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Research Article

JAMCEN: A Gamified Fitness Application Using Real-Time Pose Estimation

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Abstract. The growing demand for engaging, accessible fitness solutions has driven the integration of digital technologies with physical activity. However, many existing systems rely on complex machine learning models or specialized hardware, which may limit accessibility and interpretability. This study presents JAMCEN, a gamified fitness application that integrates real-time MediaPipe pose estimation and rule-based movement recognition to transform physical exercises into interactive gameplay. The study aimed to develop and evaluate a system that detects user movements and supports engagement through gamification without relying on computationally intensive models. The system was implemented as a mobile and web-based application integrating camera-based pose estimation, threshold-based movement interpretation, and game-driven interaction. We developed two exercise-based games, ZomJack and Splashy Fish, to represent full-body and upper-body movement activities. Evaluation included quantitative assessment of movement-detection accuracy and a user evaluation of 30 respondents focused on usability and engagement. The system achieved movement detection accuracies of 99.26% for jumping jacks and 99.31% for lateral arm raises. User evaluation yielded ratings of 5.0/5.0 for ease of use, 4.5/5.0 for responsiveness, and 4.6/5.0 each for engagement and clarity of feedback. Gameplay metrics also documented user interaction during the evaluated sessions. These findings suggest that combining real-time pose estimation, rule-based movement recognition, and gamification can support an interpretable and accessible interactive fitness experience. JAMCEN demonstrates the potential of user-centered, AI-assisted fitness applications to integrate physical exercise with digital gameplay.

Keywords: *Gamified fitness; Human-computer interaction; Computer vision; Pose estimation; Rule-based movement recognition.*

The growing prevalence of sedentary lifestyles among adolescents and young adults has become a significant public health concern, especially amid widespread digital device use and reduced physical activity (Khanani *et al*., 2025; Kolle *et al*., 2025). Mobile fitness applications offer an accessible way to support physical activity; however, their effectiveness may be limited by repetitive exercise routines, limited interactivity, and inadequate real-time feedback (Guo *et al*., 2022; Attri *et al*., 2025; Alzate *et al*., 2026). These limitations highlight the need for fitness applications that combine accessible movement monitoring with interactive experiences that make exercise more engaging.

Gamification and computer vision have emerged as complementary approaches to improving digital fitness experiences. Gamification involves incorporating game-design elements, such as points, rewards, and progression systems, into non-game contexts to encourage participation and motivation (Alzghoul, 2024; Orhan *et al*., 2025). Meanwhile, advances in computer vision have enabled pose-estimation systems to identify and track human body landmarks using camera-based input. Tools such as MediaPipe support real-time movement tracking without

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requiring specialized motion-capture equipment (Yue *et al*., 2022; Amanulla & Varma, 2026; Asmawi & Kumaresan, 2026). Researchers have explored these technologies in applications involving rehabilitation, sports training, and human–computer interaction (Rasa, 2024; García-Gil *et al*., 2025). However, the availability of pose-estimation and gamification technologies does not, by itself, show how effectively they can integrate into an interactive fitness application.

This study addresses the research gap in implementing and empirically evaluating a fitness application that connects real-time pose estimation to rule-based exercise recognition and translates recognized movements directly into gameplay. In such a system, the camera-derived body landmarks must be interpreted as exercise movements, and the system must trigger appropriate game responses and feedback for recognized movements. This integration poses a practical development challenge: the movement-recognition mechanism must be sufficiently accurate for the selected exercises, while the game interface must respond to user actions in a way that supports understandable, interactive gameplay. Although previous studies have investigated gamification and pose estimation in fitness-related contexts, this study focuses on integrating these components through an explicit, rule-based movement-recognition mechanism and evaluating both movement-detection performance and user perceptions. The contribution is therefore not the invention of pose estimation or gamification individually, but the implementation and evaluation of their integration in JAMCEN.

The effectiveness of gamified fitness applications also requires cautious interpretation. Gamification may increase immediate interest without necessarily producing sustained behavioral change, particularly when longer-term participation and intrinsic motivation have not been evaluated (García-López *et al*., 2023). In addition, pose-estimation performance may vary with environmental conditions, camera positioning, and the visibility of body landmarks (Han *et al*., 2025; Francia *et al*., 2026). These considerations underscore the importance of evaluating technical performance and user experience separately. Movement-detection accuracy indicates how reliably the system recognizes selected exercises under the tested conditions, whereas user ratings provide preliminary evidence of usability, responsiveness, engagement, and feedback clarity. Neither measure alone establishes long-term adherence to physical activity.

To address this gap, this study presents JAMCEN, a gamified fitness application that integrates real-time MediaPipe pose estimation, rule-based movement recognition, and interactive gameplay. The implemented application includes two exercise-based games: ZomJack, which incorporates jumping-jack movements, and Splashy Fish, which uses lateral arm raises. The system processes camera-derived pose landmarks, applies predefined movement-recognition rules, and maps recognized movements to game actions. Gamification features, including experience points (XP) and progression-related elements, support the interactive experience. The team implemented JAMCEN as a mobile and web-based application and evaluated it through movement-detection tests and a preliminary user evaluation.

The objectives of this study are to: (1) develop a working gamified fitness application that integrates real-time pose estimation with rule-based recognition of selected exercise movements; (2) evaluate the movement-detection accuracy of the system for jumping jacks and lateral arm raises; and (3) assess users' perceptions of the application's ease of use, responsiveness, engagement, and clarity of feedback. By addressing these objectives, the study empirically assesses a practical approach to integrating camera-based movement recognition with game-driven fitness interaction. The findings may inform the development of accessible interactive fitness applications, while recognizing that longer-term effects on physical activity and user retention require further investigation.

Methodology

This study used a developmental research design with quantitative technical testing and preliminary user evaluation to develop and examine JAMCEN. This gamified fitness application integrates real-time pose estimation, rule-based movement recognition, and interactive gameplay. The developmental component involved implementing the system architecture and its core functions, while the quantitative component assessed movement-recognition performance and user perceptions. Technical testing focused on recognizing jumping jacks in ZomJack and lateral arm raises in Splashy Fish. User evaluation assessed four criteria: ease of use, responsiveness, engagement, and feedback clarity. The study summarized quantitative results using descriptive statistics. The study did not use a mixed-methods design because it collected no qualitative interviews or open-ended responses.

Theoretical Framework

JAMCEN's design is grounded in two complementary theoretical foundations: gamification theory and interactive feedback systems in human-computer interaction. Gamification theory suggests that incorporating game elements—such as points, levels, achievements, and progress indicators—can increase user motivation by appealing to both intrinsic and extrinsic drivers. Concepts such as goal-setting, reward reinforcement, and progression are widely recognized as mechanisms that sustain engagement over time. In fitness applications, these elements turn routine physical activity into a structured, rewarding experience.

In parallel, HCI principles emphasize the importance of real-time feedback in maintaining user attention and improving task performance. Immediate system responses allow users to adjust their actions dynamically, creating a sense of interactivity and control. Pose estimation technologies, particularly those enabled by computer vision, capture and interpret human movement in real time, enabling direct interaction between the user's physical actions and the system. Integrating these two frameworks forms the conceptual basis of JAMCEN. It is assumed in this study that (1) real-time pose estimation using accessible tools such as MediaPipe is sufficiently accurate for general fitness movements, and (2) gamification elements, when properly structured, can enhance user engagement without requiring complex behavioral interventions.

System Architecture Design

The JAMCEN system is designed as a modular system that integrates motion detection, interaction logic, and user feedback into a unified workflow. The system architecture follows a sequential pipeline that captures user movements, processes them, and translates them into interactive digital outputs. As shown in Figure 1, the framework begins with the user performing physical movements in front of a mobile device camera, which serves as the primary input channel. The camera continuously captures visual data, enabling real-time analysis of user motion. A MediaPipe-based pose estimation module then processes this input to identify key body landmarks, such as joints and limb positions.

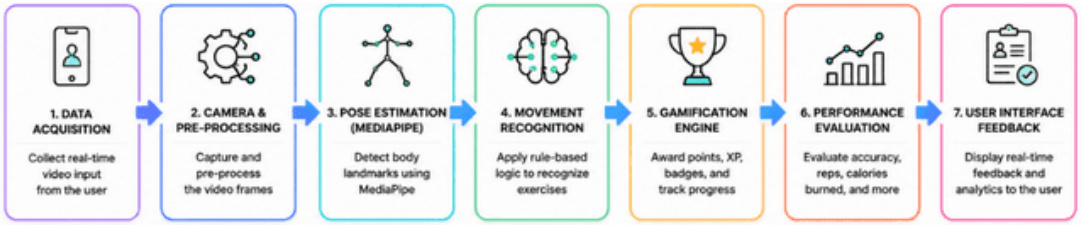


Figure 1. *Horizontal system architecture of the JAMCEN fitness system illustrating the transformation of user physical movement into interactive game-based feedback through real-time pose estimation, movement interpretation, and gamification mechanisms.*

Following this initial processing stage, a movement interpretation layer translates detected poses into predefined exercise actions (e.g., jumping jacks or arm raises). These actions are then mapped into game mechanics through a rule-based interaction engine. For example, correctly executing a movement may let the player avoid obstacles in a game scenario or earn points in a challenge environment. The system passes the processed outputs to a game engine, which governs gameplay dynamics such as scoring, progression, and difficulty. At the same time, a reward system assigns experience points (XP), levels, badges, and streaks based on user performance. Finally, the system presents results through a graphical user interface (GUI), which includes dashboards, achievement screens, and real-time visual feedback. This architecture shows how physical movement can be seamlessly converted into interactive digital outcomes, supporting the study's central claim. To summarize the system components and their roles, Table 1 maps inputs, processing methods, and outputs for each module.

Table 1. *Mapping of System Components, Inputs, Processing, and Outputs in the JAMCEN Gamified Fitness Platform*

Component	Input	Processing Method	Output
Camera Input	User movement (video frames)	Real-time image capture	Frame data
Pose Estimation	Frame data	Keypoint detection (MediaPipe)	Body landmarks
Movement Interpretation	Body landmarks	Rule-based thresholds	Recognized actions
Game Engine	Recognized actions	Event mapping	Game responses
Reward System	Game outcomes	Scoring logic	XP, badges, levels
User Interface	System outputs	Visualization	Dashboard & feedback

As shown in Table 1, the JAMCEN system follows a sequential transformation process in which modular components progressively interpret, process, and convert user-generated movement data into interactive outputs.

Pose Estimation and Movement Mapping

The pose estimation module utilizes computer vision techniques to detect and track human body key points from camera input. These key points form the basis for identifying specific exercise movements. In JAMCEN, movement recognition uses a rule-based mapping approach, where predefined thresholds and positional relationships between key points determine whether a movement is performed correctly. As Figure 2 illustrates, the pose estimation process identifies and maps these body joints into a structured digital skeleton, enabling the system to capture spatial relationships and movement patterns. Each detected keypoint provides positional data that can be analyzed to determine the orientation and motion of different body segments.

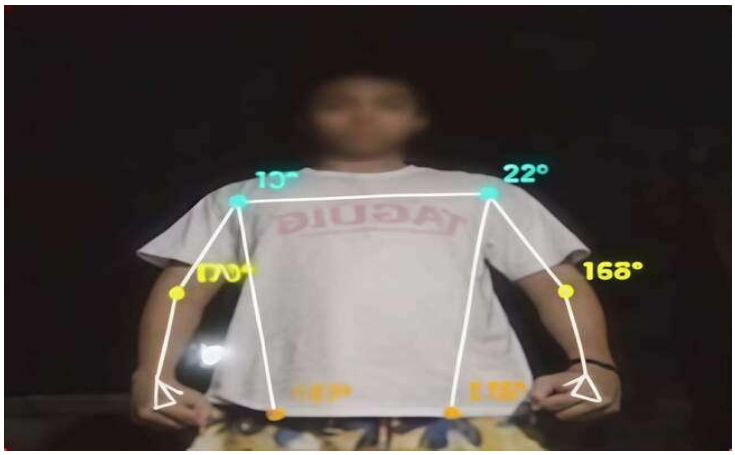


Figure 2. *Example pose estimation output showing detected human body keypoints and skeletal connections used to interpret movement within the JAMCEN gamified fitness system.*

Building on this representation, the system translates raw pose data into meaningful exercise actions using predefined rules and thresholds. Instead of relying on complex machine learning classifiers, the system uses predefined thresholds and geometric relationships between key points to evaluate movement correctness. For example, in a jumping jack exercise, the system evaluates the relative positions of the arms and legs over time. When the detected pose satisfies the defined criteria (e.g., arms raised above shoulder level and legs extended), the system registers a successful repetition. This approach prioritizes simplicity, transparency, and real-time responsiveness over complex machine learning classification models. Rule-based mapping supports the study's analytical objective by providing a clear, interpretable mechanism to translate physical actions into system inputs.

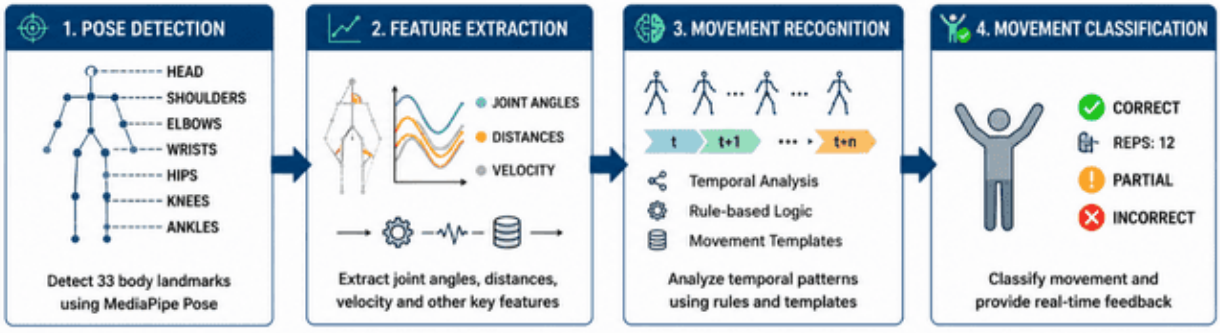


Figure 3. *Rule-based movement interpretation process illustrating the extraction of pose features (e.g., joint angles and distances), application of threshold-based conditions, and classification of physical movements into predefined exercise actions.*

As shown in Figure 3, the movement interpretation process begins by extracting relevant features from pose key points, such as joint angles and distances between body segments. The system then evaluates these features using threshold-based conditions, where specific criteria must be met for a movement to be considered valid. For example, the system can compare arm angles and leg distance against predefined thresholds to determine whether a jumping jack was performed correctly.

Once these conditions are satisfied, the system classifies the movement into a corresponding exercise category, such as jumping jack or arm raise. This classification lets the system translate physical actions into digital inputs that drive gameplay and reward mechanisms. A rule-based approach offers several methodological advantages. It ensures transparency in how movements are evaluated, reduces computational complexity, and allows for real-time feedback without requiring large training datasets. By directly linking pose-estimation outputs to interpretable decision rules, the system creates a clear, efficient pipeline for converting human motion into interactive system responses.

Gamification and Interaction Design

JAMCEN's gamification layer enhances user engagement by turning physical exercise into an interactive, rewarding experience. Rather than treating fitness activities as repetitive tasks, the system uses structured reward mechanisms to encourage sustained participation and reinforce behavior. As Figure 4 illustrates, the gamification framework operates as a continuous feedback loop in which user actions trigger reward-based responses that reinforce motivation and engagement. When a user performs a physical movement, the system translates this action into measurable outputs such as experience points (XP). These points contribute to level progression, letting users see advancement over time. As users reach specific milestones, the system unlocks achievements and badges, providing visual recognition of progress and accomplishment.



Figure 4. *Gamification feedback loop illustrating how user actions translate into experience points, level progression, achievement unlocking, and sustained motivation within the JAMCEN platform.*

Unlocking achievements and progression indicators increases user motivation, which in turn encourages continued interaction with the system. This cyclical process creates a reinforcing loop in which engagement leads to rewards, and rewards, in turn, promote engagement. This mechanism aligns with established principles in gamification theory, where immediate feedback and visible progress drive user adherence. While the feedback loop describes the conceptual mechanism of engagement, the user interface design implements it in practice. The gamification elements are embedded in an interactive system that lets users select workouts, track progress, and receive real-time feedback. To illustrate the application's structure, Figure 5 presents a wireframe of the JAMCEN user interface. The wireframe format emphasizes layout, functionality, and interaction flow without color, styling, or aesthetic elements, allowing evaluation of usability and logical organization.



Figure 5. *Wireframe representations of the JAMCEN user interface illustrating key screens, including workout selection, progress dashboard, achievements, and game interaction.*

As shown in Figure 5, the interface is composed of multiple interconnected screens that support different aspects of user interaction. The workout selection screen lets users choose from various exercises or mini-games, while the dashboard summarizes performance metrics such as XP, workout frequency, and activity trends. The achievements screen highlights badges and milestones, reinforcing motivation through visible recognition of accomplishments. In addition, the game interaction screen shows how physical movement integrates into gameplay, with real-time camera input as the primary interaction mechanism.

In this study, wireframe representations serve a methodological purpose by clearly presenting the system's functional structure while abstracting away implementation-specific design details. This approach aligns with established practices in system design and human-computer interaction research, where wireframes communicate interface logic and user flow during early-stage development. The methodological assumption underlying this design is that combining a structured gamification framework with an intuitive interface creates a self-reinforcing system that sustains user participation. By linking physical effort to immediate rewards, visible progression, and clear interaction pathways, the framework supports the central claim that gamified, pose-based interaction can enhance engagement in digital fitness applications.

User Evaluation and Testing Procedure

Participants were recruited through convenience sampling. The reported user-evaluation analysis included 30 adults aged 18–34 years. Participants were eligible if they were at least 18 years old, provided informed consent, and participated in the JAMCEN testing and evaluation procedure. We excluded individuals younger than 18 years from the reported analysis. Initially, 33 individuals participated in the evaluation. We excluded data from three participants younger than 18 years because formal institutional ethics clearance had not been obtained for their participation. Accordingly, this study reports user-evaluation results based on the 30 adult participants.

We conducted testing using a Motorola Moto G Power (2023) smartphone positioned approximately 1.5 m above the ground. The reported environmental conditions were room temperature (23–25 °C) and relative humidity (45–55%). Participants interacted with the application by performing the exercises supported by ZomJack and Splashy Fish. A typical user session lasted approximately 20 minutes. During the session, the application processed camera input, evaluated detected body landmarks using predefined movement-recognition rules, and generated corresponding game interactions and feedback. After interacting with the application, participants completed a structured questionnaire assessing ease of use, responsiveness, engagement, and feedback clarity. Participants responded using a five-point rating scale. The technical movement-recognition assessment and questionnaire-based user evaluation were analyzed separately because they measured different aspects of the system.

Research Instrument

Researchers used a researcher-developed, four-item questionnaire to assess participants' perceptions of JAMCEN. Each item addressed one evaluation criterion: ease of use, responsiveness, engagement, or clarity of feedback. Participants responded on a five-point scale, with 1 representing very poor and 5 representing excellent. The questionnaire was designed to gather brief, criterion-specific feedback after participants interacted with the application. Each criterion was represented by a single item. The instrument was not subjected to a separate formal validation study; therefore, its results are interpreted as preliminary descriptive user feedback rather than measurements obtained using a formally validated psychometric instrument. We did not calculate Cronbach's alpha because each evaluation criterion was measured with only one item, making internal-consistency analysis at the criterion level inappropriate.

Technical Testing of Movement Recognition

We conducted technical testing separately for jumping jacks and lateral arm raises. The application testing records contained 1,774 recorded jumping-jack attempts and 1,780 recorded lateral arms raise attempts. These totals were used as the denominators for calculating movement-recognition accuracy. We determined the number of correctly recognized attempts by comparing the application's recorded recognition outcomes with the manual verification records used as the reference. Recognition accuracy was calculated as the number of correctly recognized attempts divided by the total number of recorded attempts, multiplied by 100, as shown in equation 1.

$$\%Recognition\ Accuracy(\%) = \frac{Correctly\ Recognized\ Attempts}{Total\ Recorded\ Attempts} x\ 100 \quad (1)$$

For jumping jacks, 1,763 of the 1,774 recorded attempts were correctly recognized, corresponding to an accuracy of 99.38%. For lateral arm raises, 1,767 of the 1,780 recorded attempts were correctly recognized, corresponding to an accuracy of 99.27%. These results describe movement-recognition performance under the study conditions. They do not establish equivalent performance across all users, camera positions, lighting conditions, or exercise variations.

Data Analysis

We analyzed quantitative data using descriptive statistics. We calculated movement-recognition accuracy separately for jumping jacks and lateral arm raises using the number of correctly recognized attempts and the total attempts for each exercise. We summarized questionnaire responses by calculating the mean rating for each of the four evaluation criteria. We obtained an overall descriptive mean by averaging the four criterion-level mean scores, giving each criterion equal weight. The questionnaire used a five-point response scale, with higher ratings indicating more favorable evaluations. The analysis was descriptive and summarized observed technical performance and reported user perceptions. We did not conduct qualitative thematic analysis or inferential statistical tests. Accordingly, the results do not support claims of statistical significance or causal relationships between gamification and user engagement.

Analytical Evaluation Approach

The evaluation focused on JAMCEN's functional operation, its movement-recognition performance, and participants' perceptions of its interaction features. The functional assessment examined whether the system translated detected movements into the intended game actions and whether the application provided the designed feedback and performance indicators. We assessed technical performance using movement-recognition accuracy for jumping jacks and lateral arm raises. We assessed user perceptions using the four-item questionnaire described above. These evaluations provided complementary information about the system's technical operation and preliminary user experience. No comparative evaluation against another fitness application was conducted as part of the analysis reported here.

Derivation of Conclusions

Conclusions were derived from the JAMCEN prototype implementation, observed movement-recognition accuracy, and the descriptive results of the user evaluation. We interpreted technical findings in relation to the two exercises tested, while using questionnaire results to characterize participants' reported perceptions of ease of use, responsiveness, engagement, and feedback clarity. The findings provide a preliminary evaluation of JAMCEN under the specified testing conditions. They do not establish that gamification independently causes increased engagement, that the application improves long-term exercise adherence, or that the observed technical

performance generalizes to all users and environments.

Ethics Statement

This study involved voluntary participation in preliminary testing and user evaluation of the JAMCEN application. We obtained written informed consent from the 30 adult participants whose data were included in the reported analysis. Participants were informed of the evaluation's purpose and procedures, and their responses were anonymized and analyzed in aggregate. Initially, 33 individuals participated in the evaluation. We excluded data from the three participants younger than 18 years because we had not obtained formal institutional ethics clearance for their participation. The study did not receive formal approval or clearance from an institutional research ethics committee, and no formal exemption determination was obtained. This limitation is acknowledged. JAMCEN uses camera input for pose estimation and movement recognition and was not designed to perform facial recognition or biometric identification. The manuscript includes photographs to document the testing procedure, with facial features blurred where applicable to protect participants' identities. The study involved application testing, not medical diagnosis, treatment, or clinical assessment.

Results and Discussion

Prototype Demonstration and System Functionality

The JAMCEN prototype demonstrates real-time pose estimation, rule-based movement recognition, and gamified interaction within a unified application. The system translates selected physical movements into game actions, allowing users to interact with digital environments through body movements rather than conventional input devices. To illustrate how these components operate together, Figure 6 presents representative gameplay interfaces for the two implemented game modules, ZomJack and Splashy Fish.



Figure 6. *Gameplay interfaces of the JAMCEN prototype featuring "ZomJack" and "Splashy Fish", where real-time pose detection is used to control in-game actions through physical movements.*

As shown in Figure 6, ZomJack maps jumping-jack movements to discrete gameplay actions, allowing users to interact with in-game elements through detected physical movements. In contrast, Splashy Fish uses lateral arm raises to control vertical movement in a side-scrolling game. These implementations demonstrate how different exercise movements can serve as input mechanisms for interactive gameplay within a common system

architecture. Specifically, they illustrate applying rule-based movement recognition to both full-body and upper-body movements. The two game modules show how physical movement interacts with game mechanics, while the underlying processing workflow remains consistent. The pose-estimation component processes camera input to identify body landmarks, which are then evaluated using predefined movement-recognition rules. When the required conditions are met, the system maps the recognition output to the corresponding game action. This workflow connects the system architecture described in the Methodology with the gameplay interactions illustrated in Figure 6. Beyond the gameplay interfaces, it is also important to consider how JAMCEN may be used during physical exercise. Figure 7 conceptually illustrates the system in a real-world exercise setting, showing a user performing physical movements while pose-estimation information and gameplay are displayed. The illustration contextualizes the relationship between physical activity, camera-based movement analysis, and interactive feedback within the intended application environment.



Figure 7. *Conceptual real-world application of the JAMCEN system showing simultaneous gameplay interaction (Splashy Fish) and pose estimation-based movement analysis during physical exercise.*

Figure 7 depicts pose-estimation outputs, including body landmarks and joint positions, alongside the game interface. These outputs provide positional information that the movement-recognition component can use to evaluate whether detected movements satisfy predefined exercise criteria. The illustration therefore highlights the intended dual role of camera-based pose estimation within JAMCEN: supplying movement information for game control and supporting the interpretation of exercise-related body positions. However, the illustration is intended to demonstrate the system concept and interaction workflow; it does not independently establish the accuracy of biomechanical measurements or the reliability of movement recognition under all usage conditions.

The transition from the prototype interface to a real-world exercise scenario also highlights practical factors that may influence system performance. Lighting conditions, camera placement, background complexity, and variations in users' body positions and movement execution may affect pose estimation and movement recognition. In addition, presenting gameplay and movement-analysis information simultaneously may require users to divide their attention between exercise performance and on-screen feedback. These factors warrant further testing rather than conclusions drawn from the illustrative figures alone.

Taken together, Figures 6 and 7 show the implemented gameplay interactions and how physical movements connect to pose estimation, rule-based recognition, and game responses within JAMCEN. The figures show the prototype's design and functional implementation, but visual demonstrations alone cannot establish movement-recognition accuracy, consistent performance across environments, improved physical fitness, or sustained user

engagement. These outcomes require separate empirical assessment. Accordingly, the next stage of evaluation examines the system's observed movement-recognition performance for the two implemented exercises. This quantitative assessment complements the functional demonstration by examining how frequently the system correctly recognizes recorded jumping-jack and lateral arm raise attempts under the study's testing conditions.

Movement Detection Performance

To complement the qualitative and conceptual demonstrations of system functionality, we conducted a quantitative evaluation of movement detection performance. The system's accuracy in recognizing user movements was assessed across multiple trials for the implemented game-based exercises. The results of this evaluation are summarized in Table 2.

Table 2. *Movement Detection Accuracy of the JAMCEN System*

Variables	Jumping Jack (ZomJack)	Lateral Arms Raise (Splashy Fish)
Total Attempts	1,774	1,780
Correctly Detected	1,763	1,767
Incorrectly Detected	11	13
Accuracy (%)	99.38	99.27

As shown in Table 2, the JAMCEN system correctly detected 1,763 of 1,774 recorded jumping-jack attempts, corresponding to a recognition accuracy of 99.38%. For lateral arm raises, the system correctly detected 1,767 of 1,780 recorded attempts, yielding an accuracy of 99.27%. The remaining attempts were recorded as incorrectly detected: 11 for jumping jacks and 13 for lateral arm raises. These results indicate that the implemented rule-based recognition process achieved high observed accuracy for both exercises under the conditions in which the system was tested. The difference between the two accuracy values is small, with jumping jacks producing a slightly higher observed accuracy than lateral arm raises. However, the available results do not establish why this difference occurred. Although the exercises involve different movement patterns, attributing the difference to spatial variability, movement complexity, or other specific factors would require additional evidence. The results are therefore best interpreted as descriptive measures of recognition performance for the two tested exercises rather than evidence that one movement type is inherently easier for the system to recognize.

The results show that predefined thresholds and positional relationships between body landmarks can recognize the selected movements within the JAMCEN prototype. Because the recognition process follows explicit rules, its decision logic is interpretable and can be examined in relation to the specified movement criteria. Nevertheless, the present study did not directly compare the rule-based approach with a machine-learning-based movement classifier. Consequently, the findings do not establish that rule-based recognition is more accurate, more efficient, or an effective alternative to machine-learning methods in general. Such a conclusion would require a controlled comparison using the same exercise data, reference labels, evaluation procedures, and testing conditions.

It is also important to distinguish recognition accuracy from broader system performance. The accuracy values reported in Table 2 describe the proportion of recorded attempts classified correctly; they do not, by themselves, establish processing speed, responsiveness, robustness across different environments, or generalizability to other exercises and user populations. Similarly, high recognition accuracy does not directly demonstrate that the gamification features increase motivation or produce sustained engagement.

Taken together, the results provide preliminary quantitative evidence that JAMCEN can recognize jumping-jack and lateral arm raise movements with high observed accuracy in the evaluated setting. These findings support the technical feasibility of integrating rule-based movement recognition into the two game modules. Further testing across a broader range of users, movement styles, camera configurations, and environmental conditions would be necessary to determine how consistently this performance can be maintained. A direct comparison with machine-learning-based methods would also help establish the relative strengths and limitations of the rule-based approach. The next subsection examines participants' ratings of the user interface and interaction experience, providing a complementary perspective on the system beyond technical movement-recognition performance.

User Interface and Interaction Design Evaluation

In addition to the gameplay interactions presented in Figure 6, JAMCEN provides a graphical user interface for accessing exercise-based games and viewing activity-related information. Figure 8 presents representative prototype screens, including the home dashboard, workout selection interface, profile summary, and achievements module. These interfaces show how the application organizes game access, performance information, and progress indicators in a unified interface.



Figure 8. *User interface screens of the JAMCEN prototype showing (top) home dashboard with daily quests and workout selection, and (bottom) profile and achievements interfaces displaying XP, activity metrics, and badge progression.*

The home dashboard includes daily quests, workout options, and access to exercise-based games such as ZomJack and Splashy Fish. It also displays indicators such as completed workouts, streak counts, and earned badges. The profile interface provides a consolidated view of user progress, including experience points (XP), level status, and cumulative activity metrics. Meanwhile, the achievements module displays unlocked badges and progress toward specified milestones. Together, these features demonstrate how the application implements game-related rewards and progress feedback within its interface. Although these features support user interaction and make progress visible, their presence alone does not show that they increase motivation or sustain participation over time. To examine how participants perceived the interface and interaction experience, we conducted a preliminary user evaluation. Table 3 summarizes ratings for the four evaluation criteria—ease of use, responsiveness, engagement, and clarity of feedback.

Table 3. *User Evaluation Ratings of the JAMCEN System (n=30)*

Criterion	Rating (1–5), mean ± SD
Ease of use	5.00 ± 0.00
Responsiveness	4.50 ± 0.32
Engagement	4.60 ± 0.10
Clarity of feedback	4.60 ± 0.08

Note: Ratings were based on a five-point scale, where 1 = very poor and 5 = excellent. SD = standard deviation.

As shown in Table 3, ease of use received the highest rating (5.0 out of 5), followed by engagement and clarity of feedback, both rated 4.6. Responsiveness received a rating of 4.5. These results indicate that respondents evaluated the application favorably across the four assessed criteria. The ease-of-use rating reflects participants' positive

assessment of interacting with the prototype. In contrast, the engagement and clarity-of-feedback ratings reflect their perceptions of the game-based experience and the information the system provides. Responsiveness received the lowest rating among the four criteria, although its mean score remained favorable on the five-point scale. These findings provide an initial indication of how users perceived the application's interface and interaction features during testing. However, each criterion was measured using a single questionnaire item, and the evaluation was preliminary. Therefore, interpret the results as descriptive user feedback rather than a comprehensive assessment of usability or engagement. In particular, the engagement rating reflects participants' perceptions after interacting with JAMCEN; it does not establish sustained engagement, long-term retention, or continued exercise participation. The study did not include longitudinal measurements to determine whether participants continued using the application over time.

The interface also illustrates how user actions connect to the application's feedback mechanisms. Interactions within the game modules generate game-related outputs, such as scores and XP, while the dashboard and achievements module display progress-related information. This arrangement demonstrates how the gamification features described in the Methodology are implemented in the working prototype. Nevertheless, this evaluation does not establish that these features independently increased motivation or engagement because an experimental comparison did not isolate the effects of individual design elements. Respondents rated responsiveness slightly lower than the other three criteria. Although this result identifies responsiveness as an area that may warrant further examination, the questionnaire data do not identify the cause of the difference. Dedicated performance measurements, rather than inferences from the rating alone, would need to investigate potential factors such as processing latency or environmental conditions.

Taken together, the interface demonstrations and questionnaire results show that JAMCEN incorporates structured navigation, visible progress indicators, game-related rewards, and immediate interaction feedback, and that participants rated the assessed aspects of the experience favorably during the preliminary evaluation. These findings support the feasibility of the interface design but do not establish that the system improves long-term engagement or exercise adherence. Future evaluation could investigate these outcomes through repeated sessions, longitudinal usage records, and more comprehensive usability measures.

In addition to participants' subjective ratings, JAMCEN records gameplay-related metrics, including scores, repetitions, session duration, and XP. Whereas Table 3 summarizes participants' perceptions of the application, these metrics describe the activity recorded during gameplay. The following subsection examines these measures for ZomJack and Splashy Fish to complement the description of interaction with the two game modules. However, gameplay activity recorded during the evaluation should not, by itself, be interpreted as evidence of sustained engagement or continued use over time.

Gamification Features and Gameplay Activity

The JAMCEN prototype incorporates gamification features, including experience points (XP), levels, achievements, and progress tracking, into the gameplay experience. These features provide reward-based feedback in response to user interactions with the two implemented games, ZomJack and Splashy Fish. To describe gameplay activity during the evaluation, we examined recorded metrics—including scores, repetitions, session duration, and XP gained—for both games. Table 4 summarizes the results.

Table 4. *Average Gameplay Metrics for ZomJack and Splashy Fish*

Variables	ZomJack, mean ± SD*	Splashy Fish, mean ± SD*
Score	420 ± 5.09	350 ± 6.36
Repetitions	25 ± 3.22	20 ± 1.23
Session duration (min)	6.50 ± 0.14	5.20 ± 0.07
XP gained	180 ± 7.01	150 ± 2.19

Note. Values are presented as mean ± standard deviation (SD), calculated from 30 recorded gameplay sessions for each game.

As shown in Table 4, ZomJack outperformed Splashy Fish, with an average score of 420, average repetitions of 25, and average XP gained of 180. In contrast, Splashy Fish recorded an average score of 350, average repetitions of 20, and average XP gained of 150. Additionally, ZomJack had a slightly longer average session duration (6.5 minutes) than Splashy Fish (5.2 minutes). These differences may reflect the movements involved in each game. ZomJack requires full-body coordination through jumping jack exercises, which may produce more pronounced, easier-to-detect movements, contributing to higher performance metrics. In contrast, Splashy Fish relies on upper-

body movements, which may be less dynamic and more susceptible to detection variability, potentially affecting user performance.

Despite these differences, both games demonstrate consistent user interaction and sustained engagement, as reflected in the relatively high number of repetitions and session durations. The accumulation of XP across sessions further indicates that users are actively progressing within the system, reinforcing the effectiveness of the gamification framework. Overall, these findings support gamification's role in enhancing participation and sustaining engagement, validating the design assumption that integrating reward-based mechanisms with real-time interaction can create a motivating feedback loop within the JAMCEN system. These results show that integrating physical activity with reward-based game mechanics can sustain user engagement while maintaining functional interaction with the system. However, these results are based on a limited evaluation setting, and further validation with a larger, more diverse user population is recommended. Taken together, the qualitative demonstrations, quantitative performance results, and user interaction evaluations collectively support the feasibility and effectiveness of the JAMCEN system as a gamified, pose-based fitness system.

Real-World Testing and System Deployment

To examine the JAMCEN system's practical operation beyond prototype demonstrations, we conducted testing in indoor and outdoor settings. These settings introduced variation in environmental and operating conditions, including lighting, background complexity, camera positioning, and user movement. Figure 9 presents representative examples of system use during testing.

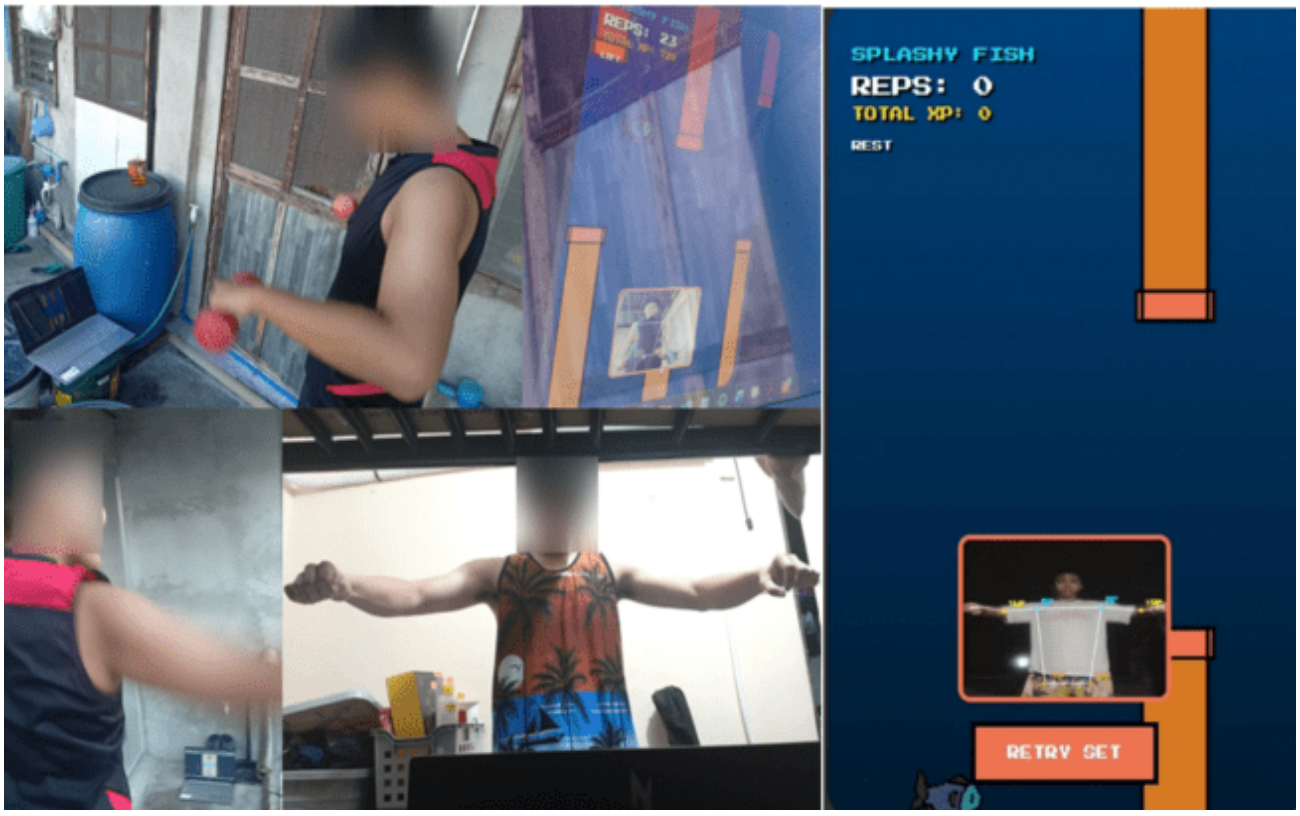


Figure 9. *Real-world testing and deployment of the JAMCEN system in indoor and outdoor environments, demonstrating practical usage scenarios using a web-based interface and standard camera devices.*

The system operated using standard laptop cameras, allowing users to perform jumping jacks and arm raises while interacting with the web-based interface without specialized camera hardware. These demonstrations provide preliminary evidence that JAMCEN can operate in the tested settings and support its design objective of using readily available equipment. However, these observations should not be interpreted as evidence of consistent performance across all indoor and outdoor environments. During testing, variations in lighting,

background conditions, and camera positioning affected pose-estimation stability and movement detection. These observations identify environmental conditions that may influence system operation.

Nevertheless, because the study did not systematically quantify performance across environmental conditions, the magnitude of these effects and their influence on recognition accuracy cannot be established from the available results. Similarly, the testing does not establish the system's robustness across different users, camera configurations, or movement patterns beyond those evaluated. Overall, the real-world testing demonstrates the JAMCEN prototype's practical operation in the settings examined while highlighting environmental factors that warrant further investigation. Future work could include systematic testing under controlled variations in lighting, camera distance, and background complexity, as well as evaluation across a broader range of users and movement patterns. Researchers could also investigate adaptive thresholding and environmental calibration as potential approaches to improving performance. Although JAMCEN may have potential applications in home-based fitness and educational settings, further evaluation would be needed to establish its reliability and suitability for these contexts.

System Limitations and Practical Constraints

Although the results provide preliminary evidence of the JAMCEN framework's feasibility, several limitations should be considered when interpreting the findings. One potential constraint is the pose-estimation module's dependence on environmental and operating conditions. Variations in lighting, background complexity, and camera positioning may affect body-landmark detection and, consequently, movement recognition. Although the system was tested indoors and outdoors, the study did not systematically quantify how individual environmental factors affect recognition accuracy. Therefore, the extent to which these factors influence system performance remains to be established.

Another limitation concerns the rule-based movement-recognition approach. Predefined thresholds and geometric relationships between body landmarks make the recognition logic explicit and interpretable. However, these rules may not accommodate all variations in body proportions, movement styles, and execution speeds. We evaluated the current implementation using two exercises—jumping jacks and lateral arm raises—and have not established its performance on other movements, particularly more complex or multi-phase exercises. Because the study did not directly compare the rule-based approach with a machine-learning-based classifier, the present results cannot determine the relative accuracy, adaptability, or computational efficiency of these approaches.

Additional practical considerations relate to real-time interaction and interface design. Although JAMCEN integrates movement recognition with gameplay feedback, the study did not independently quantify processing latency across different device specifications or computational loads. Likewise, the study did not directly measure users' cognitive load while performing exercises and interacting with the interface. These aspects therefore represent areas for further investigation rather than established limitations demonstrated by the current evaluation.

Future work could address these limitations through systematic testing under varied lighting and camera-positioning conditions, evaluation across a broader range of users and exercises, and direct comparison of rule-based and machine-learning-based recognition methods using consistent datasets and evaluation procedures. Measuring processing latency and assessing the usability of simultaneous physical activity and on-screen feedback would also provide a more comprehensive understanding of system performance. Overall, the current findings support the feasibility of integrating pose estimation, rule-based movement recognition, and gamified interaction in a fitness prototype. Further validation is needed to establish the system's robustness, generalizability, and suitability for broader real-world use.

Implications of the JAMCEN Framework

This study demonstrates the technical feasibility of integrating pose estimation, rule-based movement recognition, and gamification into a web-based fitness prototype. By translating detected body movements into interactive game actions, JAMCEN illustrates how camera-based pose estimation can support real-time physical interaction without requiring specialized camera hardware. The implementation provides a foundation for exploring low-cost, camera-based fitness applications, particularly in home-based and educational settings where readily available equipment may be preferable.

Integrating experience points, achievements, and performance tracking provides structured feedback during gameplay. The user evaluation results and recorded gameplay metrics describe participants' perceptions of the interface and their interactions with the implemented game modules. However, these findings do not show that gamification increases motivation, improves exercise participation compared with conventional approaches, or sustains engagement over time. Further evaluation, including comparisons with non-gamified versions and longitudinal assessments, is needed to determine how these features affect user motivation and sustained participation.

More broadly, JAMCEN illustrates a potential application of computer vision in interactive systems that translate body movements into digital actions and provide immediate feedback. The explicit movement-recognition rules also make the implemented decision logic interpretable and amenable to inspection and modification. Nevertheless, the study did not compare this approach directly with machine-learning-based classifiers; therefore, its relative accuracy, computational efficiency, and adaptability remain undetermined. Future work could investigate these characteristics through controlled comparisons, broader exercise coverage, and testing across different users and operating conditions.

Overall, JAMCEN contributes a working prototype that integrates pose-based movement recognition with gamified interaction. The findings support the feasibility of this integration in the evaluated setting, but further research is needed to establish its generalizability, comparative performance, and potential effects on participation in physical activity and sustained engagement.

Conclusion

This study developed and evaluated JAMCEN, a gamified fitness system integrating real-time pose estimation, rule-based movement recognition, and interactive gameplay. The prototype implemented two game modules, ZomJack for jumping jacks and Splashy Fish for lateral arm raises. Under the evaluated conditions, the system achieved movement-recognition accuracies of 99.38% for jumping jacks and 99.27% for lateral arm raises. These results provide preliminary evidence that predefined movement rules can translate detected body movements into game actions.

The user evaluation indicated favorable perceptions of the system, with ratings of 5.0 for ease of use, 4.5 for responsiveness, 4.6 for engagement, and 4.6 for clarity of feedback on a five-point scale. The recorded gameplay metrics also demonstrated the implementation of score tracking, repetition counting, session-duration recording, and experience-point allocation. However, these findings describe participants' perceptions and recorded gameplay activity during the evaluation; they do not establish the long-term effectiveness of gamification in increasing motivation or sustaining participation.

From a practical perspective, JAMCEN shows that pose-based movement recognition and gamified feedback can be integrated into a fitness application using standard camera hardware. This approach may inform the development of low-cost interactive fitness applications for potential home-based and educational use. Nevertheless, the findings are limited to two exercises and the conditions evaluated. Environmental variability may affect pose estimation, while the predefined movement rules may not accommodate the full range of user movements and exercise variations. Furthermore, the study did not directly compare the system with machine-learning-based classifiers or include a longitudinal assessment of user engagement. Therefore, the relative performance of these recognition approaches and the long-term effects of the gamification features remain undetermined.

Future work should evaluate the system across a broader range of exercises, users, camera configurations, and environmental conditions. Direct comparisons between rule-based and machine-learning-based recognition methods, objective measurements of processing latency, and longitudinal studies of participation would provide further evidence of system performance and practical utility. Overall, this study establishes a functional prototype and provides preliminary evidence supporting the technical feasibility of combining pose estimation, rule-based movement recognition, and gamified interaction in an interactive fitness application.

Contributions of Authors

James C. Alcarde: Conceptualization, methodology, software development, investigation, data analysis, visualization, and writing – original draft preparation.
David J. Alcarde Jr.: Investigation, software testing, data collection, validation, and writing – review and editing.
Jancen Cesar D. Tabag: Software testing, investigation, data collection, validation, and visualization.
All authors reviewed and approved the final version of the manuscript.

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Conflict of Interests

The authors declare no conflict of interest.

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