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Empowering Gameplay: AI-driven Generative Distraction to Enhance Exercise Engagement

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Exergames and gamification require continuous innovation to sustain user engagement, as the novelty of emerging technologies gradually diminishes and static modules often fail to maintain long-term interest. Dynamic, generative AI-driven interactions offer a promising solution to these challenges by revitalizing user experiences. When integrated with traditional dissociative strategies, such interactions have the potential to transform routine exercise into a more enjoyable activity. Building on the growing interest in AI agents, in this study, we introduce empowering gameplay (EG), a novel approach that leverages an automated AI system to reduce perceived exertion and enhance exercise enjoyment during a brief exercise session. A randomized controlled trial was conducted to evaluate the effects of EG on exercise load and enjoyment in 60 university students. Participants were randomly assigned to one of the following three groups: the EG group, the prerecorded gameplay group (RG), or a no-intervention control group (CG). Outcome measures included the physical activity enjoyment scale (PACES), the Borg rating of perceived exertion, and average heart rate. In addition, a customized video game recreational preference (VGRP) scale was administered to account for individual gaming preferences and their potential effects on engagement and perceived exertion. Results indicated that the EG achieved significantly higher PACES scores than both RG and CG, even after adjusting for VGRP. These findings demonstrate that EG effectively enhances exercise enjoyment and reduces perceived exertion while maintaining comparable physiological exertion levels. Overall, EG leverages AI agents to improve exercise enjoyment and engagement regardless of prior gaming experience. This study highlights AI-driven distraction as a promising acute engagement strategy, with implications for future longitudinal research on exercise motivation, rehabilitation support, and technology-enhanced fitness.

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1. Introduction

Sustained engagement in regular physical activity is widely acknowledged as essential for long-term health; however, dropout rates of newly initiated exercise programs remain high, reaching 40–65% within the first six months.[1] Previous studies indicate that long-term adherence is strongly associated with participation in moderate-to-vigorous physical activity accompanied by enjoyment and positive affect.[2] Nevertheless, global health challenges such as obesity and sedentary lifestyles continue to prevail. Distraction has long been explored as a dissociative strategy to improve exercise adherence by redirecting attention away from physical exertion.[3] Traditional dissociative strategies, including music, television, or their combination,[4–7] help reduce perceived exertion during exercise by serving as distractions, although they often lack the interactive elements needed for prolonged engagement. In contrast, gamification[8,9] and exergaming[10] offer dynamic, immersive[11] experiences by integrating gameplay mechanics,[12] real-time feedback,[13] challenges,[14] narrative structures,[15] and reward systems.[16]

Despite their initial appeal, both gamification and exergaming exhibit inherent limitations. Gamification, while typically lightweight, accessible, and slow-paced, often depends on extrinsic reward mechanisms such as badges, points, and leaderboards,[17] which may lose their effectiveness as their novelty diminishes.[18] In contrast, exergaming offers higher levels of immersion and engagement but frequently imposes substantial cognitive and physical demands, potentially resulting in cognitive overload, physical discomfort, mental fatigue, or visual strain. These factors constrain its suitability for prolonged or repetitive exercise sessions.[19] Accordingly, there remains a need for alternative approaches that integrate the accessibility and low cognitive burden of gamification with the immersive and motivating qualities of exergaming, while mitigating their respective limitations.

Motivated by the increasing prevalence of AI agents, our preliminary work employed a Generative Pre-trained Transformer 3 (GPT-3)-based virtual coach to achieve modest improvements in exercise motivation.[20] In this study, we focused specifically on an exergame to assess its intrinsic effects on engagement and exertion. The empowering gameplay (EG) framework leverages AI-driven generative mechanisms to introduce unpredictable, strategic distractions that sustain user attention. An adaptive AI agent and a soft uncertainty policy ensure that player actions yield varied outcomes, shifting focus from immersive reaction to slow-paced strategic interaction.[21]

In this study, we examine the feasibility and effectiveness of EG as an independent, mild digital intervention for enhancing exercise engagement. To secure methodological rigor and isolate EG's core effects, the experiment was designed with minimal complexity to reduce confounding factors. A basic Pong game was implemented without visual or audio embellishments, and a streamlined rule-based AI was used to align with the study's objectives. Our main contributions are listed as follows: (1) We propose EG, an AI-mediated exergame design paradigm based on intermittent strategic empowerment rather than continuous reactive control. (2) We operationalize this paradigm through a sensor-integrated IoT dumbbell-lifting system with tunable AI agents. (3) We introduce the notion of generative enjoyment as a structured form of pleasure derived from indirectly affecting an evolving generative system. (4) We empirically evaluate acute effects on enjoyment and perceived exertion through a randomized controlled study.

2. Related Work

Prior work has established an emerging technical foundation for integrating resistance training with interactive systems. In particular, StrengthGaming demonstrated that free-weight exercise can be embedded into an exergame by using a wearable orientation sensor to continuously map repetition progress to avatar position in a Flappy Bird-inspired game while structuring obstacles and rewards according to target repetition tempo.(22) This design preserves key resistance-training variables such as repetition structure and time under tension, while improving user experience through interactive engagement.

Beyond exergames, a substantial body of work has explored sensing-based support for resistance training. Systems such as free-weight exercise monitoring (FEMO)(23) platform and ProxiFit(24) demonstrate that free-weight exercises can be recognized and segmented at the repetition level through radio-frequency identification (RFID) or mobile sensing, enabling automatic counting and activity classification. Similarly, lightweight exercise tracker for athletes and novices (LEAN)(25) and related approaches show that resistance-training movements can be analyzed in real time to provide form assessment and feedback. Additional work has explored the real-time correction of free-weight exercise form and rule-based guidance for dumbbell movements using vision-based sensing (e.g., Kinect-based systems).(26,27) Collectively, these studies indicate that resistance-training performance can already be sensed, segmented, and interpreted with considerable granularity, supporting both interactive and feedback-oriented systems.

Despite these advances, existing work still assigns sensed exercise data to relatively narrow roles. In exergames such as StrengthGaming, sensing is used primarily for direct and continuous control mapping, tightly coupling exercise progress to avatar behavior, even when structured by tempo guidance. In sensing-oriented systems, exercise data are mainly used for monitoring, counting, assessment, and correction. As a result, sensed performance is typically treated either as a control signal or as an evaluation target, and extending such mappings with additional parameters does not fundamentally change this paradigm. What remains underexplored is a different role for sensed exercise performance: not as low-level control or feedback, but as an indirect, intermittent, and strategically consequential input to gameplay progression. Rather than directly moving an avatar or merely evaluating performance, exercise activity may instead affect high-level game dynamics such as state transitions, resource systems, or event generation. Addressing this gap, in the present work, we propose the EG framework in which lifting performance exerts a strategically meaningful effect over a generative gameplay process.

In addition to resistance-training systems, prior studies on exergaming and distraction-based exercise interventions have shown that interactive or audiovisual environments can improve acute exercise experience. Virtual reality (VR)-based exercise biking has been reported to produce more favorable psychological responses than traditional stationary cycling, including higher enjoyment and self-efficacy during exercise.[28] Cycle-ergometer exergaming has also been shown to increase positive psychological responses despite higher physiological work, suggesting that game-based interaction can make exercise feel more enjoyable even when users work harder.[29] In parallel, distraction-based interventions using music and video have demonstrated that audiovisual stimuli can reduce perceived exertion during high-intensity exercise.[30] These studies support the broader premise that exercise experience can be shaped not only by the physical task itself, but also by the attentional and interactive context surrounding the task.

3. Proposed Methods

3.1 Procedures

Each participant completed the experiment individually, beginning with a preparatory phase during which they were equipped with a wearable heart rate smartwatch. An assistant provided a standardized briefing on the study objectives and procedures, ensuring that participants remained unaware of their group assignments under the single-blind design. Participants were informed that the relationship between exercise bouts and their acute effects was investigated. To ensure procedural consistency, all participants used the same IoT-enabled dumbbell and smartwatch. The primary experimental manipulation involved dissociative condition, which was designed to modulate engagement during the exercise bouts.

The experimental procedure consisted of three sequential phases: baseline assessment, exercise intervention, and post-intervention assessment. During the baseline assessment, participants provided demographic information and completed the video game recreational preference (VGRP) survey. In the exercise intervention phase, participants performed group-specific tasks: the no-intervention control group (CG) completed six sets of ten dumbbell lifts without additional intervention, the EG group followed the same lifting protocol while interacting with the EG system, and the prerecorded gameplay group (RG) performed the lifting protocol while viewing a pre-recorded EG video. Heart rates were continuously monitored throughout the intervention. Following the exercise session, the post-intervention assessment involved the completion of the physical activity enjoyment scale (PACES) and the Borg rating of perceived exertion (RPE) scale to evaluate enjoyment and perceived exertion, respectively.

3.2 Exergame design

3.2.1 Gameplay design

EG, an experimental module from previous work,[20] introduces an interval-based, indirect interaction model with an empowerable AI agent. Unlike traditional exergames that require continuous, reactive control, EG shifts the focus to strategic decision-making during exercise breaks. Users empower their AI agent to engage in dynamically generated contests, reducing cognitive load while maintaining effective distraction. This approach enhances enjoyment and promotes long-term participation by bridging the gap between passive distractions and fully immersive gameplay.

3.2.2 Empowerable AI

Empowerable AI is a framework for adaptive intelligence in which user inputs affect gameplay without requiring continuous real-time control. The framework consists of two components: an inducing module, which extracts efficiency-aware features from workout data, and a tunable AI agent, which adapts its behavior on the basis of these signals. In the present experiment, the inducing module monitored dumbbell lifts using a counter with a low-pass filter, whereas the tunable AI agent, implemented as a rule-based system based on classic Pong game rules, generated interactive and engaging gameplay, as shown in Fig. 1. The algorithms governing the tunable AI agents are summarized in Fig. 2.

3.2.3 Game flow and equipment

In the dumbbell-lifting intervention, participants earn one game point for every ten successful lifts, which they can use to empower an AI agent's capability. The empowerable attributes include energy, control, and speed, which are all initialized to zero and increase by 0.1 for each consumed game point. Although the empowered AI becomes more competitive, victory remains uncertain owing to random factors. After each set of ten lifts, participants take a rest while the lift count is paused. Sessions end after 60 lifts, although participants may stop early if they experience fatigue or discomfort. A 1.5 kg dumbbell with an IoT module featuring accelerometer and gyroscope sensors captured real-time acceleration and rotational data. Low-pass filtering removed noise and accurately detected completed lifts, triggering a signal to a personal computer

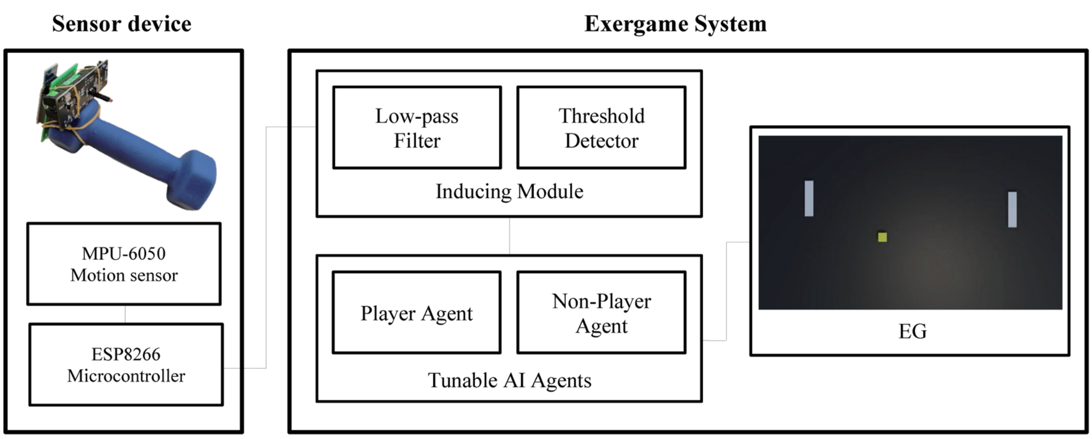

Fig. 1. (Color online) Block diagram of the proposed exergame system with sensor device.

Algorithm 1: Rule-based AI agent movement.
Input:
- y_a: current y position of AI agent
- y_b: current y position of the ball
- $s \in [0,1]$: speed empowerment level of the AI agent
- s_0: base movement speed, set to 100 pixels/s
- Δt: simulation time step
- ε: deadzone threshold
- y_{min}, y_{max}: movement bounds on y-axis

Output:
- y_{next}: next y position of the AI agent

Steps:
1. $d \leftarrow y_b - y_a$
2. **if** $|d| < \varepsilon$ **then**
   $m \leftarrow 0$
   else
   $m \leftarrow \mathrm{sign}(d) \cdot (s + 1) \cdot \Delta t$
3. $y_{next} \leftarrow \mathrm{clamp}(y_a + m, y_{min}, y_{max})$
4. **return** y_{next}

Algorithm 2: Ball bouncing controlled by tunable AI attributes
Input:
- θ_{in}: angle of incidence of the ball
- v_{ref}: reference speed of the ball
- control $\in [0,1]$: angular perturbation strength
- energy $\in [0,1]$: probability of ball speed boost
- θ_{min}, θ_{max}: valid outgoing angle range
- v_{max}: maximum allowed ball speed

Outputs:
- θ_{out}: outgoing angle
- v_{ball}: ball speed after bounce

Steps:
1. $v_{ball} = v_{ref}$
2. delta = random value sampled from Uniform(-10 · control, 10 · control)
3. $\theta_{out} = \mathrm{clamp}(\theta_{in} + \text{delta}, \theta_{min}, \theta_{max})$
4. u = random value sampled from Uniform(0, 1)
5. **if** u < energy
   $v_{ball} = \min(1.5 * v_{ref}, v_{max})$
6. **return** (θ_{out}, v_{ball})

Fig. 2. Algorithms for tunable AI agents.

(PC)-based exergame program that recorded cumulative lift counts. Additionally, heart rate monitoring was performed using Realme Watch 3 to collect comprehensive physiological data.

The exergame employed a minimalist visual design with solid color blocks, intentionally reducing distractions from elaborate effects and enabling participants to focus on core gameplay mechanics.

3.3 Study design

This single-session randomized controlled trial examined the effects of EG on exercise enjoyment and perceived exertion following a 10 min moderate-to-high intensity activity. Participants were assigned to one of the three groups: (a) the EG, which engaged with AI-driven dynamic distractions requiring interval interaction; (b) the RG, which passively viewed recorded EG sessions, providing a non-interactive distraction; and (c) the CG, which performed the activity without distractions. Post-session measures were used to assess the acute effects of each condition. Including the RG allowed us to isolate the effect of interactivity because participants viewed the same visual gameplay content as in the EG condition but without interacting with it.

3.3.1 Participants and measured scales

Sixty college students, selected from an initial pool of 65 recruited through classroom visits and student networks, were randomly assigned to the three groups (N = 20 per group). The demographic and gender distributions of the groups were as follows: EG : 20.2 ± 2.4 years, 40% male; RG: 19.2 ± 0.9 years, 35% male; CG: 20.1 ± 2.4 years, 45% male. All participants were in good health, nonsmokers, nondrinkers, and free of conditions that might interfere with the exercise regimen, including pregnancy and dietary restrictions.

3.3.2 PACES and Borg RPE

In this study, the primary dependent variables were participants' enjoyment of physical activity and their perceived exertion. Enjoyment was assessed using the PACES,(31) a validated 7-point Likert scale that captures exercise-related sensations. To tailor the scale for student participants, items 5 and 11 were removed, aligning the instrument with the study's needs. Perceived exertion was measured using the Borg RPE scale, ranging from 6 (no exertion) to 20 (maximal effort). Additionally, average heart rate (AHR) was monitored with a wearable smartwatch to provide an objective measure of exercise intensity, validating self-reported data.

3.3.3 VGRP

To address the potential effects of individual video game preferences on the experimental distraction media, a four-item VGRP scale was developed and administered at baseline. VGRP was designed to measure recreational preference for video games rather than game addiction. Therefore, three nonclinical involvement-related items, corresponding to item codes GA01, GA02, and GA04, were adapted from the game addiction scale for adolescents,(32) representing cognitive salience, leisure-time involvement, and engagement persistence, respectively. Items reflecting pathological consequences, such as withdrawal, conflict, and problems, were excluded because they were outside the scope of this study. In addition, one custom item assessing the proportion of recreational time spent on video games over the past six months was included as a direct behavioral indicator of gaming preference. Responses were recorded on a 5-point Likert scale, and the total score was used to quantify each participant's baseline preference for video games.

4. Experiment Results and Analysis

4.1 Results

Table 1 presents the descriptive statistics for all groups. The EG exhibited the highest mean PACES score at 5.33 [95% confidence interval (*CI*): 4.99 to 5.68], compared with the RG at 4.29 (95% *CI*: 3.79, 4.80) and the CG at 4.05 (95% *CI*: 3.56, 4.55), suggesting that participants under the EG condition experienced greater enjoyment. In terms of perceived exertion, as measured by the Borg RPE scale, the EG also recorded the lowest mean score at 9.55 (95% *CI*: 8.26, 10.84), with the RG and CG reporting higher mean scores of 11.50 (95% *CI*: 10.28, 12.72) and 12.75 (95% *CI*: 11.30, 14.20), respectively, indicating reduced perceived exertion in the EG. Figure 3

Table 1
Descriptive statistics for all groups.

	Age	VGRP	PACES					Borg RPE				
	Mean	Mean	Mean	Variance	Median	95% *CI* lower	95% *CI* upper	Mean	Variance	Median	95% *CI* lower	95% *CI* upper
EG	20.15	9.95	5.33	0.54	5.22	4.99	5.68	9.55	7.63	8.5	8.26	10.84
RG	19.15	11.60	4.29	1.16	4.47	3.79	4.80	11.50	6.79	11.5	10.28	12.72
CG	20.05	11.65	4.05	1.12	4.28	3.56	4.55	12.75	9.57	13.0	11.30	14.20
Total	19.78	11.07	4.56	1.22	4.59	4.27	4.85	11.27	9.49	12.0	10.47	12.06

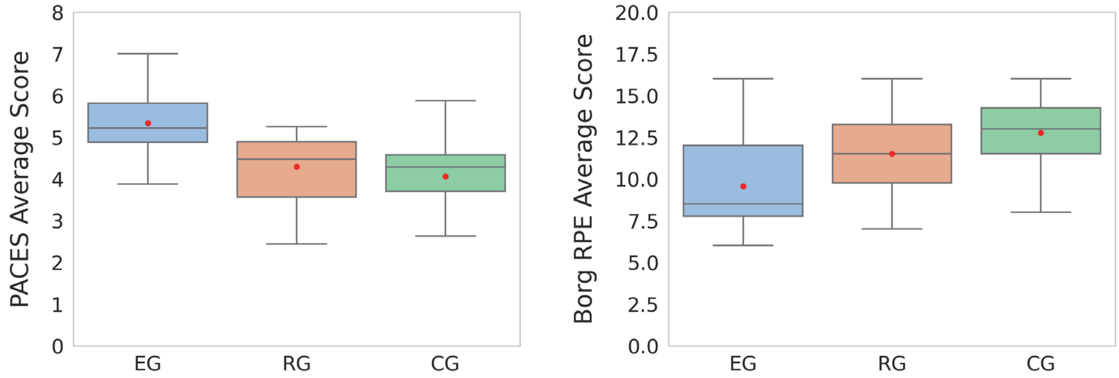

Fig. 3. (Color online) PACES and Borg RPE raw scores of three groups with different interventions.

further illustrates these findings through boxplots that display the intra-group distributions of PACES and Borg RPE scores, with the visual spread corroborating the statistical variability observed in Table 1.

The results of the z-score and effect size analyses in Table 2 indicate that the EG significantly enhanced exercise enjoyment as measured by PACES, with a positive z-score of 1.4 (95% *CI*: 0.78 to 2.02) and a large effect size (Cohen's $d = 1.4$) compared with the CG. In contrast, the RG showed only marginal improvement ($z = 0.23$, 95% *CI*: −0.39 to 0.85; Cohen's $d = 0.23$), suggesting that passive observation offers limited benefits relative to the interactive, AI-driven dissociative intervention employed by the EG. Furthermore, the EG achieved a significant reduction in perceived exertion (Borg RPE) with a z-score of −1.09 (95% *CI*: −1.71 to −0.47; Cohen's $d = -1.09$), while the RG exhibited a smaller decrease ($z = -0.44$, 95% *CI*: −1.06 to 0.18; Cohen's $d = -0.44$), underscoring the superior efficacy of dynamic interaction in mitigating perceived effort. Notably, no significant differences emerged in AHR between groups (EG vs CG: $z = 0.1$, 95% *CI*: −1.86 to 2.06; RG vs CG: $z = -0.14$, 95% *CI*: −2.10 to 1.82), indicating that the interventions had a limited physiological impact in this regard.

To validate the appropriateness of subsequent analyses, Levene's test confirmed the homogeneity of variances for PACES [$F(2, 57) = 0.675$, $p = 0.513$], Borg RPE [$F(2, 57) = 0.039$,

Table 2
Effects of the EG on raw and *z*-scores.

	EG vs CG			RG vs CG			Levene's test	
	z-score	95% *CI*	Cohen's *d*	*z*-score	95% *CI*	Cohen's *d*	*F*-value	*p*-value
PACES	1.4	(0.78, 2.02)	1.4	0.23	(−0.39, 0.85)	0.23	0.675	0.513 (>0.05)
Borg RPE	−1.09	(−1.71, −0.47)	−1.09	−0.44	(−1.06, 0.18)	−0.44	0.039	0.962 (>0.05)
AHR	0.1	(−1.86, 2.06)	0.07	−0.14	(−2.10, 1.82)	−0.13	1.016	0.368 (>0.05)

$p = 0.962$], and AHR [$F(2, 57) = 1.016$, $p = 0.368$]. Building on these findings, the results of the analysis of variance (ANOVA) in Table 3 revealed significant group differences for PACES [$F(2, 57) = 9.87$, $p = 0.0002$]. Subsequent post-hoc comparisons using Tukey's honestly significant difference (HSD) demonstrated that the EG reported significantly higher PACES scores than both the CG ($p = 0.0003$) and the RG ($p = 0.0036$). These results were further corroborated by the Bonferroni correction, which confirmed the significant differences between the EG and the other groups (EG vs CG: $p = 0.0002$; EG vs RG: $p = 0.003$). Collectively, these analyses underscore the effectiveness of interactive, AI-driven dissociative interventions in enhancing exercise enjoyment and reducing perceived exertion, while also affirming the statistical robustness of the methodological approach.

Another ANOVA revealed significant group differences in Borg RPE, $F(2, 57) = 6.51$, $p = 0.0029$. Post-hoc Tukey's HSD comparisons demonstrated that the EG reported significantly lower exertion scores than the CG ($p = 0.002$), while the RG did not differ significantly from either the EG or CG. These findings were corroborated by the Bonferroni correction, which confirmed a significant reduction in perceived exertion for the EG relative to the CG ($p = 0.0041$), with no notable differences involving the RG. In contrast, no significant group differences were observed in AHR, $F(2, 57) = 0.17$, $p = 0.85$, suggesting that the intervention did not have a measurable impact on physiological responses. Overall, these results highlight the efficacy of the AI-driven EG in reducing perceived exertion without altering cardiovascular indicators.

Because individual video game preference may affect participants' responses to gameplay-based distraction, VGRP was considered a potential covariate in the analysis of PACES and Borg RPE outcomes. Although the EG showed a numerically lower mean VGRP score ($M = 9.95$) than the RG ($M = 11.60$) and CG ($M = 11.65$), this baseline difference was not statistically significant, as indicated by a one-way ANOVA, $F(2, 57) = 1.86$, $p = 0.164$. Therefore, the observed difference in VGRP should not be interpreted as a significant pre-existing group imbalance. Nevertheless, VGRP was retained as a covariate to account for the possible effects of baseline video game preference on enjoyment and perceived exertion. The internal consistency of the VGRP scale was acceptable, with Cronbach's alpha = 0.855, supporting its use as a covariate in the present analysis. After controlling for VGRP, analysis of covariance (ANCOVA) showed that the group effect remained significant for both PACES [$F(2, 56) = 9.52$, $p = 0.0003$] and Borg RPE [$F(2, 56) = 6.65$, $p = 0.0026$]. As shown in Table 4, these results indicate that the observed group differences were not explained by baseline differences in video game preference.

Table 3
ANOVA results for PACES, Borg RPE, and AHR.

	F-value	p-value	Significant? ($p < 0.05$)	Cohen's f	Tukey's HSD	Bonferroni correction
PACES	9.87	0.0002	Yes	0.59	EG > CG ($p = 0.0003$) EG > RG ($p = 0.0036$) RG ~ CG ($p = 0.7139$)	EG > CG ($p = 0.0002$) EG > RG ($p = 0.0030$) RG ~ CG ($p = 1.0000$)
Borg RPE	6.51	0.0029	Yes	0.478	EG < CG ($p = 0.0020$) EG ~ RG ($p = 0.0832$) RG ~ CG ($p = 0.3487$)	EG < CG ($p = 0.0041$) EG ~ RG ($p = 0.0817$) RG ~ CG ($p = 0.5249$)
AHR	0.17	0.85	No	0.077	Not applicable	Not applicable

Table 4
ANCOVA results for PACES and Borg RPE with VGRP as a covariate.

	Source	Sum of squares	Degrees of freedom	F-value	p-value
PACES	Group	18.18	2	9.52	0.0003
	VGRP	0.13	1	0.13	0.7157
	Residual	53.46	56	Not applicable	Not applicable
Borg RPE	Group	107.33	2	6.65	0.0026
	VGRP	3.57	1	0.44	0.5088
	Residual	452.13	56	Not applicable	Not applicable

4.2 Analysis and discussion

4.2.1 Size of future experiment

In this study, we demonstrated medium to large primary effects on both PACES and Borg RPE, with the estimated minimum sample size per group calculated as 11 and 16 participants, respectively, based on a power of 0.8 and an alpha of 0.05. Notably, these estimates are well aligned with the sample size of 20 participants per group used in our experiments, thereby confirming that the chosen sample size is robust enough to detect meaningful effects. These results suggest that the current experimental designs are both statistically sound and adequately powered.

4.2.2 Concept of generative enjoyment

Generative enjoyment refers to the pleasure users derive from observing and subtly affecting the evolution of a generative system. Our results suggest that this form of enjoyment can support AI-assisted dissociative strategies in exercise by enhancing engagement through strategically timed interventions rather than continuous, high-intensity interactions. By shifting the user's role from direct control to indirect inducement, the experience maintains cognitive engagement without overwhelming participants, thereby enabling sustained and rewarding interaction. EG illustrates this principle: users make occasional, meaningful decisions that guide the system's evolution, in contrast to traditional approaches that rely on continuous, reflexive input. Rather than a byproduct of generative systems, generative enjoyment constitutes a structured experience grounded in guided user intervention. Preliminary evidence indicates that systems designed to evoke generative enjoyment can increase engagement and cognitive absorption, highlighting potential applications for interactive media and exercise motivation.

4.2.3 Potential applications of generative enjoyment in rehabilitation

The concept of generative enjoyment shows significant promise in rehabilitation settings through an EG framework that leverages an adaptive, AI-driven agent. By nurturing a sense of contribution to another living entity, this approach may enhance self-efficacy and motivation during recovery. Our preliminary investigation minimized complex game elements to focus on validating the core phenomenon via EG, and the findings lay a critical foundation for future research. Subsequent studies should refine design principles, integrate innovative AI systems, and develop richer interactive formats to further bolster motivational support for patients.

4.2.4 Advantages and challenges addressed by EG

Traditional skill-based immersive exergames effectively blend gameplay with physical exercise, but their design faces several key challenges. EG tackles these challenges through the following innovations: (1) Improved exertion stability: real-time unpredictable challenges can elevate excitement but may also induce irregular exertion, increasing the risk of poor posture or injury. EG's inducement module minimizes sudden, irregular, and reactive user actions, promoting stable and controlled exertion during gameplay. This balanced design effectively mitigates risks by reducing posture deviations associated with excessive randomness. (2) Reduced overuse risks: skill-based exergames, reliant on intense real-time control, demand significant time and effort from users to reach a "flow state," which may lead to fatigue and overuse from extended play. Additionally, maintaining an appropriate skill-challenge balance for diverse players remains a challenge. In contrast, EG uses a dissociative strategy that indirectly engages users, reducing the need for full immersion. By partially redirecting cognitive resources, EG minimizes both cognitive and physical strains, balancing exercise benefits with entertainment to maintain engagement and steady workout efficacy. (3) Accessibility for non-gamers: ANCOVA analysis showed that EG participants reported significantly higher enjoyment, as indicated by PACES scores, even after controlling for VGRP as a covariate. These findings reveal that EG's appeal goes beyond prior gaming experience, marking it as a versatile and inclusive tool for common exercise interventions. (4) Integration with existing routines: in contrast to most exergames that require modifications to established workout regimens, EG seamlessly integrates into existing routines. This allows users to maintain their preferred exercise forms while enhancing motivation and engagement without disrupting proven workout structures.

4.2.5 Comparison with prior exergaming and distraction-based interventions

In the present study, we observed large effects for both exercise enjoyment and perceived exertion. Specifically, the EG showed a large improvement in PACES compared with the CG (Cohen's d = 1.40) and a large reduction in Borg RPE (Cohen's d = −1.09). These effects are broadly comparable to large effects reported in prior acute exergaming and VR-based exercise studies. For example, Zeng *et al.* reported that VR-based exercise biking produced higher enjoyment than traditional stationary biking (Cohen's d = 0.89 in magnitude) and a lower perceived exertion during VR-based exercise biking than traditional stationary biking (Cohen's d = 0.68).[28] Similarly, Glen *et al.* used PACES to assess exercise enjoyment and found a large mode effect of exergaming on enjoyment, as indicated by eta-squared (η^2 = 0.51).[29] In distraction-based exercise research, Chow and Etnier reported that combined music-and-video distraction reduced perceived exertion during high-intensity exercise, with a large effect across time, as indicated by partial eta-squared (partial η^2 = 0.36).[30] Taken together, these findings suggest that the magnitude of the present enjoyment and perceived-exertion effects falls within the range of large effects reported in prior acute interactive or distraction-based exercise interventions. However, because the studies differ in design, exercise modality, sample characteristics, and effect-size metrics, these comparisons should be interpreted cautiously. The present effects should therefore be considered promising but preliminary, pending replication in longer and more diverse exercise contexts.

5. Conclusions

EG presents an AI-driven generative distraction model designed to enhance exercise enjoyment and reduce perceived exertion by shifting user engagement from continuous direct control to intermittent strategic empowerment. In contrast to conventional gamification and exergaming approaches, EG introduces generative enjoyment, a novel interaction paradigm in which users affect gameplay selectively, thereby mitigating cognitive overload while enhancing short-term exercise enjoyment. This adaptive framework supports stable exertion levels, alleviates fatigue, and extends accessibility beyond experienced gamers, indicating its suitability for a broad range of users, including those in rehabilitation and general fitness contexts. By integrating seamlessly into existing exercise routines, EG demonstrates how AI-driven generative systems may support enjoyable exercise experiences in brief intervention contexts. Whether such effects translate into sustained physical activity requires longitudinal validation. Overall, EG highlights the potential of dynamic, AI-enhanced engagement to reshape motivational mechanisms and provides a foundation for future research in exergaming and technology-assisted health interventions.

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