Trigger Screen Restriction Framework, iOS use Case Towards Building a Gamified Physical Intervention

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***Abstract*—The growing trend of inactive lifestyles caused by excessive use of mobile devices raises severe concerns about people's health and well-being. This paper illustrates the technical implementation of the Trigger Screen Restriction (TSR) framework, which integrates advanced technologies, including machine learning and gamification techniques, to address the limitations of traditional gamified physical interventions. The TSR framework encourages physical activity by leveraging the fear of missing out phenomenon, strategically restricting access to social media applications based on activity goals. The framework's components, including the Screen Time Restriction, Notification Triggers, Computer Vision Model, and Reward Engine, work together to create an engaging and personalized experience that motivates users to engage in regular physical activity. Although the TSR framework represents a potentially significant step forward in gamified physical activity interventions, it remains a theoretical model requiring further investigation and rigorous testing.**

Keywords*—*Gamification; physical activity; screen-time restriction; triggered screen restriction framework; TSR Framework; personalized interventions; gamified physical intervention

I. Introduction

The increasing prevalence of sedentary lifestyles, driven by excessive screen time and mobile device use, raises significant public health concerns. Research indicates that prolonged screen time is associated with various health issues, including hypertension, type 2 diabetes, depression, and sleep disorders [1]. Sedentary behaviors are spreading worldwide due to increased occupational sedentary behaviors, such as office work, and the increased usage of mobile phones and video game devices [2]. Most adults fail to follow the World Health Organization guidelines that recommend moderate to vigorous physical activity [3]. The lack of physical activity worsens the health risks linked to spending too much time being sedentary, emphasizing the necessity for interventions aimed at reducing sedentary behavior [4]. People tend to seek comfort and immediate gratification despite being aware of the potential long-term health implications [5].

To counter sedentary lifestyles, gamified physical interventions have emerged as promising strategies to combat sedentary habits [6]. Gamification, the application of game-design elements in non-game contexts, aims to boost motivation and engagement by tapping into the human psychological need for reward, achievement, and competition [7], [8]. Elements such as points, leaderboards, and badges have been successfully integrated into physical activity interventions, demonstrating significant potential to enhance user engagement and foster sustained physical activity [9]. Despite the advances in gamified physical intervention, traditional gamified approaches often fall short in maintaining behavioral change and overly rely on positive reinforcement, indicating the necessity for more innovative solutions [10].

The growing evidence linking screen-based sedentary behavior to adverse health outcomes further underscores the need for a novel intervention. A systematic review highlighted the significant negative association between screen time and components of metabolic syndrome among adolescents, emphasizing the urgency of developing effective interventions to mitigate these risks [11]. Additionally, research on lifestyle intervention effects on daily physical activity patterns has shown promising directions for reducing sedentary behavior and increasing moderate-to-vigorous physical activity, further validating the potential of structured interventions [12]. The findings of the studies validate the critical need for interventions that address sedentary lifestyles and encourage physical activity.

The Trigger Screen Restriction (TSR) framework emerges as a novel interdisciplinary approach that uses advanced technologies to address the limitations of traditional gamified physical intervention [10]. By leveraging the Fear of Missing Out (FOMO) phenomenon, the TSR aims to encourage physical activity through the strategic restriction of access to social media applications based on activity goals, potentially providing a more sustainable model for gamified physical interventions [13]. This novel framework, which has yet to be empirically tested, may represent a promising avenue for enhancing the efficacy of gamified interventions in promoting physical activity.

The remainder of the paper is structured as follows:

- Objective: Outlines the paper's aim, emphasizing the TSR's innovative approach to integrating different technologies to encourage physical activity.
- The TSR Framework: Explores the TSR framework's innovative approach to integrating advanced technologies, such as machine learning, computer vision, and gamification, to create an engaging and personalized experience that encourages users to participate in regular physical activity.
- Conclusion and Future Work: Summarizes the potential impact of the TSR framework on promoting physical activity and outlines directions for future research, including the need for empirical testing to evaluate the framework's effectiveness in real-world applications.

II. Objective

The primary objective is to examine the technical details of the TSR framework, a novel gamified physical intervention that integrates interdisciplinary techniques to encourage physical activity [13]. The aim is to provide an in-depth look at the TSR framework's main components, the Screen Time Restriction, Notification Triggers, Computer Vision Model, and Reward Engine. The paper will highlight the TSR's components' roles in creating a captivating and tailored user experience. Each component's technical architecture and implementation specifics will be explored, demonstrating the seamless incorporation of interdisciplinary techniques within the TSR framework.

Furthermore, the paper intends to illustrate how the various components collaborate to promote physical activity, offer near real-time feedback, and provide personalized rewards and challenges. The integration of the machine learning model in the recommendation engine within the TSR framework will also be discussed, underlining the recommendation engine component's role in enabling adaptive and personalized interventions based on user behavior and preferences.

Preliminary investigation will demonstrate the TSR framework's potential for accurate and efficient activity recognition. The investigation compares the prediction model's sliding window and static window mechanisms. The paper will also outline the future direction of research and development for the TSR framework, stressing the necessity for rigorous empirical studies to assess its effectiveness in promoting physical activity, enhancing health outcomes, and improving user experience.

By addressing these objectives, the paper will contribute to the expanding research of gamified physical activity interventions and establish a foundation for developing and implementing the TSR framework as a practical solution for promoting physical activity.

III. Literature Review

The growing trend of inactive lifestyles, driven by excessive screen time, has been strongly associated with severe health concerns, such as obesity, heart disease, and mental health problems, highlighting the need for creative interventions to encourage physical activity. Research has identified screen-based sedentary behaviors as a critical factor contributing to negative cardiovascular health outcomes, emphasizing the urgent need for action to reverse this trend [14]. Moreover, sedentary lifestyles are increasingly recognized as significant risk factors for diabetes and all-cause mortality, with the link between lengthy sedentary time and high blood pressure and low levels of good cholesterol levels stressing the importance of addressing this issue [15]. Excessive recreational screen time is also associated with significant mental health problems, like depression and anxiety, which further highlights the critical need for targeted interventions to reduce screen time and encourage more active and engaged lifestyles [16]. Together, these findings demonstrate the significant health implications of sedentary behaviors worsened by excessive screen time, emphasizing the urgent need for innovative gamified physical activity interventions.

The purposeful use of FOMO within gamification frameworks can promote physical activity by leveraging the emotions associated with screen time [13]. Through gamification, this negative reinforcement approach taps into the inherent human fear of being left out, making physical activity an attractive alternative to screen-based sedentary habits [17]. Moreover, by presenting other activities as opportunities that demand immediate action, gamified interventions might effectively use FOMO to counter passive screen time, encouraging a healthier, more active lifestyle [18]. By limiting screen time and concurrently offering engaging alternative activities, gamified frameworks can capitalize on the psychological impact of FOMO to promote healthier activities and reduce the risks linked to sedentary behaviors.

Traditional gamified physical interventions have encouraged physical activity with limited success. These interventions often rely heavily on external motivators, which can hinder long-term effectiveness [19]. While traditional gamified physical interventions can increase initial engagement, their appeal often diminishes over time as the novelty fades and motivation decreases [20].

A randomized study across three groups discovered that although all participants lost weight, those in the gamified intervention groups did not significantly outperform the control group, emphasizing the variability and often short-lived benefits of gamified interventions [20]. Moreover, while personalized goal-setting within gamified interventions initially boosts user engagement and performance, this positive trend must persist consistently, implying that initial gains in motivation may not lead to long-term behavior change [21].

Moreover, traditional gamification strategies focus heavily on positive reinforcement, often failing to maintain engagement as users' intrinsic motivation decreases [22]. The challenge lies in the superficial engagement these gamified elements promote, primarily focusing on completing tasks for points rather than fostering a genuine, lasting interest in physical activity [23], [24].

Most gamified health interventions, including well-known ones like Nike+ Running and Zombies, Run!, only incorporate essential gamification elements, which fail to fully utilize the potential of gamification elements to bring about meaningful behavior change, offering an opportunity to develop more innovative, comprehensive gamification strategies that engage users and promote lasting health benefits [25].

Personalized and adaptive interventions in gamified physical activities are increasingly seen as essential for supporting and improving user engagement. Personalized gamification interventions, which customize challenges and rewards to individual preferences and abilities, can improve motivation and performance [26]. Personalized intervention adjusts the difficulty and nature of tasks based on real-time data, ensuring that the challenges are appropriately stimulating and within the user's ability to achieve [26].

Adaptive gamification goes a step further by using machine learning models that predict and react to changes in a user's affective state—such as their emotional condition—to optimize the timing and type of gamified prompts provided [27]. By analyzing task performance data alongside physiological responses, such as facial expressions, these models adjust in real-time, improving their predictive accuracy and the personal relevance of the interventions [27].

The dynamic and personalized nature of the gamified interventions represents a significant improvement over traditional methods, which often need to be more responsive to individual user profiles. By capitalizing on advanced technology to tailor experiences to individual users, these approaches enhance initial engagement and promote physical activity, contributing to better health outcomes. Developing such adaptive interventions marks a promising direction in designing a gamified physical intervention, indicating a shift towards more personalized, responsive, and effectively engaging fitness promotion tools.

IV. The TSR Framework: A Novel Approach to Gamified Physical Interventions

The TSR framework is a novel, interdisciplinary approach that utilizes different technologies to overcome the shortcomings of conventional gamified physical interventions [10]. By integrating machine learning, computer vision, and gamification techniques, the TSR framework aims to create an engaging and personalized experience that encourages users to engage in physical activity. The framework's unique combination of screen time restriction, adaptive gamification elements, and real-time, privacy-respecting activity verification sets it apart from existing interventions [13].

The TSR framework's primary strategy lies in its strategic use of the FOMO phenomenon to motivate users toward physical activity. By restricting access to social media applications based on activity goals, the framework taps into the intrinsic human desire to stay connected and informed, making physical activity a prerequisite for accessing these platforms [13]. The TSR approach is complemented by personalized notification triggers, a computer vision model for activity detection, and an adaptive reward engine that adjusts difficulty based on individual user performance [10]. These components work together to create a comprehensive and engaging experience that promotes sustained physical activity and improves overall health outcomes. By providing a personalized and dynamic experience, the TSR framework addresses the limitations of traditional gamified approaches that often fall short in maintaining behavioral change and overly rely on positive reinforcement [10].

The following subsections will explore the technical aspects of the TSR components:

- Screen Time Restriction: Details the technical architecture and user flow of the Screen Time Restriction component, which leverages the FOMO phenomenon to encourage physical activity by restricting access to selected apps.
- Notification Triggers: Explores the Notification Triggers component, which delivers personalized, context-aware notifications to motivate users towards physical activity.
- Computer Vision Model: Discusses the Computer Vision Model's role in detecting and classifying user activities in real time while ensuring user privacy.
- Reward Engine: Describes the Reward Engine's design and its function in enhancing user engagement and motivation through personalized gamified rewards and incentives.

A. Screen Time Restriction

The Screen Time Restriction component is developed to promote and encourage users to engage in physical activity through a screen time management system on mobile devices. The Screen Time Restriction utilizes comprehensive components with specific roles within the iOS ecosystem to implement user-specific screen time policies via technical mechanisms and customizable options (see Fig. 1).

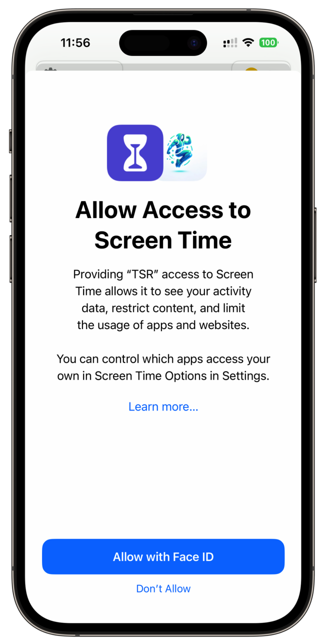

Fig. 1. Screen time restriction - user consent.

1) Technical architecture: The system architecture incorporates several key components that work together to enforce screen time restrictions based on user preferences and predictive measures using machine learning (see Fig. 2).

The architecture consists of the following key components:

- ScreenRestriction: Serves as the central controller, managing the screen restriction protocol by evaluating factors such as time of day, user activity, and established guidelines.
- SelectedAppsForRestrictionDB: Handles a database of applications marked for screen time limitations, enabling CRUD operations and confirming that only selected applications face restrictions.
- SchedulingClass: Utilizes scheduling algorithms to determine the timing of restrictions, relying on either user-set schedules or a prediction from the model to initiate.

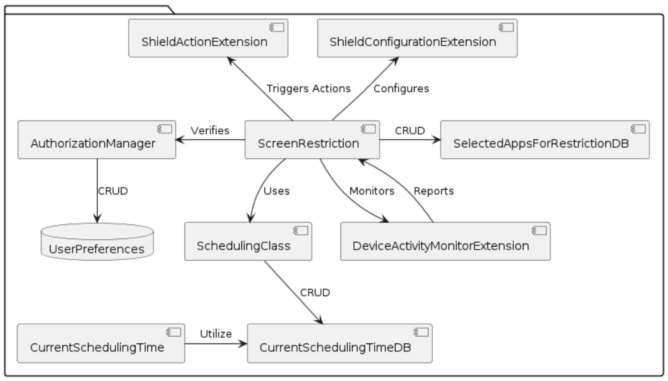

Fig. 2. Screen time restriction's system architecture.

- Current Scheduling Time DB and Current Scheduling Time: Work to store and communicate the active screen time schedules, ensuring the system's restriction logic operates based on the most current and relevant scheduling information.
- AuthorizationManager: Ensures that screen restrictions comply with user agreements and iOS app permission standards, upholding user confidence and regulatory compliance.
- DeviceActivityMonitorExtension: Extends base monitoring capabilities to include specific metrics relevant to screen time management, enabling more informed and dynamic application of screen restrictions.
- Shield Configuration Extension and Shield Action Extension: Allow for the personalization of the visual presented to users during restricted screen times, promoting and encouraging the users to engage in physical activity during restriction times.

2) User flow: To better comprehend the operation of the Screen Time Restriction component from the user perspective, refer to the following diagram (see Fig. 3):

- Authorization: The system verifies the required permissions upon app initiation. Without proper authorization, the Screen Time Restriction feature cannot be enabled.
- Setup: Once authorized, the user can enable Screen Time Restrictions and proceed to select the apps they want to restrict.
- Daily Usage: The daily usage function continuously monitors device interaction, comparing it against defined time constraints and activity levels.
- Notifications and Restrictions: Approaching the time limit without detected physical activity triggers a notification. Exceeding the limit enforces the restriction, blocking access to chosen applications.
- Physical Activity Detection: Physical activity detection automatically removes restrictions.
- Override Request: Users can request an override without physical activity, which is granted based on predefined conditions.
- Normal Use: Effective screen time management and physical activity result in unrestricted device usage.

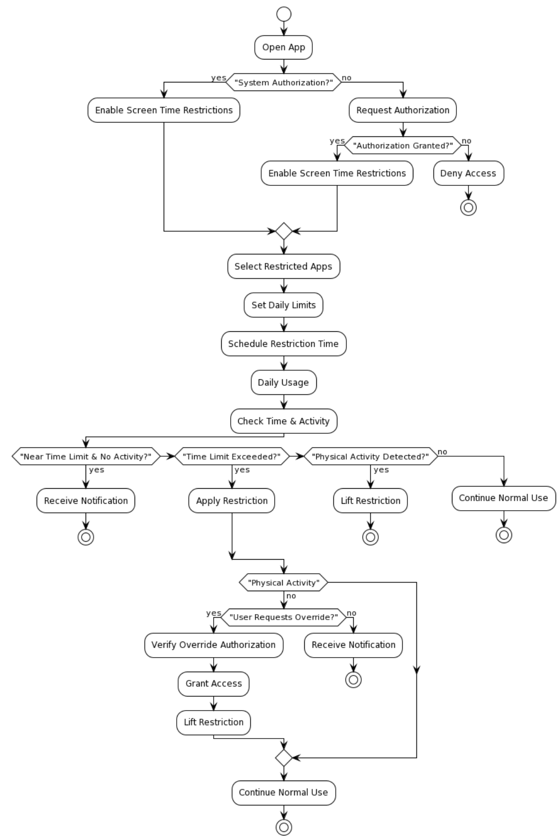

Fig. 3. Screen time restriction's user flow.

3) Machine learning integration: The Screen Time Restriction component anticipates the user's behavior and adapts accordingly. Models such as Linear regressions, Decision Trees, and Random Forests are evaluated for predicting exercise times, each with pros and cons (See Table I). Integrating the machine learning model allows the Screen Time Restriction component to adapt to the user's changing schedule [28]. For instance, if the model identifies an increasing trend in evening exercise sessions, it can automatically adjust screen restrictions to encourage and promote users to engage in physical activity during the active periods. Leveraging native iOS features and frameworks, such as CreateML for machine learning, ensures that the Screen Time Restriction component operates efficiently and securely [29]. Integrating the machine learning model in the Screen Time Restriction component prompts near-real-time data processing and contributes to a fluid user experience.

The decision to employ a Linear regression model in the context of predicting exercise times within the Screen Time Restriction component was based on several factors:

1) Simplicity: The simplicity of Linear regression is crucial for applications requiring near-real-time predictions [30].

TABLE I. COMPARISON OF MACHINE LEARNING MODELS

Model Name	Pros	Cons
Linear Regression [30]	Simple, fast	Limited with non-linearity
Boosted Trees [31]	Manages complex data	Prone to overfitting
Decision Trees [32]	Intuitive, clear	Risk of instability
Random Forests [33]	Excels in complexity	Resource-intensive

2) Speed: The speed of Linear regression in training and prediction is particularly beneficial for systems running on resource-limited devices such as smartphones or tablets [30].

The Screen Time Restriction component of the TSR framework embodies a blend of user-centric design and technical implementation. By harnessing the power of machine learning and leveraging native iOS features and frameworks, the Screen Time Restriction component actively encourages and promotes physical activity in a novel way. The dual approach of restriction and motivation sets a new standard in gamified physical activity interventions, positioning the Screen Time Restriction component as a powerful tool for pursuing an active lifestyle.

B. Notification Triggers

The Notification Triggers component is designed to provide context-aware engagement messages to foster user interaction delivered through push notifications. The primary intent of the Notification Triggers is to motivate users to engage in physical activity by nudging them when they are inactive [34]. The Notification Triggers component leverages a well-structured system crafted to deliver personalized, context-aware notifications to encourage physical activity (see Fig. 4).

Fig. 4. Notification triggers.

1) Technical architecture: The technical structure consists of distinct components that enable customized notification delivery mechanisms to encourage users towards physical activity. The notifications are crafted based on user behavior and serve the broader goals of the TSR framework (see Fig. 5).

Fig. 5. Notification trigger's class diagram.

The architecture consists of the following key components:

1) NotificationTrigger: This component manages the notification delivery by analyzing user activity data. It ensures that motivational messages reach the users effectively, fostering their engagement in physical activities.
2) OpenAppHours and OpenAppHoursDB: These components are essential in storing how users interact with their devices. They log activity times, offering vital insights that help time the notification delivery accurately. By logging periods of user inactivity, these components ensure that notifications are sent when they can have the most significant impact.
3) OpenAppHoursManager: This component bridges the stored user data and the NotificationTrigger mechanism. It handles the collection of historical user data, allowing the NotificationTrigger to tailor and time notifications that are in tune with the user's daily habits.
4) RecommenderEngine: This component employs data analysis to pinpoint optimal moments for sending out notifications. By understanding user behavior, it determines the best times to encourage user interaction, which in turn, promotes physical activity.

2) User flow: To better comprehend the operation of the Notification Triggers component from the user perspective, refer to the following diagram (see Fig. 6):

1) Authorization and Permissions:
   - The process begins with the Initialization state, where the application requests

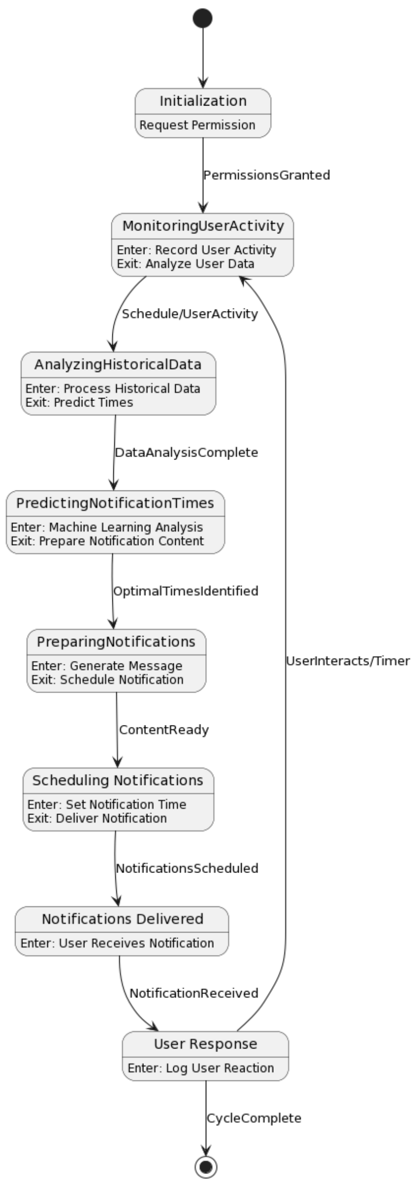

Fig. 6. User flow diagram for notification triggers.

necessary permissions from the user to send notifications.

- Upon receiving Permissions Granted, the application transitions into the Monitoring User Activity state. Here, the app starts recording user activities, ensuring the foundation for personalized notifications is set.

2) Activity Monitoring:
   - In the Monitoring User Activity state, the application logs the user's device interactions throughout the day.
   - This continuous monitoring enables gathering essential data and marking periods of activity and inactivity, which is necessary for the subsequent analytical phase.

3) Notification Timing:
   - During this phase, the collected data undergoes comprehensive analysis, identifying potential idle periods that could benefit from an intervention.
   - Upon completion, the system advances to the Predicting Notification Times state, employing a linear regression model to determine the most effective notification delivery times.

4) Notification Delivery:
   - The system then transitions into the Scheduling Notifications state, where these notifications are scheduled for delivery at the predicted optimal times.
   - Upon successful scheduling, the system enters the Notifications Delivered state, where notifications are dispatched to the user, serving as timely nudges toward physical activity.

5) User Interaction and Feedback:
   - This phase captures the user's interaction with the notification, whether they dismiss it or engage with it.
   - The feedback from user interactions, recorded during the User Response state, informs future notifications, contributing to a cycle of continuous improvement and personalization.
   - Finally, based on the user's action or after a set time, the flow loops back to Monitoring User Activity, initiating a new cycle of monitoring and engagement.

3) Recommendation engine: The Notification Triggers component integrates a linear regression model and a recommendation algorithm to provide personalized and timely messages. An evaluation of various recommendation algorithms was conducted to list their benefits and challenges (Table II):

TABLE II. COMPARISON OF RECOMMENDATION ALGORITHMS FOR NOTIFICATION TIMING

Algorithm	**Pros**	**Cons**
Collaborative Filtering [35]	Personalized recommendations	Cold start problem
Content-based Filtering [36]	Handles new items	Limited to user preferences
Hybrid Approaches [37]	Best of both worlds	Complexity, data sparsity, and Cold start problem
Matrix Factorization [38]	Large dataset handling	Data sparsity and Complexity and Cold start problem

The decision to implement a Collaborative Filtering algorithm was made after carefully considering the unique requirements of the Notification Triggers component. Several factors influenced the choice:

1) Personalization: Collaborative filtering offers a high level of personalization, which is critical for engaging users with relevant notifications based on collective user behaviors [39].
2) Adaptability: The ability of collaborative filtering to adapt to new user data and evolving interaction

patterns align with the dynamic nature of user engagement and physical activity routines [40].

Integrating Collaborative Filtering and a linear regression model into the Notification Triggers component represents a strategic approach to enhancing user engagement through timely and personalized notifications.

C. Computer Vision Model

The Computer Vision Model is designed to detect and classify user activities in real-time using the device's camera. The Computer Vision model leverages the CoreML framework to provide seamless activity recognition, enabling the TSR framework to deliver personalized interventions and promote physical activity [41].

1) Technical architecture: The Computer Vision model's architecture ensures seamless integration with the iOS ecosystem while delivering efficient activity classification. The following diagram illustrates the key components and their interactions within the Computer Vision Model (see Fig. 7).

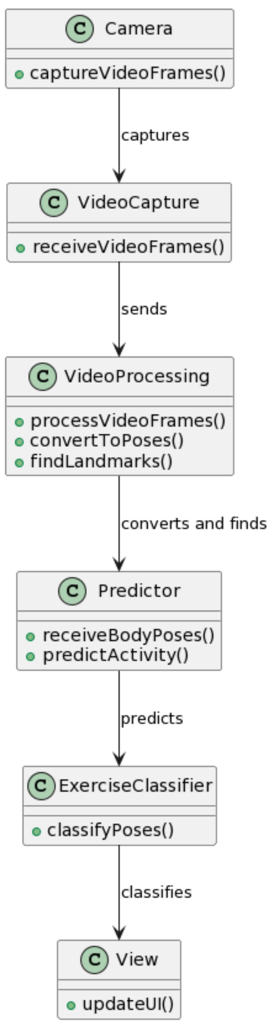

Fig. 7. Computer vision model's technical details.

The architecture consists of the following key components:

1) Camera: The Camera component captures video frames from the device's camera. It leverages the AVFoundation framework to access the camera and capture real-time video data, ensuring a steady input stream for the subsequent components [42].
2) VideoCapture: The VideoCapture component receives the captured video frames from the camera and forwards them to the VideoProcessing component for further analysis. This intermediary role allows for a clear separation of concerns and promotes efficient data flow within the architecture.
3) VideoProcessing: The VideoProcessing component takes on the critical task of processing the incoming video frames to detect human body poses and landmarks, harnessing the power of the Vision framework [43]. By converting the video frames into body poses and extracting relevant body landmarks, the VideoProcessing component lays the foundation for activity recognition.
4) Predictor: The Predictor component receives the processed body poses from the VideoProcessing component and employs a sliding window approach to determine the most probable current activity. By considering a sequence of poses over a specified time window, the Predictor ensures relevant predictions, considering the temporal context of the user's movements.
5) ExerciseClassifier: The ExerciseClassifier model takes the data from the Predictor and classifies the poses into specific physical activities.
6) View: The View component interfaces the Computer Vision Model and the user. It updates the user interface based on the classified activity received. By displaying relevant feedback to the user, the View component encourages engagement in physical activity and provides gamified points for the user's efforts.

2) Sliding window mechanism for pose prediction: The sliding window mechanism allows the model to process a sequence of poses over a specified time window, ensuring efficient predictions and continuous feedback to the user.

In contrast, the static window prediction method suffers from delays due to the need to clear the buffer after each prediction. The static window mechanism may limit the prediction's ability to provide near real-time feedback to the user.

The researcher conducted a controlled experiment on himself to evaluate the effectiveness of the sliding window mechanism for counting repetitions during exercise. The experiment used an iPhone 11 Pro as the data collection device. All trials were conducted in the same controlled environment with uniform lighting conditions to ensure consistency. Additionally, all trials were performed at a consistent height of 120 centimeters measured from the floor to ensure consistent data acquisition by the phone's camera. The researcher then compared the performance of the sliding window mechanism against a static window approach. The researcher performed ten continuous repetitions of jumping jacks for each mechanism. The accuracy of each approach in counting repetitions and the average feedback time were measured and compared (see Table III).

TABLE III. Comparison of Sliding Window and Static Window Mechanisms

Test	Mechanism	Actual Continuous Reps	Counted Reps	Average Feedback Time (s)
1	Sliding Window	10	8	1.42
2	Static Window	10	3	3.09
3	Static Window	10	4	3.33
4	Sliding Window	10	9	1.46

The functionality of the sliding window mechanism, as outlined in Table IV, illustrates the seamless integration of initialization, pose estimation, and sliding window analysis stages. This well-structured design enables the mechanism to process incoming pose data efficiently, make near-accurate predictions, and manage the pose window effectively.

TABLE IV. Stages of the Sliding Window Mechanism

Stage	Description
Initialization	• Load the ExerciseClassifier • Initialize posesWindow with a capacity to store up to 128 poses • The posesWindow serves as a buffer to hold incoming poses for analysis
Pose Estimation	• Camera captures frames • VideoProcessing component extracts human body poses from each frame • Extracted poses are added to the posesWindow • The posesWindow is continuously updated with the sequence of poses for analysis
Sliding Window Analysis	• Triggered when the posesWindow accumulates 64 or more poses • Consists of two parallel processes: ○ **Prediction**: ▪ Collected poses are prepared and passed to the ExerciseClassifier for activity classification ▪ Classifier assesses the poses to identify recognizable activities ▪ Confidence of the prediction is calculated ○ **Window Management**: ▪ Adjusts the posesWindow based on the prediction result ▪ If an activity is recognized, the window size is reduced by removing a portion of the oldest poses ▪ If no activity is detected, only the oldest poses are removed ▪ Allows the window to slide forward while retaining relevant pose information

In the gamified physical activity intervention context, the sliding window mechanism's ability to count continuous repetitions and provide timely feedback is essential for maintaining user engagement and motivation.

D. Reward Engine

The Reward Engine aims to enhance user engagement and motivation by providing personalized gamified rewards and incentives based on the user's physical activity performance. The Reward Engine leverages gamification techniques to create challenges and rewards to encourage users to engage in physical activity regularly [44].

1) Technical architecture: The Reward Engine's technical architecture ensures seamless integration and efficient communication between its components. The following diagram illustrates the interactions between the key components of the Reward Engine (see Fig. 8).

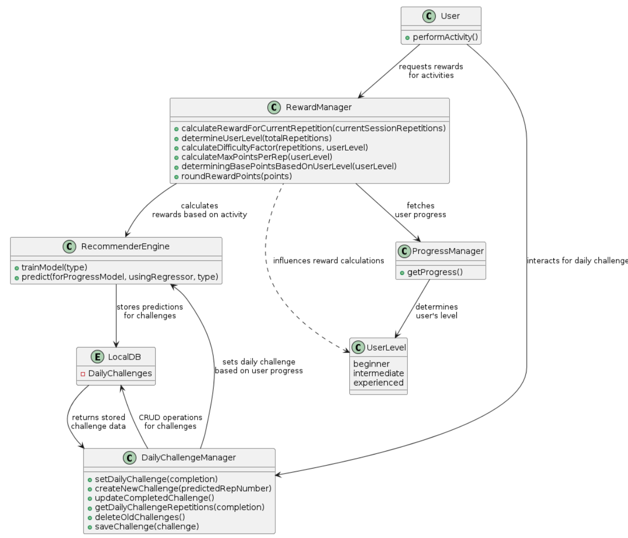

Fig. 8. Reward engine's technical details.

The architecture consists of the following key components and their interactions:

- User: Users perform physical activities, which are tracked by the system. They engage with daily challenges and receive rewards based on their activity levels. The User interacts with the RewardManager to request rewards for their activities and with the DailyChallengeManager to receive and complete daily challenges.
- RewardManager: The RewardManager is responsible for calculating rewards for user activities. It fetches user progress data from the ProgressManager and utilizes the RecommenderEngine to calculate precise rewards based on the user's activity. The RewardManager determines the user's level based on their total repetitions, calculates the difficulty factor and maximum points per repetition, and rounds the reward points to ensure a user-friendly format.
- ProgressManager: The ProgressManager fetches user progress data, including historical activity data, essential for calculating rewards and setting challenges. The ProgressManager assesses the user's current level and performance trends and provides this information to the RewardManager and the DailyChallengeManager.
- RecommenderEngine: The RecommenderEngine component uses machine learning to personalize the difficulty and targets of daily challenges based on user progress. It trains models using the user's progress data and predicts future performance,

helping to tailor the rewards and challenges further. The RecommenderEngine interacts with the RewardManager to calculate precise rewards and with the DailyChallengeManager to set appropriate daily challenges.

- DailyChallengeManager: The DailyChallengeManager manages daily challenges' CRUD operations. It interacts with the RecommenderEngine to set attainable yet challenging challenges based on the user's predicted capabilities. The DailyChallengeManager also performs CRUD operations on the LocalDB to ensure that challenges are current and accurately reflect the user's progress.
- UserLevel: This enumeration categorizes users into beginner, intermediate, and experienced levels based on their total repetitions and progress. The UserLevel influences how rewards and challenges are calculated and presented to the user. It is utilized by the RewardManager and the DailyChallengeManager to provide level-appropriate rewards and challenges.
- LocalDB: The local database stores and manages data related to daily challenges. It ensures that challenges persist and can be retrieved as needed. The DailyChallengeManager interacts with the LocalDB to save, update, and retrieve challenge data, which is then used to notify and engage the user.

2) Setting daily challenge process: Setting daily challenges aims to help maintain user interest and promote regular physical activity [45]. The following activity diagram illustrates the steps in setting a daily challenge and rewarding users for achieving their goals (see Fig. 9).

The process consists of the following stages:

1) Initialize Challenge:
   - The system retrieves the user's historical data, including total repetitions of physical activities and points earned, providing a foundation for setting a new challenge.
   - Accumulated data from the user's activity history is aggregated to understand their performance over time.
   - The system calculates the number of days the user has been active, aiding in the analysis of daily average performance.
2) Calculate Average and Set Base:
   - The average daily activity and points are computed based on the user's history to establish a performance baseline.
   - The system checks for sufficient progress data to predict the next challenge accurately.
     - If Yes: The system utilizes the detailed progress data for a new challenge setting.
     - If No: The system defaults to predefined challenge values, ensuring new users without extensive history still receive engaging challenges.
3) Predict Challenge Target:

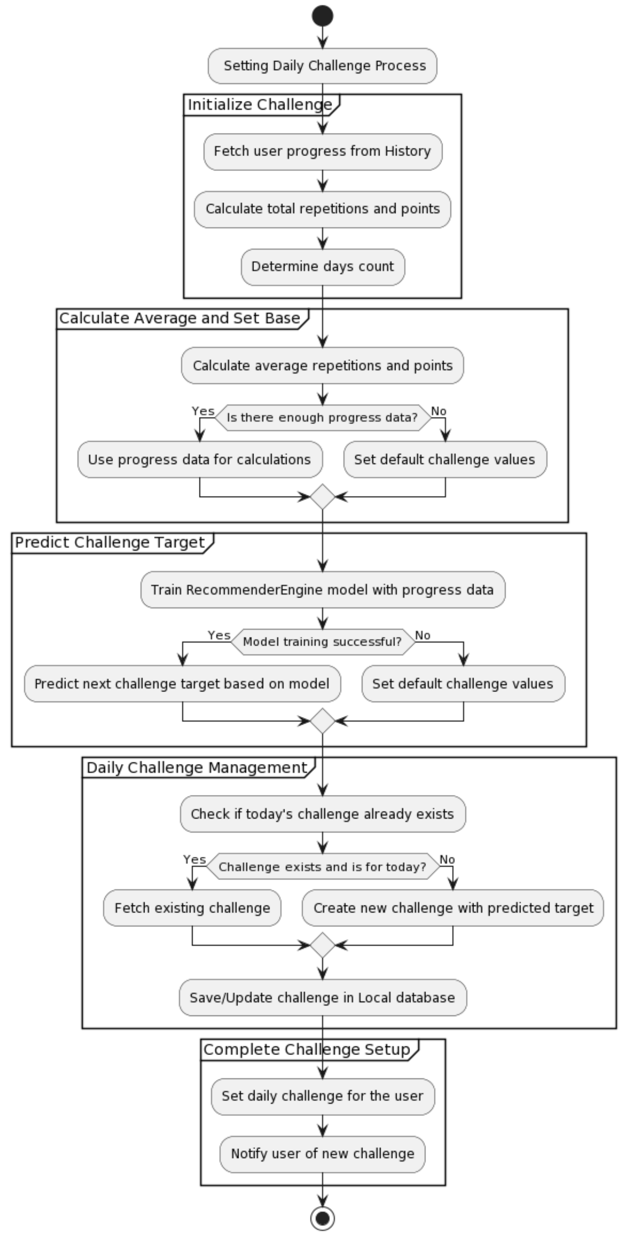

Fig. 9. Setting daily challenge process.

   - The RecommenderEngine is fed user progress data to train a predictive model tailored to the user's activity patterns.
   - Model Training Outcome:
     - If Successful: The model predicts the next challenge target, aligning with the user's potential for improvement.
     - If Unsuccessful: The system reverts to default challenge values, ensuring continuity in user engagement despite predictive model challenges.
4) Daily Challenge Management:
   - The system verifies if a challenge for the current day already exists to avoid duplications.

- Challenge Evaluation:
  - If Exists for Today: The existing challenge is retrieved, maintaining consistency in daily goals.
  - If No Challenge for Today: A new challenge is created using either the predicted target or default values, ensuring the user always has a goal to strive for.
- The newly set or updated challenge is saved or modified in the local database, ensuring the persistence and accessibility of challenge data.

5) Complete Challenge Setup:
- The daily challenge is finalized and set for the user, marking the culmination of the challenge-setting process.
- The user is informed of the new or updated challenge, encouraging engagement and participation in the daily activity goal.

Once the daily challenge is set, the RewardManager calculates the appropriate rewards based on the user's level, difficulty factor, and maximum points per repetition. The reward for achieving the daily challenge is then presented to the user, providing a sense of accomplishment and motivation to continue engaging with the TSR framework (see Fig. 10).

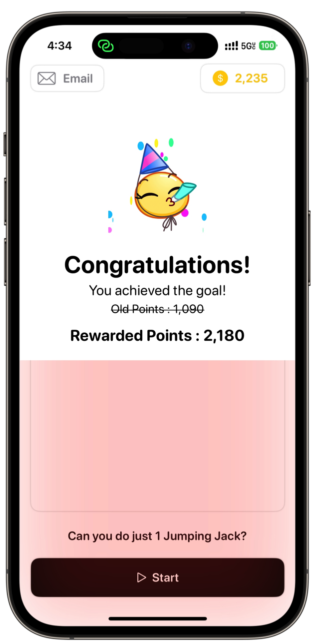

Fig. 10. Daily challenge user interface.

Setting challenges highlights the Reward Engine's ability to create personalized, adaptive challenges considering each user's unique progress and performance. By leveraging predictive modeling and fallback strategies, the Reward Engine ensures that every user receives engaging and attainable goals regardless of their history, which might encourage consistent participation in physical activity.

V. Conclusion and Future Work

The TSR framework, as discussed in this paper, is a comprehensive and innovative approach to gamified physical activity interventions. The TSR framework leverages advanced technologies, including machine learning and gamification techniques, to create an engaging and personalized experience that encourages users to engage in physical activity regularly [13].

The TSR framework's components seamlessly integrate to create a cohesive and effective system that prompts gamified physical interventions. The Screen Time Restriction component enforces restrictions while actively promoting physical activity. The Notification Triggers component employs personalized notifications to motivate users. The Computer Vision Model enables continuous activity recognition, and the Reward Engine creates a dynamic and immersive experience through personalized rewards, incentives, and adaptive daily challenges.

While the TSR framework represents a significant step forward in gamified physical activity interventions, it is essential to note that it remains a theoretical model at present. Its potential applications and impact require further investigation and rigorous testing. This paper does not claim to have achieved specific outcomes but instead seeks to outline the implementation of the TSR framework.

To this end, future work will focus on evaluating the effectiveness of the TSR framework through an empirical study. Future work will investigate the TSR framework's impact on various aspects of physical activity and user experience to determine the framework's effect in promoting physical activity. The future study will examine the TSR framework's influence on physical activity levels compared to a control group without the TSR intervention. Future work will also assess the framework's impact on body composition, perceived autonomy, competence, relatedness, ease of use, system reliability, and usefulness in promoting physical activity.

In conclusion, the TSR framework represents a promising approach to addressing the challenge of physical inactivity. As we rigorously test and refine the TSR framework, we aim to contribute to a future where engaging, personalized, and effective gamified physical activity interventions are accessible to all, empowering individuals to be more physically active.

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Code Availability

The code of this paper is available in the ‘tsr‘ repository at https://github.com/haririmajed/tsr.git. Readers are encouraged to use and cite the materials provided, with appropriate credit given to this paper.

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