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An experimental study on the teaching of a physical education teaching system based on AI emotion recognition feedback for anxiety regulation and exercise motivation stimulation in cancer survivors

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Abstract : Background: encounters difficulties in emotional sensitivity and personalized adaptation. **Objective:** This study aimed to investigate the effectiveness of an AI emotion recognition feedback-based: Anxiety prevalence is high in cancer survivors, and the traditional physical education teaching physical education teaching system in improving anxiety levels and stimulating exercise motivation among cancer survivors. **Methods:** The randomized controlled trial used a stratified block randomization procedure (by cancer type and baseline GAD-7 tertile) with sealed-envelope allocation concealment and blinded outcome assessment, randomly assigning cancer survivors into an AI intervention group or a traditional teaching control group. A 12-week progressive exercise intervention was implemented, integrating multimodal emotion recognition with adaptive feedback mechanisms based on self-determination theory and emotion regulation theory. **Results:** The AI intervention group showed greater anxiety reduction than the control group, with larger within-group effect sizes and higher rates of clinically meaningful improvement; exercise motivation shifted toward intrinsic regulation, and exploratory structural equation modelling was compatible with an “AI feedback → intrinsic motivation → exercise behaviour → anxiety improvement” pathway, in which intrinsic motivation served as a significant mediator. **Conclusion:** The AI emotion recognition feedback teaching system appears to extend traditional instructional practice through real-time emotional monitoring and personalized feedback. These preliminary findings warrant replication in multi-centre trials with larger samples, longer follow-up, and active comparators before broader claims can be drawn, and may inform the design of emotion-aware intervention models for related populations pending dedicated validation.

Keywords: cancer survivors, artificial intelligence, emotion recognition, exercise motivation, anxiety regulation.

1. Introduction

With the constant improvement in technologies for the diagnosis and treatment of cancer and the prolongation of the survival period of patients, the mental health problems of cancer survivors have become increasingly prominent. Among these, the prevalence of anxiety disorders is as high as 30% to 40% [1]. This not only seriously affects the process of recovery and the quality of life of patients but also has become a key bottleneck that restricts the effectiveness of whole-course management in cancer. As a kind of non-pharmacological treatment method, exercise intervention has been proven to greatly improve the physical and mental health of cancer survivors. Nutrition and Physical Activity Guidelines issued by the American Cancer Society

explicitly recommend that regular exercise be incorporated into the core strategy of cancer rehabilitation [2]. However, serving the special group of cancer survivors poses many challenges to the traditional physical education teaching model. It is difficult for the uniform teaching plan to meet the significant emotional fluctuation difference among individuals. In addition, coaches lack effective means to identify and respond to the emotional states of the trainees in real time in the classroom situation. Moreover, the high dropout rate caused by the common difficulty in maintaining the exercise motivation of cancer survivors further restricts the full play of potential benefits of exercise intervention.

Recent research evidence indicates that exercise intervention has a positive effect on the improvement of anxiety in survivors of various cancer types. Systematic reviews and meta-analyses of breast cancer survivors show that exercise can effectively alleviate their anxiety and depression symptoms [3]. Similar mental health benefits were also observed for the group of lung cancer survivors [4]. Larger meta-analysis studies have further confirmed that exercise intervention can improve the fatigue and quality of life of cancer patients [5], and even in the stage of palliative care for advanced cancer, moderate physical activity can still bring psychological comfort and symptom alleviation to patients [6]. With the accelerating development of artificial intelligence, multimodal emotion recognition based on deep learning has reached acceptable accuracy and provides technical feasibility for monitoring emotional expressions of exercise participants in real time [7, 8]. The methodological review on the use of artificial intelligence in physical activity interventions further highlights that intelligent personalized feedback may improve intervention relevance and efficiency [9]. The implementation of intelligent teaching systems in education [10] and the role of affective tutoring systems in learning outcomes [11] provide conceptual support for applying artificial intelligence to physical education teaching.

At the theoretical level, self-determination theory suggests that the satisfaction of autonomy, competence, and relatedness needs is central to sustaining motor motivation [12, 13], while systematic reviews of emotion regulation point to the mediating role of regulation strategies in the link between anxiety and mental health outcomes [14]. Despite progress in AI emotion recognition, exercise intervention, and theoretical mechanisms, systematic reviews note that work integrating AI with exercise and mental well-being remains fragmented [15, 16].

Three gaps are directly relevant to the present study. First, existing AI-assisted exercise programmes in oncology rarely integrate real-time multimodal emotional monitoring with closed-loop instructional adjustment. Second, most published emotion-recognition work has been validated on healthy populations and has not been transferred into cancer rehabilitation classrooms. Third, the pathway linking emotional feedback, motivational quality, and anxiety improvement has not been empirically specified in this population. Accordingly, this study tested three hypotheses: (H1) the AI emotion recognition feedback system produces greater reductions in anxiety (GAD-7, HADS-A) than conventional teaching across 12 weeks; (H2) the AI condition yields a larger shift toward autonomous motivation (BREQ-3 / RAI); and (H3, exploratory) intrinsic motivation and exercise behaviour sequentially mediate the association between AI feedback exposure and anxiety reduction.

To test these hypotheses, a multimodal AI emotion recognition feedback physical education teaching system for cancer survivors was built by integrating deep-learning emotion recognition with instructional feedback guided by self-determination theory and emotion regulation theory, and its effects on anxiety regulation and exercise

motivation were evaluated in a randomized controlled trial. The study offers a technical contribution in the integration of multimodal emotion recognition with adaptive teaching feedback, an applied contribution in translating this integration into cancer rehabilitation classrooms, and a theoretical contribution in empirically probing the “emotion monitoring – motivation – behaviour change” loop.

2. Methodology

2.1 Research Design and Participants

A two-arm parallel randomized controlled trial design was used in the present study. The random allocation sequence was generated by an independent statistician using the R package *blockrand* with random block sizes of 4 and 6 and a 1:1 allocation ratio, stratified by cancer type (breast / lung / gastrointestinal / other) and baseline GAD-7 tertile to balance clinical heterogeneity. Allocation concealment was implemented through sequentially numbered, opaque, sealed envelopes prepared by the same statistician, who had no role in recruitment or delivery; envelopes were opened only after baseline assessment. Because of the behavioural nature of the intervention, participants and instructors could not be blinded; however, outcome assessors and the data analyst were blinded to group assignment throughout the study. In the current study, the sample size for efficacy analysis was calculated using G*Power 3.1 software. Referring to the moderate effect size reported in previous exercise intervention studies for older cancer patients, Cohen’s d was set at 0.5 [17]. With a significance level α of 0.05 and power $1-\beta$ of 0.80, 32 subjects per group were required. Considering a 20% drop-out rate, 40 people were recruited in each group, for a total of 80. Subjects were recruited through the oncology department, cancer rehabilitation centre, and patient support organization of a tertiary hospital in a certain city. Inclusion criteria were: end of cancer treatment between 3 months and 5 years; age 18–65 years; GAD-7 score ≥ 5 ; no medical contraindications for exercise as evaluated by a physician; able to use smart devices; and voluntary participation. Exclusion criteria were: severe cardiovascular disease (NYHA $\geq$ class III); bone metastasis or severe osteoporosis; cognitive impairment or psychiatric illness; ongoing systematic psychotherapy; and regular exercise participation in the past three months.

2.2 AI Feedback Physical Education Teaching Plan Design

Teaching planning followed the American College of Sports Medicine cancer rehabilitation exercise guidelines combined with the principle of progressive overload, covering cognitive, skill, and affective objectives. The programme was delivered over 12 weeks in three stages. During the adaptation period (weeks 1–4), low-intensity aerobic exercise of 40 min per session was used. During the improvement period (weeks 5–8), moderate-intensity aerobic exercise was combined with mild resistance training, 50 min per session. During the consolidation period (weeks 9–12), moderate-to-high-intensity comprehensive training was used, 60 min per session. Sessions were delivered three times per week throughout.

The teaching strategy incorporated the psychological-need-satisfaction mechanism of self-determination theory. When the AI system detected a high-anxiety state, it automatically reduced exercise intensity by 10–20%, played soothing music, provided encouraging voice feedback, and extended rest time; when a positive affective state was detected, it delivered positive reinforcement. Individualized stage goals were set for each participant, progress was visualized in real time, and virtual

achievement badges were issued on goal attainment, drawing on established practice in self-determination-theory-based goal setting [18]. Autonomy support was provided through optional programme settings and negotiated language, consistent with evidence that personalized strategies enhance autonomous motivation [19].

A standardized four-stage session structure was adopted: introduction (within 5 min), warm-up and emotional baseline collection; main period (40–50 min), content-based training with emotional assessment every 5 min and dynamic adjustment; feedback period (5 min), a performance summary report; and closing period (3 min), relaxation and stretching. The AI system was positioned as an intelligent teaching assistant rather than a replacement for human instructors. The control group received traditional teaching matched for frequency, duration, and content, delivered by coaches following a fixed plan without any AI emotion recognition function, with feedback limited to 2–3 times per class.

2.2.1 Multimodal Inputs and Hardware

Three synchronized input channels fed the recognition pipeline. Facial expressions were captured by a 1080p USB camera at 30 fps, with face regions detected and resized to 224×224 pixels. Voice signals were captured by a directional condenser microphone at 16 kHz / 16-bit using a 3-second sliding window with a 1-second step. Heart rate and heart rate variability were recorded by a Polar H10 chest strap at 1 Hz, with RMSSD, SDNN, pNN50, and LF/HF computed over 5-minute rolling windows. All streams were processed on a local workstation (NVIDIA RTX 3060, 12 GB), yielding a measured mean end-to-end latency of 1.8 s.

2.2.2 Model Architecture

A three-branch late-fusion network was used. The facial branch used a ResNet-50 backbone pre-trained on AffectNet and fine-tuned on RAF-DB, outputting seven basic emotion probabilities that were re-mapped to four functional labels (Anxious/Tense, Neutral, Positive, Fatigued). The voice branch used 64-dimensional log-Mel spectrograms together with 88-dimensional eGeMAPS prosodic features as input to a 2-layer Bi-LSTM (128 hidden units), pre-trained on the combined IEMOCAP and RAVDESS corpora. The physiological branch used a 3-layer multilayer perceptron on the HR/HRV feature vector, pre-trained on WESAD. Branch logits were combined by weighted soft-voting, with weights learned on a held-out validation set by maximizing macro-F1.

2.2.3 Ground-Truth Labelling, Fine-Tuning, and Threshold Definition

Prior to the trial, a pilot corpus was collected from 20 cancer survivors who did not enter the RCT sample but provided independent informed consent. Each contributed two 45-minute exercise sessions, yielding approximately 48 hours of multimodal data for domain-specific fine-tuning. Ground-truth labels combined (a) synchronous self-reported anxiety on a 6-item short-form State-Trait Anxiety Inventory (STAI-S) administered every 5 minutes, and (b) independent double-blind annotation of video segments into the four functional labels by two raters with a master's degree or higher in psychology, reaching Cohen's $\kappa = 0.78$, with disagreements adjudicated by a senior third rater. The operational threshold for “high anxiety” was set at a fused posterior probability ≥ 0.65 for the Anxious/Tense class, calibrated on the pilot corpus to correspond to STAI-S scores at or above the 45th percentile, preserving convergent validity with self-reported anxiety.

2.2.4 Validation Strategy and Error Analysis

Model performance was estimated using subject-level 5-fold cross-validation

and Leave-One-Subject-Out (LOSO) as a stricter robustness check, ensuring that no participant's data appeared in both training and validation partitions. Per-modality LOSO accuracy was 83.2% (facial), 78.6% (voice), and 71.4% (physiological); the fused model reached 91.4% accuracy and macro-F1 of 0.89. The main residual confusion occurred between Tense and Neutral states (6.1%). Subgroup accuracy by sex, age band, and cancer type differed by less than 2.5 percentage points, indicating no systematic subgroup bias. A confidence-based safety fallback was implemented: when the fused posterior fell below 0.55, intensity modulation was disabled and the system reverted to standardized verbal feedback to prevent low-confidence misclassifications from driving inappropriate adjustments.

2.2.5 Adherence Monitoring and Safety

Attendance, peak-heart-rate triggers, and early-exit events were logged automatically for every session. Pre-specified stop criteria included heart rate exceeding 85% of $(220 - \text{age})$, SpO_2 below 92%, Borg RPE ≥ 17 , or subjective chest pain / dizziness. A collaborating physician conducted a brief telephone screen before each session. Over 12 weeks, three mild adverse events were recorded (one in the AI arm, two in the control arm; all muscular soreness resolving within 48 h). No serious adverse events occurred.

2.3 Measuring Tools, Data Acquisition and Statistical Analysis

The Generalized Anxiety Scale (GAD-7, 7 items, 0–21 points, ≥ 5 indicating mild anxiety) and the anxiety subscale of the Hospital Anxiety and Depression Scale (HADS-A, 7 items, 0–21 points, ≥ 8 indicating clinical anxiety) were used for anxiety assessment, with Cronbach's $\alpha > 0.85$ for both. Exercise motivation was measured with the Behavioural Regulation in Exercise Questionnaire-3 (BREQ-3), covering five dimensions (amotivation, external, introjected, identified, and intrinsic regulation; four items each, 1–5 Likert scale), and the Relative Autonomy Index (RAI) was computed to capture overall motivation quality [20]. Exercise-behaviour indicators included weekly frequency, single-session duration, and total weekly MET-minutes across 12 weeks (3.5 METs for brisk walking, 7.0 METs for jogging, 5.0 METs for resistance training). Course adherence was the actual attendance rate. Teaching quality was further assessed using a satisfaction questionnaire (1–5), the short flow experience scale (9 items), and physical-capacity tests (6-minute walk, 30-second sit-to-stand) [21].

Data were collected at baseline (T0), week 4 (T1), week 8 (T2), week 12 (T3), and a 16-week follow-up (T4). All scales were administered by independent blinded assessors. Data quality control included double entry, logical verification, and 10% sample recheck. Descriptive statistics are reported as mean $\pm$ standard deviation or frequency percentage. Baseline equivalence was examined with independent-sample t-tests and chi-square tests. The primary analysis followed a per-protocol framework, including the 71 participants who completed all five assessment points (T0–T4); the comparability of attrition between arms is reported in Section 3.1 and the implications of this analytic choice are addressed in Section 4. A 2 (group) $\times$ 5 (time) repeated-measures analysis of variance was used for the main analysis, focusing on the group, time, and group $\times$ time effects. Mauchly's test was used to examine sphericity, with Greenhouse–Geisser correction applied when violated; when the interaction was significant, simple-effects analyses were conducted with Bonferroni-corrected post-hoc comparisons. Effect sizes were reported as Cohen's d and partial η^2 . Mediation effects were examined with bias-corrected bootstrap resampling (5 000 replicates). The significance level was $\alpha = 0.05$ (two-sided). SPSS 27.0 and Mplus 8.0 were used.

3. Results

3.1 Subject Process and Baseline Characteristics

A total of 107 cancer survivors were screened during the study period; 27 were excluded for not meeting the inclusion criteria (12 below-threshold anxiety scores, 10 exercise contraindications, 5 refusals). Finally, 80 subjects were randomly assigned and entered the intervention phase. During intervention, 4 subjects dropped out of the AI intervention group (2 personal reasons, 1 disease recurrence, 1 relocation), and 5 dropped out of the control group (3 personal reasons, 1 disease recurrence, 1 loss of contact). Ultimately, 71 subjects completed the study and were included in the analysis (36 in the AI intervention group, 35 in the control group), with an overall dropout rate of 11.3%. Dropout rates did not differ between arms (AI 10.0% vs control 12.5%; $\chi^2 = 0.12$, $P = 0.73$), and dropout reasons were comparably distributed, supporting the per-protocol analytic framework. The complete process of recruitment and follow-up is shown in **Figure 1**.

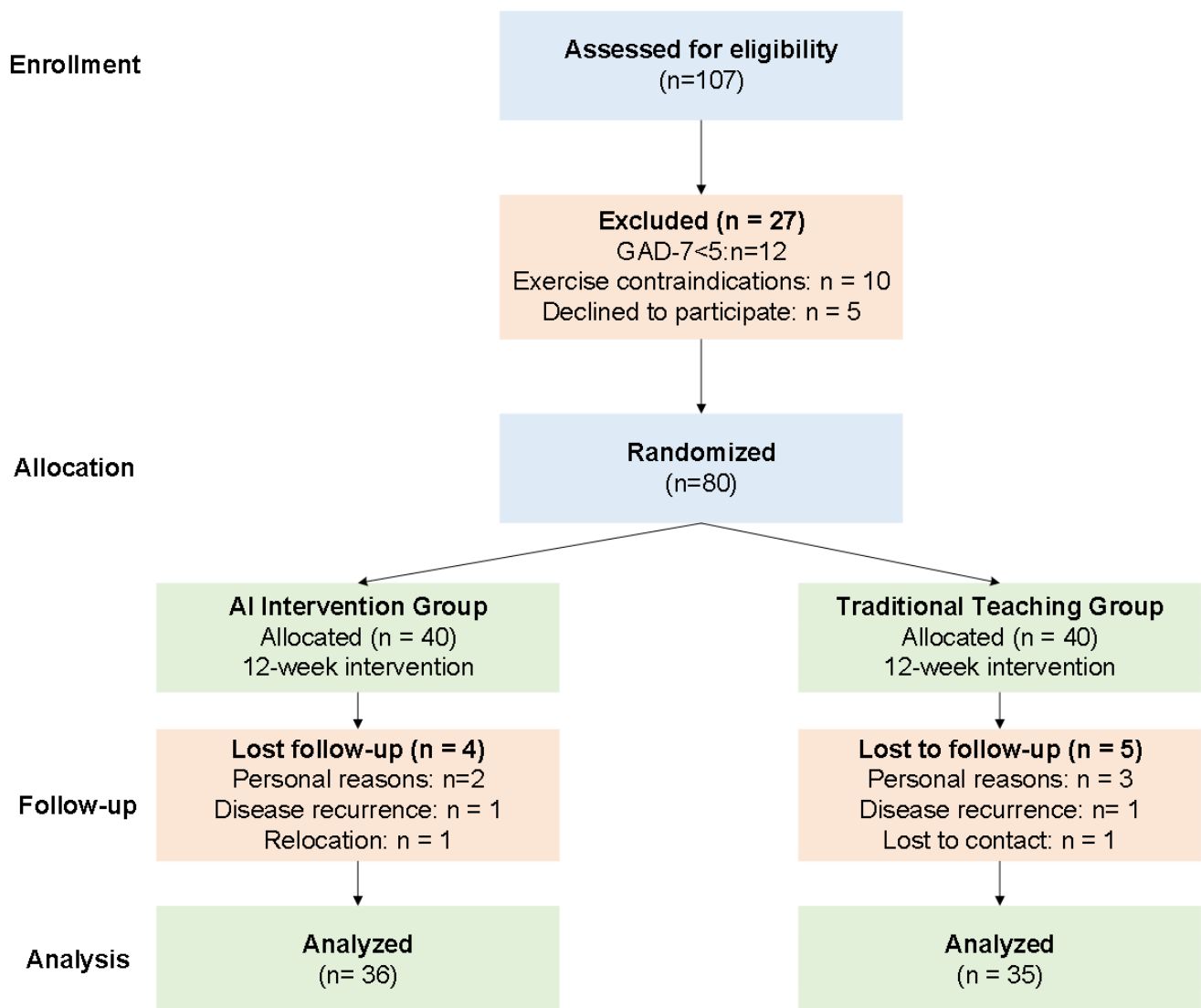


Figure 1. CONSORT Subject Flowchart

Figure 1 illustrates the flow of all subjects from screening through the final analysis. The dropout rate was almost evenly distributed between the two groups and

did not have a significant impact on the internal validity of the study.

The baseline characteristics of the two groups are compared in **Table 1**. No significant between-group differences were observed in age, sex, cancer type, time since treatment completion, baseline anxiety (GAD-7, HADS-A), or baseline motivation dimensions (all $P > 0.05$), indicating that random allocation effectively balanced baseline characteristics.

Table 1. Baseline Characteristics and Between-Group Comparisons.

Characteristic	AI Intervention Group ($n = 36$)	Traditional Teaching Group ($n = 35$)	Test Statistic	P -value
Demographic Characteristics				
Age (years), $M \pm SD$	52.3 $\pm$ 8.6	53.1 $\pm$ 9.2	$t = 0.38$	0.71
Female, n (%)	25 (69.4)	25 (71.4)	$\chi^2 = 0.03$	0.86
Cancer type, n (%)			$X^2 = 0.31$	0.96
Breast cancer	14 (39)	13 (37)		
Lung cancer	8 (22)	9 (26)		
Gastrointestinal cancer	8 (22)	7 (20)		
Other	6 (17)	6 (17)		
Time since treatment completion (months), $M \pm SD$	18.5 $\pm$ 12.3	19.2 $\pm$ 13.1	$t = 0.24$	0.81
Baseline Anxiety				
GAD-7 score, $M \pm SD$	9.8 $\pm$ 3.2	9.6 $\pm$ 3.4	$t = 0.27$	0.79
HADS-A score, $M \pm SD$	10.2 $\pm$ 2.8	9.9 $\pm$ 3.1	$t = 0.42$	0.68
Baseline Exercise Motivation				
Intrinsic regulation, $M \pm SD$	2.8 $\pm$ 0.9	2.7 $\pm$ 0.8	$t = 0.50$	0.62
Identified regulation, $M \pm SD$	3.2 $\pm$ 0.8	3.1 $\pm$ 0.9	$t = 0.56$	0.58
Relative Autonomy Index (RAI), $M \pm SD$	-1.3 $\pm$ 3.2	-1.5 $\pm$ 3.0	$t = 0.28$	0.78

3.2 Evaluation of the Operational Effectiveness and Teaching Quality of the AI Teaching System

The assessment of system performance and teaching quality is shown in **Table 2**. The overall system uptime reached 98.7% with a mean response latency of 1.8 s, and multimodal emotion recognition accuracy was 91.4% under LOSO validation (see Section 2.2.4). The detection rate of high-anxiety states fell from 32.1% in the first four weeks to 14.8% in the last four weeks, while the detection rate of positive emotional states rose from 18.3% to 41.6%. An average of 6.8 feedback events occurred per session. For teaching quality, course adherence in the AI intervention group ($89.7 \pm 8.3\%$) was significantly higher than in the control group ($82.3 \pm 12.6\%$) ($t = 3.15$, $P = 0.002$, $d = 0.70$). Teaching satisfaction (4.6 ± 0.4 vs 3.9 ± 0.6 , $t = 6.24$, $P < 0.001$, $d = 1.38$) and flow experience (3.8 ± 0.5 vs 3.2 ± 0.6 , $t = 4.92$, $P < 0.001$, $d = 1.09$) favoured the AI intervention group, as did the 6-minute walking distance gain (82.5 ± 23.4 vs 58.3 ± 28.7 m, $t = 4.21$, $P = 0.001$).

Table 2. AI Teaching System Performance Indicators and Teaching Quality Assessment.

Indicator	AI Intervention Group (<i>n</i> = 36)	Traditional Teaching Group (<i>n</i> = 35)	Test Statistic	<i>P</i> -value
System Performance				
System uptime rate (%)	98.7	-	-	-
Average response latency (seconds)	1.8	-	-	-
Multimodal emotion recognition accuracy (%)	91.4	-	-	-
Emotion Monitoring Results				
High anxiety detection rate - Early phase (%)	32.1	-	-	-
High anxiety detection rate - Late phase (%)	14.8	-	-	-
Positive emotion detection rate - Early phase (%)	18.3	-	-	-
Positive emotion detection rate - Late phase (%)	41.6	-	-	-
Personalized Feedback				
Average feedback triggers per session, M±SD	6.8±2.1	-	-	-
Feedback type distribution				
Exercise intensity adjustment (%)	42	-	-	-
Verbal encouragement (%)	31	-	-	-
Music/environment adjustment (%)	15	-	-	-
Goal resetting dialogue (%)	12	-	-	-
Teaching Quality Assessment				
Course attendance rate (%), M±SD	89.7±8.3	82.3±12.6	<i>t</i> = 3.15	0.002
Teaching satisfaction score (1-5), M±SD	4.6±0.4	3.9±0.6	<i>t</i> = 6.24	< 0.001
Flow experience score (1-5), M±SD	3.8±0.5	3.2±0.6	<i>t</i> = 4.92	< 0.001
6-minute walking distance gain (meters), M±SD	82.5±23.4	58.3±28.7	<i>t</i> = 4.21	0.001

3.3 Inter-group Comparative Analysis of Changes in Anxiety Levels

The changing trends of anxiety levels at five time points are shown in **Figure 2**. The GAD-7 score of the AI intervention group decreased continuously from 9.8 ± 3.2 at baseline to 4.0 ± 2.1 at week 12 and remained stable at 4.2 ± 2.3 at follow-up. The control group score fell from 9.6 ± 3.4 to 6.4 ± 2.7 at week 12, with a slight rebound to 6.7 ± 2.9 at follow-up. HADS-A showed a similar pattern (AI intervention $10.2 \pm 2.8 \rightarrow 5.3 \pm 2.4$; control $9.9 \pm 3.1 \rightarrow 7.1 \pm 2.8$).

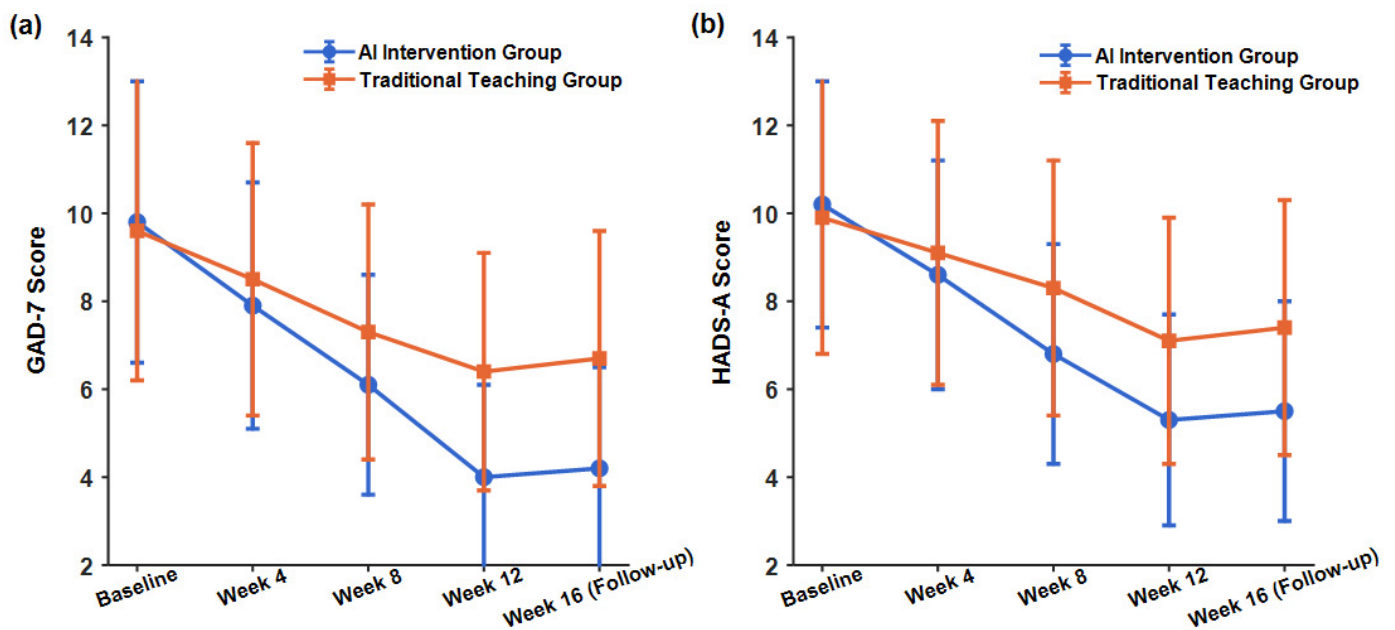


Figure 2. Trend Charts of Anxiety Levels

The repeated-measures ANOVA (**Table 3**) showed significant group main effects (GAD-7: $F = 19.84$, $P < 0.001$, partial $\eta^2 = 0.223$; HADS-A: $F = 16.52$, $P < 0.001$), time main effects (GAD-7: $F = 48.72$; HADS-A: $F = 41.35$; both $P < 0.001$), and group $\times$ time interaction effects (GAD-7: $F = 9.38$, partial $\eta^2 = 0.120$; HADS-A: $F = 7.89$, partial $\eta^2 = 0.103$; both $P < 0.001$). Post-hoc comparisons showed a GAD-7 reduction of 5.8 points (95% CI 4.9–6.7, $d = 1.68$) in the AI intervention group versus 3.2 points (95% CI 2.3–4.1, $d = 0.93$) in the control group, with a between-group d of 0.96 at T3. Clinically, 63.9% of the AI intervention group reached clinically meaningful improvement versus 37.1% of controls ($\chi^2 = 5.08$, $P = 0.024$), corresponding to a number-needed-to-treat of 3.7.

Table 3. Repeated Measures ANOVA Results for Anxiety Levels.

Source of Variance	Measure	F	df	P -value	Partial η^2
Main Effects and Interaction					
Group	GAD-7	19.84	1, 69	< 0.001	0.223
	HADS-A	16.52	1, 69	< 0.001	0.217
Time	GAD-7	48.72	4, 276	< 0.001	0.414
	HADS-A	41.35	4, 276	< 0.001	0.375
Group $\times$ Time	GAD-7	9.38	4, 276	< 0.001	0.120
	HADS-A	7.89	4, 276	< 0.001	0.103
Pairwise Comparisons (T3 vs T0)					
AI Intervention Group	Comparison	Mean Difference	95% CI	P -value	Cohen's d
	GAD-7	-5.8	[-6.7, -4.9]	< 0.001	1.68
Traditional Teaching Group	HADS-A	-4.9	[-5.9, -3.9]	< 0.001	1.52
	GAD-7	-3.2	[-4.1, -2.3]	< 0.001	0.93
	HADS-A	-2.8	[-3.7, -1.9]	< 0.001	0.85

Continuation Table:

Source of Variance	Measure	<i>F</i>	df	<i>P</i> -value	Partial η^2
Between-Group Difference at T3		Effect Size (Cohen's <i>d</i>)	95% CI	<i>P</i> -value	
GAD-7		0.96	[0.47, 1.45]	< 0.001	
HADS-A		0.89	[0.41, 1.37]	< 0.001	

3.4 Inter-group Comparative Analysis of Changes in Exercise Motivation

The variation patterns of exercise-motivation dimensions are shown in **Figure 3**. Intrinsic regulation rose from 2.8 ± 0.9 to 4.3 ± 0.7 in the AI intervention group (+1.5) and from 2.7 ± 0.8 to 3.4 ± 0.8 in the control group (+0.7); the group $\times$ time interaction was significant ($F = 12.65$, $P < 0.001$). Identified regulation rose from 3.2 ± 0.8 to 4.4 ± 0.6 versus 3.1 ± 0.9 to 3.8 ± 0.8 ($F = 8.42$, $P < 0.001$). External regulation and amotivation declined in both groups, more markedly in the AI intervention group ($F = 6.21$ and 10.53 ; both $P < 0.01$). The Relative Autonomy Index rose by 5.8 in the AI intervention group and by 3.1 in the control group, with a between-group *d* of 1.03 at T3. By week 12, 72.2% of the AI intervention group was classified as intrinsic-motivation-dominated versus 48.6% of controls ($\chi^2 = 4.21$, $P = 0.040$). During follow-up, the AI intervention group's RAI remained stable (4.2 ± 2.9 ; $P = 0.64$ vs T3) whereas the control group's declined to 1.2 ± 3.1 ($P = 0.03$ vs T3).

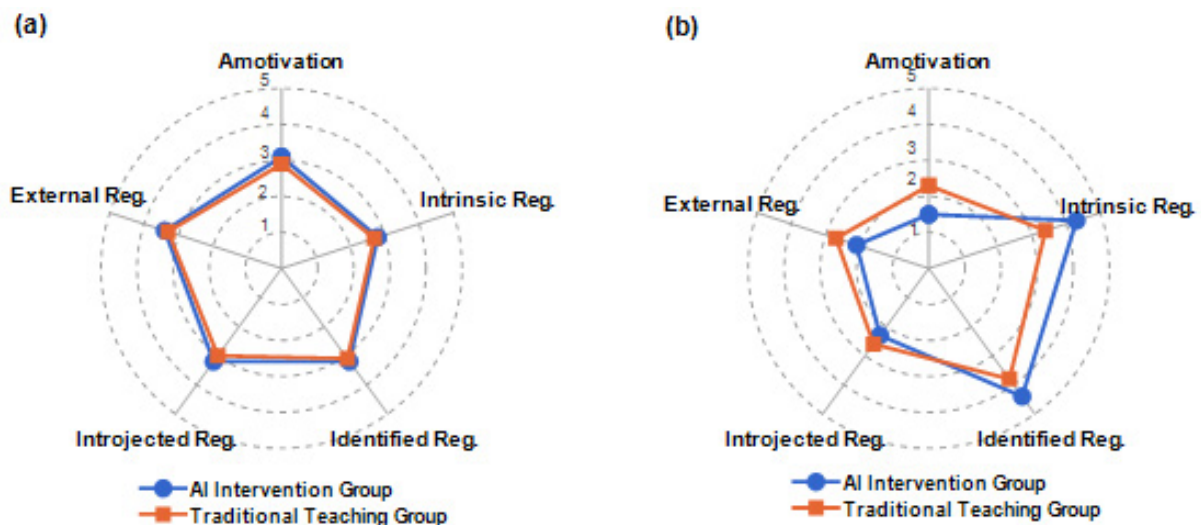


Figure 3. Radar Chart of Motivation Dimensions

Table 4. Repeated Measures ANOVA Results for Exercise Motivation and Between-Group Comparisons.

Variable/Comparison	Source/Group	<i>F</i> /Mean Change	df/95% CI	<i>P</i> -value	Partial η^2 /Cohen's <i>d</i>
Intrinsic Regulation					
ANOVA	Group	16.74	1, 69	< 0.001	0.195
	Time	38.29	4, 276	< 0.001	0.357
	Group $\times$ Time	12.65	4, 276	< 0.001	0.155
Change (T3-T0)	AI Intervention	+1.5	[1.1, 1.9]	< 0.001	1.82
	Traditional Teaching	+0.7	[0.3, 1.1]	0.002	0.84

Continuation Table:					
Variable/Comparison	Source/Group	<i>F</i> /Mean Change	df/95% CI	<i>P</i> -value	Partial η^2 /Cohen's <i>d</i>
Identified Regulation					
	Between-group at T3	-	-	< 0.001	1.18
ANOVA	Group	14.38	1, 69	< 0.001	0.172
	Time	42.17	4, 276	< 0.001	0.379
	Group $\times$ Time	8.42	4, 276	< 0.001	0.109
External Regulation					
ANOVA	Group	9.63	1, 69	0.003	0.122
	Time	24.51	4, 276	< 0.001	0.262
	Group $\times$ Time	6.21	4, 276	0.001	0.083
Amotivation					
ANOVA	Group	12.85	1, 69	< 0.001	0.157
	Time	31.46	4, 276	< 0.001	0.313
	Group $\times$ Time	10.53	4, 276	< 0.001	0.132
Relative Autonomy Index (RAI)					
ANOVA	Group	21.47	1, 69	< 0.001	0.237
	Time	56.93	4, 276	< 0.001	0.452
	Group $\times$ Time	15.28	4, 276	< 0.001	0.181
Change (T3-T0)	AI Intervention	+5.8	[4.6, 7.0]	< 0.001	1.91
	Traditional Teaching	+3.1	[1.9, 4.3]	< 0.001	1.02
	Between-group at T3	-	-	< 0.001	1.03
Overall Motivation Quality					
ANOVA	Group	18.36	1, 69	< 0.001	0.210
	Time	52.47	4, 276	< 0.001	0.432
	Group $\times$ Time	11.92	4, 276	< 0.001	0.147

3.5 Exploratory Path Analysis Linking AI Exposure, Motivation, Exercise Behaviour, and Anxiety

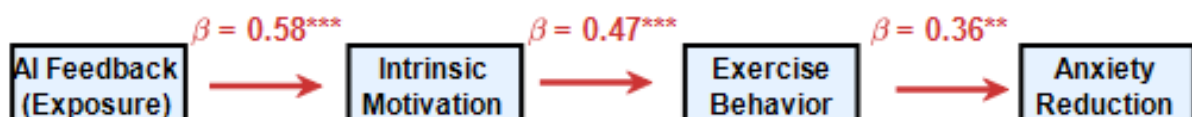
Given the modest completed sample ($n = 71$) and the overlapping measurement windows across mediators and outcome, the following path analysis is presented as exploratory rather than confirmatory. Pearson correlation analysis (**Table 5**) showed that anxiety reduction was positively associated with increases in intrinsic motivation and RAI ($r = 0.61$ and 0.58 , both $P < 0.001$), intrinsic-motivation increase was associated with exercise frequency and course adherence ($r = 0.52$ and 0.64 , both $P < 0.001$), and exercise frequency was associated with anxiety reduction ($r = 0.48$, $P < 0.001$). In a bias-corrected bootstrap mediation test, the total effect of AI feedback on anxiety improvement was compatible with a mediated pathway ($\beta = 0.52$, $P < 0.001$),

decomposed into a direct effect ($\beta = 0.31$, $P = 0.008$) and an indirect effect through RAI ($\beta = 0.21$, 95% CI 0.08–0.37), with the indirect component accounting for 40.4% of the total effect. The chain indirect effect through intrinsic motivation and exercise behaviour was also significant ($\beta = 0.10$, 95% CI 0.03–0.19).

Table 5. Correlation Analysis and Mediation Effect Test Results.

Analysis Type	Variable Relationship	Coefficient	95% CI	P-value
Pearson Correlations		<i>r</i>		
	Anxiety reduction ↔ Intrinsic motivation increase	0.61	[0.46, 0.73]	< 0.001
	Anxiety reduction ↔ RAI increase	0.58	[0.42, 0.71]	< 0.001
	Intrinsic motivation ↔ Exercise frequency increase	0.52	[0.35, 0.66]	< 0.001
	Intrinsic motivation ↔ Course adherence	0.64	[0.49, 0.75]	< 0.001
	Exercise frequency ↔ Anxiety reduction	0.48	[0.30, 0.63]	< 0.001
Mediation Effect Analysis		β		
Total Effect	AI feedback → Anxiety reduction	0.52	[0.31, 0.73]	< 0.001
Direct Effect	AI feedback → Anxiety reduction (controlling mediator)	0.31	[0.09, 0.53]	0.008
Indirect Effect	AI feedback → RAI → Anxiety reduction	0.21	[0.08, 0.37]	-
Mediation Proportion	Indirect/Total effect	40.4%	-	-
Chain Mediation Effect		β		
	AI feedback → Intrinsic motivation → Exercise behavior → Anxiety reduction	0.10	[0.03, 0.19]	-

The structural equation model (**Figure 4**) showed acceptable fit ($\chi^2/\text{df} = 1.82$, CFI = 0.96, TLI = 0.94, RMSEA = 0.054, SRMR = 0.052). Path estimates indicated that AI feedback was positively associated with intrinsic motivation ($\beta = 0.58$, $P < 0.001$), which in turn was positively associated with exercise frequency ($\beta = 0.47$, $P < 0.001$), and exercise frequency was positively associated with anxiety improvement ($\beta = 0.36$, $P = 0.002$). Because motivation, behaviour, and anxiety were measured within the same intervention window, the model is compatible with the hypothesized pathway but does not establish temporal precedence; this is discussed further in Section 4.



Model Fit Indices:

$\chi^2/\text{df} = 1.82$ CFI = 0.96 TLI = 0.94 RMSEA = 0.054

*** $P < 0.001$, ** $P < 0.01$

Figure 4. Anxiety–Motivation–Behaviour Path Structural Equation Model

4. Discussion

This randomized controlled trial suggests that the AI emotion recognition feedback teaching system offers advantages over traditional physical education in improving anxiety levels among cancer survivors. The within-group effect size in the AI intervention group (Cohen's $d = 1.68$) exceeded pooled estimates from meta-analyses of traditional exercise interventions ($d \approx 0.5\text{--}0.8$), a magnitude that should be interpreted with caution (see below). This finding resonates with recent evidence on wearable-device emotion recognition, where personalized approaches outperform generalized ones in accuracy and user acceptance [22], and real-time physiological stress prediction can support timely mental-health intervention [23]. The multimodal fusion strategy integrating facial, voice, and heart-rate data reached 91.4% accuracy, in line with recent deep-learning frameworks for multimodal physiological emotion recognition [24].

Several factors may have inflated the observed effect sizes and should temper their interpretation: (i) single-centre recruitment with relatively homogeneous motivation to enrol in a technology-assisted trial; (ii) reliance on self-report anxiety instruments in an unblinded behavioural context, which may introduce expectancy effects; (iii) a per-protocol rather than intention-to-treat framework; (iv) relatively high baseline anxiety, leaving ample room for regression to the mean; and (v) the bundled nature of the intervention, described below. These magnitudes should therefore be treated as upper-bound estimates pending independent replication.

The accelerated improvement in the AI intervention group likely reflects the high-frequency emotional assessment and dynamic adjustment triggered every 5 minutes, which compensates for the limited capacity of instructors to track each trainee's affective fluctuations in real time. The effect of emotion-regulation strategies on learning and mental health has been documented in educational settings [25], and wearable-device emotion datasets provide a technical basis for context-sensitive systems [26]. In the present study, high-anxiety detection fell from 32.1% in the early phase to 14.8% in the later phase, while positive-emotion detection rose from 18.3% to 41.6%, a bidirectional pattern consistent with the "early identification – timely intervention – capacity cultivation" loop described in emotion-regulation theory.

The dynamic $\pm 10\text{--}20\%$ intensity modulation aims to keep participants within their zone of proximal development, aligned with the basic-psychological-need satisfaction emphasized by self-determination theory [27]. Systematic reviews of mobile-health interventions further support that personalized feedback mechanisms can enhance the practicality and effectiveness of interventions [28]. The observed adherence (89.7% vs 82.3%) and flow experience (3.8 vs 3.2) are compatible with the hypothesis that technical systems can contribute to the satisfaction of psychological needs, complementing rather than replacing interpersonal interaction.

Empirical research in digital health supports the applicability of this model among special populations. Intelligent digital interventions for hypertension have been shown to enhance self-management behaviour [29], and community-embedded structured exercise programmes can support long-term adherence among cancer survivors [30]. During follow-up, the AI intervention group's anxiety levels and exercise motivation remained stable while the control group showed a slight rebound, suggesting greater durability of the patterns fostered by the AI-assisted programme, although this pattern requires replication in longer follow-up windows.

Integrated applications of AI across education and health show broad prospects. Adaptive intelligent tutoring systems and AI-driven tutoring in K-12 education have

been linked to improved learning outcomes [31, 32], while post-pandemic mobile health shows two-way integration of smartphones and wearables [33] and requires attention to digital-health readiness for inclusive deployment [34, 35]. Among our participants, 91.7% reported that the system helped alleviate their anxiety and 94.4% indicated willingness to continue using it. The “people-oriented” design positioning the AI as an assistant to human coaches, rather than a replacement, is consistent with the balance between innovation and practicality emphasized in recent reviews [35]. Recent work on multimodal emotional AI further highlights both the technical maturation of fusion-based recognition and its translational potential in healthcare contexts [7, 8, 22–26]. These developments converge with the present system's integration of facial, voice, and physiological streams, and position the observed recognition performance within a broader literature rather than as an isolated technical result.

Several limitations must be acknowledged. First, the single-centre design and modest final sample ($n = 71$) limit generalizability, and within-group effect sizes should be regarded as upper-bound estimates pending multi-centre replication. Second, the 16-week follow-up is short relative to the chronic course of post-cancer anxiety. Third, primary outcomes relied on self-report instruments in an unblinded behavioural context, which may amplify expectancy effects. Fourth, the AI arm combined real-time emotion monitoring, adaptive intensity modulation, high-frequency reinforcement, achievement feedback, and autonomy-supportive language; the present design therefore cannot disentangle which component, or which combination, causally drives the observed benefits, and factorial dismantling trials are needed. Fifth, the analysis used a per-protocol rather than intention-to-treat framework; although attrition was balanced across arms (10.0% vs 12.5%), this choice may favour the observed effects. Sixth, the structural equation model should be interpreted as exploratory: the sample is below conventional recommendations for chain-mediation SEM, and because motivation, exercise behaviour, and anxiety were all measured within the same intervention window, temporal precedence of the mediators was not established; cross-lagged designs with staggered measurement are needed for causal mediation claims. Finally, this trial was not registered in any public registry, either prospectively or retrospectively; this falls short of current CONSORT best practice, and the planned multi-centre replication will incorporate prospective registration as a non-negotiable requirement.

5. Conclusion

This randomized controlled trial provides preliminary evidence that a multi-component AI-assisted physical education package, integrating emotion recognition with adaptive feedback, is associated with greater anxiety reduction and a clearer shift toward autonomous motivation among cancer survivors than a matched traditional teaching condition. Specifically, GAD-7 scores decreased by an average of 5.8 points (effect size $d = 1.68$) in the AI intervention group, 63.9% reached clinically meaningful improvement, the Relative Autonomy Index rose by 5.8 points, and 72.2% transformed into an intrinsic-motivation-dominated profile. Exploratory structural equation modelling was compatible with an “AI feedback → intrinsic motivation → exercise behaviour → anxiety improvement” pathway, with intrinsic motivation accounting for 40.4% of the total effect.

Given the single-centre design, the bundled nature of the intervention, the modest completed sample, and the absence of prospective trial registration, these findings

should be regarded as preliminary and require replication in multi-centre trials with larger samples, longer follow-up, factorial dismantling, and active comparators (for example, matched-frequency human feedback without emotion recognition) before firm conclusions about clinical deployment can be drawn. Pending such validation, the intervention model may inform the design of emotion-aware teaching approaches for related clinical populations.

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