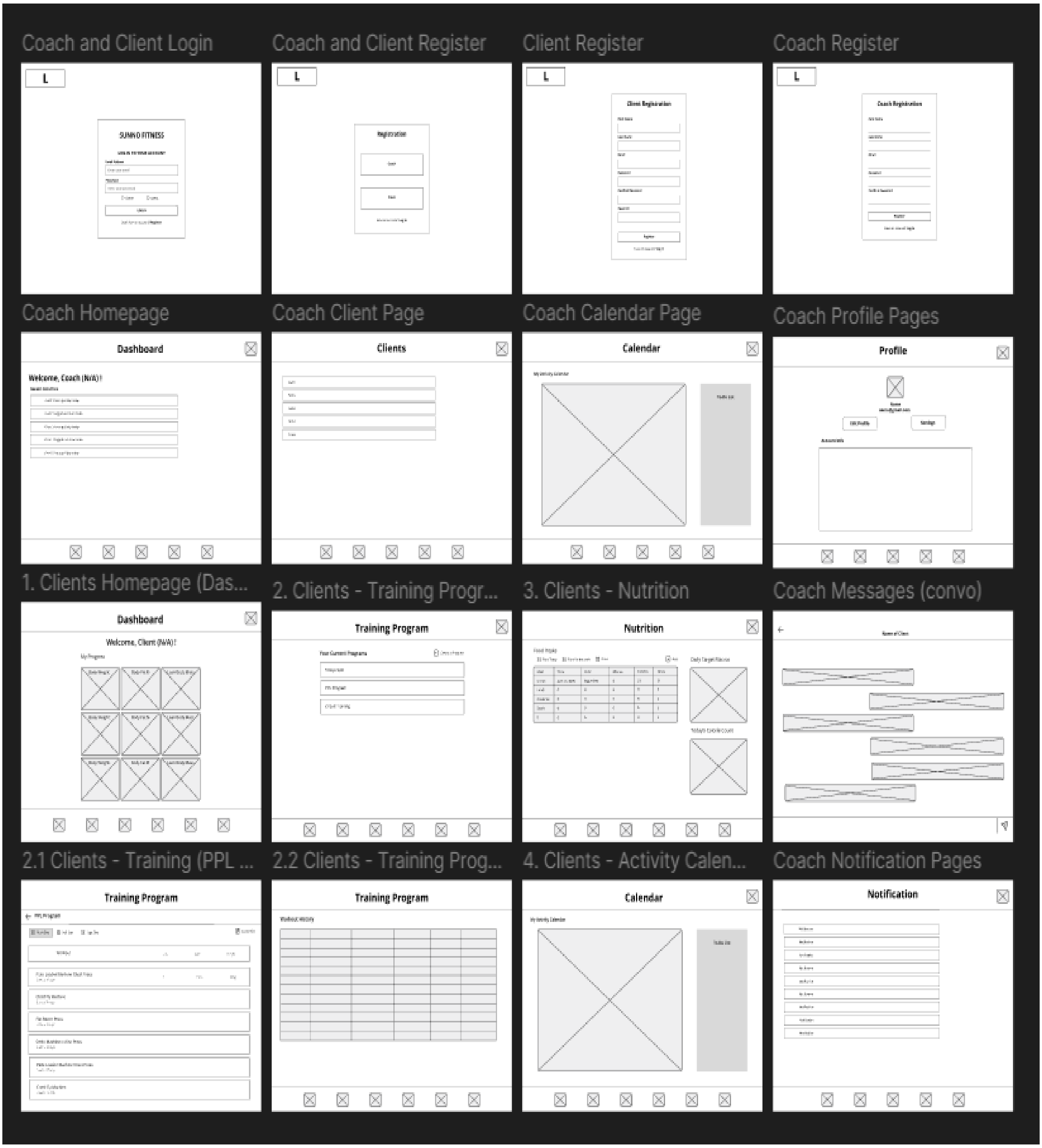
Figure 3.8 illustrates the logical structure of the database, centered on the Coach and Client entities in a one-to-many relationship. Physical progress is tracked through the BodyFatMeasurements entity, while operational activities are managed via WorkoutPlan and NutritionPlan tables linked to their respective log entities for monitoring daily adherence. The DataDrivenInsight entity serves as an aggregation point, referencing logs and measurements to detect anomalies that subsequently trigger alerts via the Notification table.

Wireframe



System Requirements

To successfully develop and implement the Sunno Fitness System, the researchers identified specific software and hardware requirements. These are categorized into the tools necessary for the system's digital components and the materials required for the physical fabrication of the integrated digital skinfold caliper.

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Software Requirements

This section presents details of the software tools and platforms utilized in the development process.

Table 3.1 System Software Requirement

Category	**Software/Tool**
Integrated Development Environment (IDE)	Visual Studio Code
Database Management System	MySQL
Frontend Development	HTML, CSS, and JavaScript
Backend Development	PHP, Python, and REST API
UI/UX Wireframing	Figma
3D Modeling and Design	Sketchbook and Autodesk Fusion 360
Microcontroller Platform	Arduino IDE
Communication Protocols	SPI/I2C

The web application frontend was developed using HTML, CSS, and JavaScript for a responsive user interface. PHP handles server-side logic on the backend, while Python processes the Isolation Forest algorithm for generating data-driven insights. These components communicate via a REST API that bridges the web interface and external hardware. MySQL was selected for secure and reliable data management. Figma was used for wireframing and user flow design; Sketchbook and Autodesk Fusion 360 were employed for the caliper's conceptualization and precise 3D modeling, respectively. The Arduino IDE provided the embedded development environment for the ESP32 microcontroller, utilizing SPI and I2C protocols for stable sensor communication.

Hardware Requirements

The hardware requirements are divided into the development environment used by the researchers and the Bill of Materials (BOM) for the *Sunno Fitness* prototype.

Table 3.2 Hardware Requirement

Component/Device	**Specification/Model**	**Purpose**
Desktop/Laptop	Acer Aspire 7, AMD Ryzen 5 5500U, 8GB of RAM, and a 512GB NVMe SSD	Utilized as the primary machine for full-stack development, database management, and training the Isolation Forest algorithm.
Mobile/Tablet	iPad (10th Gen) and iPhone 15 Pro Max	Used to validate the web application's responsiveness and cross-platform compatibility on iOS and iPadOS environments.

The Acer Aspire 7 laptop served as the primary development machine for full-stack development, database management, and machine learning model training. Apple mobile devices (iPad 10th Gen and iPhone 15 Pro

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Max) were used to validate the web application's responsiveness and cross-platform compatibility across iOS and iPadOS environments.

Table 3.3 Hardware Bill of Materials

Part Name	**Description/Specification**	**Qty.**	**Unit Cost (₱)**	**Total Cost (₱)**
Microcontroller & Display	ESP 32 Arduino LVGL Wifi 2.8" Resistive Touchscreen Module	1	880	880
Sensor	AS5047P Magnetic Rotary Rotation Sensor	1	1,234	1,234
Power Supply	18650 Lithium-ion Battery	2	55	110
Battery Holder	2-cell 18650 Holder	1	55	55
Voltage Regulator	UBEC 5V 3A Step-Down Converter	1	607	607
Input Button	Tactile Push Button	1	45	45
Enclosure & Mechanics	3D Printed Parts (Jaws, Enclosure), Screw, Nuts, and Spring	1 set	1,956	1956
			Grand Total	**(₱) 4,887**

The digital caliper's core components include the ESP32 microcontroller (central processing unit with built-in Wi-Fi and Bluetooth), the AS5047P magnetic rotary sensor (for precise angular displacement measurement), a 2.8-inch resistive touchscreen (for real-time data display), two 18650 lithium-ion batteries (for portable power), and a UBEC 5V 3A voltage regulator (for stable sensor power supply). Additional components — including a tactile push button and a 3D-printed enclosure with caliper jaws, screws, and springs — complete the physical assembly, providing both functionality and portability for practical fitness assessment.

Methods and Tools

This section details the specific methodologies, hardware configurations, software tools, formulas, and algorithms applied to achieve each project objective.

Body Fat Measurement Using a Digital Skinfold Caliper

To design and develop a prototype digital skinfold caliper that accurately measures body fat percentage and synchronizes with the web platform — the following components and methods were employed.

The ESP32 microcontroller serves as the caliper's central processor, providing the wireless connectivity necessary for seamless data transmission to the Sunno Fitness web platform. An AS5047P magnetic rotary encoder accurately measures jaw displacement to determine skinfold thickness. Designed in Autodesk Fusion 360 for ergonomics, the 3D-printed enclosure and jaws are assembled with mechanical screws and springs, ensuring precise alignment and smooth movement during physical assessments.

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System Flowchart

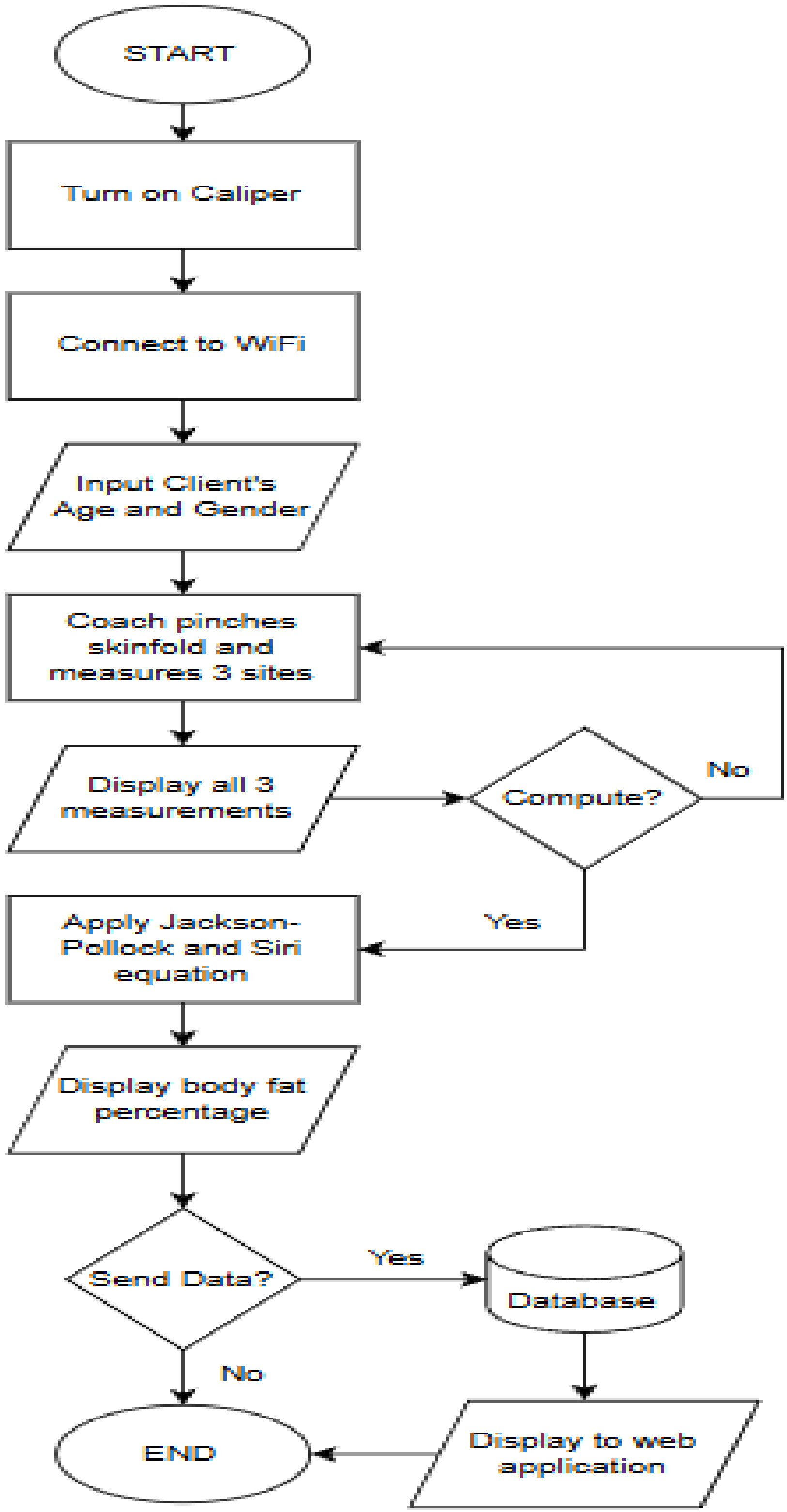

Figure 3.9 Body Fat Percentage Measurement Flowchart

Figure 3.9 illustrates the operational workflow of the digital skinfold caliper, initiating with device startup and Wi-Fi connectivity for real-time data transmission. The process requires the input of the client's demographic data followed by the measurement of skinfolds at three distinct anatomical sites. After validation, the system computes body fat percentage using the Jackson–Pollock and Siri equations, stores results in the database, and synchronizes them with the web application.

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Data Flow Diagram (DFD)

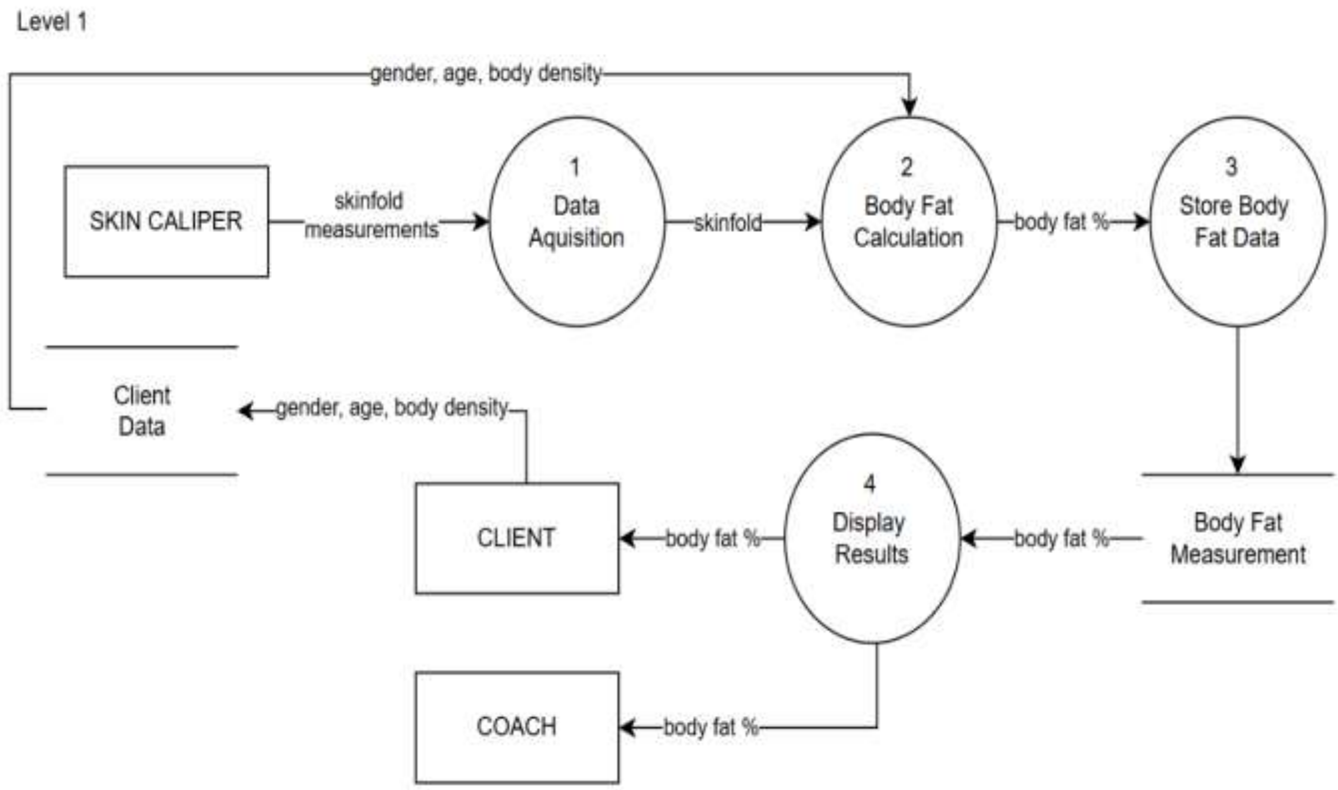

Figure 3.10 Body Fat Percentage DFD

Figure 3.10 presents the Level 1 Data Flow Diagram (DFD) for the body fat percentage system, illustrating the movement of data between processes and external entities. The flow initiates with inputs from the SKIN CALIPER (providing skinfold measurements) and Client Data (providing gender, age, and body density). This information is processed by 'Data Acquisition' (Process 1) and subsequently by 'Body Fat Calculation' (Process 2). Once calculated, the "body fat %" result is sent to 'Store Body Fat Data' (Process 3), which populates the 'Body Fat Measurement' data store. This result is also sent to the 'Display Results' (Process 4), which delivers the final percentage to the external entities, the CLIENT and the COACH.

Entity Relationship Diagram (ERD)

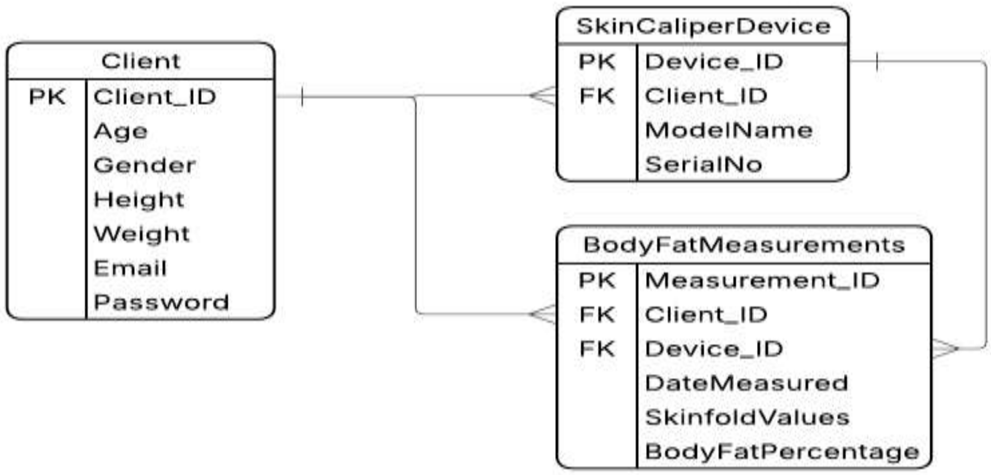

Figure 3.11 Body Fat Percentage ERD

Figure 3.11 illustrates the Entity Relationship Diagram (ERD) for the system, detailing the structural connections between the Client, *SkinCaliperDevice*, and *BodyFatMeasurements* entities. The Client entity acts as the central repository for user demographics, such as age and gender, which are critical inputs for the calculation formulas. This entity maintains a one-to-many relationship with *BodyFatMeasurements*, enabling the system to store a history of assessments for longitudinal progress tracking. Furthermore, the *SkinCaliperDevice* entity is linked to these measurements, ensuring that every recorded data point is traceable to the specific hardware used during the session.

Caliper Design

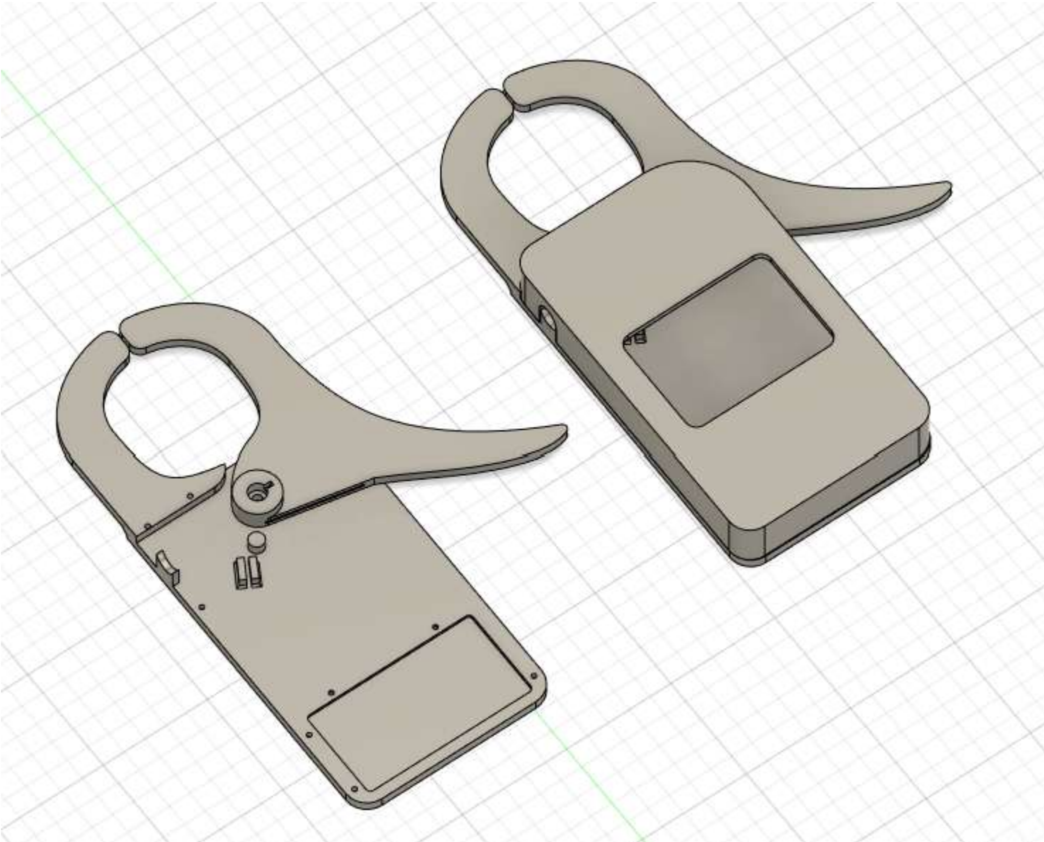

Figure 3.12 Digital Skinfold Caliper 3D Model.

Figure 3.12 presents the Fusion-rendered 3D model of the digital skinfold caliper, showing the internal component layout (sensor placement, battery slot, structural screws) and the external enclosure with the integrated LCD display. The ergonomic jaws are designed to replicate the consistent skinfold compression of traditional calipers, while the housing protects electronic components and provides accessibility for maintenance.

Jackson-Pollock Formula

Body fat percentage estimation employs the Jackson–Pollock 3-site formula, a widely used anthropometric method originally developed by Jackson and Pollock (1985) and recently revalidated by Heyward and Pietrobelli (2022). Body density is first calculated using gender-specific equations:

$$\text{Body Density (BD)} = 1.10938 - 0.0008267(\Sigma SF) + 0.0000016(\Sigma SF)^2 - 0.0002574(\text{Age})$$

Equation 3.1 Jackson-Pollock 3-Site Formula for Males (Body Density)

$$\text{Body Density (BD)} = 1.0994921 - 0.0009929(\Sigma SF) + 0.0000023(\Sigma SF)^2 - 0.0001392(\text{Age})$$

Equation 3.2 Jackson-Pollock 3-Site Formula for Females (Body Density)

Body density is then converted to body fat percentage using the Siri equation (Siri, 1961), which remains a standard in body composition assessment (Baglietto et al., 2024):

$$\text{Body Fat \%} = \left(\frac{4.95}{\text{BD}} - 4.50\right) \times 100$$

Equation 3.3 Siri Equation for Body Fat Percentage

In these equations, ΣSF represents the sum of skinfolds in millimeters (chest, abdomen, and thigh for males; triceps, suprailiac, and thigh for females), Age is the subject's age in years, and BD is body density in g/cm^3. The integration of these validated formulas into the digital caliper's firmware enables automated, real-time body fat computation, eliminating the need for manual calculation.

Data-Driven Insights Using Isolation Forest

To achieve the second objective — integrating machine learning algorithms that analyze client data and generate personalized insights — the Sunno Fitness system employs the Isolation Forest algorithm alongside complementary analytical techniques.

Isolation Forest was selected over alternative anomaly detection methods based on three criteria established in the literature: (1) computational efficiency — its linear time complexity makes it suitable for real-time web-based applications (Kareem & Muhammed, 2024); (2) minimal distributional assumptions — unlike methods such as One-Class SVM, Isolation Forest does not require prior knowledge of data distribution (Agyemang, 2024); and (3) demonstrated performance — comparative studies have shown it achieves the best balance between precision and recall among unsupervised anomaly detection methods (Agyemang, 2024; Tabassum et al., 2024). To further enhance detection accuracy, variants including Extended Isolation Forest (EIF) and Rotated Isolation Forest (RIF) were also integrated, addressing known limitations of axis-aligned splits in the standard algorithm (Hariri, Kind, & Brunner, 2019; Monemizadeh & Kiani, 2025).

The system processes structured inputs including body fat percentage, workout logs, and nutrition records as time-series data. Three complementary analytical techniques are applied:

1. **Isolation Forest (with EIF/RIF variants):** Identifies individual data points that deviate significantly from the majority through recursive partitioning. Anomalies are detected based on path length — data points requiring fewer partitions to isolate are more likely to be outliers (Liu et al., 2008).

2. **Rolling Slope Analysis:** Monitors gradual directional changes over time by computing the slope of a rolling window across the data series. This enables the detection of sustained improvements, regressions, or plateaus in client progress that individual anomaly flags would not capture.

3. **Variance Analysis:** Detects irregularities in user behavior by measuring the consistency of data points within rolling windows. High variance periods indicate inconsistent training, dietary habits, or measurement patterns.

The algorithm executes automatically upon new data submission or at scheduled intervals, comparing recent values to historical trends. Results are visualized on the coach's dashboard through color-coded insight cards, enabling coaches to interpret findings and make data-driven decisions in real time.

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System Flowchart

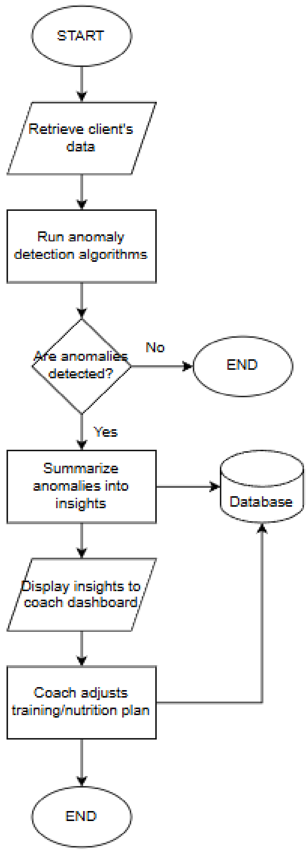

Figure 3.13 Data-Driven Insights Flowchart

Figure 3.13 illustrates the Anomaly Detection and Response workflow within the Sunno Fitness System. The process initiates by retrieving the client's historical data and executing the anomaly detection algorithms (such as Isolation Forest) to identify potential irregularities. If an anomaly is detected, the system summarizes the findings into actionable insights, which are simultaneously logged in the database and visualized on the coach's dashboard. Finally, the workflow concludes with the coach reviewing these insights to adjust the training or nutrition plan, ensuring the updated strategies are saved back into the database for future tracking.

Data Flow Diagram (DFD)

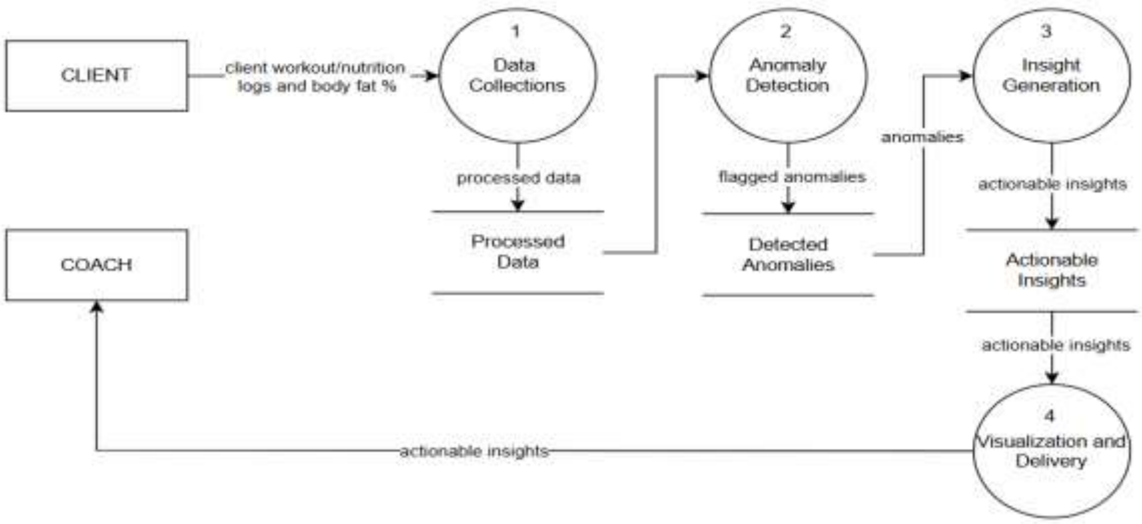

Figure 3.14 Data-Driven Insights DFD

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Figure 3.14 shows the data flow within the insights module, starting with the Client providing workout logs, nutrition records, and body fat percentage data. These raw inputs are processed through the Data Collections stage and forwarded to the Anomaly Detection component, which identifies irregular patterns and stores them in the database. The flagged data points are then synthesized through the Insight Generation process to produce actionable recommendations. The workflow concludes with the Visualization and Delivery stage, where the final insights are presented to the Coach, supporting informed decision-making regarding the client's program.

Entity Relationship Diagram (ERD)

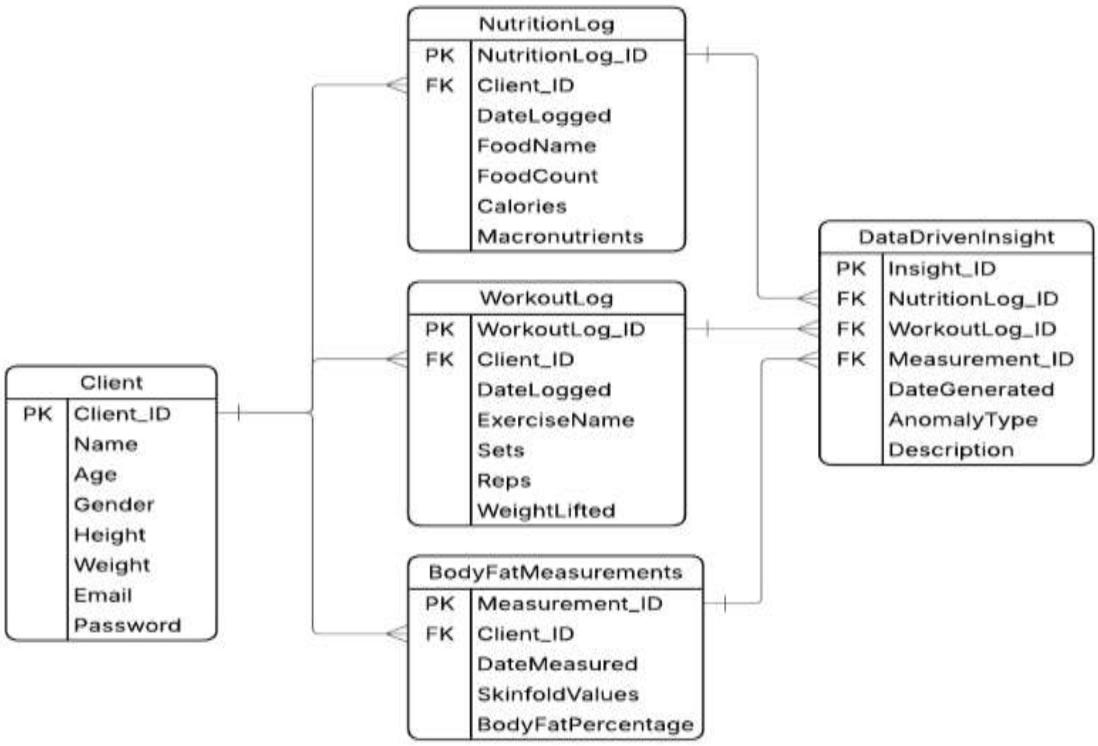

Figure 3.15 Data-Driven Insights ERD

Figure 3.15 shows the database schema that supports the data-driven insights generation. At the center of the schema is the Client entity, which maintains a one-to-many relationship with the *NutritionLog*, *WorkoutLog*, and *BodyFatMeasurements* tables. These entities capture daily activities and key physiological metrics, forming the primary data sources for the system. The *DataDrivenInsight* entity functions as an associative table that links each insight to specific entries within the log tables through foreign keys. This structure ensures that every generated insight has a clear and traceable origin, allowing the system to identify the exact workout session, meal, or measurement that contributed to an anomaly.

Implementation

The algorithm was implemented in Python using scikit-learn, NumPy, and Pandas for model development, data processing, and statistical computation. Visual Studio Code served as the development environment. Datasets are stored in MySQL and communicated via the REST API. Dashboard visualizations are rendered using HTML, CSS, and JavaScript.

Progress Tracking

To achieve the third objective — designing a web-based platform for progress tracking, data visualization, and coach–client communication — the following methods and tools were employed.

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PHP and Python scripts automate the computation of key fitness metrics, including Body Fat Percentage, Lean Body Mass, Body Fat Mass, Basal Metabolic Rate (BMR), Total Daily Energy Expenditure (TDEE), and Suggested Calorie Intake. These computations process client inputs (weight, height, activity level) and display real-time results on personalized dashboards.

HTML, CSS, and JavaScript provide a responsive and user-friendly interface for workout logging, nutrition tracking, and progress visualization. The interface was prototyped in Figma to ensure logical layout, accessibility, and responsiveness across devices.

Structured data are securely stored in MySQL and accessed through the REST API, ensuring smooth communication between backend and frontend components. An activity calendar, messaging system, and push notifications enable real-time communication and reminders.

System Flowchart

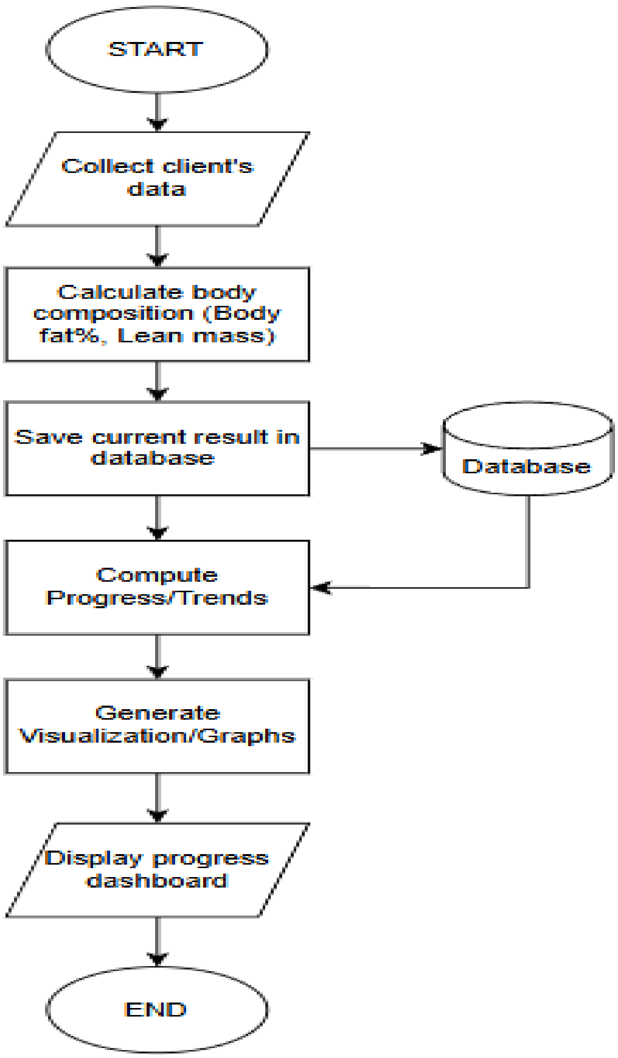

Figure 3.16 Progress Tracking Flowchart

Figure 3.16 illustrates the workflow for the Progress Tracking Module. The process begins with the collection of the client's latest assessment data, which is immediately processed to calculate key body composition metrics such as body fat percentage and lean mass. These current results are then archived in the system database. To visualize improvement, the system retrieves historical records from the database and compares them against the new data to compute progress trends. Finally, the system generates graphical visualizations of these trends and displays the updated progress dashboard to the user.

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Data Flow Diagram (DFD)

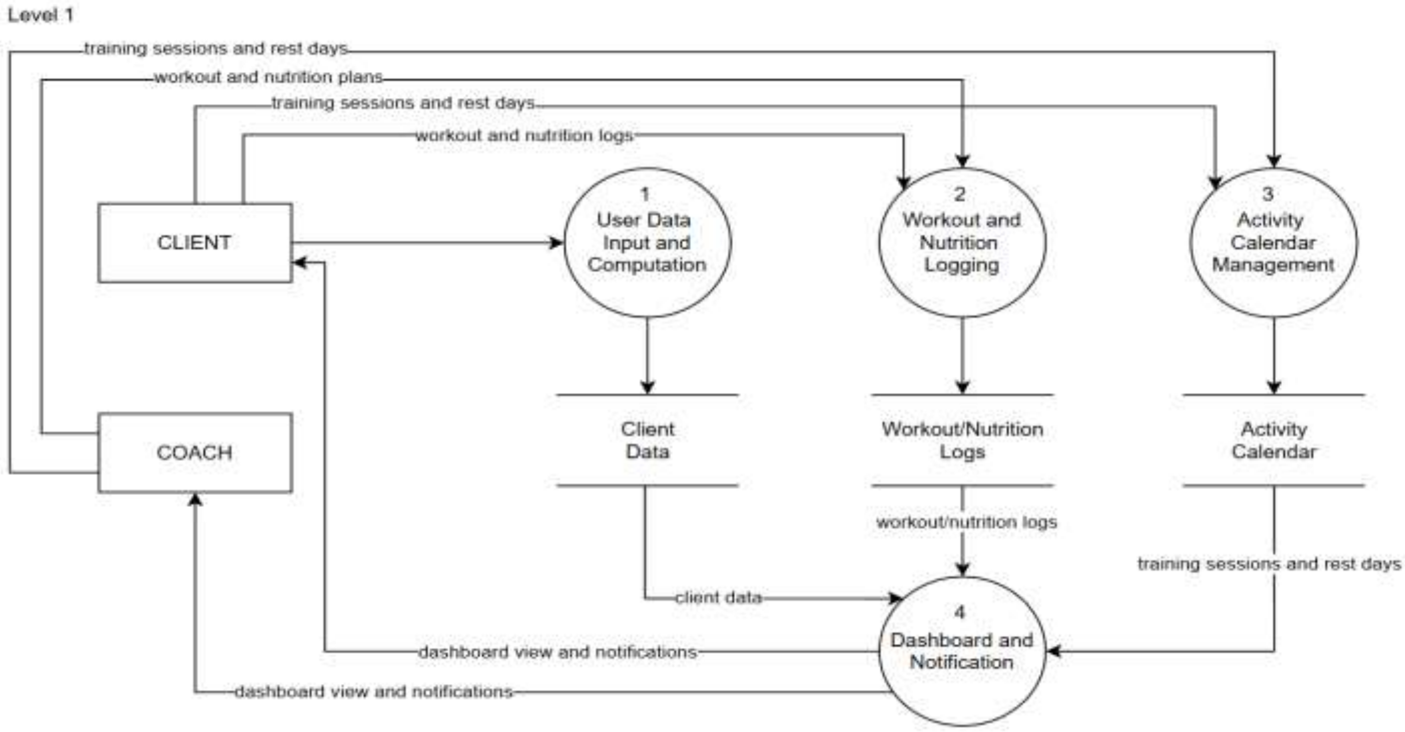

Figure 3.17 Progress Tracking DFD

Figure 3.17 illustrates the Level 1 Data Flow Diagram for progress tracking and shows how the Client and Coach interact with the system's core functionalities. Data flows from the users into three main processes: User Data Input and Computation, Workout and Nutrition Logging, and Activity Calendar Management. Each of these processes updates its corresponding data store. These separate data streams, which include personal metrics, logs, and scheduled activities, are then consolidated by the Dashboard and Notification process. This integration enables the system to deliver comprehensive progress updates and timely alerts to both the Client and the Coach.

Entity Relationship Diagram (ERD)

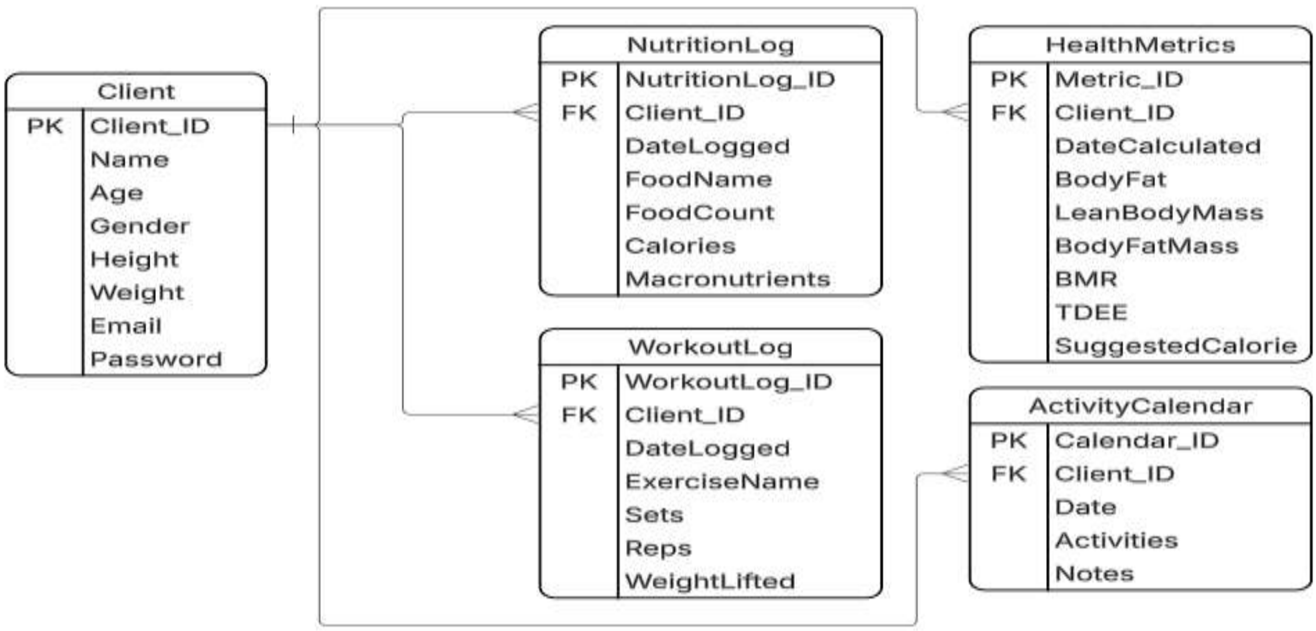

Figure 3.18 Progress Tracking ERD

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Figure 3.18 illustrates the database schema developed to support detailed progress monitoring. The Client entity serves as the primary key holder and central reference point. The ERD has one-to-many relationships between the Client and four supporting tables: *NutritionLog, WorkoutLog, HealthMetrics,* and *ActivityCalendar*. This structure ensures that all data, from daily caloric intake and exercise records to computed values such as BMR and TDEE, is accurately linked to the appropriate user profile.

Science-Validated Formulas

The progress tracking module employs the following evidence-based formulas:

Lean Body Mass and Body Fat Mass

$$\mathrm{LBM} = \mathrm{BW} \times \left(1 - \frac{\mathrm{BF\%}}{100}\right)$$

Equation 3.4 Lean Body Mass Calculation

$$\mathrm{BFM} = \mathrm{BW} \times \frac{\mathrm{BF\%}}{100}$$

Equation 3.5 Body Fat Mass Calculation

These formulas derive lean and fat mass from total body weight (BW) and body fat percentage (BF%) as measured by the digital caliper. Both have been validated against DXA measurements (Heymsfield et al., 2015; Baglietto et al., 2024).

Basal Metabolic Rate and Total Daily Energy Expenditure

$$\mathrm{BMR} = 370 + (21.6 \times \mathrm{LBM\ in\ kg})$$

Equation 3.6 Katch-McArdle Equation for BMR

The Katch–McArdle formula calculates BMR from lean body mass rather than total body weight, providing superior accuracy for individuals with known body composition data (McArdle & Katch, 1973; Stults-Kolehmainen et al., 2020).

$$\mathrm{TDEE} = \mathrm{BMR} \times \mathrm{Activity\ Multiplier}$$

Equation 3.7 Activity Multiplier Method for TDEE

Activity factors range from 1.375 (Lightly Active) to 1.9 (Extra Active). This multiplier approach has been validated against doubly-labeled water measurements (Prado-Nóvoa et al., 2024).

Caloric Needs and Macronutrient Distribution

$$\mathrm{Daily\ Calorie\ Target} = \mathrm{TDEE} \pm 500\ \mathrm{kcal}$$

Equation 3.8 Calculation for Daily Calorie Target

Adjustments of −250 to −500 kcal/day for fat loss or +250 to +500 kcal/day for muscle gain are applied based on the energy balance principle (Hall et al., 2011; Bray et al., 2021; Iraki et al., 2019).

$$\text{Protein (g)} = \text{Body Weight (kg)} \times 1.6\text{–}2.2$$

Equation 3.9 Protein Intake Calculation

Protein intake is based on body weight, with 1.6–2.2 g/kg/day supporting muscle growth, recovery, and lean mass (Phillips and Van Loon, 2011; Morton et al., 2019).

$$\text{Fat (g)} = \frac{\text{Total Calories} \times 0.20\text{–}0.30}{9}$$

Equation 3.10 Fat Intake Calculation

Dietary fat is set at 20–30% of total calories to support hormones, cell function, and vitamin absorption (Kris-Etherton et al., 2021).

$$\text{Carbs (g)} = \frac{\text{Total Calories} - (\text{Protein (g)} \times 4) - (\text{Fat (g)} \times 9)}{4}$$

Equation 3.11 Carbohydrate Intake Calculation

Carbohydrates fill remaining calories after protein and fat, supporting glycogen, performance, and recovery in active individuals (Gejl et al., 2021).

These formulas work together to create a tailored nutritional framework: the daily calorie target defines total energy availability, while macronutrient allocation optimizes the distribution of that energy for performance, recovery, and body composition goals specific to each client.

RESULTS AND DISCUSSION

This chapter presents the results of the Sunno Fitness system evaluation, organized according to the study's three objectives. Each section demonstrates system functionality through outputs, statistical analyses, and validation results, followed by a critical discussion of the findings. A summary table at the end of the chapter maps each objective to its corresponding validation outcome.

Digital Skin Caliper Accuracy and Reliability

System Output

The digital skinfold caliper built using the ESP32 microcontroller, AS5047P magnetic rotary sensor, and Jackson–Pollock formula, successfully measured skinfold thickness, computed body fat percentage, and displayed the result directly on its integrated touchscreen. Upon completion of each measurement session, data was transmitted wirelessly to the Sunno Fitness web platform, where it was stored in the client's profile, processed by backend computation modules, and immediately reflected on the progress tracking dashboard.

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Date	Body Fat %	Site 1 (mm)	Site 2 (mm)	Site 3 (mm)
11/18/2025	**18.8%**	23.0	21.1	20.9
11/18/2025	**18.1%**	23.9	20.5	18.0
11/18/2025	**19.5%**	27.7	21.9	18.2
11/18/2025	**15.6%**	16.7	19.7	17.3
11/18/2025	**15.8%**	18.3	20.5	15.7

Figure 4.1 Body Fat % System Visualization

Figure 4.1 displays the client's body composition history, showing the latest body fat percentage of 18.8% across five recorded data points. The interface features a trend graph visualizing fluctuations over time, with a detailed table logging specific dates, calculated body fat percentages, and raw skinfold measurements (mm) for each anatomical site.

Figure 4.2 Digital Skinfold Caliper Device

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Figure 4.2 presents the fully assembled digital skinfold caliper prototype. The custom 3D-printed enclosure houses the ESP32 microcontroller and AS5047P sensor, while the ergonomic jaw mechanism ensures consistent skinfold compression. The integrated touchscreen displays connectivity and calibration status, confirming operational readiness.

Participants Demographics

A total of 31 participants were voluntarily recruited for validation testing. Baseline demographic data — including age, gender, height, weight, self-reported fitness level, and average weekly physical activity — was collected via a Google Form that included an informed consent agreement in compliance with the Data Privacy Act (R.A. No. 10173).

Table 4.1 Demographics Profile of Participants

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	17	54.84%
	Female	14	46.16%
	Total	**31**	**100%**
Fitness Level	Inactive / Sedentary	7	22.58%
	Beginner	11	35.48%
	Intermediate	10	32.26%
	Advanced	3	9.68%
	Total	**31**	**100%**
Physical Activity	Inactive / Sedentary	7	22.58%
	Lightly Active	8	25.81%
	Moderate	9	29.03%
	Very Active	7	22.58%
	Extra Active	0	0.00%
	Total	**31**	**100%**
Characteristic	**Mean**	**Std. Deviation (SD)**	**Range (Min - Max)**
Age (years)	26	5.53	**22-27**
Height (cm)	170.23	12.18	**137-185**
Weight (kg)	68.29	17.02	**40-115**

Table 4.1 presents the demographic profile of the 31 participants involved in the validation study. The cohort comprised 17 males (54.84%) and 14 females (45.16%), with an average age of 26 years, mean height of 170 cm, and mean weight of 68.29 kg. Fitness levels ranged from Sedentary (22.58%) to Very Active (12.90%), ensuring the caliper's accuracy was tested across diverse body compositions and subcutaneous fat levels for a robust validation.

Data Presentation

Validation was conducted through two phases: (1) raw skinfold thickness comparison between the digital and manual calipers (precision testing), and (2) computed body fat percentage comparison across the digital caliper, manual caliper, and InBody BIA device (accuracy testing).

Table 4.2 Comparison of skinfold thickness (mm) between manual and digital calipers

Test	Sunno Digital Caliper				Manual Caliper				
1	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	16.15	16.38	16.61	16.38	16	15	16	15.67	0.71
	13.36	12.27	13.52	13.05	12	14	14	13.33	-0.28
	13.85	12.17	13.59	13.20	11	12	12	11.67	1.54
2	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	14.41	13.1	13.43	13.65	13	13	12	12.67	0.98
	19.23	19.56	19.87	19.55	20	18	18	18.67	0.89
	21.24	19.12	19.05	19.80	22	20	19	20.33	-0.53
3	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	17.63	18.57	17.23	17.81	16	18	18	17.33	0.48
	13.24	12.67	13.86	13.26	12	14	13	13.00	0.26
	19.03	22.08	20.98	20.70	22	20	20	20.67	0.03
4	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	15.56	14.11	16.84	15.50	16	15	15	15.33	0.17
	6.08	5.71	6.46	6.08	6	5	6	5.67	0.42
	13.79	14.09	13.26	13.71	12	14	13	13.00	0.71
5	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	13	12.87	13.23	13.03	14	13	13	13.33	-0.30
	29.12	29.34	29.78	29.41	30	30	29	29.67	-0.25
	34.06	33.98	34.21	34.08	36	34	35	35.00	-0.92

Table 4.2 presents a representative sample of precision testing data, with three trials recorded per test case to ensure consistency. The final column documents the specific difference between digital and manual averages.

Table 4.3 Comparison of Computed Body Fat Percentage between Manual and Digital Calipers

Test	Physical Activity	Manual Caliper (BF%)	Sunno Digital Caliper (BF%)
1	Lightly Active	11.88	11.54
2	Very Active	14.89	15.57
3	Moderate	19.86	20.04
4	Very Active	10.16	10.04
5	Moderate	21.22	21.74
6	Sedentary	39.31	39.38
7	Very Active	21.99	21.66
8	Moderate	29.16	29.35
9	Lightly Active	21.98	21.88
10	Sedentary	22.37	22.22

Table 4.3 displays the body fat percentage calculations derived from both instruments across participants spanning sedentary to very active fitness levels, demonstrating consistent agreement between the two methods.

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Table 4.4 Comparison of Computed Body Fat Percentage between InBody and Digital Calipers

Test	Physical Activity	Inbody (BF%)	Sunno Digital Caliper (BF%)
1	Lightly Active	13.6	11.54
2	Very Active	17.1	15.57
3	Moderate	25.8	20.04
4	Very Active	13.3	10.04
5	Very Active	9	13.82
6	Lightly Active	20.2	24.87
7	Moderate	26.9	23.06
8	Very Active	9.53	11.85
9	Moderate	26.5	22.05
10	Very Active	16.12	18.64

Table 4.4 presents the supplementary comparison against the InBody BIA device ($n = 10$). Numerical variances observed in this comparison reflect the distinct measurement methodologies — Bioelectrical Impedance Analysis versus skinfold anthropometry — rather than limitations of the digital caliper's precision.

Statistical Analysis

Three statistical parameters were computed to validate the caliper's performance: mean difference, standard deviation, and percent error. The mean difference determines the average deviation between the readings of the digital and manual calipers. The smaller the value, the closer the measurements are between two devices. It was computed using the formula:

$$\text{Mean Difference} = \frac{\sum |X_d - X_m|}{n}$$

Equation 4.1 Mean Difference Formula

where Xd represents the digital caliper reading, Xm the manual caliper reading, and n the number of measurements.

The standard deviation (SD) measures how consistent the differences are across multiple test points. A low SD indicates that the readings are stable and not widely dispersed. The formula used is:

$$SD = \sqrt{\frac{\sum (X - \bar{X})^2}{n - 1}}$$

Equation 4.2 Standard Deviation Formula

Lastly, percentage error evaluates the relative deviation between the digital caliper and the reference device (manual or InBody). This quantifies the degree of measurement accuracy and is calculated using:

$$\text{Percentage Error} = \frac{|X_d - X_r|}{X_r} \times 100$$

Equation 4.3 Percent Error Formula

where Xd is the digital caliper value and Xr is the reference reading.

Phase 1: Skinfold Thickness Precision (Manual vs. Digital Caliper)

Table 4.5 Statistical Results of Measurement Precision (Manual vs Digital Caliper)

Metrics	Values
Number of paired tests	15
Mean Difference (mm)	0.01 mm
Standard Deviation (mm)	0.65 mm
Percent Error	2.15%

Table 4.5 illustrates the high level of agreement between the two instruments, revealing a negligible mean difference of −0.01 mm and a low standard deviation of 0.65 mm. These metrics indicate that the digital caliper produced measurements closely matching those of the manual caliper with consistent precision across all trials. Furthermore, the 2.15% error rate falls well within acceptable limits for professional skinfold measurement instrumentation and validation.

Phase 2a: Body Fat Percentage (Manual vs. Digital Caliper)

Table 4.6 Statistical Result of Manual and Sunno Fitness Caliper Comparison

Physical Activity	N	MD	SD	% Error
Sedentary	7	0.05	0.15	**0.45%**
Lightly Active	8	-0.03	0.3	**1.08%**
Moderate	9	0.15	0.21	**0.93%**
Very Active	7	-0.17	0.54	**2.47%**
Total	**31**	**0.01**	**0.35**	**1.21%**

Table 4.6 demonstrates the strong agreement between the two instruments, showing an overall mean difference of 0.01 percentage points and a percent error of 1.21%. These results validate the accuracy of the digital caliper's automated computation across all activity levels. Although the very active group recorded a slightly higher error of 2.47%, this remains well within acceptable measurement limits for reliable body composition assessment.

Phase 2b: Body Fat Percentage (InBody vs. Digital Caliper)

Table 4.7 Statistical Result of InBody and Sunno Fitness Caliper Comparison

Physical Activity	N	MD	SD	% Error
Sedentary	0	-	-	-
Lightly Active	2	1.31	4.76	**19.14%**
Moderate	3	-4.68	0.99	**17.80%**
Very Active	5	0.97	3.34	**25.40%**
Total	**10**	**-0.66**	**3.84**	**21.87%**

Table 4.7 highlights a low mean difference of −0.66 percentage points, indicating minimal average bias between the two devices. However, the higher standard deviation of 3.84 and a total percent error of 21.87% reflect notable variability at the individual level. This variance is largely attributable to the fundamentally different measurement principles employed by each device, as mechanical skinfold pressure and bioelectrical impedance often yield divergent results.

DISCUSSION OF RESULTS

The two-phase validation confirms that the Sunno Fitness digital caliper achieves high precision and accuracy for its intended purpose.

In Phase 1, the AS5047P sensor demonstrated measurement precision closely matching manual caliper readings, with a mean difference of only −0.01 mm and an error rate of 2.15%. In Phase 2, the automated body fat computation (Jackson–Pollock 3-site formula with Siri equation) was validated with a mean difference of 0.01 percentage points and an error rate of 1.21% against manual calculation — confirming that the firmware-embedded formulas were implemented correctly.

The higher discrepancy observed against the InBody device (21.87% error) warrants specific contextualization. This variance does not reflect a hardware limitation but rather an expected consequence of comparing two fundamentally different assessment modalities. The digital caliper measures subcutaneous fat through direct skinfold compression, while InBody uses bioelectrical impedance analysis (BIA) based on electrical conductivity and total body water content. BIA readings are influenced by hydration status, food intake, electrolyte balance, and muscle mass variability — factors that do not affect skinfold measurements. This methodological divergence is well-documented in the literature (Escamilla et al., 2024) and accounts for the observed individual-level variability.

The slightly elevated error rates observed in the very active participant subgroup can be attributed to physiological characteristics including increased muscle density, reduced subcutaneous fat layers, and fluctuating hydration levels — all of which affect both caliper compression dynamics and BIA conductivity readings.

The Sunno Fitness caliper's performance compares favorably with established digital alternatives. Leão et al. (2023) reported correlation coefficients ranging from 0.724 to 0.991 for the Lipowise digital caliper against the Harpenden manual caliper, with no significant differences detected ($p > 0.05$). While a direct correlation analysis was outside the scope of the current validation protocol, the Sunno Fitness caliper's negligible mean differences and low error rates against manual measurement suggest comparable accuracy. Unlike Lipowise, however, the Sunno Fitness caliper integrates wireless data transmission and automated body fat computation, adding functional value beyond the measurement itself.

Effectiveness of Data-Driven Insights

System Output

The Data-Driven Insights Module applies the Isolation Forest algorithm together with rolling slope and variance analysis to generate automated assessments of client progress across four key metrics: body fat percentage, exercise volume, nutrition variety, and physical activity (step count).

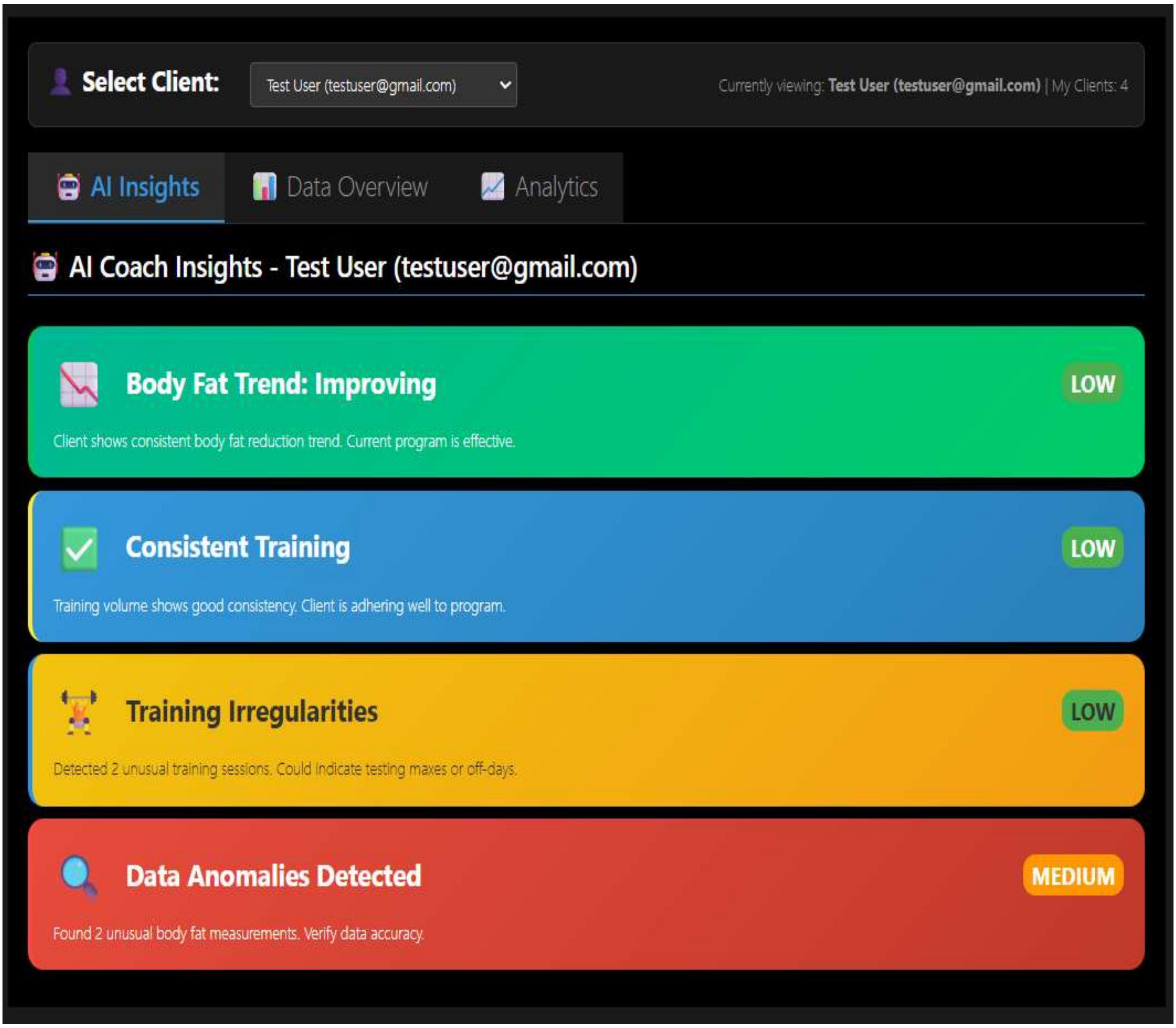

Figure 4.3 Data-Driven Insights Displayed on the Coach Dashboard

Figure 4.3 illustrates the "AI Coach Insights" dashboard, which uses color-coded cards to display key findings such as trend status and anomaly alerts. Each card includes a priority level and brief description, enabling coaches to quickly interpret client progress and identify areas requiring attention.

Public Proxy Datasets Used for Algorithm Validation

Because live longitudinal client data was not yet available at the time of validation, four publicly available proxy datasets were used to evaluate the algorithm's performance. Each dataset was selected based on its relevance to the metrics monitored by the system.

Table 4.8 Summary of Proxy Datasets Used for Algorithm Validation

Dataset	Metric Represented	Sample Size (N)	Description
Body Fat Percentage	Body Fat Percentage Trends	292	Contains BF% values based on skinfold-derived estimates, used to simulate changes in body composition over time.
Daily Step Count	Physical Activity Level	5,748	Provides daily step counts that replicate varying activity behaviors useful for detecting irregular movement patterns.
Daily Exercise Volume	Training Volume	1,086	Includes smoothed daily volume data that models variations in training intensity and workout consistency.
Weekly Food Variety	Dietary Variety	294	Represents weekly counts of different food items consumed, used to simulate dietary diversity and adherence patterns.

Table 4.8 presents the data distribution used for testing, with datasets ranging from 292 weekly summary points for body composition to over 5,700 daily entries for step counts. This variety simulated diverse real-world behavioral patterns, providing a robust evaluation of the algorithm's adaptability across different data characteristics. Such a comprehensive range ensures that the system can effectively handle both sparse and high-frequency fitness metrics.

Proxy datasets were employed for two reasons: (1) the Isolation Forest algorithm's cold-start constraint requires 12–14 days of accumulated data for reliable outputs, and live client data at the time of validation was insufficient in both volume and temporal span; and (2) publicly available datasets with known characteristics enabled systematic, reproducible evaluation of algorithmic performance — an approach that provides a more controlled baseline than early-stage client data with limited variability.

Cross-Metric Validation Results

The Isolation Forest algorithm was evaluated across two dimensions: (1) anomaly detection — the ability to distinguish genuine outliers from data noise, and (2) trend classification — the ability to correctly categorize progress as improving, regressing, or plateauing.

Anomaly Detection Performance

Across all four datasets, the RIF/EIF anomaly detection rate remained stable at approximately 10%, indicating consistent identification of genuine structural outliers regardless of data characteristics. In contrast, variance anomaly detection adapted dynamically to data quality: the body fat percentage dataset (which was inherently volatile) showed a 19.9% variance anomaly rate, the step count dataset showed 15.0%, exercise volume showed 10.0%, and the comparatively stable nutrition variety dataset showed only 5.1%.

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This adaptive behavior is a critical strength — the algorithm correctly differentiated between inherently noisy data (where high variance is expected and should be handled through smoothing) and genuinely anomalous data points (which warrant coach attention). A fixed-threshold system would not achieve this discrimination.

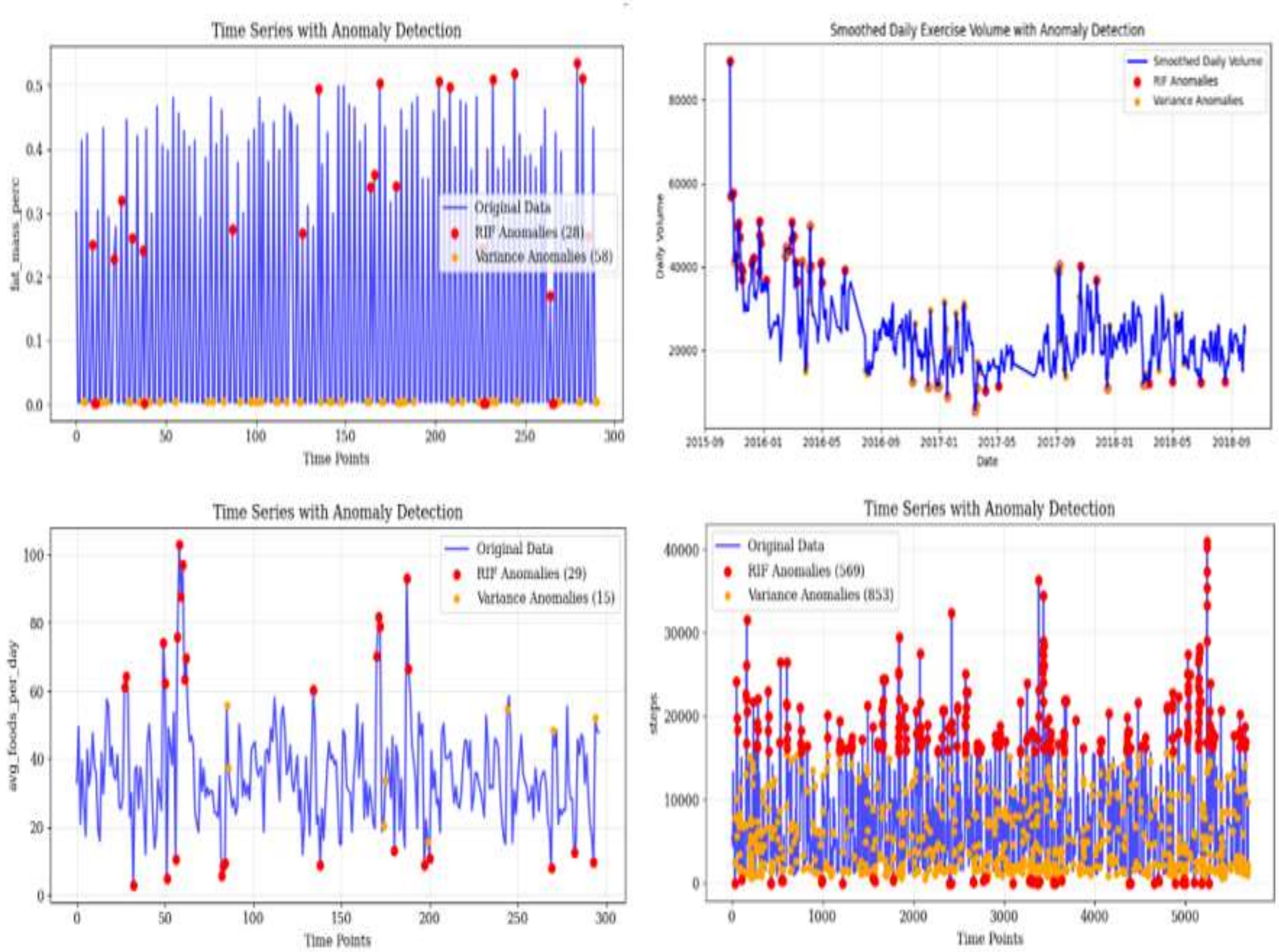

Figure 4.4 Time-Series Plots with Anomaly Detection Across All Four Metrics

Figure 4.4 presents anomaly detection results for all four datasets. Body fat percentage (top-left) was the noisiest metric, with 86 total flagged points (28 RIF, 58 variance). Exercise volume (top-right) showed anomalies concentrated in the volatile early phase (2015–2017), with minimal flags during the stable maintenance period. Nutritional intake (bottom-left) had the fewest anomalies (44 total), confirming it as the cleanest dataset. Physical activity (bottom-right) exhibited the highest anomaly count (569 RIF, 853 variance), reflecting the inherent daily variability of step count data. Collectively, these results confirm context-sensitive detection — more flags in volatile data, fewer in stable data.

Trend Classification Performance

Trend classification accuracy ranged from 46.2% (body fat percentage) to 59.0% (step count), with exercise volume at 51.6% and nutrition variety at 55.7%.

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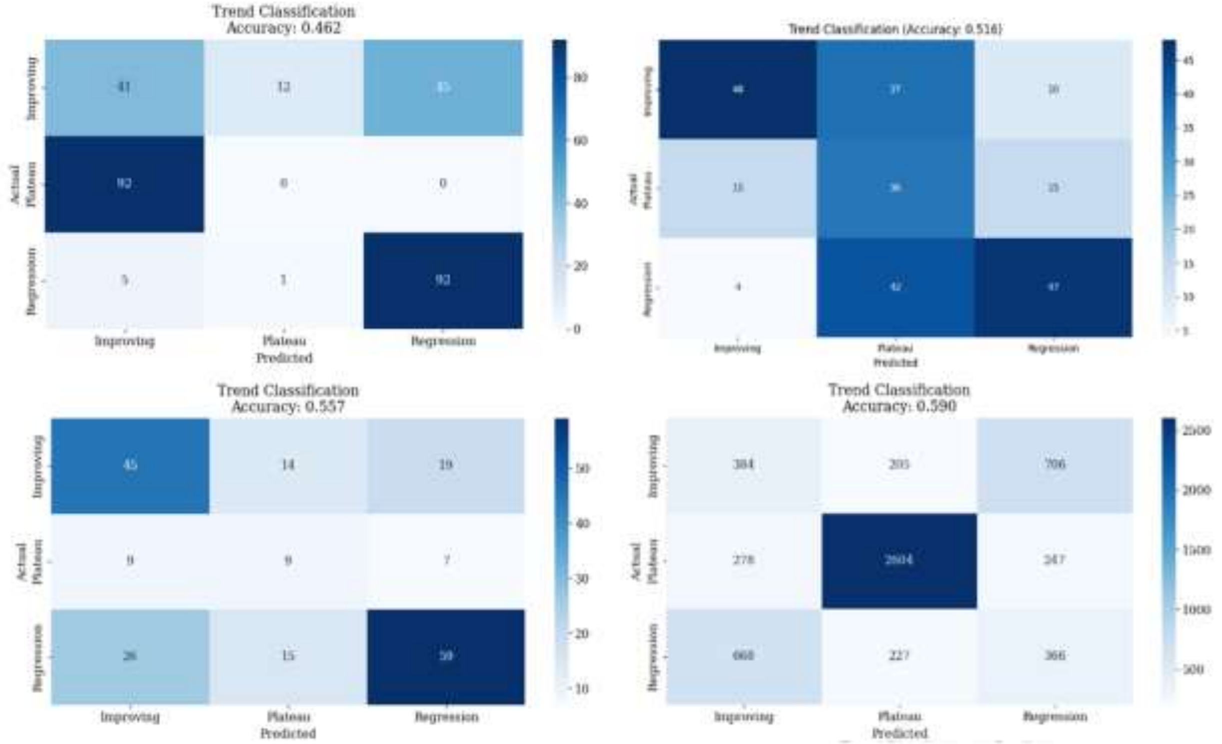
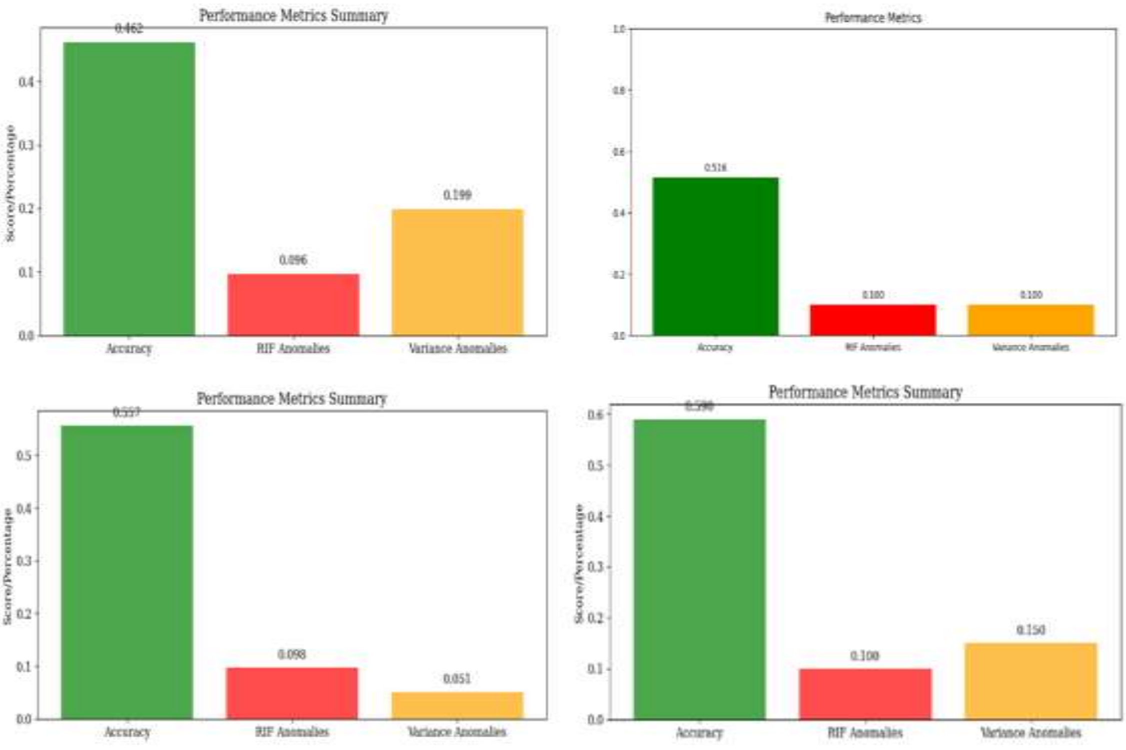


Figures 4.5 Confusion Matrices Across All Four Metrics

Figure 4.5 compares predicted classifications against ground truth labels. Step count (top-right) achieved 2,604 correct "Plateau" classifications, demonstrating strong stability detection. Nutritional intake (bottom-left) performed best on directional trends, with 59 correct "Regression" and 45 correct "Improving" classifications. Exercise volume (top-left) correctly identified 48 "Improving" and 47 "Regression" trends but occasionally misclassified subtle shifts as plateaus. Body fat percentage (top-left) showed zero correct plateau identifications — all 92 plateau instances were reclassified as directional trends, reflecting intelligent smoothing of volatile data.



Figures 4.6 Performance Metrics Summaries Across All Four Metrics

Figure 4.6 quantifies accuracy, RIF anomaly rate, and variance anomaly rate per dataset. Physical activity achieved the highest accuracy (0.590) despite a 25% total irregularity rate, demonstrating algorithmic robustness. Nutritional intake recorded 0.557 accuracy with the lowest irregularity (14.9%). Exercise volume achieved 0.516 with balanced anomaly rates. Body fat percentage had the lowest accuracy (0.462) and highest irregularity (nearly 30%). Notably, the RIF rate remained stable at 9.6%–10.0% across all metrics, confirming uniform outlier detection.

Figures 4.7 Trend Distribution Charts Across All Four Metrics

Figure 4.7 shows the distribution of predicted trends. Physical activity and exercise volume were dominated by "Plateau" predictions (53.4% and 46.9%, respectively), corresponding to stable behavioral patterns. Nutritional intake was dominated by directional predictions — "Regression" (40.5%) and "Improving" (40.1%). Body fat percentage showed the most polarized distribution, split nearly evenly between "Improving" (47.9%) and "Regression" (47.6%), with only 4.5% classified as "Plateau."

The variation in accuracy across metrics reflects the algorithm's context-sensitive behavior rather than inconsistent performance:

Step count (59.0% — highest accuracy): The algorithm excelled at detecting periods of stable user activity, correctly classifying "Plateau" 2,604 times — the largest single value across all confusion matrices. This demonstrates reliable identification of behavioral consistency, which is a valuable insight for fitness coaching.

Nutrition variety (55.7%): The algorithm performed strongly on directional trend detection, correctly classifying 59 "Regression" trends and 45 "Improving" trends. The dataset's low noise level (5.1% variance anomaly rate) facilitated clearer trend identification.

Exercise volume (51.6%): The time-series data exhibited two distinct phases — an initial period of high and volatile volume followed by a longer period of stable, lower-volume activity. The algorithm correctly captured both the volatility of the early phase and the stability of the maintenance phase.

Body fat percentage (46.2% — lowest accuracy): This dataset was the most volatile, with nearly 30% of data points flagged as anomalies (9.6% RIF + 19.9% variance). The confusion matrix revealed that in 92 instances where the ground truth labeled a "Plateau," the algorithm classified all 92 as "Improving." Rather than representing a failure, this behavior reflects intelligent smoothing — the algorithm filtered minor fluctuations to identify the dominant long-term trend, prioritizing meaningful insight over strict correlation with noisy ground truth labels. For coaching purposes, this behavior is preferable: coaches need to know whether a client is trending toward improvement or regression, not whether daily values fluctuated around a temporary plateau.

In summary, the algorithm demonstrated two complementary strengths suited for fitness coaching. For stable, high-volume data such as step count, it excelled at plateau detection — recognizing behavioral consistency. For volatile data such as body fat percentage and nutrition variety, it prioritized directional trend detection — surfacing meaningful long-term trajectories by smoothing short-term noise.

DISCUSSION OF RESULTS

The validation confirms that the Isolation Forest–based module functions as an adaptive and context-aware analytical engine with two complementary strengths.

The algorithm reliably identifies periods of consistent behavior, as demonstrated by its strong plateau classification in step count data (2,604 correct classifications). This capability is essential for recognizing when a client is maintaining habits effectively.

The algorithm effectively identifies sustained improvements or regressions in body composition and dietary patterns, even when individual data points are volatile. Its tendency to resolve noisy data into directional trends — rather than defaulting to "Plateau" — represents intelligent smoothing that prioritizes actionable coaching insights.

The choice of Isolation Forest over alternative anomaly detection algorithms was validated by the results. The algorithm's stable 10% RIF anomaly rate across all datasets, combined with its adaptive variance detection, confirms the properties identified in comparative studies (Agyemang, 2024; Neupane et al., 2024): computational efficiency, minimal distributional assumptions, and effective performance without labeled training data. While more complex deep learning approaches might achieve marginally higher accuracy, they would require substantially greater computational resources — an impractical constraint for a web-based coaching platform.

These results were obtained using proxy datasets rather than live client data. While the proxy data simulated realistic health and fitness patterns, validation with longitudinal real-world client data over extended periods is necessary to confirm the algorithm's performance in production conditions and is recommended as a priority for future work.

System Functionality and Progress Tracking

System Output

The Progress Tracking Module enables coaches and clients to monitor workouts, nutrition logs, and activity records through an integrated dashboard. Client entries are recorded, processed, and displayed in real time, with automated notifications generated for newly added workouts, updated nutrition logs, and upcoming scheduled activities.

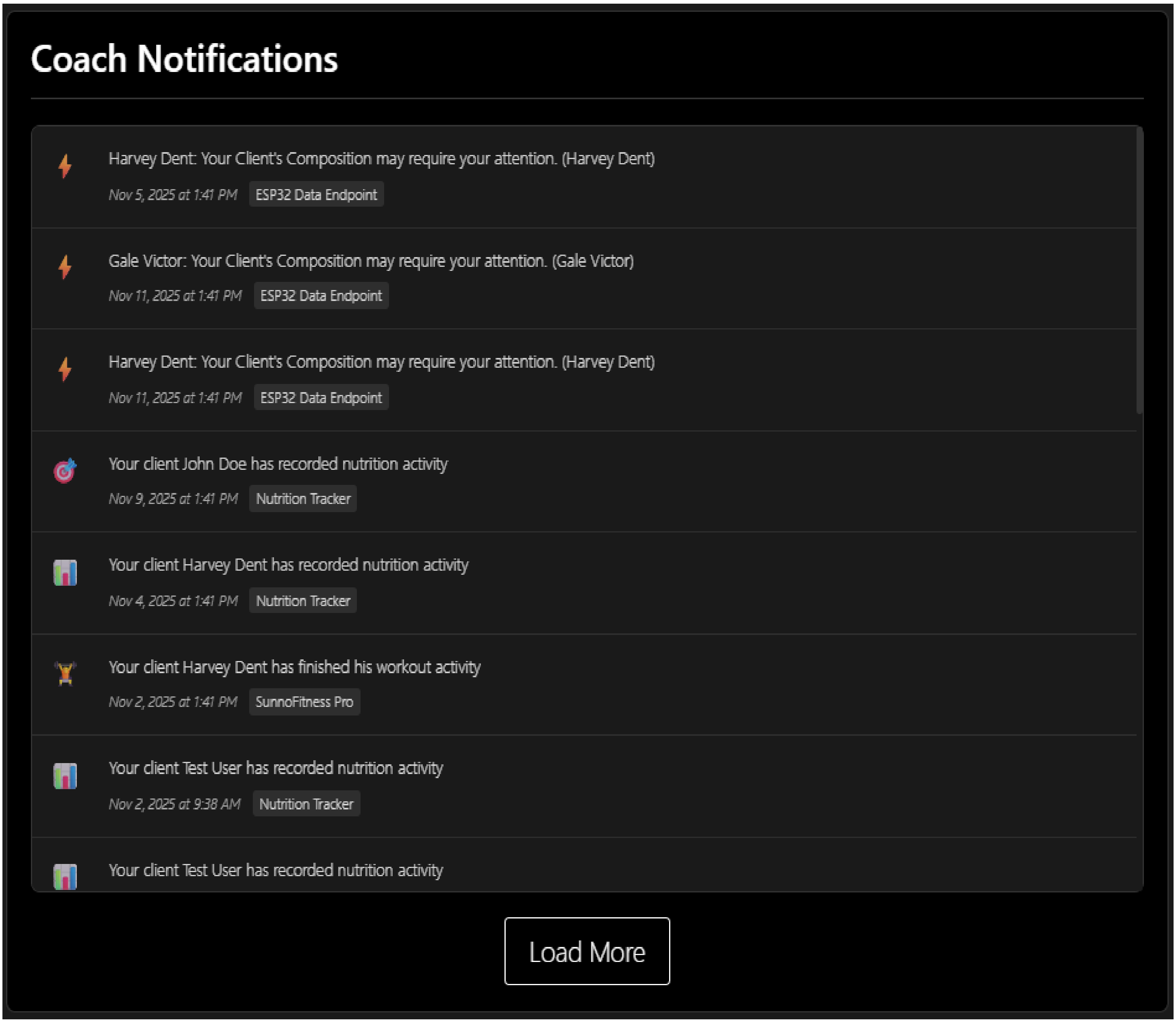


Figure 4.8 Coach Notification Dashboard

Figure 4.8 displays the Coach Notifications interface, which centralizes real-time alerts from both hardware-generated body composition data and client-submitted logs. Each notification includes the client's name, activity type, and timestamp, enabling coaches to monitor adherence efficiently.

Latency Testing and Performance Evaluation

The module's responsiveness was evaluated through 40 latency tests across four core notification events, measuring the time between user actions (or system triggers) and notification delivery.

Table 4.9 Latency Test Data

Test	Test Scenario	Trigger Event	Delivered	Latency (ms)	Status
1	Add new workout	Client submits new workout entry	Yes	745	Pass
2	Add new workout	Client submits new workout entry	Yes	812	Pass
3	Add new workout	Client submits new workout entry	Yes	789	Pass
4	Add new workout	Client submits new workout entry	Yes	750	Pass
5	Add new workout	Client submits new workout entry	Yes	720	Pass
6	Update Nutrition	Client log food intake	Yes	770	Pass
7	Update Nutrition	Client log food intake	Yes	580	Pass
8	Update Nutrition	Client log food intake	Yes	610	Pass
9	Update Nutrition	Client log food intake	Yes	595	Pass
10	Update Nutrition	Client log food intake	Yes	630	Pass
11	New Measurement Notification	New body measurement logged	Yes	890	Pass
12	New Measurement Notification	New body measurement logged	Yes	920	Pass
13	New Measurement Notification	New body measurement logged	Yes	850	Pass
14	New Measurement Notification	New body measurement logged	Yes	910	Pass
15	New Measurement Notification	New body measurement logged	Yes	880	Pass
16	Analytics Reminder	New insight available	Yes	-	Pass
17	Analytics Reminder	New insight available	Yes	-	Pass
18	Analytics Reminder	New insight available	Yes	-	Pass
19	Analytics Reminder	New insight available	Yes	-	Pass
20	Analytics Reminder	New insight available	Yes	-	Pass

Table 4.9 confirms the Progress Tracking Module's reliability, achieving a 100% delivery success rate across 20 scenarios. User-initiated actions remained highly responsive with latencies below 1,000 ms. Both manual entries and automated notifications were delivered promptly, ensuring the real-time communication necessary for effective engagement and coaching plan adherence.

Table 4.10 Notification Latency Test Results

Test Scenario	Trails	Delivered	Avg Latency (ms)	Min (ms)	Max (ms)	Std Dev	Success Rate (%)	Status
Add New Workout	10	10	768.1	720	812	30.4	100%	Pass
Update Nutrition	10	10	591.5	550	630	26.3	100%	Pass
New Measurement	10	10	891.5	850	935	27.1	100%	Pass
Reminders	10	10	N/A	-	-	-	100%	Pass
Overall System	40	40	750.4	550	935	132.8	100%	Pass

Table 4.10 reveals a 100% success rate across 40 trials, confirming the notification system's reliability. With average latencies ranging from 591.5 ms to 891.5 ms, the module maintained a 750.4 ms global average. This remains well below the 1,000 ms threshold, ensuring responsive communication and engagement within Sunno Fitness.

DISCUSSION OF RESULTS

The latency testing results demonstrate that the Progress Tracking Module of Sunno Fitness performs with high efficiency and reliability in delivering real-time updates between the coach and client interfaces. All test scenarios achieved a 100% success rate in notification delivery, confirming that the system's backend communication and event-handling mechanisms are functioning properly. The recorded latency values, ranging from 591.5 ms to 891.5 ms and averaging 750.4 ms, indicate that the system provides near–real-time responsiveness suitable for interactive fitness tracking applications. Latencies below 1,000 ms are widely considered acceptable for modern web and mobile systems, ensuring interactions remain smooth and uninterrupted.

The observed variations in latency can be attributed to the computational load required by each event type. For instance, "Update Nutrition" submissions exhibited the lowest latency at 591 ms, reflecting minimal server-side processing. Conversely, the highest latency was recorded during "New Measurement" logging (891 ms), as this process involves additional validation for physiological data before triggering notifications. Slightly higher latencies in other events, such as workout updates and reminders, were due to data validation and synchronization with the MySQL database through REST API calls.

These findings confirm that the Progress Tracking Module meets the system's design objectives of ensuring real-time communication, accurate synchronization, and dependable data flow between client and coach dashboards. The minimal delays observed are within acceptable thresholds for web-based fitness applications and do not hinder the user experience. Therefore, the module's latency performance validates its operational efficiency and reliability as a core component of the Sunno Fitness system.

Summary: Objective to Validation Mapping

The following table provides a consolidated view of how each study objective was validated and the key metrics achieved.

Table 4.11 Objective to Validation Mapping

Objective	Validation Method	Key Results	Status
Obj. 1: Develop a digital skinfold caliper for accurate body fat measurement with real-time platform integration	Two-phase comparison: (1) raw skinfold thickness vs. manual caliper (n=31); (2) computed BF% vs. manual caliper (n=31) and InBody BIA (n=10)	Skinfold precision: MD = −0.01 mm, PE = 2.15%. BF% accuracy: MD = 0.01 pp, PE = 1.21% (vs. manual). BIA comparison: PE = 21.87% (methodological difference). 100% wireless sync success.	Validated
Obj. 2: Integrate ML algorithms to analyze client data and generate personalized insights	Isolation Forest validation using 4 proxy datasets (body fat, exercise volume, nutrition variety, step count) with confusion matrices, anomaly rates, and trend classification	Adaptive anomaly detection: stable ~10% RIF rate; context-sensitive variance detection (5.1%–19.9%). Trend classification: 46.2%–59.0% accuracy with demonstrated intelligent smoothing.	Validated
Obj. 3: Develop a web-based platform for progress tracking, visualization, and communication	Latency testing: 40 trials across 4 notification event types	100% notification delivery rate. Average latency: 750.4 ms (range: 591.5–891.5 ms). All latencies < 1,000 ms threshold.	Validated

ACKNOWLEDGEMENTS

This study, *Sunno Fitness*, is a product of perseverance, curiosity, and a commitment to innovation. Although the development of this capstone project was completed individually, its success would not have been possible without the guidance, support, and encouragement of many individuals. The researcher extends his deepest gratitude to the following:

First and foremost, to Prof. Ryan Paul Obligar, my thesis adviser, for his invaluable mentorship and unwavering patience. Your expert insights shaped both the technical design of the system and the overall structure of this manuscript. Thank you for helping me navigate the complexities of the development process and for consistently challenging me to refine my work.

To the distinguished faculty members of the Pamantasan ng Lungsod ng Maynila, especially the panel members: Prof. Vivien A. Agustin, Prof. Diony S. Abando, Prof. Mark Anthony S. Mercado, and coordinator Dr. Khatalyn E. Mata, thank you for your time, expertise, and valuable recommendations during the evaluation of this study.

To my friends and peers, thank you for being my support system throughout this journey. Your encouragement, conversations, and shared moments of relief helped lighten the long nights of coding, testing, and revision.

To my family, who have always been my foundation and inspiration. Completing an individual capstone project was a significant challenge, and there were many moments when exhaustion nearly overtook me. Thank you for your patience, understanding, and unwavering belief in my capabilities. Your support gave me the strength to continue. This achievement is one we share together.

Above all, to Almighty God, thank You for the wisdom, endurance, and resilience that guided me from beginning to end.

CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes the key findings of the study in relation to the stated objectives, acknowledges the limitations that frame these conclusions, and proposes recommendations for future improvement and extension of the Sunno Fitness system. A phased implementation roadmap is provided to guide the prioritization of recommended enhancements.

Conclusions

The Sunno Fitness system was developed and evaluated to address the need for an integrated fitness monitoring platform that combines a digital skinfold caliper, data-driven insights, and web-based progress tracking. The conclusions are organized according to the study's three specific objectives.

1. **Digital Skinfold Caliper Accuracy and Reliability.** The design and development of the Sunno Fitness digital caliper prototype achieved a high standard of measurement accuracy and reliability. A two-phase validation confirmed that the AS5047P sensor produced skinfold thickness readings with a negligible mean difference of −0.01 mm and a percent error of 2.15% relative to a standard manual caliper. The system's automated body fat computation — implementing the Jackson–Pollock 3-site formula and Siri equation — was validated with a mean difference of 0.01 percentage points and an error rate of 1.21%, confirming that the embedded computational pipeline was implemented accurately. While an expected discrepancy (21.87% error) was observed when compared with InBody BIA technology, this variance was attributed to fundamental methodological differences between skinfold anthropometry and bioelectrical impedance analysis rather than limitations of the digital caliper's hardware or firmware. The caliper's performance compares favorably with established digital alternatives such as Lipowise (Leão et al., 2023), while additionally offering wireless data transmission and automated computation capabilities not present in comparable devices.

2. **Machine Learning for Personalized Insights.** The Isolation Forest algorithm was successfully validated as an adaptive and context-aware analytical engine for client progress monitoring. Using four proxy datasets representing body fat percentage, exercise volume, nutrition variety, and step count, the algorithm demonstrated two critical capabilities: (1) adaptive anomaly detection, maintaining a stable ~10% RIF anomaly rate while dynamically adjusting variance detection sensitivity from 5.1% (clean data) to 19.9% (volatile data); and (2) intelligent trend classification with accuracy ranging from 46.2% to 59.0%, where the algorithm consistently prioritized meaningful long-term trends over minor fluctuations. The confusion matrices revealed that lower accuracy scores were not indicative of poor performance but of deliberate intelligent smoothing — the model resolved noisy data into actionable directional insights rather than mirroring volatile ground truth labels. This behavioral characteristic is well-suited for a coaching context where sustained trends are more informative than daily fluctuations.

3. **Web-Based Platform for Progress Tracking and Communication.** The web-based platform was validated through latency testing, achieving a 100% notification delivery success rate across 40 test trials. All interactions averaged below 1 second (global average: 750.4 ms, range: 591.5–891.5 ms), well within the accepted threshold for real-time web applications. The low standard deviation across latency measurements confirmed the platform's stability and predictability, validating it as an effective and reliable solution for progress tracking, data visualization, and coach–client communication.

Limitations

The following limitations should be considered when interpreting the findings and conclusions of this study:

1. **Proxy dataset dependency.** The machine learning component was validated using publicly available proxy datasets rather than live longitudinal client data. While these datasets simulated realistic fitness and lifestyle patterns and enabled controlled evaluation, the algorithm's real-world performance under production conditions — including diverse client populations, irregular data submission patterns, and extended time horizons — remains to be confirmed.

2. **Limited BIA comparison sample.** The supplementary comparison with InBody BIA technology was conducted on a reduced subset of 10 participants due to equipment availability constraints. While this comparison served its intended purpose as a cross-technology benchmark, the smaller sample size limits the generalizability of the InBody comparison findings.

3. **Operator dependency.** Accurate skinfold measurement requires trained professionals with proper technique. Despite the caliper's digital enhancements, measurement reliability remains partially dependent on operator skill in identifying anatomical sites and applying consistent pressure.

4. **Population constraints.** The Jackson–Pollock 3-site method is designed for individuals within a general fitness range. The caliper's accuracy may be reduced for populations with extreme body compositions, particularly obese individuals with excessive subcutaneous fat.

5. **Algorithm cold-start period.** The Isolation Forest algorithm requires approximately 12–14 days of accumulated client data before generating reliable insights, limiting the system's utility during the initial onboarding phase.

6. **Absence of commercial platform benchmarking.** The current study did not include a formal comparative evaluation against existing commercial fitness platforms (e.g., Trainerize, TrueCoach, My PT Hub). Such a comparison would contextualize the system's competitive advantages and identify areas where further development is needed.

RECOMMENDATIONS

The following recommendations are proposed to expand the system's capabilities, strengthen its validation, and position the technology for broader adoption. A phased implementation roadmap is provided to guide prioritization.

Phase 1: Validation Strengthening (Short-Term, 0–6 Months)

1. **Live Client Data Validation.** The highest-priority recommendation is to conduct longitudinal validation using real client data collected over extended periods (minimum 3–6 months). This would confirm the Isolation Forest algorithm's performance under production conditions, including diverse user populations, irregular data submission patterns, and real-world data quality challenges. Success in this phase would substantially strengthen the system's credibility for both academic publication and commercial deployment.

2. **Comparative Benchmarking Against Commercial Platforms.** A formal comparative analysis should be conducted against established commercial fitness coaching platforms such as Trainerize, TrueCoach, and

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My PT Hub. This benchmarking should evaluate feature coverage, measurement accuracy, user experience, pricing, and data analytics capabilities to clearly position Sunno Fitness within the existing market landscape and identify its unique competitive advantages.

Phase 2: Hardware and Analytics Enhancement (Medium-Term, 6–18 Months)

3. **Industrial Design Refinement.** To transition the digital caliper from a functional prototype to a market-ready device, industrial design principles should be applied. This includes optimizing internal electronics for mass production, adopting manufacturing methods such as injection molding for a more compact and durable enclosure, and enhancing ergonomics for professional use. These improvements would increase the device's portability, durability, and professional presentation.

4. **Predictive Analytics and Adaptive Coaching.** Building on the demonstrated anomaly detection capabilities, the system should incorporate predictive analytics that forecast potential plateaus, fatigue trends, or adherence declines before they occur. This would enable proactive coaching interventions — such as recommending deload weeks, adjusting training volume, or modifying nutrition targets — shifting the system from reactive monitoring to adaptive coaching assistance.

5. **Expansion into Clinical and Athletic Research.** With the digital caliper's demonstrated precision and consistency, the system holds potential for deployment in specialized research settings involving elite athletes, rehabilitation patients, or individuals in structured medical weight-management programs. This would elevate Sunno Fitness from a coaching tool to a credible instrument for longitudinal health monitoring and performance profiling.

Phase 3: Ecosystem Expansion (Long-Term, 18–36 Months)

6. **Native Mobile Applications and Wearable Integration.** Developing native iOS and Android applications would enhance accessibility and daily engagement. A mobile-first ecosystem would also enable integration with popular wearable devices (Apple Watch, Garmin, Fitbit), enriching the platform's dataset with heart rate, sleep, and activity data. This multi-source data integration would improve the anomaly detection algorithm's comprehensiveness and reduce reliance on manual input.

7. **AI-Powered Nutrition Tracking via Computer Vision.** Incorporating computer vision capabilities for meal logging — allowing clients to capture photos for automatic caloric and macronutrient estimation — would reduce the effort required for daily tracking, increase data accuracy, and improve user compliance with the nutrition module.

Scalability Considerations

For long-term implementation, the following scalability factors should be addressed:

- **Database architecture:** As the user base grows, migration from a single MySQL instance to a distributed or cloud-managed database (e.g., Amazon RDS, Google Cloud SQL) may be necessary to maintain query performance and data reliability.

- **Algorithm processing:** As client data volume increases, the Isolation Forest computation pipeline may require optimization through batch processing, scheduled execution, or migration to a dedicated microservice to avoid degrading web application responsiveness.

- **Hardware manufacturing:** Scaling caliper production beyond individual prototypes will require establishing relationships with contract manufacturers, developing quality assurance protocols, and securing relevant certifications (e.g., CE marking) for commercial distribution.

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These scalability considerations ensure that the system's architecture can accommodate growth without requiring fundamental redesign, supporting a sustainable transition from academic prototype to commercially viable fitness technology platform.

Approval Sheet

The Capstone Project hereto titled

Sunno Fitness: A Fitness Coaching Platform Using

Digital Skinfold Caliper Data And Isolation Forest Algorithm For Data-Driven Performance Monitoring

prepared and submitted by **Madridano, Sunny E**., in partial fulfilment of the requirements for the degree of **Bachelor of Science in Information Technology** has been examined and is recommended for acceptance and approval for **ORAL EXAMINATION**.

____

Prof. Ryan Paul Obligar

Capstone Adviser

PANEL OF EXAMINERS

Approved by the Committee on Oral Examination

with a grade of _________ on _______.

____

Dr. Khatalyn E. Mata

Capstone Coordinator

______________________	____________________	________________________
Prof. Vivien A. Agustin	**Prof. Diony S. Abando**	**Prof. Mark Anthony S. Mercado**
Panel Member	Panel Member	Panel Member

Accepted and approved in partial fulfilment of the requirements for the degree of Bachelor of Science in Information Technology.

________________________	________________________
Prof. Ariel Antwaun Rolando C. Sison	**Dr. Khatalyn E. Mata**
Chairperson	Dean
Information Technology	College of Information Systems
Department	and Technology Management

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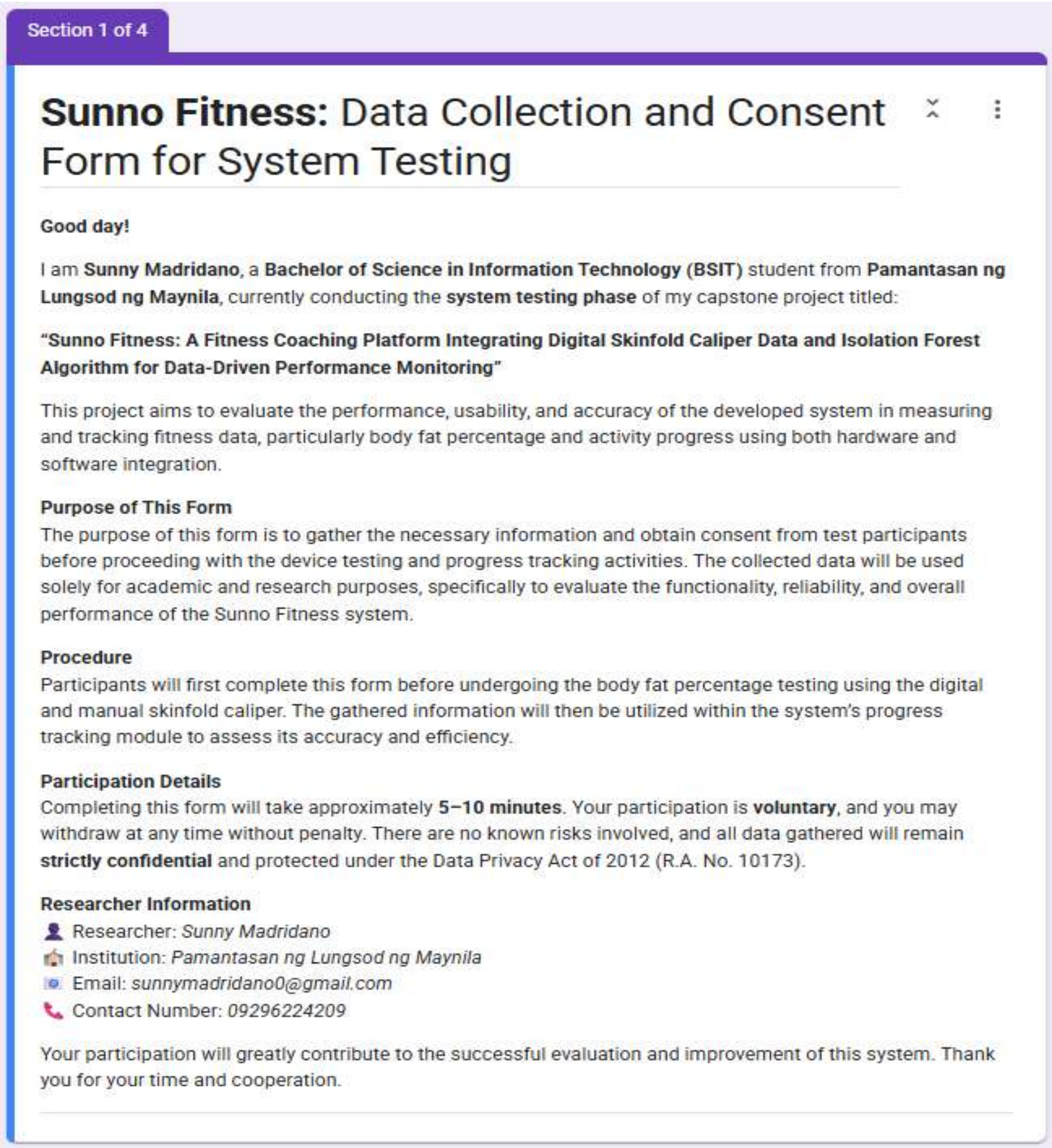
Appendix A: Supporting Documents

Google Form Questionnaires



Section 1 of 4

Sunno Fitness: Data Collection and Consent Form for System Testing

Good day!

I am **Sunny Madridano**, a **Bachelor of Science in Information Technology (BSIT)** student from **Pamantasan ng Lungsod ng Maynila**, currently conducting the **system testing phase** of my capstone project titled:

"Sunno Fitness: A Fitness Coaching Platform Integrating Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring"

This project aims to evaluate the performance, usability, and accuracy of the developed system in measuring and tracking fitness data, particularly body fat percentage and activity progress using both hardware and software integration.

Purpose of This Form
The purpose of this form is to gather the necessary information and obtain consent from test participants before proceeding with the device testing and progress tracking activities. The collected data will be used solely for academic and research purposes, specifically to evaluate the functionality, reliability, and overall performance of the Sunno Fitness system.

Procedure
Participants will first complete this form before undergoing the body fat percentage testing using the digital and manual skinfold caliper. The gathered information will then be utilized within the system's progress tracking module to assess its accuracy and efficiency.

Participation Details
Completing this form will take approximately **5–10 minutes**. Your participation is **voluntary**, and you may withdraw at any time without penalty. There are no known risks involved, and all data gathered will remain **strictly confidential** and protected under the Data Privacy Act of 2012 (R.A. No. 10173).

Researcher Information
Researcher: *Sunny Madridano*
Institution: *Pamantasan ng Lungsod ng Maynila*
Email: *sunnymadridano0@gmail.com*
Contact Number: *09296224209*

Your participation will greatly contribute to the successful evaluation and improvement of this system. Thank you for your time and cooperation.

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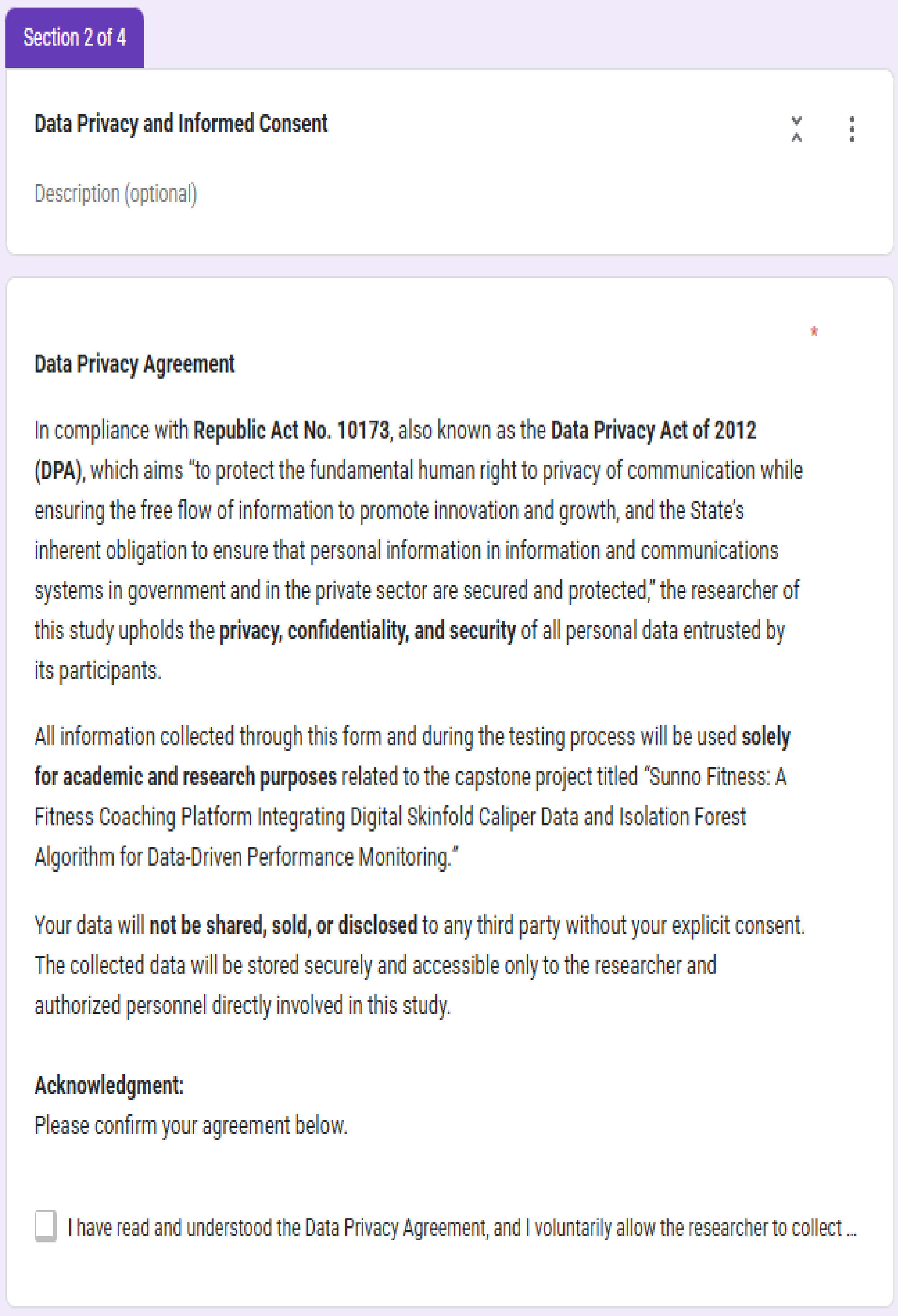

Section 2 of 4

Data Privacy and Informed Consent

Description (optional)

Data Privacy Agreement *

In compliance with **Republic Act No. 10173**, also known as the **Data Privacy Act of 2012 (DPA)**, which aims "to protect the fundamental human right to privacy of communication while ensuring the free flow of information to promote innovation and growth, and the State's inherent obligation to ensure that personal information in information and communications systems in government and in the private sector are secured and protected," the researcher of this study upholds the **privacy, confidentiality, and security** of all personal data entrusted by its participants.

All information collected through this form and during the testing process will be used **solely for academic and research purposes** related to the capstone project titled "Sunno Fitness: A Fitness Coaching Platform Integrating Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring."

Your data will **not be shared, sold, or disclosed** to any third party without your explicit consent. The collected data will be stored securely and accessible only to the researcher and authorized personnel directly involved in this study.

Acknowledgment:
Please confirm your agreement below.

☐ I have read and understood the Data Privacy Agreement, and I voluntarily allow the researcher to collect ...

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Informed Consent *

I understand that I am being invited to participate in the system testing for the capstone project “Sunno Fitness: A Fitness Coaching Platform Integrating Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring.”

I acknowledge that the purpose of this study is to evaluate the accuracy, usability, and effectiveness of the system in measuring and tracking fitness-related data. I am aware that my participation will involve the collection of personal and fitness information, including body measurements such as body fat percentage, which will be used for the system’s progress tracking and analysis.

I understand that:

"My participation is voluntary, and I may withdraw at any time without penalty."

"My data will be treated with confidentiality and used only for research and academic purposes."

"There are no known risks associated with participation in this testing."

"I may contact the researcher for any questions or concerns regarding the study."

By agreeing below, I voluntarily give my consent to participate in this system testing and for my data to be used in accordance with the terms stated above.

☐ I have read and understood the Informed Consent Statement, and I voluntarily agree to participate in the ...

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Section 3 of 4

Participant Profile

This section collects basic demographic and physical information from the participant. The information provided will help in generating accurate results during the system testing and data analysis phase. All details will remain confidential and used only for this academic research.

Name *

Short answer text

Age *

Short answer text

Sex *

- Male
- Female

Height (cm) *

Short answer text

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Weight (kg) *

Short answer text

Fitness Level *

- Beginner (Less than 1 year of consistent training)
- Intermediate (1-3 years of consistent training)
- Advanced (More than 3 years of consistent training)
- Currently Inactive/Sedentary

Physical Activity Level *

- Sedentary (Little to no exercise)
- Lightly Active (Light exercise/sports 1-3 days/week)
- Moderately Active (Moderate exercise/sports 3-5 days/week)
- Very Active (Hard exercise/sports 6-7 days/week)
- Extra Active (Very hard exercise, physical job, or training twice a day)

Section 4 of 4

Section title (optional)

Thank you for providing your information!

You may now proceed with the **system testing** for the capstone project **"Sunno Fitness: A Fitness Coaching Platform Integrating Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring."**

Your cooperation and participation are greatly appreciated!

Responses

Timestamp	Data Priv In compli All inform Your data Acknowle Please co	Informed I understa I acknowl I understa "My partic "My data "There are "I may co By agreei	Name	Age	Sex	Height (cm)	Weight (kg)	Fitness Level	Physical Activity Level
10/25/2025 7:56:24	I have rea	I have rea	Rochelle Mercado	22	Female	154	46	Beginner (Less than 1 year of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
10/25/2025 8:14:21	I have rea	I have rea	Adre Lucero	23	Male	173	56	Beginner (Less than 1 year of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
10/25/2025 12:44:59	I have rea	I have rea	Nathaniel Macaranas	22	Male	176	71	Intermediate (1-3 years of consistent training)	Very Active (Hard exercise/sports 6-7 days/week)
10/25/2025 18:23:04	I have rea	I have rea	Jericho Merilleno	27	Male	172	63	Beginner (Less than 1 year of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
10/27/2025 23:53:36	I have rea	I have rea	Rege Galicia	23	Male	180	86	Currently Inactive/Sedentary	Lightly Active (Light exercise/sports 1-3 days/week)
11/2/2025 0:47:30	I have rea	I have rea	Kenneth Carl Prado	22	Male	174.9	80	Beginner (Less than 1 year of consistent training)	Sedentary (Little to no exercise)
11/2/2025 0:55:11	I have rea	I have rea	John Carlo Narito	25	Male	176	70	Currently Inactive/Sedentary	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/2/2025 0:57:26	I have rea	I have rea	Evert Rodriguez	24	Male	173	90	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/2/2025 1:02:36	I have rea	I have rea	Cedric A. Agbunag	22	Male	185	115	Beginner (Less than 1 year of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)
11/2/2025 1:06:08	I have rea	I have rea	Andrea Rondael	23	Female	162	47	Intermediate (1-3 years of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)
11/2/2025 1:17:59	I have rea	I have rea	Mary Grace Galicia	47	Female	125	57	Currently Inactive/Sedentary	Lightly Active (Light exercise/sports 1-3 days/week)
11/2/2025 1:20:40	I have rea	I have rea	Gwenn Mico	23	Female	155	45	Beginner (Less than 1 year of consistent training)	Sedentary (Little to no exercise)
11/3/2025 19:22:09	I have rea	I have rea	Rhealiza Madridano	37	Female	167	68	Beginner (Less than 1 year of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)
11/3/2025 20:36:21	I have rea	I have rea	Jas Serrano	22	Female	152	40	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/7/2025 8:08:43	I have rea	I have rea	Dan Madridano	31	Male	184	81	Intermediate (1-3 years of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/7/2025 21:41:13	I have rea	I have rea	Marieton Faith Fernanc	23	Female	155	53	Beginner (Less than 1 year of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/7/2025 23:15:01	I have rea	I have rea	Lander javier	26	Male	160	60	Beginner (Less than 1 year of consistent training)	Sedentary (Little to no exercise)
11/7/2025 23:15:50	I have rea	I have rea	Marc dave javier	24	Male	161	64	Beginner (Less than 1 year of consistent training)	Sedentary (Little to no exercise)
11/8/2025 7:17:31	I have rea	I have rea	Jhan Paolo Laluces	22	Male	178	70	Advanced (More than 3 years of consistent trainin	Very Active (Hard exercise/sports 6-7 days/week)
11/8/2025 8:30:16	I have rea	I have rea	Leo Manahan	23	Male	176	67	Intermediate (1-3 years of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/8/2025 8:38:50	I have rea	I have rea	Hamish Reyes	23	Female	167	56	Intermediate (1-3 years of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/8/2025 16:24:14	I have rea	I have rea	Christian Co	28	Male	175	86	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/9/2025 2:35:32	I have rea	I have rea	Chester Chua	24	Male	180	68	Advanced (More than 3 years of consistent trainin	Very Active (Hard exercise/sports 6-7 days/week)
11/9/2025 2:43:40	I have rea	I have rea	Ivan Ferrer	25	Male	177	72	Beginner (Less than 1 year of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)
11/9/2025 22:48:39	I have rea	I have rea	Donnaliza Nopre	22	Female	166	52	Advanced (More than 3 years of consistent trainin	Very Active (Hard exercise/sports 6-7 days/week)
11/10/2025 17:50:33	I have rea	I have rea	Celina Pangilinan	29	Female	167	63	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/10/2025 19:23:46	I have rea	I have rea	Robert Padrinao	30	Male	182	90	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/10/2025 20:38:48	I have rea	I have rea	Jian Rosete	26	Male	180	78	Intermediate (1-3 years of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/10/2025 20:45:46	I have rea	I have rea	John Lexter Mesina	24	Male	162	54	Beginner (Less than 1 year of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)
11/11/2025 9:55:32	I have rea	I have rea	Rexie Mae Gula	23	Female	155	51	Intermediate (1-3 years of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/11/2025 10:26:36	I have rea	I have rea	Janeth David	27	Female	157	60	Currently Inactive/Sedentary	Sedentary (Little to no exercise)
11/11/2025 13:18:10	I have rea	I have rea	Christian Vinas	25	Male	180	74	Beginner (Less than 1 year of consistent training)	Moderately Active (Moderate exercise/sports 3-5 days/week)
11/11/2025 20:29:47	I have rea	I have rea	Paola Dela Pena	25	Female	164	57	Beginner (Less than 1 year of consistent training)	Lightly Active (Light exercise/sports 1-3 days/week)

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Data Collection

Test	Sunno Digital Caliper				Manual Caliper				
1	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	16.15	16.38	16.61	16.38	16	15	16	15.67	0.71
	13.36	12.27	13.52	13.05	12	14	14	13.33	-0.28
	13.85	12.17	13.59	13.20	11	12	12	11.67	1.54
2	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	14.41	13.1	13.43	13.65	13	13	12	12.67	0.98
	19.23	19.56	19.87	19.55	20	18	18	18.67	0.89
	21.24	19.12	19.05	19.80	22	20	19	20.33	-0.53
3	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	17.63	18.57	17.23	17.81	16	18	18	17.33	0.48
	13.24	12.67	13.86	13.26	12	14	13	13.00	0.26
	19.03	22.08	20.98	20.70	22	20	20	20.67	0.03
4	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	15.56	14.11	16.84	15.50	16	15	15	15.33	0.17
	6.08	5.71	6.46	6.08	6	5	6	5.67	0.42
	13.79	14.09	13.26	13.71	12	14	13	13.00	0.71
5	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	13	12.87	13.23	13.03	14	13	13	13.33	-0.30
	29.12	29.34	29.78	29.41	30	30	29	29.67	-0.25
	34.06	33.98	34.21	34.08	36	34	35	35.00	-0.92
6	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	30.78	30.57	31.02	30.79	32	30	30	30.67	0.12
	47.14	47.33	46.12	46.86	48	46	46	46.67	0.20
	39.06	38.79	38.93	38.93	39	38	39	38.67	0.26
7	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	20.1	20.12	20.34	20.19	23	20	22	21.67	-1.48
	14.68	14.59	15.02	14.76	14	14	14	14.00	0.76
	19.09	18.78	19.12	19.00	20	20	19	19.67	-0.67
8	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	26.97	26.74	26.51	26.74	25	26	26	25.67	1.07
	30.09	30.12	30.02	30.08	32	32	31	31.67	-1.59
	20.95	21.12	20.45	20.84	18	20	20	19.33	1.51
9	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	19.52	19.34	19.85	19.57	20	21	21	20.67	-1.10
	34.68	34.33	33.91	34.31	35	34	32	33.67	0.64
	24.55	24.07	24.16	24.26	26	25	25	25.33	-1.07
10	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	11.52	11.17	11.3	11.33	10	12	11	11.00	0.33
	32.74	31.5	32.25	32.16	29	31	34	31.33	0.83
	29.18	39.56	40.11	39.67	40	41	41	40.67	-1.00
11	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	14.71	14.1	14.65	14.49	15	15	16	15.33	-0.85
	17.65	18.45	17.96	18.02	18	20	18	18.67	-0.65
	17.89	18.14	17.12	17.72	18	18	19	18.33	-0.62
12	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	15.33	14.68	15.12	15.04	16	14	16	15.33	-0.29
	28.65	27.84	28.95	28.48	29	27	29	28.33	0.15
	28.74	28.12	28.33	28.40	28	27	28	27.67	0.73

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13	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	25.12	24.46	24.59	24.72	25	24	24	24.33	0.39
	16.25	16.14	16.54	16.31	16	17	16	16.33	-0.02
	35.36	34.23	35.41	35.00	35	34	34	34.33	0.67
14	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	19.46	19.65	19.27	19.46	20	19	19	19.33	0.13
	21.11	21.35	21.18	21.21	22	21	22	21.67	-0.45
	20.13	19.87	19.95	19.98	19	20	20	19.67	0.32
15	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	17.65	17.23	17.56	17.48	18	17	18	17.67	-0.19
	10.54	10.12	10.65	10.44	11	10	10	10.33	0.10
	23.87	24.1	24.21	24.06	24	23	24	23.67	0.39
16	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	16.68	16.47	16.54	16.56	17	16	16	16.33	0.23
	11.51	11.45	11.68	11.55	12	11	12	11.67	-0.12
	20.82	21.11	20.95	20.96	21	21	19	20.33	0.63
17	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	15.08	15.47	15.23	15.26	15	16	15	15.33	-0.07
	18.79	18.93	19.04	18.92	18	19	19	18.67	0.25
	22.05	22.14	22.15	22.11	22	23	22	22.33	-0.22
18	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	12.28	12.52	15.43	13.41	12	13	12	12.33	1.08
	14.69	14.98	14.9	14.86	14	15	15	14.67	0.19
	15.22	15.27	15.32	15.27	15	15	16	15.33	-0.06
19	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	25.63	25.78	25.91	25.77	25	26	26	25.67	0.11
	38.55	38.74	38.56	38.62	38	39	38	38.33	0.28
	34.83	34.97	34.92	34.91	34	35	36	35.00	-0.09
20	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	16.52	16.63	16.61	16.59	16	17	17	16.67	-0.08
	23.61	23.7	23.83	23.71	23	24	24	23.67	0.05
	26.78	26.81	26.93	26.84	26	27	27	26.67	0.17
21	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	18.04	18.18	18.16	18.13	18	18	19	18.33	-0.21
	27.42	27.56	27.45	27.48	27	28	28	27.67	-0.19
	30.12	30.34	30.31	30.26	30	30	31	30.33	-0.08
22	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	11.83	11.97	11.96	11.92	11	12	12	11.67	0.25
	16.28	16.39	16.44	16.37	16	17	17	16.67	-0.30
	14.01	14.07	13.97	14.02	13	14	14	13.67	0.35
23	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	26.33	26.46	26.37	26.39	26	27	26	26.33	0.05
	33.91	33.45	34.12	33.83	34	33	33	33.33	0.49
	37.23	37.71	37.45	37.46	38	37	37	37.33	0.13
24	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	15.73	15.89	15.84	15.82	16	15	16	15.67	0.15
	17.04	17.11	17.03	17.06	17	17	18	17.33	-0.27
	21.51	21.64	21.57	21.57	21	22	22	21.67	-0.09

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25	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	18.29	18.41	18.36	18.35	18	19	18	18.33	0.02
	20.45	20.43	20.54	20.47	20	21	22	21.00	-0.53
	25.27	25.68	25.54	25.50	26	25	25	25.33	0.16
26	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	13.05	13.12	13.24	13.14	14	13	13	13.33	-0.20
	14.58	14.61	14.84	14.68	16	14	14	14.67	0.01
	18.09	17.98	18.23	18.10	17	18	18	17.67	0.43
27	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	20.83	21.17	20.96	20.99	22	21	20	21.00	-0.01
	24.14	24.56	24.19	24.30	25	24	24	24.33	-0.04
	31.66	31.79	31.21	31.55	32	31	31	31.33	0.22
28	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	19.48	19.53	20.11	19.71	19	20	20	19.67	0.04
	21.59	21.74	21.63	21.65	22	21	21	21.33	0.32
	27.05	26.87	27.13	27.02	28	26	27	27.00	0.02
29	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	17.09	17.18	17.14	17.14	16	17	17	16.67	0.47
	18.53	18.45	18.54	18.51	19	18	18	18.33	0.17
	22.82	22.9	22.34	22.69	22	22	23	22.33	0.35
30	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	22.36	22.41	22.57	22.45	21	20	22	21.00	1.45
	25.07	25.19	25.14	25.13	26	25	26	25.67	-0.53
	30.75	30.65	30.54	30.65	31	30	30	30.33	0.31
31	Trial 1	Trial 2	Trial 3	Ave	Trial 1	Trial 2	Trial 3	Ave	Diffrence
	14.48	14.75	14.56	14.60	15	14	15	14.67	-0.07
	19.64	19.85	19.22	19.57	20	19	20	19.67	-0.10
	21.98	21.87	21.93	21.93	22	22	21	21.67	0.26

Test	Physical Activity	Inbody (BF%)	Sunno Fitness Caliper (BF%)
1	Lightly Active	13.6	11.54
2	Very Active	17.1	15.57
3	Moderate	25.8	20.04
4	Very Active	13.3	10.04
5	Very Active	9	13.82
6	Lightly Active	20.2	24.87
7	Moderate	26.9	23.06
8	Very Active	9.53	11.85
9	Moderate	26.5	22.05
10	Very Active	16.12	18.64

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Test	Physical Activity	Inbody (BF%)	Sunno Fitness Caliper (BF%)
1	Lightly Active	11.88	11.54
2	Very Active	14.89	15.57
3	Moderate	19.86	20.04
4	Very Active	10.16	10.04
5	Moderate	21.22	21.74
6	Sedentary	39.31	39.38
7	Very Active	21.99	21.66
8	Moderate	29.16	29.35
9	Lightly Active	21.98	21.88
10	Sedentary	22.37	22.22
11	Lightly Active	20.68	20.53
12	Lightly Active	27.30	27.69
13	Sedentary	25.42	25.44
14	Lightly Active	29.27	29.54
15	Moderate	20.92	21.09
16	Very Active	14.71	13.82
17	Moderate	16.12	16.19
18	Very Active	11.93	11.76
19	Sedentary	27.79	28.10
20	Lightly Active	19.31	19.25
21	Moderate	21.92	22.05
22	Very Active	12.06	11.85
23	Sedentary	27.56	27.66
24	Moderate	21.93	21.71
25	Lightly Active	25.25	24.87
26	Very Active	18.80	18.64
27	Sedentary	29.25	29.36
28	Lightly Active	26.36	26.47
29	Moderate	22.81	23.06
30	Sedentary	29.23	29.12
31	Moderate	16.25	16.32

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Test	Test Scenario	Trigger Event	Delivered	Latency (ms)	Status
1	Add new workout	Client submits new workout entry	Yes	745	Pass
2	Add new workout	Client submits new workout entry	Yes	812	Pass
3	Add new workout	Client submits new workout entry	Yes	789	Pass
4	Add new workout	Client submits new workout entry	Yes	750	Pass
5	Add new workout	Client submits new workout entry	Yes	720	Pass
6	Add new workout	Client submits new workout entry	Yes	795	Pass
7	Add new workout	Client submits new workout entry	Yes	760	Pass
8	Add new workout	Client submits new workout entry	Yes	805	Pass
9	Add new workout	Client submits new workout entry	Yes	735	Pass
10	Add new workout	Client submits new workout entry	Yes	770	Pass
11	Update Nutrition	Client log food intake	Yes	580	Pass
12	Update Nutrition	Client log food intake	Yes	610	Pass
13	Update Nutrition	Client log food intake	Yes	595	Pass
14	Update Nutrition	Client log food intake	Yes	630	Pass
15	Update Nutrition	Client log food intake	Yes	550	Pass
16	Update Nutrition	Client log food intake	Yes	575	Pass
17	Update Nutrition	Client log food intake	Yes	600	Pass
18	Update Nutrition	Client log food intake	Yes	625	Pass
19	Update Nutrition	Client log food intake	Yes	560	Pass
20	Update Nutrition	Client log food intake	Yes	590	Pass
21	New Measurement	New body measurement logged	Yes	890	Pass
22	New Measurement	New body measurement logged	Yes	920	Pass
23	New Measurement	New body measurement logged	Yes	850	Pass
24	New Measurement	New body measurement logged	Yes	910	Pass
25	New Measurement	New body measurement logged	Yes	880	Pass
26	New Measurement	New body measurement logged	Yes	905	Pass
27	New Measurement	New body measurement logged	Yes	870	Pass
28	New Measurement	New body measurement logged	Yes	935	Pass
29	New Measurement	New body measurement logged	Yes	860	Pass
30	New Measurement	New body measurement logged	Yes	895	Pass
31	Analytics Reminder	New insight available	Yes	-	Pass
32	Analytics Reminder	New insight available	Yes	-	Pass
33	Analytics Reminder	New insight available	Yes	-	Pass
34	Analytics Reminder	New insight available	Yes	-	Pass
35	Analytics Reminder	New insight available	Yes	-	Pass
36	Workout Reminder	Scheduled workout reminder	Yes	-	Pass
37	Workout Reminder	Scheduled workout reminder	Yes	-	Pass
38	Nutrition Reminder	Scheduled nutrition reminder	Yes	-	Pass
39	Nutrition Reminder	Scheduled nutrition reminder	Yes	-	Pass
40	Nutrition Reminder	Scheduled nutrition reminder	Yes	-	Pass

Appendix B: Simulation

Objective 1: To design and develop a prototype of a digital skin caliper that accurately measures body fat percentage and syncs with a web platform for real-time data integration, prioritizing simplicity and reliability.

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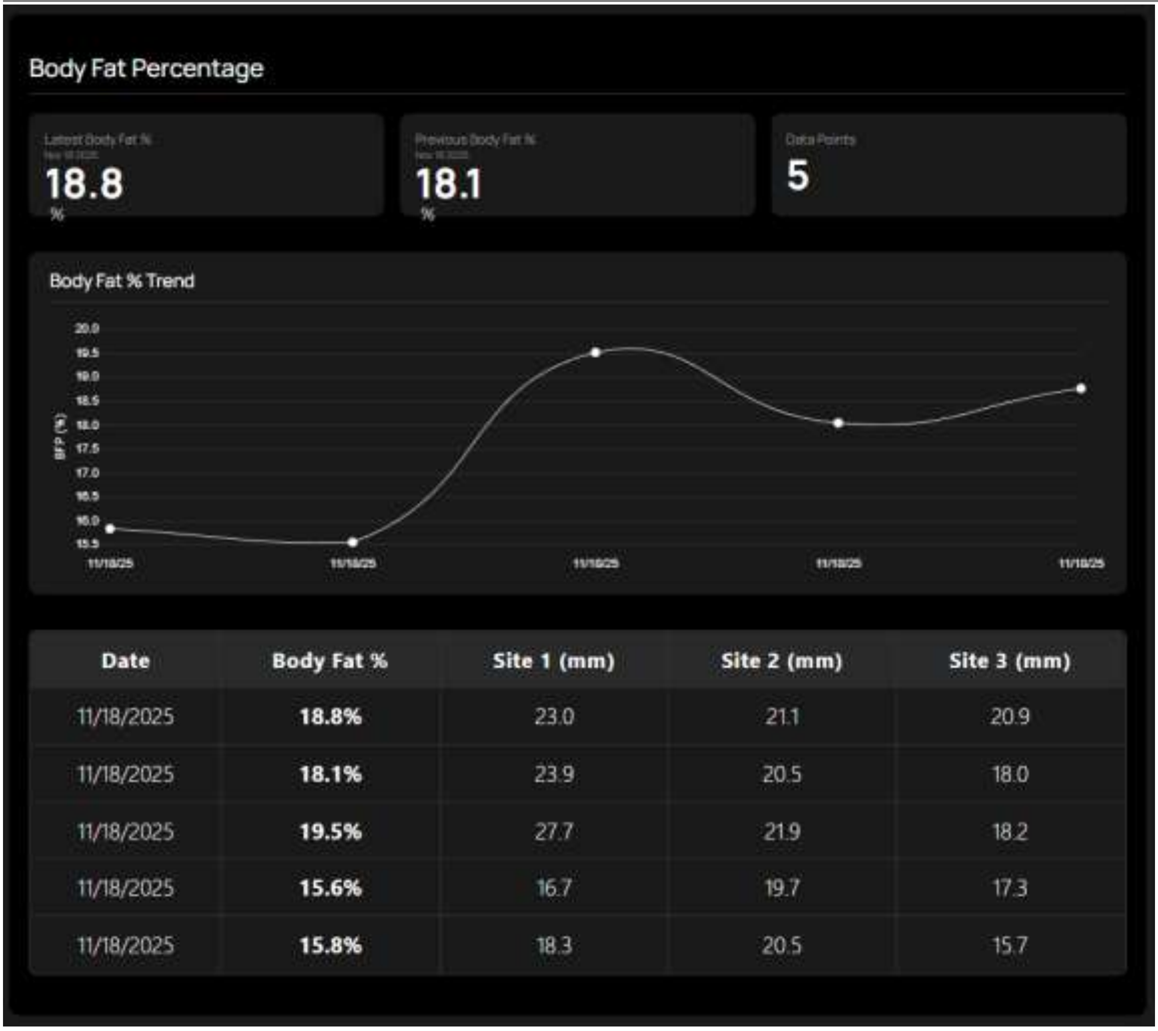
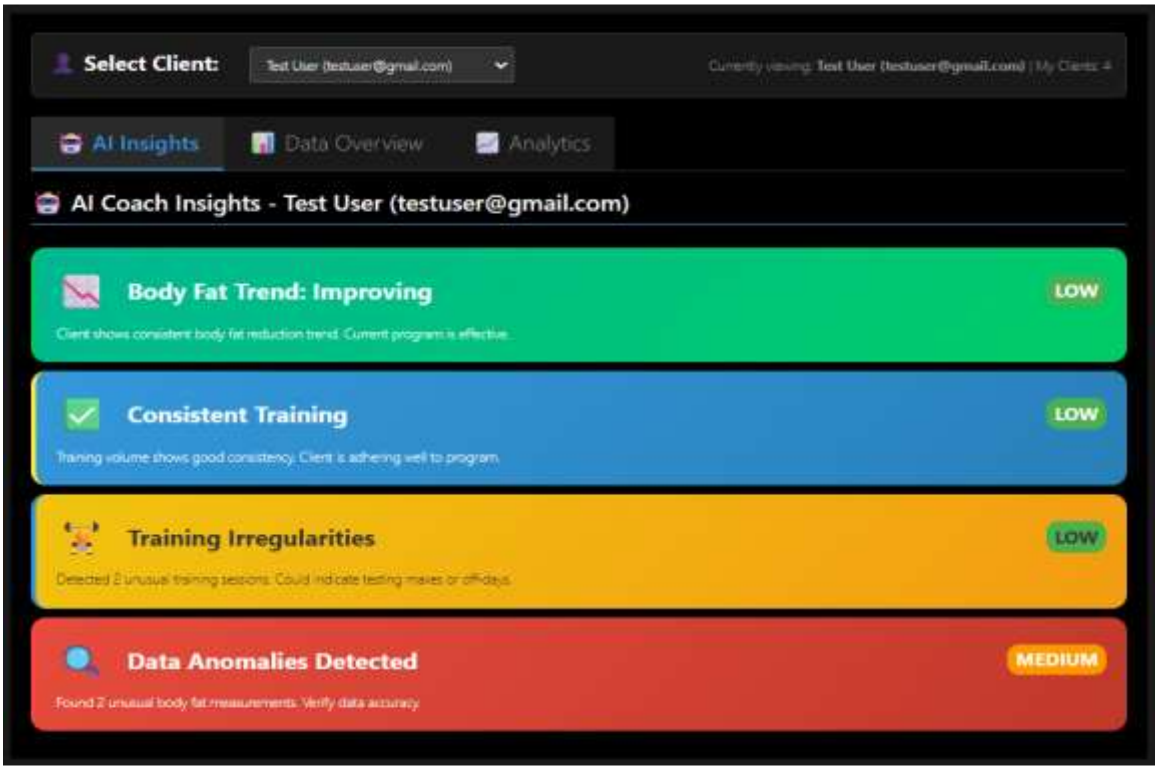


Objective 2: To integrate machine learning algorithms that analyze client data and generate clear, personalized insights on a web platform, enabling coaches to make effective and informed decisions for goals such as weight loss or muscle gain.



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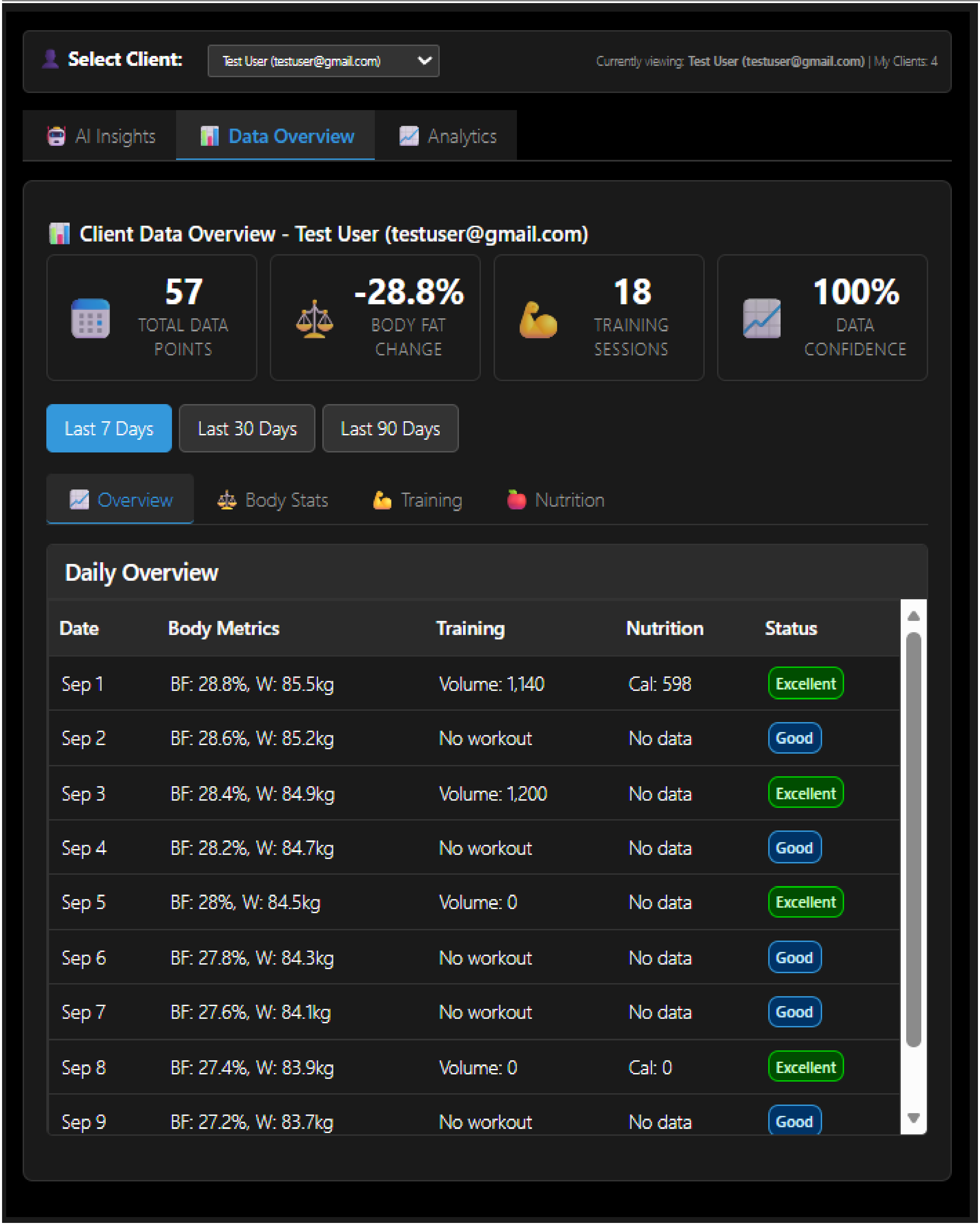

Objective 3: To design and develop a web-based platform that allows coaches and clients to track progress, visualize data from digital skinfold caliper measurements, and communicate effectively, ensuring efficiency and usability.

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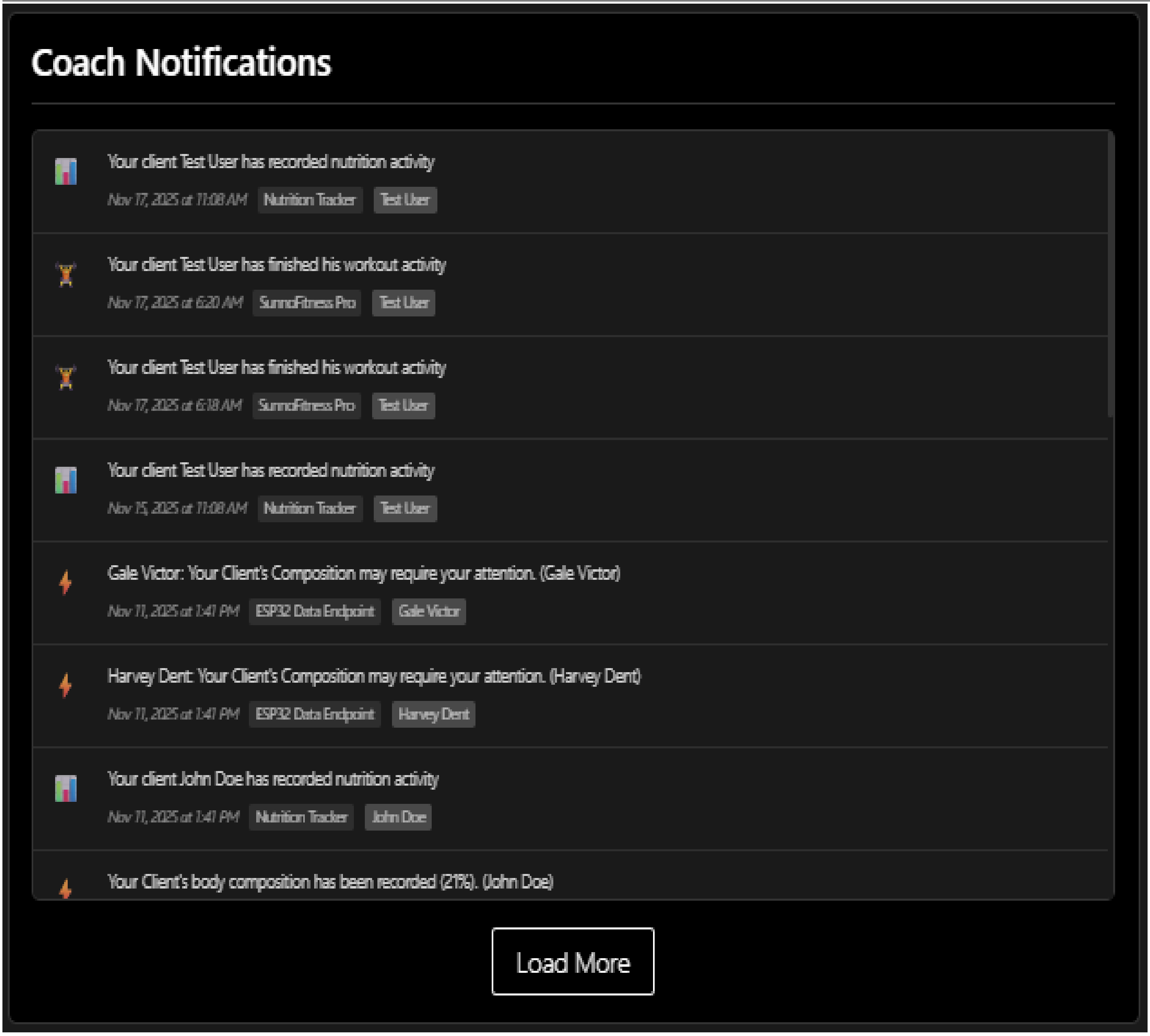

Appendix C: Source Code Data Validation

Digital Skin Caliper

```
#include <lvgl.h>

#include <TFT_eSPI.h>

#include <XPT2046_Touchscreen.h>

#include <WiFi.h>

#include <HTTPClient.h>

#include "ui.h"

volatile bool g_resetScreen5 = false;

volatile bool g_calibrate = false;
```

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```
volatile bool g_isMale = true;
float g_startAngleDeg = 170.0f;
int g_age = 25;
char g_node[64] = "";   // FIX: use char array instead of String
float g_bodyFatPercent = 0.0f;
#define TFT_BL 21   // backlight pin (ESP32-2432S028R default)
bool backlightOn = true;
unsigned long powerButtonPressStart = 0;
bool powerButtonHeld = false;
const unsigned long LONG_PRESS_MS = 5000;
TFT_eSPI tft = TFT_eSPI();
#define AS_CS   22
#define AS_SCK  27
#define AS_MISO 35
#define AS_MOSI -1
#define PULSE_DELAY 2
void initAS5047() {
  pinMode(AS_CS, OUTPUT);
  pinMode(AS_SCK, OUTPUT);
  pinMode(AS_MISO, INPUT);
  digitalWrite(AS_CS, HIGH);
  digitalWrite(AS_SCK, LOW);}
uint16_t read_angle_raw() {
  uint16_t val = 0;
  digitalWrite(AS_CS, LOW);
  delayMicroseconds(PULSE_DELAY);
  for (int i = 15; i >= 0; i--) {
    digitalWrite(AS_SCK, HIGH);
    delayMicroseconds(PULSE_DELAY);
```

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```
        if (digitalRead(AS_MISO)) val |= (1 << i);
        digitalWrite(AS_SCK, LOW);
        delayMicroseconds(PULSE_DELAY);    }
    digitalWrite(AS_CS, HIGH);
    return val & 0x3FFF; // 14-bit angle}
#define XPT2046_IRQ 36
#define XPT2046_MOSI 32
#define XPT2046_MISO 39
#define XPT2046_CLK 25
#define XPT2046_CS 33
SPIClass touchscreenSpi = SPIClass(VSPI);
XPT2046_Touchscreen touchscreen(XPT2046_CS, XPT2046_IRQ);
#define TFT_HOR_RES 320
#define TFT_VER_RES 240
float alphaX = 0.09053, betaX = 0.0, deltaX = -38.03;
float alphaY = 0.0, betaY = 0.06764, deltaY = -17.40;
#define DRAW_BUF_SIZE (TFT_HOR_RES * TFT_VER_RES / 10 * (LV_COLOR_DEPTH / 8))
lv_indev_t *indev;
uint8_t* draw_buf;
unsigned long lastTick = 0;
static String pendingSSID;
static String pendingPASS;
static bool wifiConnectRequested = false;
static bool wifiConnecting = false;
static unsigned long wifiConnectStart = 0;
static const unsigned long WIFI_CONNECT_TIMEOUT_MS = 15000;
void requestWiFiConnect(const char* ssid, const char* pass) {
    pendingSSID = ssid ? ssid : "";
    pendingPASS = pass ? pass : "";
```

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```
  wifiConnectRequested = true;}
void requestAgeUpdate(const char* ageText) {
  int val = atoi(ageText);
  if (val > 0 && val < 120) {
    g_age = val;
    Serial.printf("🎂 Age updated → %d\n", g_age);
  } else {
    Serial.printf("⚠ Invalid age input: %s\n", ageText);    }}
void requestNodeUpdate(const char* nodeText) {
  if (nodeText && strlen(nodeText) > 0) {
    strncpy(g_node, nodeText, sizeof(g_node) - 1);
    g_node[sizeof(g_node) - 1] = '\0'; // ensure null-termination
    size_t len = strlen(g_node);
    if (len > 0 && g_node[len - 1] != '/' && len < sizeof(g_node) - 1) {
      strcat(g_node, "/");
      len++;        }
    // Ensure wp-json/ at the end
    const char* suffix = "wp-json/";
    size_t suffixLen = strlen(suffix);
    if (len < suffixLen || strcmp(g_node + len - suffixLen, suffix) != 0) {
      if (len + suffixLen < sizeof(g_node)) {
        strcat(g_node, suffix);
      } else {
        Serial.println("⚠ g_node too short to append wp-json/");           }       }
    Serial.printf("📡 Final g_node → %s\n", g_node);    } else {
    Serial.println("⚠ Empty node input");    }}
static inline int16_t clamp16(int32_t v, int32_t lo, int32_t hi) {
  if (v < lo) return lo;
```

```
    if (v > hi) return hi;
    return (int16_t)v;}
void my_touchpad_read(lv_indev_t * indev, lv_indev_data_t * data) {
    if (touchscreen.touched()) {
        TS_Point p = touchscreen.getPoint();
        int16_t x = alphaX * p.x + betaX * p.y + deltaX;
        int16_t y = alphaY * p.x + betaY * p.y + deltaY;
        data->point.x = clamp16(x, 0, TFT_HOR_RES - 1);
        data->point.y = clamp16(y, 0, TFT_VER_RES - 1);
        data->state = LV_INDEV_STATE_PRESSED;
    } else {
        data->state = LV_INDEV_STATE_RELEASED;    }}
#define BTN_PIN 34
const float ARM_LENGTH_MM = 87.0;
unsigned long lastMeasurementTime = 0;
const unsigned long MEASUREMENT_COOLDOWN_MS = 2000;
bool isButtonPressed() {
    return (digitalRead(BTN_PIN) == HIGH);}
void setScreenPower(bool on) {
    backlightOn = on;
    if (on) {
        // Restore WiFi
        WiFi.mode(WIFI_STA);
        // Turn backlight on
        digitalWrite(TFT_BL, HIGH);
        // Force a redraw of the active LVGL screen when the loop resumes LVGL handling
        lv_obj_invalidate(lv_scr_act());
        Serial.println("💡 Backlight ON, WiFi ON");
    } else {
```

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Data-Driven Insights

```
private function generate_real_insights($client_id) {
    $real_data = $this->get_real_client_data($client_id);
    if (empty($real_data) || !$real_data['hasRealData']) {
        return [
            [
                'type' => 'info',
                'icon' => 'ℹ',
                'title' => 'Data Collection Needed',

'message' => 'No client data found in database tables for client ID '
                . $client_id . '. Connect devices and trackers to generate insights.',
                'priority' => 'medium'
            ]
        ];
    }

    $insights = [];

    // Enhanced insights using the proper algorithms
    $trend_insights = $this->generate_trend_analysis_insights($real_data);
    $anomaly_insights = $this->generate_anomaly_insights($real_data);
    $performance_insights = $this->generate_performance_insights($real_data);

    $insights = array_merge($insights, $trend_insights, $anomaly_insights, $performance_insights);

    // ESP32-specific insights
```

```
    $esp32_insights = $this->generate_esp32_insights($real_data);

    $insights = array_merge($insights, $esp32_insights);


    // If no specific insights, provide general analysis

    if (empty($insights)) {

        $insights[] = [

            'type' => 'info',

            'icon' => '📊',

            'title' => 'Data Analysis Complete',

            'message' => 'All metrics are within expected ranges. Continue current program.',

            'priority' => 'low'            ];        }

            return $insights;    }

    /**

  * Generate ESP32-specific insights using proper algorithms

  */

 private function generate_esp32_insights($real_data) {

    $insights = [];

            if (!empty($real_data['esp32Data'])) {

        $body_fat = $real_data['esp32Data']['body_fat'];

        $thigh = $real_data['esp32Data']['thigh'];

        $suprailiac = $real_data['esp32Data']['suprailiac'];

        $triceps = $real_data['esp32Data']['triceps'];

                // Body fat trend analysis using proper algorithm

        if (count($body_fat) >= 3) {

            $trend_predictions = $this->step2_rolling_slope($body_fat, $this->BF_PLATEAU/100);

                    // Count trend types

            $trend_counts = array_count_values($trend_predictions);

            $improving_count = $trend_counts['Improving'] ?? 0;

            $regression_count = $trend_counts['Regression'] ?? 0;
```

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```
if ($improving_count > $regression_count) {
    $insights[] = [
        'type' => 'excellent',
        'icon' => '📉',
        'title' => 'Body Fat: Positive Trend',
        'message' => 'Algorithm detects consistent body fat reduction based on caliper measurements.',
        'priority' => 'low'
    ];
} elseif ($regression_count > $improving_count) {
    $insights[] = [
        'type' => 'warning',
        'icon' => '📈',
        'title' => 'Body Fat: Concerning Trend',
        'message' => 'Body fat measurements show increasing trend. Consider nutritional adjustments.',
        'priority' => 'high'
    ];
}


// Check for significant changes
if (count($body_fat) >= 2) {
    $latest_change = $body_fat[0] - $body_fat[1];
    if (abs($latest_change) > 1.0) {
        $insights[] = [
            'type' => 'info',
            'icon' => '⚡',
            'title' => 'Significant Body Fat Change',
                'message' => 'Recent body fat measurement changed by ' . abs($latest_change) . '%. Verify measurement consistency.',
```

```
                'priority' => 'medium'                    ];                }              }           }

            // Skinfold consistency analysis using proper variance algorithm

        if (count($thigh) >= 3) {

            list($variance_anomalies, $threshold) = $this->step3_rolling_variance($thigh, 3, 85);

            $variance_count = count(array_filter($variance_anomalies));


            if ($variance_count > 2) {

                $insights[] = [

                    'type' => 'warning',

                    'icon' => '🎯',

                    'title' => 'Measurement Consistency',

                        'message' => 'Skinfold measurements show high variability. Ensure consistent measurement technique.',

                    'priority' => 'medium'

                ];

            }

        }

    }


    return $insights;

}


/**

 * Enhanced trend analysis using proper algorithms

 */

private function generate_trend_analysis_insights($real_data) {

    $insights = [];


    // Body fat trend analysis
```

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```
if (!empty($real_data['bodyStats']['body_fat'])) {
    $body_fat_values = $real_data['bodyStats']['body_fat'];
    $trend_predictions = $this->step2_rolling_slope($body_fat_values, $this->BF_PLATEAU/100);

    // Count trend types
    $trend_counts = array_count_values($trend_predictions);
    $improving_count = $trend_counts['Improving'] ?? 0;
    $regression_count = $trend_counts['Regression'] ?? 0;
    $plateau_count = $trend_counts['Plateau'] ?? 0;

    if ($improving_count > $regression_count && $improving_count > $plateau_count) {
        $insights[] = [
            'type' => 'excellent',
            'icon' => '📉',
            'title' => 'Body Fat: Strong Improving Trend',
            'message' => 'Algorithm detects consistent body fat reduction. Current program is highly effective.',
            'priority' => 'low'
        ];
    } elseif ($regression_count > $improving_count) {
        $insights[] = [
            'type' => 'warning',
            'icon' => '📈',
            'title' => 'Body Fat: Regression Trend Detected',
            'message' => 'Algorithm identifies increasing body fat pattern. Consider nutritional review.',
            'priority' => 'high'
        ];
    }
```

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```
        // Check for anomalies using proper algorithm
        $anomalies = $this->step1_rif_eif($body_fat_values);
        $anomaly_count = count(array_filter($anomalies));
        if ($anomaly_count > 0) {
            $insights[] = [
                'type' => 'info',
                'icon' => '🔍',
                'title' => 'Body Fat Data Anomalies',
              'message' => "Isolation Forest detected $anomaly_count unusual measurements. Verify data quality.",
                'priority' => 'medium'
            ];
        }
    }

    // Training volume analysis
    if (!empty($real_data['exerciseData']['volumes'])) {
        $volumes = $real_data['exerciseData']['volumes'];
        $trend_predictions = $this->step2_rolling_slope($volumes, $this->ACTIVITY_THRESHOLD);

        $trend_counts = array_count_values($trend_predictions);
        $improving_count = $trend_counts['Improving'] ?? 0;

        if ($improving_count > 0) {
            $insights[] = [
                'type' => 'good',
                'icon' => '💪',
                'title' => 'Training Volume: Progressive Overload',
                'message' => 'Algorithm detects increasing training volume. Excellent for strength gains.',
```

```
                'priority' => 'low'
            ];
        }

        // Variance analysis using proper algorithm
        list($variance_anomalies, $threshold) = $this->step3_rolling_variance($volumes, 3, 85);
        $variance_count = count(array_filter($variance_anomalies));

        if ($variance_count > 2) {
            $insights[] = [
                'type' => 'info',
                'icon' => '🔄',
                'title' => 'Training Consistency Alert',
                'message' => "Variance analysis detected $variance_count irregular training patterns.",
                'priority' => 'medium'
            ];
        }
    }

    return $insights;
}

/**
 * Anomaly detection using proper Isolation Forest algorithm
 */
private function generate_anomaly_insights($real_data) {
    $insights = [];
        $anomaly_count = count(array_filter($anomalies));
```

Progress Tracking

```
public function ajax_add_exercise() {
        $this->verify_nonce();

        global $wpdb;

        $exercise_data = array(
            'program_id' => 1, // Default to first program
            'muscle_group' => sanitize_text_field( $_POST['muscle_group'] ),
            'exercise_name' => sanitize_text_field( $_POST['exercise_name'] ),
            'sets' => intval( $_POST['sets'] ),
            'reps' => intval( $_POST['reps'] ),
            'post_id' => NULL
        );

        // Check if exercise already exists
        $existing = $wpdb->get_var($wpdb->prepare(
            "SELECT COUNT(*) FROM {$this->exercises_table} WHERE exercise_name = %s AND muscle_group = %s",
            $exercise_data['exercise_name'],
            $exercise_data['muscle_group']
        ));

        if ($existing) {
            wp_send_json_error('This exercise already exists in this muscle group.');
        }
```

```
        $result = $wpdb->insert(
                $this->exercises_table,
                $exercise_data,
                array( '%d', '%s', '%s', '%d', '%d', '%d' )
        );

        if ( $result ) {
                wp_send_json_success( array(
                        'message' => 'Exercise added successfully.'
                ) );
        } else {
                wp_send_json_error( 'Failed to add exercise.' );
        }
}

/**
 * AJAX: Edit exercise
 */
public function ajax_edit_exercise() {
        $this->verify_nonce();

        global $wpdb;

        $old_exercise_name = sanitize_text_field( $_POST['old_exercise_name'] );
        $old_muscle_group = sanitize_text_field( $_POST['old_muscle_group'] );
        $new_exercise_name = sanitize_text_field( $_POST['new_exercise_name'] );
        $new_muscle_group = sanitize_text_field( $_POST['new_muscle_group'] );
        $sets = intval( $_POST['sets'] );
        $reps = intval( $_POST['reps'] );
```

```
        // Update ALL instances of this exercise
        $result = $wpdb->update(
            $this->exercises_table,
            array(
                'exercise_name' => $new_exercise_name,
                'muscle_group' => $new_muscle_group,
                'sets' => $sets,
                'reps' => $reps
            ),
            array(
                'exercise_name' => $old_exercise_name,
                'muscle_group' => $old_muscle_group
            ),
            array( '%s', '%s', '%d', '%d' ),
            array( '%s', '%s' )
        );

        if ( $result !== false ) {
            wp_send_json_success( array(
                'message' => 'Exercise updated successfully for all instances.'
            ) );
        } else {
            wp_send_json_error( 'Failed to update exercise.' );
        }
    }

    /**
     * AJAX: Delete exercise
```

```
 */
public function ajax_delete_exercise() {
    $this->verify_nonce();

    global $wpdb;
    $exercise_name = sanitize_text_field( $_POST['exercise_name'] );
    $muscle_group = sanitize_text_field( $_POST['muscle_group'] );

    $result = $wpdb->delete(
        $this->exercises_table,
        array(
            'exercise_name' => $exercise_name,
            'muscle_group' => $muscle_group
        ),
        array( '%s', '%s' )
    );

    if ( $result !== false ) {
        wp_send_json_success( array(
            'message' => 'Exercise deleted successfully from all programs.'
        ) );
    } else {
        wp_send_json_error( 'Failed to delete exercise.' );
    }
}

/**
 * AJAX: Update exercise post association for ALL instances
 */
```

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```
public function ajax_update_exercise_post() {
    $this->verify_nonce();

    global $wpdb;
    $exercise_name = sanitize_text_field( $_POST['exercise_name'] );
    $muscle_group = sanitize_text_field( $_POST['muscle_group'] );
    $post_id = intval( $_POST['post_id'] );

    // Update ALL instances of this exercise
    $result = $wpdb->update(
        $this->exercises_table,
        array( 'post_id' => $post_id ),
        array(
            'exercise_name' => $exercise_name,
            'muscle_group' => $muscle_group
        ),
        array( '%d' ),
        array( '%s', '%s' )
    );

    if ( $result !== false ) {
        $post_title = $post_id ? get_the_title( $post_id ) : '';
        $post_link = $post_id ? get_permalink( $post_id ) : '';
        $edit_link = $post_id ? get_edit_post_link( $post_id ) : '';

        wp_send_json_success( array(
            'message' => 'Post association updated successfully for all instances.',
            'post_title' => $post_title,
            'post_id' => $post_id,
```

```
'post_link' => $post_link,
'edit_link' => $edit_link ) ); } else {
wp_send_json_error( 'Failed to update post association.' ); } }
```

Appendix D: Journal Paper

Sunno Fitness: A Fitness Coaching Platform Using Digital Skinfold Caliper Data and Isolation Forest Algorithm for Data-Driven Performance Monitoring

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Abstract

***Abstract*—The integration of digital tools into fitness coaching has become increasingly important for delivering personalized and data-informed guidance. Despite this need, many practitioners continue to rely on manual tracking or costly body composition devices that lack seamless data integration. This study developed Sunno Fitness, a web-based coaching platform that combines a custom Bluetooth-enabled digital skinfold caliper with the Isolation Forest algorithm to support data-driven performance monitoring. The project employed a Developmental Research Design guided by Agile methodology. The hardware system incorporated an ESP32 microcontroller and an AS5047P magnetic rotary sensor to digitize skinfold measurements, while the software platform automated the Jackson-Pollock 3-site method and analyzed client progress. System validation involving 31 participants showed that the digital skinfold caliper achieved high precision, with a negligible mean difference of -0.01 mm and a percent error of 2.15% relative to a manual caliper. Automated body fat computation demonstrated strong agreement with manual calculations (1.21% error). The machine learning component effectively detected anomalies and distinguished long-term trends. Sunno Fitness offers a validated, cost-effective solution that integrates accurate body composition assessment with intelligent monitoring to enhance modern fitness coaching.**

***Keywords*—Digital Skinfold Caliper, Isolation Forest, Fitness Coaching, ESP32, Body Composition, IoT, Machine Learning.**

1. INTRODUCTION

Over the last twenty years, the fitness industry has evolved from a niche interest into a massive global trend, increasing the demand for personalized guidance from qualified professionals. Fitness coaches play a critical role in helping clients achieve goals, with structured support improving adherence by up to 30% [1]. However, the effectiveness of this support relies heavily on accurate tracking.

Currently, 65% of coaches still rely on pen-and-paper logs or basic spreadsheets [2], which are prone to error. While advanced devices like the InBody 770 offer detailed analysis, they are prohibitively expensive. Conversely, traditional analog skinfold calipers are accessible but require manual calibration and expertise to avoid errors [3].

Emerging technologies such as Internet of Things (IoT) devices and machine learning algorithms offer a solution to these challenges. To address this gap, this study introduces Sunno Fitness, a digital platform that integrates a custom Bluetooth-enabled digital skinfold caliper with a web-based dashboard.

The specific objectives of this study were:

1

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1. To design a prototype of a digital skin caliper that accurately measures body fat percentage and syncs with a web platform.

2. To implement machine learning algorithms (Isolation Forest) to analyze client data and deliver personalized insights.

3. To develop a web-based platform for seamless progress tracking and communication between coaches and clients.

2. RELATED WORK

Accurate assessment of body composition is essential for individualized fitness programming. Escamilla et al. (2024) demonstrated that skinfold testing remains one of the most reliable and cost-effective tools for estimating body fat percentage, performing competitively against more expensive technologies [4].

Regarding data analysis, Kareem and Muhammed (2024) highlighted the Isolation Forest (iForest) algorithm as a robust method for anomaly detection in dynamic environments. Its ability to identify rare patterns makes it ideal for fitness tracking, where irregularities in calorie deficits or workout consistency need to be flagged promptly.

Furthermore, the use of microcontroller-based systems in health monitoring is well-supported. Studies utilizing the ESP32 microcontroller have demonstrated its reliability for real-time data acquisition and wireless communication in various health applications [5].

3. METHODOLOGY

This study adopted a Developmental Research Design (DRD) guided by the Agile Software Development Life Cycle (SDLC).

3.1. System Architecture

The system comprises a hardware component (digital caliper) and a software component (web platform). The backend is powered by a MySQL database and a server that processes data using PHP and Python.

3.2. Hardware Design

The digital skinfold caliper was developed using:

- **Microcontroller:** ESP32 with Wi-Fi/Bluetooth.
- **Sensor:** AS5047P magnetic rotary position sensor to detect jaw angle and calculate thickness.
- **Power:** 18650 Lithium-ion batteries with a UBEC 5V regulator.
- **Interface:** 2.8-inch resistive touchscreen LCD.

The device measures skinfold thickness and transmits the data to the web platform via REST API.

3.3. Body Fat Calculation

The system automates the Jackson-Pollock 3-site method. For males, measurements are taken at the chest, abdomen, and thigh. For females, sites include the triceps, suprailiac, and thigh. Body density (BD) is calculated and then converted to body fat percentage using the Siri equation:

$$\text{Body Fat \%} = \left(\frac{4.95}{BD} - 4.50\right) \times 100 \tag{1}$$

3.4. Data-Driven Insights

The system utilizes the Isolation Forest algorithm to detect anomalies in client progress. This unsupervised learning algorithm isolates observations by randomly selecting a feature and then randomly selecting a split value. Anomalies are susceptible to isolation and have shorter path lengths in the tree structure. This allows the system to flag irregular patterns in workout consistency or nutrition logs.

4. RESULTS AND DISCUSSION

4.1. Digital Caliper Accuracy

Validation was conducted with 31 participants (17 males, 14 females). The digital caliper was compared against a standard manual caliper and a Bioelectrical Impedance Analysis (BIA) device.

Table 1: Comparison: Digital vs. Manual Caliper

Metric	Value
Mean Difference (Thickness)	-0.01 mm
Standard Deviation	0.65 mm
Percent Error (Thickness)	2.15%
Mean Diff (Body Fat %)	0.01 pp
Percent Error (Body Fat %)	1.21%

As shown in Table 1, the digital caliper demonstrated high precision relative to the manual caliper. A higher percent error (21.87%) was observed when compared to BIA, attributed to methodological differences (skinfold vs. impedance) rather than hardware limitations.

4.2. Machine Learning Performance

The Isolation Forest component was validated using health-related proxy datasets. The model effectively classified trends (Improving, Plateau, Regression, Irregular).

- **Anomaly Detection:** effectively identified outliers in "noisy" datasets like daily step counts.

2

- **Trend Classification:** achieved accuracy between 46.2% and 59.0% across different metrics, proving capable of distinguishing long-term trends from daily fluctuations.

4.3. System Functionality

Latency testing of the web platform showed a 100% notification delivery rate with an average latency of under 1.5 seconds, ensuring real-time feedback for users.

5. CONCLUSION

Sunno Fitness successfully bridges the gap between manual tracking and expensive clinical devices. The digital skinfold caliper provides accurate, automated measurements comparable to manual standards. The integration of the Isolation Forest algorithm allows for intelligent, automated monitoring of client progress.

Future work will focus on expanding validation with gold-standard methods like DEXA and refining the hardware for commercial viability.

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APPENDIX E: BIONOTE

Sunny Madridano is a graduating Bachelor of Science in Information Technology student from Pamantasan ng Lungsod ng Maynila. His work focuses on the intersection of technology and fitness, which led to the development of Sunno Fitness, a system that integrates hardware design, software development, and data analytics for performance monitoring. Throughout his studies, he has been deeply involved in creating user-centered systems, contributing to projects as a designer, developer, and researcher. Outside the academic setting, he is active in the fitness industry as a coach and model, experiences that continue to shape his interest in building practical and accessible digital tools for health and personal improvement.