Smartbell: A Biofeedback-Driven Intervention to Counteract Sarcopenia and Dynapenia in LLMI through Gamified Upper-Body Resistance Training

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Abstract

Lower limb mobility impairment (LLMI) affects tens of millions of individuals worldwide, leading to muscle loss, decreased independence, and consequent health risks. Upper-body resistance and strength training can help mitigate effects, though traditional tools like dumbbells lack accessibility, feedback, and engagement, limiting their effectiveness for this population. We developed *Smartbell*, an AI-guided, sensor-integrated dumbbell system that combines computer vision (YOLOv8/YOLO11), biofeedback (IMU and PPG), and gamified elements (music response, real-time scoring, and visual targets) to offer personalized and entertaining upper-body strength training. In a crossover study of 13 participants (aged 50-76), *Smartbell* demonstrated a 5.7 × increase in "Perfect" repetitions, 99% reduction in "Fail" repetitions, and a 71% improvement in performance scores compared with traditional dumbbells. Subjective feedback indicated significantly higher engagement and willingness to continue, with no increase in perceived exertion, highlighting *Smartbell*'s capabilities at enhancing experience without adding physical strain. *Smartbell* also improved alignment between self-perceived performance and actual performance, and all results were consistent across all age groups. The study provides the first validation of an integrated, biofeedback-driven, and gamified resistance training device designed for older adults and individuals with LLMI, placing *Smartbell* as a clinically impactful tool to combat sarcopenia, dynapenia, and other causes of LLMI while promoting adherence and enjoyment to strength training.

Keywords: Lower limb mobility impairment (LLMI); Biofeedback (IMU/PPG); Gamified rehabilitation; Sarcopenia/dynapenia intervention; Artificial intelligence computer vision

Table of Contents

1 Introduction

1.1 Background and Significance

Lower limb mobility impairment (LLMI) affects tens of millions of individuals worldwide, limiting voluntary movement from the hips to the feet and leading to a substantial decline in overall well-being. LLMI diminishes independence and increases reliance on upper-body strength for basic activities of daily life (ADLs) such as dressing, bathing, and using ambulatory devices. The consequences extend far beyond mobility alone: prolonged immobility contributes to muscle loss throughout the body and accelerates systemic deconditioning, all while raising the risk of secondary complications (Avidos et al., 2025; Xu et al., 2023).

The causes of LLMI are diverse. Spinal cord injuries (SCIs) are the leading contributor, with an estimated 20.6 million people living with SCI in 2019, nearly half of whom experience paraplegia or related impairments (Center, 2019; Collaborators, 2023; Kang et al., 2017). Beyond mobility restraints, SCIs also increase intramuscular fat buildup, leading to reduced muscle strength and a heightened risk of obesity (Gorgey & Dudley, 2007). Neuromuscular conditions such as muscular dystrophy, which affects around 3.6 per 100,000 individuals globally, also contribute to a range of LLMIs (Salari et al., 2022). Age-related factors, including decline in muscle mass (sarcopenia), strength and muscular power (dynapenia), and bone density (osteoporosis), collectively compound the issue (Fan et al., 2024; Gustafsson & Ulfhake, 2024). Osteoarthritis, neuropathy, and post-stroke deficits further exacerbate these LLMIs (Bouche, 2020; Li et al., 2018; Loeser, 2017). In total, approximately 35% of individuals aged over 70, and a majority of those over 85, experience mobility limitations and impairments (Freiberger et al., 2020; Grimmer et al., 2019). With the global elderly population expected to double by 2050 (reaching nearly 2 billion), LLMI prevalence will escalate, making it an urgent public health issue (United Nations, 2022).

Targeted upper-body strength training has been consistently shown to mitigate these risks and improve functional capabilities in individuals with LLMI (Tweedy et al., 2017; Zimmerli et al., 2012). Targeted upper-body exercise can reduce the risk of secondary complications and maintain independence (Valent et al., 2007; Van der Scheer et al., 2017). However, traditional training solutions present many restraints. Gym-based exercise environments often lack accessibility accommodations, while professional guidance through personal trainers or physicians is often expensive. At-home options, most commonly handheld dumbbells, are widely available but inherently flawed. Traditional dumbbells lack real-time feedback, no instructional guidance, and engagement, which can leave users with LLMI susceptible to poor form, overuse injuries, demotivation, and fatigue. These barriers not only limit the effectiveness of exercise but can also actively discourage and harm users.

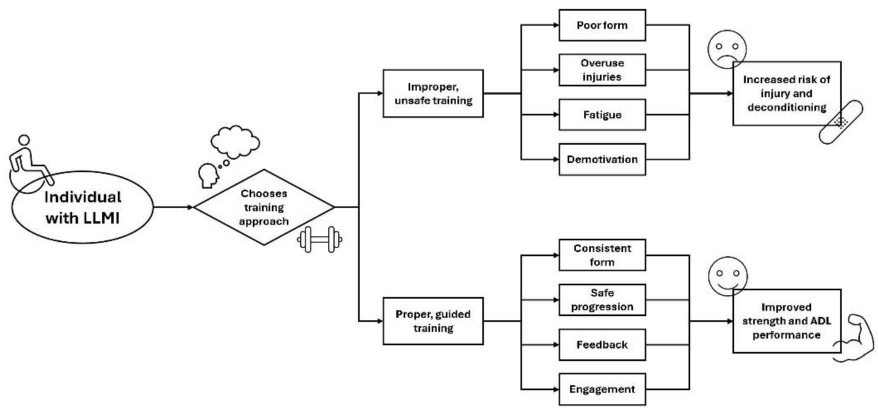

Figure 1: Flowchart of traditional vs guided training approaches. The above diagram illustrates the consequences of different training approaches for individuals with LLMI. Improper or unsafe training can lead to poor form, overuse injuries, fatigue, and demotivation, ultimately increasing the risk of injury and deconditioning. In contrast, proper guided training promotes consistent form, safe progression, feedback, and engagement, leading to improved strength and ADL performance.

The mismatch between increasing clinical needs and available tools underscores the demand for accessible, guided, and engaging upper-body strength training devices tailored to individuals with LLMI. Such a technology has the potential to reduce preventable complications, improve quality of life, and promote exercise. Our work builds on this idea by developing and evaluating an AI-assisted, chip-guided, and software-driven dumbbell system that integrates posture guidance, real-time feedback, and accessible design principles to accommodate individuals with LLMI. Nevertheless, current fitness technologies rarely address this population.

1.2 Comparative Analysis

Although the market for smart fitness devices has expanded rapidly in recent years, most systems are designed without consideration for users with limited mobility, particularly those with LLMI. While smart fitness devices, such as the Peloton Guide, offer AI-assisted rep-tracking and guidance through computer vision, they are designed primarily for fully mobile individuals, demanding high-mobility movements such as squatting and lunging. Similarly, Nintendo's Ring Fit Adventure gamifies exercises using motion sensors and a resistance ring.

However, it focuses mainly on cardiovascular activity and general fitness, rather than targeting specific muscle groups. Neither of these systems is designed for restricted users, nor do they offer adaptive and targeted exercises tailored to rehabilitation or elderly needs.

As a result, many individuals with lower-body immobility still struggle to exercise effectively, resulting in further decline in their health and fitness. Despite the surge in fitness technologies, millions of individuals with LLMI face barriers to effective upper-body strength training due to a lack of accessible, adaptive, and motivating upper-body training solutions. The lack of such an adaptive and inclusive device widens the gap between individuals with LLMI and the solutions offered by current fitness technology.

1.3 Research Objectives

The current fitness technology market lacks an upper-body-focused and adaptive training device, particularly for individuals with LLMI, the elderly population, or rehabilitation patients. To address this gap, I propose *Smartbell,* a sensor-embedded, chip-integrated dumbbell system coupled with an AI-powered training program. The goal of *Smartbell* is to help individuals with LLMI learn and perfect upper-body exercises, focusing on accurate placement of the dumbbell and effective pacing of movements. *Smartbell* is designed to do so in an engaging manner, thus implementing gamified and musical elements in our software.

To achieve this overall engineering goal, we require two components: A hardware component and a software component. The aim of the hardware component is to accurately and timely collect data about the dumbbell's general orientation and the user's biometric conditions during the workout. The hardware component must also be portable to ensure *Smartbell's* ease of use. The aim of the software component is to guide the user through beginner-friendly and effective upper-body exercises while offering real-time feedback through scoring and music. The computer will utilize AI-based computer vision technology to track the dumbbell's motion and the user's joints to be used in scoring. Additionally, the program will adapt its pacing during the exercise based on the user's heart rate, ensuring personalized workouts with fitting intensity.

To evaluate the effectiveness of *Smartbell*, we will sample a group of participants to test both *Smartbell* and a traditional dumbbell. Participants will grade themselves, assessing their engagement, perceived effectiveness, and other subjective metrics, which will be compared against system-generated performance data that indicates their overall form.

1.4 Key Innovations

Our project aims to combine hardware and software to transform traditional dumbbells into a more effective, engaging, and accessible method of exercise. We've combined studies about exercise and muscle growth with innovative technology to fill the gap in the current market of fitness devices. At the same time, our study will demonstrate the potential of implementing gamified and other smart features to enhance user engagement, retention, and performance outcomes during exercise (Ozdamli & Milrich, 2023).

2 System Implementation

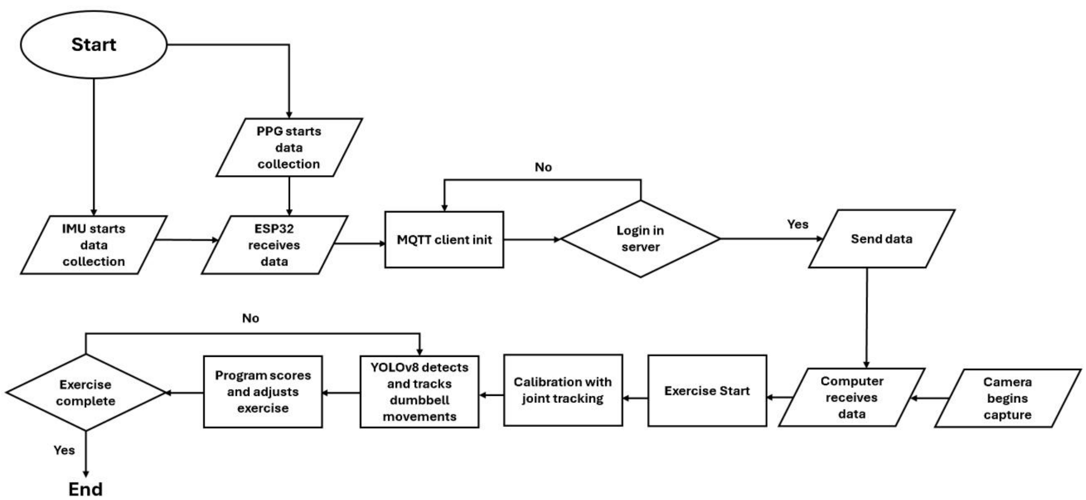

Figure 2: System architecture and workflow. The flowchart illustrates the sequence of data collection, transfer, and processing steps. Sensor data from the IMU and PPG are collected and transmitted via the ESP32 to the server through MQTT. Upon login, data are relayed to the computer, which synchronizes with camera input too. YOLOv8 detects and tracks the dumbbell, while YOLO11 detects and tracks the joint for calibration. The program continuously scores performance, adjusts target placement and exercise speed, and terminates once the exercise is completed.

Smartbell integrates a 10-axis IMU sensor for orientation tracking and a PPG sensor for heart rate monitoring. Both sensors connect via wire to an ESP32 microcontroller, which relays the data wirelessly via MQTT to a local EMQ X broker. The computer accesses the server and downloads the data, storing it in our program for further analysis. Simultaneously, the computer is wired to a depth camera capable of video and depth capture. The program analyzes each frame of the camera footage, tracking the dumbbell's position and the user's joints. As discussed in 1.3, our system consists of a hardware component and a software component to achieve its tasks.

2.1 Hardware

2.1.1 Yahboom IMU

To track the dumbbell's orientation and movement, we integrated a 10-axis IMU gyroscope and accelerometer. This allows the system to capture live motion data essential for analyzing workout intensity and providing real-time feedback. We chose a compact, high-precision IMU module by Yahboom with the following specifications:

- Accelerometer: ±16g range, ±10–20 mg of deviation
- Gyroscope: ±2000°/s range, ±0.5–1°/s deviation
- Sampling Rate: > 200 Hz via serial communication
- Dimensions: 43.9 mm × 31.4 mm × 4 mm

These features ensure rapid and low-latency motion capture, allowing our IMU to detect minute changes in the dumbbell's motion. The sensor's compact size allows it to fit in the external compartment without interfering with the user's grip or performance.

Figure 3: Image of Yahboom IMU

2.1.2 Makerbase Photoplethysmogram (PPG)

The PPG is a compact device with optical sensors that detect volumetric changes in blood circulation by measuring the amount of light absorbed or reflected by human skin. It is a low-cost and non-invasive method of taking measurements at the surface of the skin. We incorporated a Makerbase PPG into our dumbbell to measure the user's heart rate during the exercise. It can capture heart rate along with other physiological parameters, including blood oxygen saturation, blood pressure, and fatigue status. It is highly receptive and outputs the parameters via a serial connection in real time. The dimension measures 31.04 mm × 11.04 mm × 7.8 mm, allowing it to fit seamlessly onto the dumbbell for maximum user comfort.

Figure 4: Image of Makerbase PPG

2.1.3 ESP32

To enable wireless data transmission between *Smartbell* and the host computer, we utilized an ESP32 microcontroller (MCU). The ESP32 was selected for its compact form, integrated Wi-Fi and Bluetooth capabilities, and compatibility with numerous peripheral devices, making it popular amongst Internet of Things (IoT) applications with space and power constraints. Our ESP32 has the following specifications:

- I/O capabilities: 48 pins, including General Purpose Input/Output (GPIOs) and digital ↔ analog converters
- Connectivity: Integrated Wi-Fi and Bluetooth connections
- Dimensions: 51.5 mm × 28.3 mm × 4 mm

We configured and established three serial connections on the ESP32 to manage data exchange between components:

- ESP32 ↔ IMU: Receives 10-axis motion and orientation data from the IMU
- ESP32 ↔ PPG: Receives real-time heart rate data from the PPG
- ESP32 ↔ Computer: Used to test and modify the ESP32's code during configuration/development stages

Figure 5: Image of ESP32 MCU

2.1.4 OAK-D Pro 3D camera

To capture high-quality video footage for image processing, we used the OAK-D Pro 3D camera from Luxonis. Our camera has the following specifications:

- RGB Camera: 1080p at 60 FPS
- Depth Sensing: IR dot projection and stereo vision for real-time depth perception
- Low-Light Performance: IR illumination LED enables operation in low-light or no-light
- Onboard Processing: Integrated chip with 4 TOPS (trillions of operations per second) for AI computation

Although the camera supports onboard AI inference and depth perception, our current program utilizes it solely for video capture. Its adaptability across different lighting conditions and high frame rate ensures consistent video feedback regardless of external environment. This versatility ensures consistency across exercise routines, supporting accurate tracking of the dumbbell and user motion.

Figure 6: Image of OAK-D Pro 3D Camera

2.1.5 Outer Box Design

To carry the hardware components, we designed a custom external compartment that can be securely mounted onto the dumbbell's handlebar. The model was designed using CATIA, a computer-aided design (CAD) software, and printed using a 3D printer.

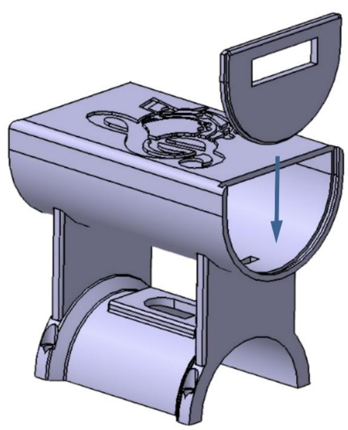

Figure 7: CATIA Render of top compartment and sliding hatch

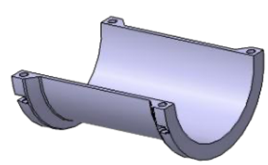

Figure 8: Bottom clamp

The mounting mechanism comprises two semi-cylindrical clamshells, each with an internal diameter of 44mm and a wall thickness of 3mm. Each shell includes 4 screw holes to enable secure attachment around the dumbbell’s handlebar. One of the shells incorporates two vertical beams extending 30mm upwards, supporting an additional semi-cylindrical housing with dimensions of 105mm × 70mm × 44mm. This upper compartment accommodates our IMU sensor, ESP32 MCU, and a battery. At the base of this same shell, a dedicated slot allows the PPG sensor to remain exposed, enabling the user to rest their finger on the PPG while gripping the dumbbell’s handle. The compartment is closed from the side with a sliding lid that fits into grooves, ensuring a seamless and secure closure. For additional customizations, the top surface of the compartment is engraved with a decorative image of a bicep, though this does not affect functionality.

2.2 Software Architecture

2.2.1 Software Overview

The software is designed to enable real-time, adaptive upper-body training for individuals with LLMI. It integrates multimodal sensor data, AI-based guidance, and gamified elements to enhance engagement and training efficiency. The system receives sensor and visual data and utilizes YOLO-based object detection models to create guided training programs for users.

2.2.2 Embedded Control and Data Transmission

To transfer PPG and IMU data wirelessly, we utilized the ESP32’s Wi-Fi capabilities by implementing an MQTT protocol, a lightweight publish-subscribe messaging system commonly used in IoT applications. The ESP32 publishes sensor data to an EMQ X local MQTT broker hosted on the same network, ready to be downloaded from nearby devices. This setup allows real-time data to be transferred wirelessly to our computer, where it can be stored and analyzed to make dynamic adjustments during the exercise. Due to the different sampling rate of both sensors—with the IMU faster than the PPG—we also leveraged the ESP32’s dual-core architecture to receive data concurrently. When PPG data were unavailable, the system would default to the most recent value. We accessed the server through dedicated Python libraries in our program.

Figure 9: Data transmission pipeline. The above diagram shows the communication between the ESP32 MCU, EMQ X MQTT broker, and the computer. Sensor data are published to the EMQ X server and subscribed by the computer for real-time processing and analysis.

2.2.3 AI-Based Tracking

The core program integrates YOLOv8 and YOLO11-pose, two real-time detection frameworks developed by Ultralytics, chosen for their balance of speed and accuracy in dynamic tracking tasks (Khanam & Hussain, 2024; Sohan et al., 2024). Both models adopt an anchor-free head architecture, which doesn't use predefined anchor boxes and instead directly predicts object centers and bounding box dimensions (for YOLOv8), or key point coordinates (for YOLO11). This design simplifies the detection process and makes it faster and more accurate.

The YOLOv8 model was used to detect and track the dumbbell throughout the exercise. To optimize real-world performance, the model was fine-tuned on a custom dataset of over 2,000 annotated frames collected from multiple recordings of the dumbbell under varying angles, lighting conditions, and motions. We used the pretrained YOLO11-pose model to detect and track key user joints—specifically the shoulder, elbow, and wrist joints. These joint coordinates were used to calibrate the position of on-screen targets, ensuring alignment with each individual's unique arm length and range of motion. This AI-driven architecture enables the system to personalize visual prompts and evaluate movement quality, both essential features in upper-body training for users with mobility impairments.

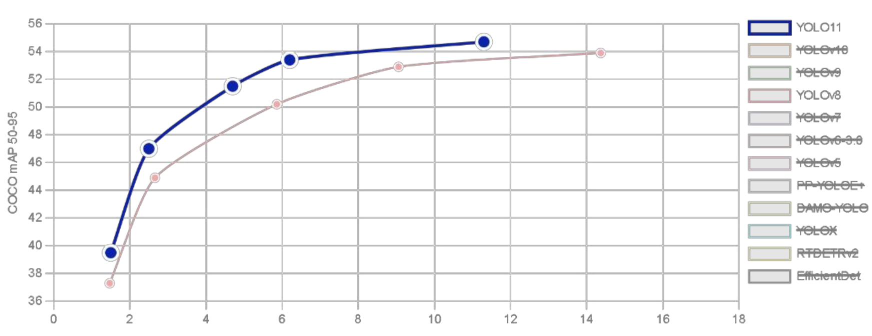

Figure 10: Comparison of YOLO11 and YOLOv8 performance. Benchmark shows that YOLO11 consistently achieved higher accuracy (mAP50-95) with lower latency compared to YOLOv8. Adapted from (Ultralytics, 2025) .

These benchmarks (Figure 10) prove that YOLOv8 provides efficient object tracking for the dumbbell, while YOLO11 offers unparalleled joint tracking accuracy and speed. Together, the two models balance speed and precision to ensure real-time feedback during the exercise.

2.2.4 Visual and Audio Interaction

To support proper exercise form and enhance user engagement, the system implements visual guidance and audio feedback. During each exercise session, the user's live camera feed is displayed on-screen, overlaid with dynamic visuals generated using OpenCV. Specifically, a series of bounding boxes is rendered to indicate spatial targets for each movement. Users were prompted to bring their device to the designated locations, and the position was verified by the YOLOv8 model. Upon successful placement, determined by spatial overlap between the detected dumbbell and the target zone, the system triggers progression to the next target and the playback of a musical note. These notes, created using the Pydub library, form a structured melody. The incorporation of musical feedback was inspired by prior research, demonstrating that music can significantly improve exercise performance and enjoyment (Karageorghis & Priest, 2012a, 2012b).

To regulate exercise pacing based on user physiological responses, a biofeedback timing algorithm was added. The system monitors the user's heart rate and uses it to alter the inter-target interval. The timing adjustment is defined by the equation:

$$Duration(ms) = 1000 + \left(HR - HR_{target}\right) \times w \tag{1}$$

where HR_{target} denotes the user's target heart rate, and w is a tunable weight that controls the sensitivity to heart rate fluctuations. If the user's heart rate exceeds the target, the duration increases, resulting in slower target generation. Conversely, if the user's heart rate drops below the target, the duration decreases, promoting a higher intensity rhythm. This adaptive module allows for personalized and optimized pacing, particularly important for individuals with LLMI who may have varied endurance capabilities and exercise experience.

2.2.5 Quantitative Feedback and Scoring

To reinforce correct form and further gamify the exercise process, a real-time scoring mechanism provided feedback on movement accuracy. Each repetition was evaluated based on the Euclidean distance between the center of the detected dumbbell (via YOLOv8) and the center of the designated target zone. Placement accuracy was categorized as Perfect, Good, Decent, and

Fail, corresponding to thresholds of increasing distance. These categories were also assigned point values from 3 to 0.

Individual scores were displayed after each movement using color-coded visual indicators. At the conclusion of every session, a cumulative score was displayed to the user, summarizing overall exercise quality. The approach draws on the gamification principles, which have been shown to improve adherence, enjoyment, and perceived value in exercises (Kari et al., 2016). By transforming accuracy into quantifiable metrics, the scoring system encourages users to refine their form and perform consistent and accurate movements.

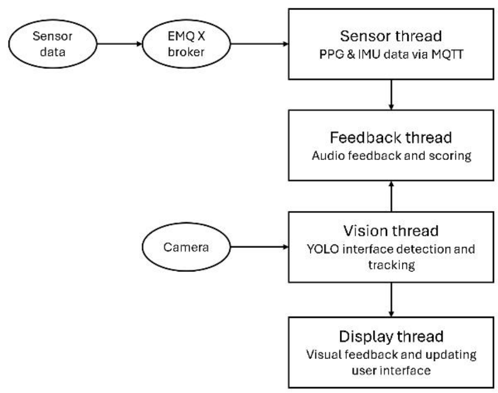

Figure 11: Multithread software architecture of Smartbell. Sensor data are streamed via MQTT to the Sensor thread, while camera input is processed in the Vision thread with YOLO algorithms. Both converge at the Feedback thread, which generates audio output and scoring. The Display thread updates the user interface concurrently.

2.2.6 Integration

All real-time processes, including visual analysis, data transmission, and feedback distribution, were implemented as concurrent threads in Python. Each major process (YOLO interface, sensor data transfer, audio feedback and scoring, and user interface) ran in a dedicated thread. This ensured that more compute-intensive tasks like YOLO detection won't block other real-time operations. The multithreading approach ensured a low-latency and high-responsiveness system during the exercise, offering an optimal experience to the participants.

3 Methods

3.1 Exercise Design

Our exercise program is designed to provide a safe and effective upper-body workout to help users develop strength for ADLs and muscle mass for overall health. The program was designed for dumbbells and is compatible with both traditional variants and *Smartbell*. It focuses on progressive training, targeting key upper-body muscles through simple movements that can be completed with limited lower mobility. The program consists of 8 sessions with 10 repetitions each, yielding a total of 80 repetitions per user. To accommodate this relatively high training volume and ensure completion without excessive fatigue or stress, we calibrated the intensity to a moderate level through real-time heart rate monitoring and 1RM-based weight selection.

3.2 Heart Rate and Intensity

Heart rate, when compared to an individual's maximal heart rate (HR_{max}), is a crucial indicator of workout intensity, helping prevent overexertion and injury. The age-predicted maximal heart rate formula (i.e., 220 – age) is widely used to predict maximal heart rates. However, this method exhibits a standard deviation of ±10–12 bpm and lacks accuracy in older adults (Shookster et al., 2020). Since our program is designed for older adults, we adopted the Tanaka formula (Tanaka et al., 2001),which has been utilized in related papers and empirically validated to better account for age-related physiological variations when predicting heart rate:

$$HR_{max} = 208 - 0.7 \times age \qquad (2)$$

For this study, we set the target heart (HR_{target}) at 65% of HR_{max}, corresponding to a low-to-medium intensity. This value serves as our primary reference point for correcting exercise intensity in our program. Heart rates exceeding 65% HR_{max} were treated as overly intense, and levels below indicated insufficient effort.

3.3 One-Repetition Maximum (1RM) Estimation

One-repetition maximum (1RM) refers to the maximum weight an individual can lift for a single repetition of a specific movement. 1RM is a foundational method for calibrating individualized training weight. While direct assessments of 1RM offer an accurate strength benchmark, it is often unsafe for beginners. To mitigate this risk, we adopted a submaximal approach (Eston & Evans, 2009). In this method, participants selected a weight they could lift for 7-10 repetitions under controlled form.

The number of repetitions (R) and the corresponding submaximal weight (W) can be input into predictive models to estimate 1RM. Among various predictive models, we chose the Bryzcki equation, which has been shown in previous studies to yield the greatest correlation with actual 1RM values for older adults performing bicep curls (Brzycki, 1993; Knutzen et al., 1999; Wood et al., 2002):

$$1\mathrm{RM} = \frac{\mathrm{W}}{1.0278 - 0.0278 \times \mathrm{R}} \quad (3)$$

To determine an appropriate load, we set the training weight at 60% of the estimated 1RM, which is often considered the lower bound for effective strength training in older populations (Fragala et al., 2019). Thus, the corresponding training weight W_t was calculated as:

$$\mathrm{W_t} = 0.6 \times 1\mathrm{RM} \quad (4)$$

To accommodate the available weight options, we rounded $\mathrm{W_t}$ down to the nearest 0.25 kg.

3.4 Movement Selection

To provide a safe, accessible, and relevant movement for developing upper body strength, we selected the bicep curl as our primary exercise movement for this program. The bicep curl is a single-joint, isolated movement that targets the biceps brachii, brachialis, and brachioradialis muscles. These muscles play a crucial role in performing ADLs such as lifting objects, pulling doors, and rising from seated positions using an arm support.

Biceps curls are easy for users to learn, as they involve predictable paths and low joint complexity. This is important for older adults, who often lack exercise experience and have declines in motor skills, joint strength, and neuromuscular control. Moreover, the movement requires no lower-limb involvement, reinforcing its suitability for individuals with LLMI or those training in seated positions.

In the future, though, additional upper-body movements could be selected to target a wider array of muscle groups. Common exercises with dumbbells include lateral raises and shoulder presses (mainly targeting the shoulders), overhead triceps extension (mainly targeting the triceps), and the Svend press (mainly targeting the chest). These movements could be completed while seated, ensuring its accessibility to individuals with LLMI.

3.5 Experimental Procedure

Prior to participation, each participant was provided with a detailed explanation of the study procedures and asked to sign a consent form permitting the temporary collection of heart rate data and video footage for analytical purposes. Afterwards, each participant was given a brief instruction on the correct execution of a standard bicep curl, as well as a demonstration of the *Smartbell* system.

Each participant performed a total of eight exercise sessions: four using traditional dumbbells and four using the *Smartbell* system. A device switch occurs after the fourth session to ensure all participants experience both modalities. Participants were assigned to alternating device sequences to ensure randomness. All participants on days 1 and 2 (n = 7) began with the traditional dumbbell, while participants on subsequent days (n = 6) began with *Smartbell*.

During each session, the participants were asked to:

1. Perform ten repetitions of a standard bicep curl based on the given instructions with their designated device.
2. Complete a post-session survey of four Likert-scale agreement-based questions and one multiple-choice selection. Questions include perceived exertion, self-reported engagement, willingness to continue, and overall performance.
3. Rest for 3-5 minutes, during which they were observed for any signs of discomfort.

The participants, facing the camera, would be scored by our software system. In sessions when they use *Smartbell*, they would also see the target visuals, scoring, and hear musical feedback. During dumbbell trials, they would simply be asked to perform the movement like normal while the computer screen was faced away.

This process was repeated until all eight sessions were complete. As mentioned earlier, a device switch occurred after the fourth session, ensuring each participant could experience both devices.

3.6 Statistical Analysis

All statistical analyses of system-recorded data and post-session survey data were conducted using R (v4.5.1). Box plots show the median, interquartile range (IQR), whiskers (1.5× IQR), and outliers. To measure outcomes between different comparisons of *Smartbell* and traditional dumbbell groups, we used Welch's two-sample t-test for all our *p*-values. This method was mainly chosen due to the unequal sample variance between groups. Statistical significance was set at $p < 0.05$. Significance levels are reported on the graph using asterisks as follows: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***). Non-significant results are labeled as "n.s." The boxplots show median, interquartile range, and outlier data points. To measure effect size, we tested Hedges' g due to its higher accuracy in depicting effect magnitude with smaller sample sizes.

4 Results and Analysis

4.1 Overview of Data Collection

A total of 13 participants ($n = 13$) were enrolled in the study. The mean age was 62.8 years old ± 10.79 years (SD; range: 50-76). Six participants identified as male and seven as female. Two participants reported a mobility impairment, and one reported a recent chest-related surgery.

Each participant performed eight sessions, resulting in a total of 104 session datasets and 1,040 individual repetition datasets. Since the participants were scored at both the top and bottom of motion, we have a total of 2,080 score datasets. After each session, participants completed a five-question survey, yielding a total of 520 survey responses across all sessions and devices. For statistical analysis, session-level data were aggregated to the participant level to avoid pseudo-replication. Three primary performance measures were derived from these data:

(1) System-graded normalized score (0-100): Each repetition was classified by the program as Perfect (3 points), Good (2 points), Decent (1 point), or Fail (0 points) based on the dumbbell's deviation from the target position (see Section 2.2.4 for detailed scoring algorithm). The normalized score on a 100 scale was then calculated as:

$$Normalized\ Score = \frac{3(Perfect) + 2(Good) + 1(Decent) + 0(Fail)}{20} \times 100 \quad (5)$$

The normalized score represents the overall movement accuracy for the session. Higher scores result from a greater proportion of high-quality repetitions (Perfect and Good), indicating better movement precision and quality.

(2) User self-rated performance score (0-100): As part of the post-session survey, participants rated their overall movement quality and accuracy on a 0-100 scale. This self-reported value indicates the participant's perceived performance, independent of the system's grading.

(3) Additional survey responses: The remaining survey questions measured user engagement, perceived exertion, and willingness to continue (each rated on a 1-10 agreement scale). These metrics provide complimentary insight into the participants' subjective experience and response to the device.

Though both the system-graded score and self-reported score are on a 0-100 scale, they differ in origin and purpose: one is an objective algorithmic evaluation, and the other is a subjective self-assessment. Direct comparison of these two provide valuable insight into user self-awareness in exercise performance. Meanwhile, the additional survey responses capture user experience, enabling a multi-faceted comparison of *Smartbell* and the dumbbell.

4.2 Objective Performance Analysis

To evaluate the effects of *Smartbell* versus the dumbbell on movement quality, we analyzed two system-graded metrics: repetition score types (Perfect, Good, Decent, and Fail) and normalized system-graded scores (see Section 4.1 for score calculation). These metrics capture both the distribution of repetition quality and overall session performance, providing an objective basis for comparing the two devices. The goal of this analysis is to determine whether *Smartbell* use resulted in a measurable shift towards higher quality repetitions and improved overall performance compared with the dumbbell.

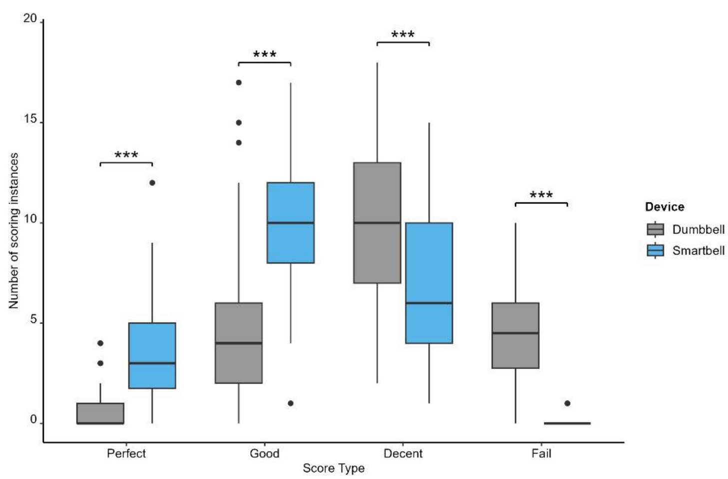

Figure 12: Distribution of scoring instances by device. Boxplots show the distribution of scoring instances across participants during *Smartbell* and dumbbell sessions. *Smartbell* sessions yielded significantly more Perfect and Good scores, and significantly less Decent and Fail scores compared with dumbbell sessions (****p*<0.001 for all comparisons).

Figure 12 shows the distribution of Perfect, Good, Decent, and Fail score counts across all sessions for *Smartbell* and the dumbbell. Each session consisted of 20 scored repetitions. On average, *Smartbell* sessions yielded higher Perfect score counts (3.5 ± 2.57) compared to dumbbell sessions (0.615 ±1.12), representing a 5.7× increase (Hedges' g = 1.44, large effect). Good score counts were also substantially higher during *Smartbell* sessions (9.79 ± 3.38) compared with dumbbell sessions (4.77 ± 3.76), representing a 2.1× increase (Hedges' g = 1.39, large effect). Conversely, Decent score counts decreased from 10.0 ± 3.83 with dumbbell to 6.67 ± 3.52 with *Smartbell*, a 33% reduction (Hedges' g = -0.907, large effect), while Fail score counts were nearly eliminated, declining from 4.52 ± 2.37 to 0.04 ± 0.19, a 99% reduction (Hedges' g = -2.64, large effect). All differences were statistically significant ($p < 0.001$). These results indicate that the use of *Smartbell* was associated with a shift toward higher-quality scores and marked a reduction in lower-quality or failed attempts.

Figure 13 compares the normalized system-graded scores (0-100) between *Smartbell* and dumbbell sessions. Average scores increased from 35.8 ± 8.57 with the dumbbell to 61.2 ± 8.78 with *Smartbell*, marking a 71% relative improvement. This difference was significant ($p <$ 0.001), with a large effect size (Hedges' g = 2.91). The distribution of scores also shifted upwards, with most *Smartbell* sessions clustering in the 55-70 range, where dumbbell sessions consistently saw scores below 40. These results suggest that *Smartbell's* guided target system improved repetition quality and enhanced session performance.

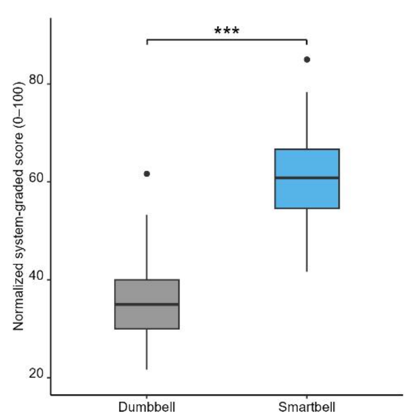

Figure 13: Normalized system-graded scores (0-100) by device. Box plots show the distribution of session scores across participants during *Smartbell* and dumbbell sessions. Participants achieved significantly (***p < 0.001) higher performance scores when using *Smartbell* compared to the traditional dumbbell.

Together, Figures 12 and 13 demonstrate that *Smartbell* use consistently shifted repetitions toward higher-quality movements and substantially improved overall session scores. The repetition-level analysis (Figure 12) showed a large effect size for an increase in Perfect and Good score counts and a reduction in Decent and Fail score counts, while the session-level analysis (Figure 13) demonstrated a gain in composite performance. These results indicate that *Smartbell* promotes more precise and accurate execution of movements than the traditional dumbbell, achieving the primary goal of comparing objective performance between both devices.

4.3 Subjective User Feedback Analysis

The next concern was whether the user's subjective perception experience differed when using *Smartbell* and the dumbbell. While objective performance metrics (See 4.2) quantify and grade movement quality, subjective user feedback offers insight about a user's experience with the device, which can determine whether a device will be used long-term. To capture this aspect, as part of our post-session survey, we asked participants to rate their engagement (Figure 14A), perceived exertion (Figure 14B), and willingness to continue (Figure 14C). These measures were selected because they represent complementary aspects of a workout: engagement reflects immediate enjoyment of using the device, exertion captures the felt physical workload, and willingness to continue indicates future usage. The goal of this analysis is to assess whether *Smartbell* enhances psychological and motivational dimensions of exercise compared with traditional dumbbells, hence providing a fuller understanding of its benefits.

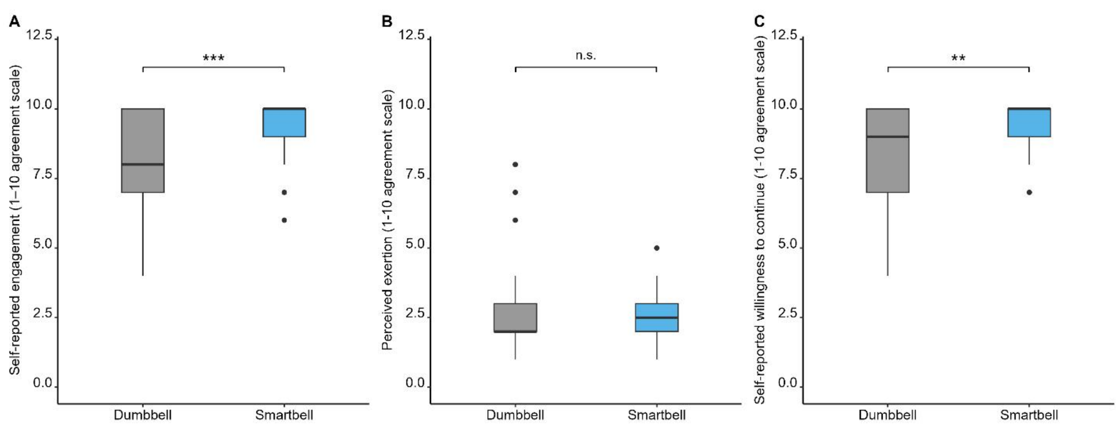

Figure 14: Comparison of post-session survey results from Smartbell and traditional dumbbell sets across three metrics. Boxplots display self-reported (A) engagement, (B) perceived exertion, and (C) willingness to continue, rated on a 1-10 agreement scale. Box plots show the distribution of survey answers. *Smartbell* showed significantly higher engagement (***$p < 0.001$) and willingness to continue (**$p < 0.01$), but no significant difference in perceived exertion (n.s.).

Figure 14 compares the self-reported engagement score, exertion, and willingness to continue between *Smartbell* and traditional dumbbell sets, based on 1-10 agreement scores from the post-session surveys. *Smartbell* sessions resulted in significantly ($p < 0.001$) higher engagement scores (9.38 ± 0.87) compared to dumbbell sessions (8.04 ± 1.93), with Hedges' $g = 0.89$, indicating a large effect. *Smartbell* sessions also exhibited a higher median (10 vs 8) and narrower interquartile range (1 vs 3), demonstrating a more consistently positive experience.

For perceived exertion, no significant difference (p = n.s.) was observed between *Smartbell* (2.56 ± 1.06) and dumbbell (2.62 ± 1.62) sessions, with Hedges' $g = -0.04$, reflecting a negligible effect. However, *Smartbell* sessions showed a tighter range (1-5 vs 1-8), indicating more consistent perceived effort across users, suggesting that *Smartbell* helped moderate exercise intensity.

Willingness to continue also showed significantly ($p < 0.01$) higher scores following *Smartbell* sessions (9.37 ± 0.768) relative to dumbbell sessions (8.5 ± 1.87), with Hedges' $g = 0.60$, representing a moderate effect. The higher median (10 vs 9) and narrower interquartile range (1 vs 3) further suggest that *Smartbell* enhanced users' motivation to sustain training over time.

Notably, engagement and willingness to continue reached statistical significance, while perceived exertion did not. This difference is largely due to the method of our study: both *Smartbell* and dumbbell users performed the same exercise with equivalent weights and duration, leading naturally to similar perceptions of physical effort. The absence of statistical significance is therefore expected, and it also demonstrates how *Smartbell* improves the psychological experience of exercise without causing additional physical strain. Additionally, the tighter range is also an indicator that *Smartbell* helped individuals stay more consistent with their exercise intensity.

In contrast, engagement and willingness to continue, two of the most prominent indicators of exercise enjoyment and adherence, were both significantly higher for *Smartbell* than for dumbbell. Participants using *Smartbell* reported greater engagement and a stronger desire to continue training. Together, these subjective results demonstrate that *Smartbell* improves motivation and enjoyment while maintaining a stable exertion.

4.4 Comparison of Self-Rated and System Scores

An important question was whether participants' self-perceptions of their performance aligned with the system's objective evaluation. While objective metrics (Section 4.2) and

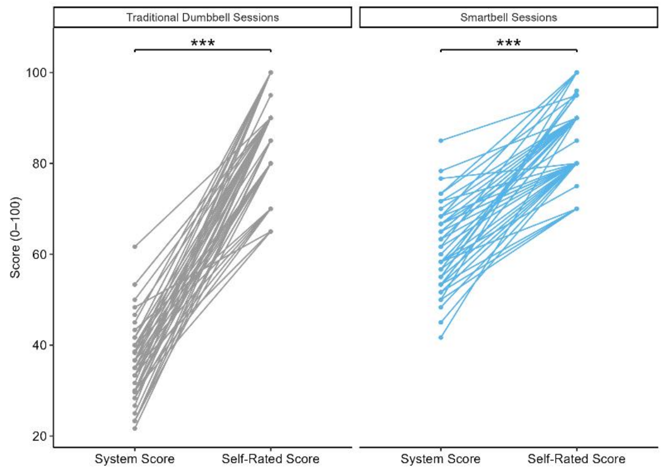

Figure 15: Paired comparison of self-rated and system-graded scores (0-100) for each session, separated by device type. Each point represents an individual participant's score, with lines connecting the self-rated and system-graded score from the same session. Across both devices, self-rated scores were significantly (***$p < 0.001$) higher than system-graded scores.

subjective feedback (Section 4.3) capture aspects of device use, discrepancies between perceived and actual performance provide critical insight into user awareness. The goal of this analysis is to evaluate the extent to which participants accurately judged their exercise performance relative to the system's evaluations. To address this, we compared their self-rated performance scores, reported in the post-session survey, with corresponding normalized system-graded scores.

Figure 15 compares self-rated performance scores to system-graded normalized scores for both devices. Each line connects the two scores from a single session (self-rated and system-graded), showing how closely the users' perceptions aligned with actual performance. In both conditions, self-rated scores were significantly ($p < 0.001$) higher than system-graded scores, indicating a consistent tendency for users to overestimate their performance. Regardless, *Smartbell* sessions exhibited higher system scores on average and a stronger correlation ($r = 0.27$) between self-rated and system-graded scores compared to dumbbell sessions ($r = 0.13$). This suggests that *Smartbell* may promote greater awareness of exercise quality and more accurate self-assessment despite a universal optimistic bias.

We defined the self-system score difference (Δ) for each device as the difference between the self-rated score (S^{self}) and the corresponding system-graded score (S^{sys}):

$$\Delta_d = S_d^{self} - S_d^{sys}, \ d \in \{Smartbell, Dumbbell\}$$

Positive values of Δ indicate overestimation of performance relative to the system's evaluation. To assess the extent of this bias and better visualize its distribution, we graphed the Δ values for both devices in a density plot (Figure 16).

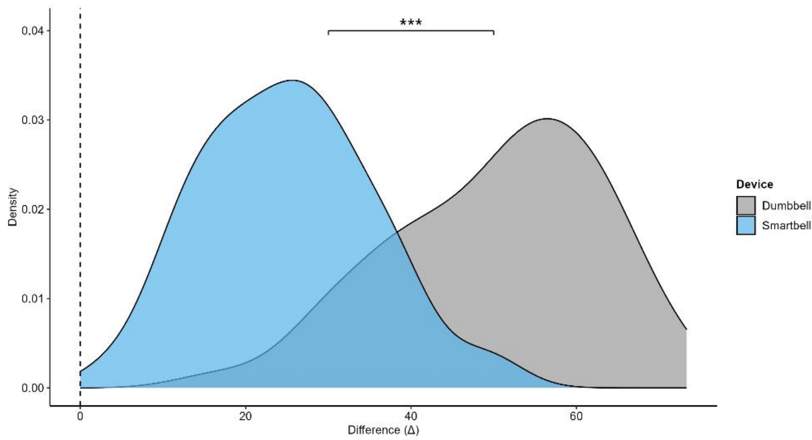

Figure 16: Density distribution of Δ for both devices. Both devices showed systematic overestimation (positive Δ values), but the distribution for *Smartbell* sessions was significantly left-skewed (***p < 0.001).

Figure 16 visualizes the density of Δ between self-rated and session scores. The distribution for *Smartbell* sessions had a smaller Δ on average (25.0 ± 10.2) compared to dumbbell sessions (50.5 ± 12.6). This indicates that the majority of *Smartbell* sessions had a significantly (p < 0.001) smaller difference between self-rated and system-graded scores, indicating smaller discrepancies and closer alignment between self-rated and system scores compared to the dumbbell sessions. Beyond Δ differences, the *Smartbell* distribution was more narrowly centered and closer to zero, reflecting greater consistency among users. Meanwhile, dumbbell sessions showed a larger Δ, suggesting greater variability in users' ability to judge their own performance.

Together, Figures 15 and 16 demonstrate that *Smartbell* use helped users reduce the gap between their self-rated performance score and the system-graded score. The paired comparison (Figure 15) illustrates greater correlation in *Smartbell* sessions compared to dumbbell sessions, and the density distribution (Figure 16) visually demonstrates a shift towards lower Δ values in *Smartbell* sessions. These results indicate that *Smartbell* promotes better user-awareness when evaluating their own performance, which may support better self-monitoring and reduce reliance on external supervision.

4.5 Demographic Impact on Performance

Our final concern was whether participants' age affected their experience with *Smartbell*. Since the device is designed for individuals with LLMI and older adults, its suitability across all age groups was crucial. Our testing group included participants aged 50-76 years (See Section 4.1 for detailed breakdown). For analysis, we divided participants into three age groups: 50-55 years (n = 5), 56-60 years (n = 2), and 71-76 years (n = 6). Performance was assessed using the normalized system-graded score.

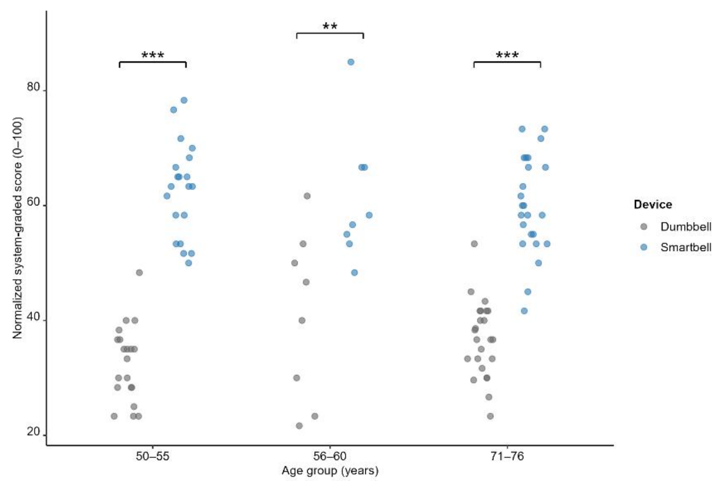

Figure 17: Dot plot of normalized system-graded score (0-100) for each age group, separated by device type. Each point represents an individual participant's score. *Smartbell* showed significantly higher system-graded normalized score for all three age groups (**$p < 0.01$, ***$p < 0.001$).

Figure 17 depicts the normalized system-graded score (0-100) between *Smartbell* and dumbbell sessions for three age groups (50-55 years, 56-60 years, and 71-76 years). Average normalized scores during *Smartbell* sessions increased significantly for all three age groups ($p < 0.001$ for 50-55 years group and 71-76 years group, $p < 0.01$ for 56-60 years group). For participants aged 50-55, *Smartbell* sessions saw a mean score of 62.8 compared to 32.7 for dumbbell, with Hedges' g = 3.98, representing a large effect. This was maintained in the 50-56 age group (61.2 vs 40.8, Hedges' g = 1.47, large effect) and in the 71-76 age group too (60.0 vs 36.7, Hedges' g = 1.46, large effect). Normalized scores during *Smartbell* sessions remained consistent across age groups, with averages clustered around 60 regardless of participant age. In contrast, dumbbell sessions saw greater fluctuations in scores, even seeing a slight drop from

40.8 in the 50-55 years group to 36.7 in the 71-76 years group. These findings suggest that *Smartbell* effectively accommodates a wide age range, maintaining performance among all users.

5 Discussion

The results of this crossover study demonstrate that an AI-guided, chip-integrated, and gamified dumbbell system can substantially enhance movement quality, user engagement, and self-awareness of exercise performance compared to traditional dumbbells, specifically for beginning individuals and those with LLMI. *Smartbell* yielded a 5.7× increase in Perfect scores, a 99% reduction in Fail scores, and substantial improvements in user engagement and willingness to continue, while maintaining accessibility for a broad range of users. Smartbell not only enhanced performance quality but also improved user perception and receptiveness to strength training exercises. These findings bear clinical significance in the context of an aging global population, the progressive strength decline in older adults, and the established benefits of strength training for individuals with LLMI (Fragala et al., 2019; Tweedy et al., 2017; Van der Scheer et al., 2017).

AI-driven home rehabilitation technology has demonstrated feasibility, improving patient health through real-time feedback (Abedi et al., 2024; Xie et al., 2025). Additionally, gamification has shown increased adherence (Mazeas et al., 2022) and strength gains in short-term resistance training through wearable sensors (Au et al., 2025), aligning with our findings of increased engagement and willingness to continue.

However, to our knowledge, no existing smart fitness system has been designed specifically for this population. Available devices either prioritize entertainment without calibrated, evidence-based exercise progression or opt for immersive training while neglecting accessibility needs. Additionally, many existing devices lack standardization before training (De Beukelaar & Mantini, 2023). *Smartbell* combines all aspects of entertainment, guided feedback, and personal calibration, demonstrating the effectiveness of this hybrid model. Current studies with resistance training tend to focus on traditional approaches, which often lack consideration of a user's personal interest to continue training in the long term.

Several factors make this paper's findings particularly robust:

1. **Multi-faceted outcome measures.**

The study combined objective performance metrics with subjective self-reports. This dual assessment provides a richer understanding of device impact, addressing and comparing the perception and actual performance with the devices.

2. **Rigorous experimental design.**

By randomizing device order during our testing phase, we effectively reduced bias from learning effects or baseline fitness differences. This allows each participant to serve as their own control set, increasing our statistical significance despite the modest sample size.

3. **Effective statistical report.**

We utilized creative and simple graphs to illustrate the effects of *Smartbell* in straightforward and impactful ways. All results were presented with *p*-values, effect sizes (Hedges' *g*), and 95% confidence intervals. These practices help indicate the magnitude of our study and allow for better comparison with related or future works.

4. **Real-world relevance.**

Unlike many lab-based prototypes, *Smartbell* has been proven to be effective in real world scenarios. Its lightweight and accessible design makes it adaptive to all environments, demonstrating its value beyond hypotheticals.

5. **Evidence-based design principles.**

The implementation of gamified elements to increase adherence and enjoyment, the integration of music and rhythm to enhance pacing, and the design of biologically beneficial exercise movements all reflect established exercise science findings (Karageorghis & Priest, 2012a, 2012b; Kari et al., 2016; Ozdamli & Milrich, 2023). *Smartbell*'s features build upon prior research and demonstrate its effectiveness in real-world scenarios.

Collectively, these methodological strengths increase confidence that the observed benefits are a result of *Smartbell'*s *core* design rather than incidental novelty events.

Nevertheless, several limitations must be addressed for our study. The sample size was small and lacked demographic diversity. Trials with individuals from more diverse age groups and varying LLMI conditions are necessary to confirm generalizability(Lorke & Stefanou, 2025). Testing occurred in controlled environments where the novelty of the device and the researcher's presence could've influenced responses and perception. Additionally, all sessions were completed within a single short-term study period. Despite these limitations, this study provides validation that such a device could be developed and used effectively. *Smartbell*'s potential aligns with insights into assistive rehabilitation technology adoption (Mitchell et al., 2023). Future studies should include larger, more diverse cohorts, longer-term home-use trials, and retention assessments to evaluate sustained engagement and functional benefits. Further developments could also enhance the device's portability, reliability, and general appeal to participants.

If validated in broader trials, *Smartbell* could represent a low-cost, scalable alternative to traditional strength training and rehabilitation tools. It can deliver guided, engaging, and personalized exercise for individuals with LLMI in settings where access to trainers or rehabilitation professionals might be limited. Such an approach has been shown to promote physical activity and adherence to training among older adults using at-home technology-based programs, with adherence rates averaging around 82% (Ashe et al., 2024). Moreover, digital rehabilitation technology has been found to improve clinical outcomes in musculoskeletal populations (Pearce et al., 2024). These findings position *Smartbell* as a clinically viable tool with the potential to improve physical function, promote long-term adherence to strength training, and contribute to the physical well-being of the aging population and individuals with LLMI.

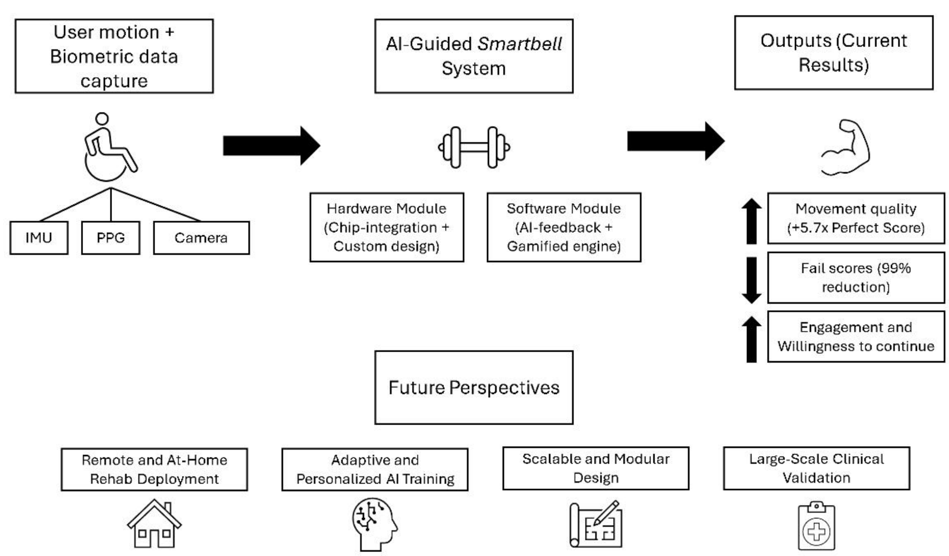

Figure 18: Schematic of Smartbell system and its future perspectives.

6 Conclusion

This study aimed to explore the possibility of creating a smart fitness device targeted at older adults and individuals with LLMI to enhance user engagement, retention, and performance outcomes of upper-body strength training. The engineering and software goal was met through the development of *Smartbell*, achieving all envisioned aspects such as AI tracking, target guidance, scoring, musical feedback, and personalized calibration. The study with participants also validated the effectiveness of such a device to increase both user performance and perception. This implies that future smart fitness technology could be developed to address the needs of individuals with LLMI by combining similar functions. To our knowledge, this is the first study to integrate AI-driven computer vision, gamification elements, and multi-modal sensor data into a unified system specifically designed for the elderly and individuals with LLMI. The study demonstrates the feasibility of such a device and validates its effectiveness through rigorous testing.

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Supplemental Information

Prior to participation, participants provided written informed consent to take part in the study. The full consent form is provided below for reference, translated into English from its original Mandarin version.

Dear Participant,

We invite you to take part in a study examining the effects of using AI-assisted upper-body strength training dumbbells compared with conventional dumbbells. Please read the following information carefully before deciding whether to participate.

I. Purpose of the Study

The purpose of this study is to evaluate and compare the safety, comfort, and effectiveness of AI-assisted dumbbells and traditional dumbbells. The findings will inform future product development and contribute to related research in rehabilitation and exercise science.

II. Data Collection

1. **Physiological Data**

   Depending on the study session, we may collect physiological data such as posture metrics, heart rate, and muscle activity using validated monitoring devices (e.g., heart rate straps, electromyography sensors). All equipment complies with safety standards and will be operated by trained personnel.

2. **Self-Reported Feedback**

   You will be asked to provide feedback on your experience through questionnaires and, if applicable, short interviews. These will cover aspects such as comfort, usability, exercise effectiveness, and any difficulties or suggestions.

III. Data Use and Confidentiality

1. **Use of Data**

   Collected data will be used solely for the purposes of this study, including performance comparisons, product evaluation, and related academic research. Data will not be used for commercial purposes or unrelated projects.

2. **Confidentiality**

   Your privacy will be protected at all times. Personally identifiable information will be stored separately from research data, and results will be analyzed anonymously. Access to your information will be restricted to the research team. Data will not be disclosed to third parties except as required by law.

IV. Voluntary Participation and Withdrawal

- Participation is voluntary. You may ask questions at any point before or during the study.
- You have the right to withdraw at any time without penalty or negative consequences. Upon withdrawal, any data you have provided will be deleted within **24 hours** of your request.

V. Risks and Responsibilities

1. **Potential Risks**
   Although all necessary precautions will be taken, the use of dumbbells may carry risks such as muscle strain or joint discomfort. You should assess your own physical condition prior to participation. If you experience pain or discomfort, you should stop exercising immediately and notify the research team.
2. **Liability**
   By participating, you acknowledge that you understand the potential risks. The research team will not be liable for injuries resulting from failure to follow instructions, disregard of discomfort signals, or pre-existing health conditions, except in cases of gross negligence or willful misconduct on our part.

VI. Agreement and Interpretation

- This consent form becomes effective once signed by you.
- Any questions or disputes regarding interpretation will be resolved in line with the objectives of the study, the wording of this agreement, and applicable regulations.

Participant Name (Print): ____________________

Date: ____________________

Signature (or Thumbprint): ____________________