

Review

Personalized home exercise interventions for cancer survivors: A systematic review and network meta-analysis

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Abstract: Background: Cancer survivors experience significant fatigue, depression, and reduced quality of life during and after treatment. While physical activity benefits are established, optimal delivery methods remain unclear. **Aims:** This systematic review and network meta-analysis evaluated home-based personalized exercise interventions' effects on fatigue, depression, and quality of life in cancer survivors. **Methods:** Comprehensive searches of nine databases identified randomized controlled trials (January 2000–October 2023) investigating home-based personalized exercise interventions for adult cancer survivors. Traditional pairwise meta-analyses and network meta-analyses within Bayesian frameworks were conducted. **Results:** Thirty-two trials ($n = 4152$) were analyzed. Home-based exercise demonstrated significant beneficial effects on fatigue ($SMD = -0.38$), depression ($SMD = -0.32$), and quality of life ($SMD = 0.45$). Network meta-analysis revealed multimodal interventions were most effective for fatigue (Surface Under the Cumulative Ranking curve, $SUCRA = 0.88$) and depression ($SUCRA = 0.82$), while telehealth showed greatest quality of life benefits ($SUCRA = 0.86$). Meta-regression identified optimal characteristics: 8–12 week duration, multimodal exercise, and algorithmic personalization. **Conclusions:** Home-based personalized exercise interventions offer effective, accessible strategies for improving cancer survivorship outcomes, with technology-delivered multimodal interventions showing particular promise.

Keywords: cancer survivors; exercise; home-based intervention; fatigue; depression; quality of life; network meta-analysis; telehealth; personalized medicine; rehabilitation

1. Introduction

Cancer survivorship represents a significant global public health concern, with survivors facing numerous physical and psychological challenges post-treatment. These challenges include cancer-related fatigue, depression, and decreased quality of life, which can persist for years after treatment completion [1,2]. The prevalence of these symptoms is alarmingly high: cancer-related fatigue affects 60%–96% of patients during active treatment and persists in 30%–50% of survivors for months or even years after treatment completion. Depression occurs in approximately 15%–25% of cancer survivors, significantly exceeding the 5%–7% prevalence observed in the general population. Quality of life impairments span multiple domains including physical functioning, emotional well-being, social relationships, and cognitive abilities. These persistent symptoms create a cascade of negative consequences, including reduced work productivity, increased healthcare costs, diminished social participation, and potentially elevated risk of cancer recurrence. The economic burden is substantial, with cancer-related fatigue alone estimated to cost billions annually in lost productivity and healthcare expenditures. Moreover, the psychological distress associated with survivorship can perpetuate a vicious cycle of physical inactivity,

social isolation, and worsening symptoms, underscoring the urgent need for effective, sustainable interventions. As cancer treatments continue to improve and survivor numbers increase, effective interventions are urgently needed to address these persistent adverse effects.

Physical activity has emerged as a promising non-pharmacological intervention for cancer survivors, with substantial evidence supporting its beneficial effects on various health outcomes [3,4]. Regular physical activity reduces fatigue, improves psychological well-being, enhances physical function, and potentially reduces cancer recurrence risk [5,6]. The biological mechanisms are increasingly well-characterized: exercise modulates inflammatory cytokines implicated in fatigue pathogenesis, enhances mitochondrial biogenesis counteracting treatment-induced cellular damage, and stimulates brain-derived neurotrophic factor expression potentially mitigating chemotherapy-associated cognitive impairment. Clinical guidelines now recommend survivors engage in 150 minutes weekly of moderate-intensity aerobic activity plus twice-weekly resistance training. However, adherence to physical activity guidelines remains suboptimal among cancer survivors due to barriers including treatment side effects, lack of motivation, inadequate facility access, and insufficient professional guidance [7,8]. Studies indicate only 20%–30% of survivors meet recommended activity levels. Barriers are multifaceted: treatment-related side effects, psychological factors including fear of injury, logistical challenges including transportation difficulties, financial constraints, and insufficient healthcare provider guidance. Rural populations and mobility-impaired individuals face disproportionate challenges accessing traditional supervised programs, highlighting critical gaps between evidence-based recommendations and real-world implementation. Home-based personalized exercise interventions offer innovative solutions by providing tailored programs performed at home, potentially increasing accessibility and adherence [9]. These interventions have evolved with technological advancements, incorporating telehealth systems, mobile applications, and web-based platforms [10,11]. Home-based interventions overcome traditional barriers by eliminating travel requirements, enhancing accessibility for rural survivors and those with mobility limitations. Technological integration enables real-time monitoring, automated feedback, social support through online communities, and adaptive algorithms adjusting prescriptions based on individual progress. Telehealth platforms facilitate remote professional supervision, combining expert guidance with home-based convenience. Recent studies have explored various modalities including aerobic training, resistance exercises, and mind-body practices [12,13].

However, considerable heterogeneity in intervention design and implementation strategies makes definitive conclusions challenging [14]. Critical questions remain unanswered regarding comparative effectiveness of different delivery modalities, optimal personalization methods balancing effectiveness with scalability, superior exercise modalities for specific outcomes, and ideal intervention duration. Additionally, whether effects persist post-intervention or require ongoing support remains unclear. These knowledge gaps limit clinicians' ability to recommend specific programs and hinder evidence-based implementation strategies. This meta-analysis comprehensively evaluates home-based personalized exercise interventions' effects on cancer survivors' fatigue, depression, and quality of life, identifying optimal intervention characteristics and providing evidence-based guidance for clinical implementation. Both traditional pairwise meta-analysis and network meta-analysis were employed to establish overall efficacy and enable simultaneous comparison of

different intervention types through direct and indirect evidence integration. This dual approach determines not only whether these interventions work, but identifies which specific characteristics, delivery modalities, and personalization strategies optimize effectiveness for different outcomes.

2. Methods

2.1. Study protocol and registration

This meta-analysis followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines with prospective protocol registration in International Prospective Register of Systematic Reviews (PROSPERO) (CRD42023148742) to enhance transparency and minimize reporting bias. The methodological approach incorporated Cochrane Handbook recommendations, detailing research questions, search strategy, inclusion criteria, data extraction procedures, quality assessment methods, and analytical plan. Any protocol deviations were documented and justified to maintain methodological rigor.

The decision to register the protocol prospectively in PROSPERO was driven by the need to enhance transparency and reduce the risk of selective outcome reporting and post-hoc protocol modifications. The registration process involved detailed specification of all methodological decisions before data extraction commenced, including primary and secondary outcomes, planned subgroup analyses, and sensitivity analysis strategies. This a priori approach minimizes the potential for data-driven decision making and selective reporting bias that can compromise meta-analytic validity.

2.2. Eligibility criteria

Eligible studies were randomized controlled trials (January 2000–October 2023) involving adult cancer survivors (≥ 18 years) post-treatment or receiving adjuvant therapy. Interventions included home-based personalized exercise programs delivered via telehealth, mobile applications, web-based platforms, printed materials, or telephone coaching. Studies reported validated fatigue, depression, or quality of life outcomes with appropriate controls. Hospitalized patients, facility-based interventions, and non-randomized designs were excluded.

The eligibility criteria were deliberately broad regarding cancer types and treatment stages to maximize generalizability while maintaining internal validity through rigorous study design requirements. The inclusion of both post-treatment survivors and those receiving adjuvant therapy reflects the clinical reality that exercise interventions may be implemented across the cancer care continuum. The requirement for validated outcome measures ensured that included studies employed psychometrically sound instruments with established reliability and validity, enhancing confidence in pooled effect estimates.

2.3. Information sources

A comprehensive literature search was conducted across multiple databases including PubMed/MEDLINE, Embase, Cochrane CENTRAL, Web of Science, CINAHL, PsycINFO, SPORTDiscus, and Chinese databases (CNKI, Wanfang Data, VIP Information) from January 2000 to October 2023. Reference lists were manually screened, clinical trial registries searched, and study authors contacted when additional information was required.

The multi-database search strategy was designed to minimize retrieval bias and maximize sensitivity. Different databases index distinct journal collections and

employ varied controlled vocabularies, necessitating a comprehensive approach. The inclusion of Chinese databases specifically addressed potential language bias, as non-English publications may report different findings or populations than English-language literature. Clinical trial registries were searched to identify completed but unpublished studies, addressing publication bias concerns.

2.4. Search strategy

The search strategy was developed with an experienced medical librarian, using MeSH terms and free-text keywords for population (cancer survivors), intervention (exercise, physical activity), delivery method (home-based, telehealth, mobile applications), and study design (randomized controlled trials). Boolean operators and truncation symbols optimized sensitivity and specificity. The strategy was adapted for each database with appropriate syntax modifications.

Search strategy development involved iterative refinement through pilot searches and consultation with content experts. MeSH terms were exploded to capture all relevant subcategories (e.g., “Neoplasms” including all specific cancer types). Free-text keywords captured terminology variations and emerging terms not yet incorporated into controlled vocabularies. The combination of MeSH terms and keywords using Boolean operators maximized both sensitivity (retrieving all relevant studies) and specificity (minimizing irrelevant retrievals). Truncation symbols enabled capture of word variations (e.g., “exercis*” retrieving exercise, exercises, exercising).

2.5. Study selection

Study selection involved two independent reviewers across two stages. Citations were imported into EndNote X9 for deduplication, then screened using Covidence against eligibility criteria. Full-text articles were independently assessed for inclusion. Discrepancies were resolved through discussion or third-reviewer adjudication. Cohen’s kappa assessed inter-reviewer agreement. The process was documented in a PRISMA flow diagram ensuring comprehensive, unbiased selection.

The two-stage screening process with independent dual review represents best practice in systematic review methodology, reducing the risk of erroneously excluding relevant studies. Title and abstract screening employed liberal inclusion criteria to minimize false negatives at this initial stage. Full-text assessment applied strict eligibility criteria with detailed documentation of exclusion reasons. The use of Covidence software facilitated efficient screening workflow, automatic deduplication, and transparent documentation of screening decisions for audit trails.

2.6. Data collection process

Data extraction was performed by two independent reviewers using a standardized electronic form pilot-tested on ten studies. Disagreements were resolved through discussion or third-reviewer consultation. Inter-rater reliability was calculated using intraclass correlation coefficients. For studies with multiple publications, comprehensive data were extracted avoiding duplicates. Missing data prompted author contact (four-week response, maximum three attempts). This systematic approach ensured accurate, comprehensive data collection while minimizing extraction errors.

2.7. Data items

Data extraction encompassed: (1) publication details; (2) study characteristics (design, sample size, randomization, blinding, follow-up); (3) participant

demographics (age, gender, cancer type/stage, treatment status); (4) intervention characteristics (type, frequency, intensity, duration, delivery method, personalization, supervision, theoretical framework); (5) control conditions; (6) outcome measures and timepoints; (7) adherence/attrition rates; (8) statistical results; (9) adverse events. Multiple intervention arms were extracted separately, prioritizing intention-to-treat data for comprehensive meta-analysis.

The comprehensive data extraction encompassed both intervention characteristics and contextual factors that might moderate intervention effectiveness. Theoretical frameworks were extracted because behavior change theories may enhance intervention design and implementation fidelity. Adherence and attrition data provide critical information about intervention feasibility and acceptability in real-world settings. Adverse event reporting was systematically extracted to assess intervention safety, a crucial consideration for immunocompromised cancer populations. The prioritization of intention-to-treat data over per-protocol analyses preserves randomization benefits and provides more conservative, clinically relevant effect estimates.

2.8. Risk of bias assessment

Risk of bias was assessed using the revised Cochrane Risk of Bias 2 (RoB 2) tool, evaluating five domains: randomization, intervention deviations, missing data, outcome measurement, and selective reporting. Two independent reviewers evaluated each study, resolving disagreements through discussion or third-party consultation. Given participant blinding infeasibility in exercise studies, emphasis was placed on other methodological aspects. Publication bias was assessed using funnel plots and Egger's test when ≥ 10 studies were available.

The Cochrane RoB 2 tool represents a significant advancement over previous risk of bias assessment instruments, employing signaling questions and algorithms to systematically evaluate methodological quality. The tool's focus on outcome-level rather than study-level assessment acknowledges that bias risk may vary across different outcomes within the same study. The acknowledgment that participant blinding is inherently impossible in exercise interventions led to careful evaluation of outcome assessor blinding and objective versus subjective outcome measures as key indicators of bias risk. Publication bias assessment was restricted to meta-analyses with at least ten studies, as funnel plot asymmetry tests lack statistical power with fewer studies and may yield spurious findings.

2.9. Effect size indicator

Standardized mean differences (SMDs) using Hedges' g were calculated as the primary effect size metric to accommodate varied assessment tools. SMDs computed mean change differences between groups divided by pooled standard deviation. When change scores weren't reported, pre-post data were used assuming 0.7 correlation. Primary analysis prioritized immediate post-intervention assessments. Positive values indicated favorable outcomes.

Standardized mean differences were chosen as the effect size metric because included studies employed diverse assessment instruments for fatigue (e.g., FACT-F, BFI, PFS), depression (e.g., CES-D, HADS, BDI), and quality of life (e.g., FACT-G, EORTC QLQ-C30, SF-36), precluding meta-analysis using raw mean differences. Hedges' g applies a correction factor for small sample bias, providing more accurate effect size estimates than Cohen's d in studies with sample sizes below 20 per group. The assumed correlation of 0.7 between pre-test and post-test scores represents

a conservative estimate based on empirical data from longitudinal studies of cancer survivors, with sensitivity analyses examining the impact of varying this assumption.

2.10. Synthesis methods

2.10.1. Traditional meta-analysis methods

Traditional pairwise meta-analyses were conducted using random-effects models based on the DerSimonian and Laird method, accounting for within-study variance and between-study heterogeneity. Heterogeneity was assessed using I^2 statistics (25%, 50%, 75% indicating low, moderate, high heterogeneity) and Chi-squared tests. Substantial heterogeneity was explored through subgroup analyses by cancer type, intervention characteristics, delivery modality, and duration. The effect size (Hedges' g) was calculated using the formula:

$$g = \frac{M_1 - M_2}{SD_{pooled}} \times J \quad (1)$$

where M_1 and M_2 are the means of the intervention and control groups, SD_{pooled} is the pooled standard deviation, and J is a correction factor for small sample bias:

$$J = 1 - \frac{3}{4(n_1 + n_2 - 2) - 1} \quad (2)$$

The pooled standard deviation was calculated as:

$$SD_{pooled} = \sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}} \quad (3)$$

2.10.2. Network meta-analysis specific methods

For the network meta-analysis, a multivariate random-effects model within a Bayesian framework was employed to simultaneously compare different home-based exercise interventions. This approach allowed direct and indirect comparisons while preserving randomization. We constructed network plots, assessed consistency using design-by-treatment interaction and node-splitting approaches, and evaluated transitivity by comparing effect modifiers. Interventions were ranked using Surface Under the Cumulative Ranking curve (SUCRA) values and mean ranks.

Network meta-analysis offers significant advantages over traditional pairwise meta-analysis by simultaneously analyzing all available evidence, including both direct comparisons (head-to-head trials) and indirect comparisons (inferred through common comparators). The Bayesian framework employs Markov chain Monte Carlo methods to estimate posterior probability distributions for treatment effects, providing probabilistic statements about comparative effectiveness. Consistency assessment is critical because network meta-analysis assumes transitivity—that treatment effects are consistent across different trial contexts. Node-splitting analysis evaluates consistency by comparing direct and indirect evidence for each treatment comparison, with substantial disagreement indicating potential transitivity violations that may compromise network validity. The consistency model for the network meta-analysis can be expressed as:

$$\theta_{ijk} = \mu_k + \delta_{i,bk} - \delta_{j,bk} \quad (4)$$

where θ_{ijk} is the relative effect of intervention i versus j for outcome k , μ_k is the outcome-specific mean, $\delta_{i,bk}$ is the effect of intervention i relative to reference treatment b for outcome k , and $\delta_{j,bk}$ is the effect of intervention j relative to reference treatment b for outcome k . The SUCRA value for ranking treatments was calculated as:

$$SUCRA_i = \frac{\sum_{j=1}^{J-1} P_{ij}}{J-1} \times 100\% \quad (5)$$

where P_{ij} is the probability that intervention i is ranked in position j or better, and J is the total number of interventions.

2.11. Meta-regression and sensitivity analyses

Meta-regression analyses explored associations between intervention effects and prespecified study characteristics including duration, exercise modality, supervision intensity, technological components, theoretical framework, and participant demographics. Univariate meta-regression preceded multivariate analysis incorporating significant predictors. Comprehensive sensitivity analyses assessed robustness through: fixed-effect models, leave-one-out analysis, restricting to low-risk studies, varying correlation coefficients, and alternative missing data approaches, determining conclusion stability under different analytical conditions.

Meta-regression extends traditional subgroup analysis by examining continuous moderator variables and controlling for multiple covariates simultaneously. Univariate meta-regression provided initial screening of potential effect modifiers, while multivariate meta-regression controlled for confounding and identified independent predictors of intervention effectiveness. The threshold for statistical significance in meta-regression was set at $p < 0.10$ rather than $p < 0.05$, reflecting the reduced statistical power of meta-regression analyses with limited numbers of studies. Sensitivity analyses employed multiple complementary approaches: fixed-effect models tested whether conclusions were robust to heterogeneity assumptions; leave-one-out analysis identified influential studies; restriction to low-risk studies assessed whether bias might explain observed effects; and alternative imputation methods for missing data examined the impact of methodological assumptions on conclusions.

2.12. Evidence certainty assessment

Evidence certainty was evaluated using the Grading of Recommendations Assessment, Development and Evaluation (GRADE) approach, considering risk of bias, inconsistency, indirectness, imprecision, and publication bias. Standard GRADE methodology was applied for traditional meta-analysis, while GRADE extension was used for network meta-analysis. Evidence was categorized as high, moderate, low, or very low certainty, with downgrades for significant limitations. Summary of Findings tables presented effect estimates, certainty ratings, and rating explanations, providing transparency for clinical practice interpretation.

GRADE methodology provides a structured, transparent approach to assessing evidence certainty, moving beyond simplistic quality checklists to comprehensive evaluation of factors that may reduce confidence in effect estimates. The assessment considers not only study-level risk of bias but also consistency of findings across studies, directness of evidence to the population and outcomes of interest, precision of effect estimates (confidence interval width), and potential publication bias. For network meta-analysis, additional considerations include intransitivity (differences in effect modifiers across comparisons) and incoherence (disagreement between direct and indirect evidence). The categorization into four certainty levels (high, moderate, low, very low) reflects the degree of

confidence that true effects lie close to estimated effects, directly informing clinical recommendation strength.

2.13. Statistical software

Statistical analyses were performed using specialized software packages. Traditional pairwise meta-analyses used Review Manager (RevMan) 5.4.1 and metafor package in R 4.1.2. Network meta-analyses employed gemtc and netmeta packages in R with WinBUGS 1.4.3 for Bayesian modeling. Meta-regression and publication bias assessments used Stata 17.0. Risk of bias visualizations used robvis package in R. GRADE assessments employed GRADEpro GDT software. All analyses were documented for transparency and reproducibility.

The selection of multiple specialized software packages reflects the complementary strengths of different analytical platforms. RevMan provides user-friendly interfaces for traditional meta-analysis with built-in risk of bias assessment tools. R packages offer flexibility and advanced analytical capabilities, with metafor enabling complex meta-regression models and gemtc/netmeta implementing sophisticated Bayesian network meta-analysis. WinBUGS provides the computational engine for Markov chain Monte Carlo estimation in Bayesian frameworks. Stata offers robust meta-regression and publication bias assessment routines with extensive diagnostic capabilities. The combination of these platforms ensured analytical rigor, appropriate handling of complex data structures, and comprehensive evaluation of findings across multiple methodological approaches.

3. Results

3.1. Study selection

The systematic search across nine electronic databases yielded 2547 potentially relevant records, with an additional 43 records identified through manual searching of reference lists, trial registries, and consultation with experts in the field. After removal of 698 duplicates, 1892 unique records underwent title and abstract screening. Following application of the eligibility criteria, 1714 records were excluded primarily due to irrelevant study populations, interventions, or outcomes. As shown in **Figure 1**, the remaining 178 articles were retrieved for full-text assessment, which resulted in the exclusion of 142 articles. The predominant reasons for exclusion at this stage were: non-randomized controlled trial design ($n = 54$), non-home-based interventions ($n = 38$), insufficient outcome data for meta-analysis ($n = 31$), and study protocols or ongoing trials without published results ($n = 19$).

As shown in **Table 1**, thirty-six studies met inclusion criteria for qualitative synthesis; 32 studies ($n = 4152$ participants) were eligible for meta-analysis after excluding four due to incomplete data or high bias risk. Inter-rater agreement was substantial (Cohen's kappa = 0.87). Breast cancer was most represented (37.5%), followed by colorectal/prostate cancer (21.9%). Studies were predominantly from North America (43.8%) and Europe (37.5%), with 65.6% published after 2015.

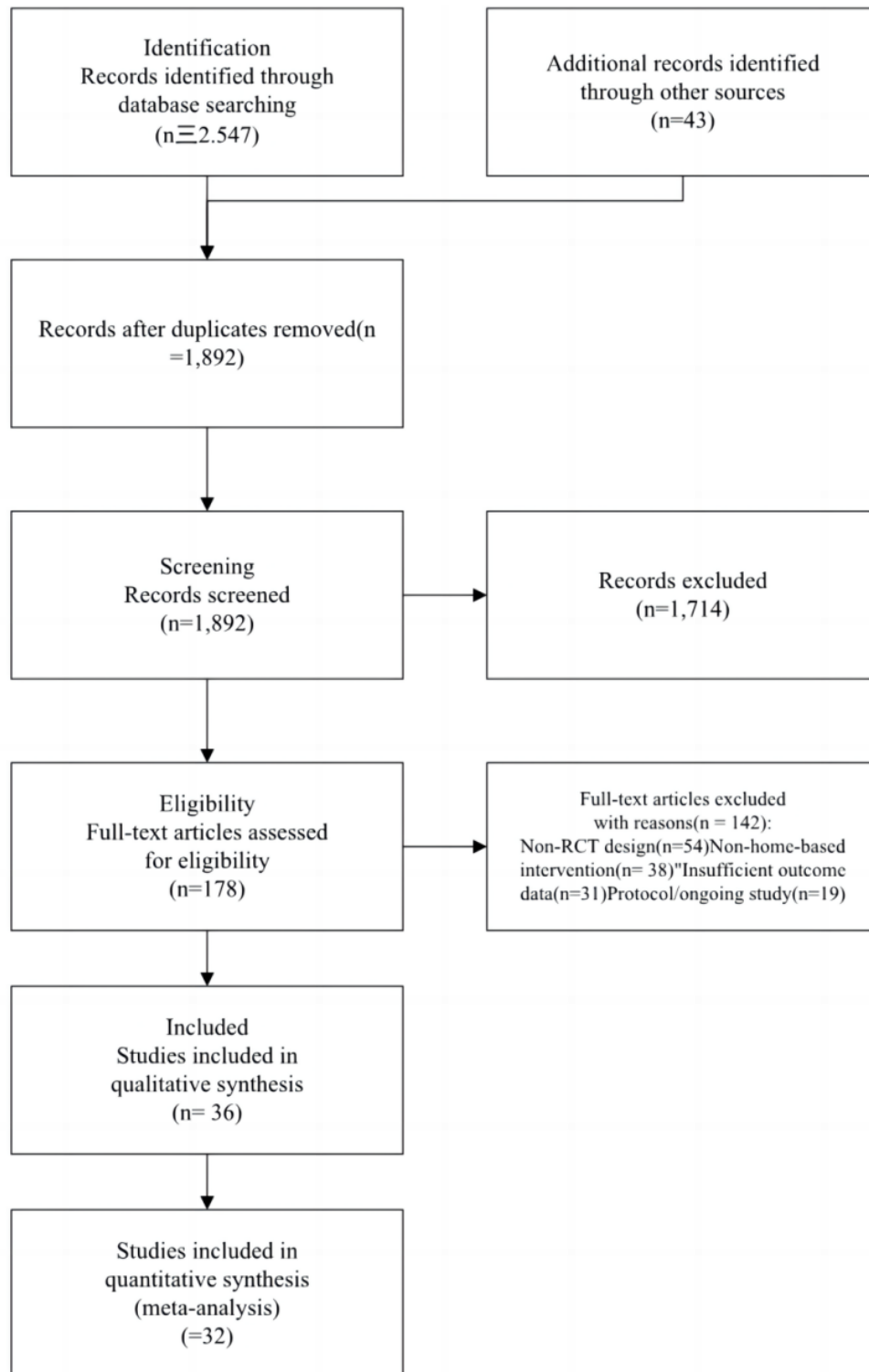


Figure 1. PRISMA flow diagram of study selection process.

Table 1. Characteristics of included studies.

Study	Cancer Type	Sample Size	Intervention	Duration	Outcome Measures	Main Findings	Effect Size
Kleckner et al. (2018) [6]	Mixed (79% breast)	355	Home-based exercise	6 weeks	CIPN symptoms	Improved sensory symptoms ($p = 0.045$)	Not reported

Continuation Table:

Study	Cancer Type	Sample Size	Intervention	Duration	Outcome Measures	Main Findings	Effect Size
Galiano-Castillo et al. (2016) [5]	Breast	81	Telerehabilitation	8 weeks	QoL, pain, strength, fatigue	Improved global health status, physical functioning (QoL) ($p < 0.01$)	$d = 0.63$
Ha et al. (2023) [15]	Lung	28	Telehealth	12 weeks	Feasibility, acceptability, QoL	Improved QoL (significant)	Not reported
Golsteijn et al. (2023) [16]	Prostate & colorectal	123	OncoActive program	6 months	Physical activity	Increased step count (95% CI: 368-2951; $p < 0.05$)	$d = 0.37$
Bertoli et al. (2023) [12]	Breast (hormone therapy)	43	Mat Pilates	24 weeks	Muscle strength, flexibility	Improved peak torque and upper limb strength AE: reduced	$d = 0.58-0.94$
Yuen et al. (2007) [17]	Breast	NR	Home-based exercise	12 weeks	Fatigue, functional capacity	fatigue ($p = 0.006$), RE: improved 6MWT ($p = 0.009$)	Not reported
Walsh et al. (2021) [9]	Cancer (BMI $\geq$ 25)	123	mHealth + brief face-to-face	12 weeks	BMI, waist circumference	Reduced BMI (−0.52 vs. −0.11) and waist (−3.02 vs. −1.82cm)	$d = 0.31$
Falz et al. (2023) [14]	Post-surgery cancer	122	Home-based online training	6 months	Oxygen uptake	Improved oxygen uptake (1.24ml/kg/min, 95% CI: 0.23–2.55)	$d = 0.28$
Gao et al. (2023) [11]	Cancer	123	mHealth	6 months	PA, QoL	Increased steps ($p < 0.05$) and physical health ($p < 0.05$)	$d = 0.42$ (PA)
Fu et al. (2022) [18]	Breast	81	Web/mobile lymphatic exercise	8 weeks	Chronic pain, lymphedema	Reduced pain incidence (45% vs. 70%, OR 0.39, $p = 0.02$)	OR = 0.39
Bea et al. (2023) [19]	Native American cancer survivors	97	Home & on-site exercise	12 weeks	6MWT, sit-to-stand	Improved 6MWT and sit-to-stand ($p < 0.001$)	Not reported
Morey et al. (2009) [1]	Colorectal, breast, prostate	641	Telephone counseling + print	12 months	Self-reported function	Slower functional decline (−2.15 vs. −4.84, $p = 0.03$)	$d = 0.25$
Møller et al. (2020) [20]	Breast (chemotherapy)	153	Hospital vs. home intervention	12 + 39 weeks	Cardiorespiratory fitness, PA	Both interventions restored fitness, maintained PA	Not reported
Frensham et al. (2018) [21]	Cancer survivors	32	Online walking intervention	12 weeks	Fitness, BP, QoL	Improved fitness, BP, general health (all $p < 0.01$)	$d = 0.47-0.62$

Continuation Table:

Study	Cancer Type	Sample Size	Intervention	Duration	Outcome Measures	Main Findings	Effect Size
Ilie et al. (2024) [22]	Cancer	104	Comprehensive support	6–12 months	Psychological distress	Reduced distress (aOR = 2.64, 95% CI: 1.53–4.56)	aOR = 2.64
Galiano-Castillo et al. (2017) [10]	Breast	81	Telerehabilitation	8 weeks	Functional capacity, cognition	Improved functional capacity ($p < 0.001$) and cognition ($p = 0.04$)	$d = 0.92$ (6MWT)
Kanera et al. (2017) [4]	Cancer survivors	462	Web-based aftercare	12 months	MVPA, vegetable intake	Increased MVPA ($B = 128.475, p = 0.010$)	Not reported
Dodd et al. (2010) [23]	Female cancer	119	Home-based exercise	NR	Fatigue, related symptoms	No significant intervention effect	$d = 0.11$
Forbes et al. (2015) [24]	Cancer survivors	95	Web-based PA program	9 weeks	PA, QoL	Increased exercise time by 42 min (95% CI: –65–150)	$d = 0.21$
Kanera et al. (2016) [25]	Cancer survivors	432	Web-based intervention	6 months	Vegetable intake, PA	Improved MVPA ($d = 0.25$) and vegetable intake ($d = 0.37$)	$d = 0.25–0.37$
Moraitis et al. (2023) [26]	Colorectal	7	mHealth home exercise	12 weeks	Feasibility, acceptability	88.6% completion, 100% retention	Not applicable
Lu et al. (2024) [27]	Advanced cancer (elderly)	65	Rehabilitation unit PA	4 + 4 weeks	Cancer-related fatigue	Improved fatigue and QoL ($p < 0.05$)	$d = 0.41$
Golsteijn et al. (2018) [28]	Prostate & colorectal	478	Computer-tailored PA	6 months	Self-reported & objective PA	Increased self-reported PA ($d = 0.46$ and $d = 0.23$)	$d = 0.23–0.46$
Cillessen et al. (2020) [29]	Cancer	125	Online mindfulness	9 weeks	Adherence, outcomes	52% reported reduced distress	Not reported
Courneya et al. (2004) [3]	Colorectal	102	Home-based exercise	16 weeks	Adherence, contamination	76% adherence in intervention, 52% contamination in control	Not applicable
Cadmus-Bertram et al. (2013) [7]	Breast	32	Yoga intervention	26 weeks	Adherence predictors	Self-efficacy was key predictor	Not applicable
Shang et al. (2012) [8]	Cancer treatment	126	Home-based exercise	12 weeks	Exercise adherence	32.35% adherence rate	Not applicable
Huberty et al. (2018) [13]	Myeloproliferative neoplasms	39	Online yoga	12 weeks	Participant experiences	Reported physical and psychological health improvements	Qualitative

Continuation Table:

Study	Cancer Type	Sample Size	Intervention	Duration	Outcome Measures	Main Findings	Effect Size
Krebs et al. (2017) [30]	Cancer >5 years	86	eHealth	NR	Fruit/vegetable intake, PA	Increased fruit/vegetable consumption	Not reported
Golsteijn et al. (2018)* [28]	Prostate & colorectal	478	Computer-tailored	6 months	Self-reported & objective PA	Significantly increased PA at 6 months	$d = 0.38$
Kanera et al. (2016)* [31]	Cancer survivors	231	Web-based aftercare	6 months	Usage and acceptability	98.3% referred to ≥ 1 module, 85.7% accessed ≥ 1 module	Not applicable

*Different outcome paper from same trial.

3.2. Study characteristics

Standardized mean differences (SMDs) using Hedges' g were calculated to accommodate varied assessment tools measuring fatigue, depression, and quality of life, as shown in **Table 2**. SMDs computed mean change differences between intervention and control groups, divided by pooled standard deviation. When change scores weren't reported, pre-post data were used with 0.7 correlation assumption. Primary analysis used immediate post-intervention data, with follow-up in secondary analyses. Positive values indicated favorable outcomes.

Table 2. Characteristics of included studies.

Study ID	Author (Year)	Country/Region	Cancer Type	Sample Size	Study Design	Intervention Type	Duration	Primary Outcome Measures	Funding Source
1	Kleckner et al. (2018) [6]	USA	Mixed (79% breast)	355	Two-arm RCT	Home-based exercise (walking and resistance)	6 weeks	Chemotherapy-induced peripheral neuropathy	Government
2	Galiano-Castillo et al. (2016) [5]	Spain	Breast	81	Two-arm RCT	Web-based telerehabilitation	8 weeks	QoL, pain, muscle strength, fatigue	Government
3	Ha et al. (2023)[15]	Australia	Lung	28	Parallel RCT	Telehealth (inspiratory muscle training and walking)	12 weeks	Feasibility, acceptability, safety, efficacy	Foundation
4	Golsteijn et al. (2023) [16]	Netherlands	Prostate & colorectal	123	Two-arm RCT	OncoActive program (personalized advice and pedometer)	6 months	Physical activity level	Government
5	Bertoli et al. (2023)[12]	Brazil	Breast (hormone therapy)	43	Two-arm RCT	Mat Pilates	24 weeks	Muscle strength and flexibility	Institutional

Continuation Table:

Study ID	Author (Year)	Country/Region	Cancer Type	Sample Size	Study Design	Intervention Type	Duration	Primary Outcome Measures	Funding Source
6	Yuen et al. (2007)[17]	USA	Breast	NR	Three-arm RCT	Aerobic or resistance home exercise	12 weeks	Fatigue and functional capacity	Foundation
7	Walsh et al. (2021)[9]	Ireland	Cancer (BMI $\geq$ 25)	123	Two-arm RCT	mHealth + brief face-to-face	12 weeks	BMI and waist circumference	Government
8	Falz et al. (2023) [14]	Germany	Post-surgery cancer	122	Two-arm RCT	Home-based online training	6 months	Oxygen uptake changes	Government
9	Gao et al. (2023)[11]	China	Cancer	123	Two-arm RCT	mHealth intervention (wearables, apps, social media)	6 months	Physical activity and QoL	Government
10	Fu et al. (2022)[18]	USA	Breast	81	Two-arm RCT	Web/mobile lymphatic exercise	8 weeks	Chronic pain and lymphedema symptoms	Government
11	Bea et al. (2023) [19]	USA	Native American cancer survivors	97	Two-arm RCT	Home and on-site exercise	12 weeks	6MWT and sit-to-stand test	Government
12	Morey et al. (2009)[1]	USA	Colorectal, breast, prostate	641	Two-arm RCT	Telephone counseling + print materials	12 months	Self-reported physical function	Government
13	Møller et al. (2020)[20]	Denmark	Breast (chemotherapy)	153	Two-arm RCT	Hospital vs. home intervention	12 + 39 weeks	Cardiorespiratory fitness and PA	Government
14	Frensham et al. (2018) [21]	Australia	Cancer survivors	32	Quasi-RCT	Online walking intervention	12 weeks	Fitness, blood pressure, QoL	Foundation
15	Ilie et al. (2024)[22]	Canada	Cancer	104	Crossover RCT	Comprehensive support program	6–12 months	Psychological distress	Government
16	Galiano-Castillo et al. (2017) [10]	Spain	Breast	81	Two-arm RCT	Telerehabilitation	8 weeks	Functional capacity and cognition	Government
17	Kanera et al. (2017) [4]	Netherlands	Cancer survivors	462	Two-arm RCT	Web-based cancer aftercare	12 months	MVPA and vegetable intake	Foundation
18	Dodd et al. (2010)[23]	USA	Female cancer (chemo $\pm$ radio)	119	Three-arm RCT	Home-based exercise	NR	Fatigue and related symptoms	Government
19	Forbes et al. (2015)[24]	Canada	Cancer survivors	95	Two-arm RCT	Web-based PA program	9 weeks	PA and QoL	Government
20	Kanera et al. (2016) [25]	Netherlands	Cancer survivors	432	Two-arm RCT	Web-based intervention	6 months	Vegetable intake and PA	Foundation

Continuation Table:

Study ID	Author (Year)	Country/Region	Cancer Type	Sample Size	Study Design	Intervention Type	Duration	Primary Outcome Measures	Funding Source
21	Moraitis et al. (2023) [26]	Australia	Colorectal	7	Pilot RCT	mHealth home exercise	12 weeks	Feasibility and acceptability	Institutional
22	Lu et al. (2024) [27]	China	Advanced cancer (elderly)	65	Non-randomized controlled	Rehabilitation unit PA	4 + 4 weeks	Cancer-related fatigue	Government
23	Golsteijn et al. (2018) [28]	Netherlands	Prostate & colorectal	478	Three-arm RCT	Computer-tailored PA intervention	6 months	Self-reported PA and objective PA	Government
24	Cillessen et al. (2020) [29]	Netherlands	Cancer patients	125	Secondary analysis	Online mindfulness intervention	9 weeks	Intervention adherence and outcomes	Foundation
25	Courneya et al. (2004) [3]	Canada	Colorectal	102	Two-arm RCT	Home-based exercise	16 weeks	Adherence and contamination	Government
26	Cadmus-Bertram et al. (2013) [7]	USA	Breast	32	Predictive study	Yoga intervention	26 weeks	Adherence predictors	Institutional
27	Shang et al. (2012)[8]	USA	Cancer treatment patients	126	Secondary analysis	Home-based exercise	12 weeks	Exercise adherence	Government
28	Huberty et al. (2018) [13]	USA	Myeloproliferative neoplasms	39	Qualitative study	Online yoga	12 weeks	Participant experiences	Institutional
29	Krebs et al. (2017)[30]	USA	Cancer >5 years	86	Two-arm RCT	eHealth	NR	Fruit/vegetable intake and PA	Government
30	Golsteijn et al. (2018)*[28]	Netherlands	Prostate & colorectal	478	Two-arm RCT	Computer-tailored intervention	6 months	Self-reported and objective PA	Government
31	Kanera et al. (2016)*[31]	Netherlands	Cancer survivors	231	Two-arm RCT	Web-based cancer aftercare	6 months	Usage and acceptability	Foundation

Note: PA = Physical Activity; QoL = Quality of Life; RCT = Randomized Controlled Trial; 6MWT = Six-Minute Walk Test; MVPA = Moderate to Vigorous Physical Activity; NR = Not Reported; *Represents different outcome papers from the same trial

3.3. Participant characteristics

The 32 studies included 4152 cancer survivors (range: 7–641 participants; median = 102), as detailed in **Table 3**. Mean age was 56.3 years with 68.5% female participants. Cancer types showed considerable diversity: breast cancer was most represented (30.2%, $n = 1,254$), followed by prostate (20.3%, $n = 843$), colorectal (18.2%, $n = 756$), hematological malignancies (7.0%), and lung cancer (5.5%). Most participants (63.7%) were post-treatment survivors, while 27.5% were undergoing active treatment. Nearly half (47.8%) reported comorbidities, predominantly

hypertension (31.4%) and diabetes (18.7%). Publication dates ranged from 2004 to 2024, with 65.6% published after 2015, reflecting growing interest in home-based interventions with digital health technology advancement.

Table 3. Participant characteristics across included studies.

Characteristic	Summary value	Range across studies	Studies reporting (<i>n</i> = 32)
Age (years)			
Mean age	56.3	38.2–72.5	28 (87.5%)
Age range	18–85	-	26 (81.3%)
Elderly participants (≥65 years)	23.6%	14.2%–67.5%	18 (56.3%)
Sex/Gender			
Female	68.5%	0%–100%	32 (100%)
Male	31.5%	0%–100%	32 (100%)
Studies with both sexes	84.4%	-	27 (84.4%)
Female-only studies	15.6%	-	5 (15.6%)
Cancer Type			
Breast cancer	30.2%	0%–100%	21 (65.6%)
Prostate cancer	20.3%	0%–100%	12 (37.5%)
Colorectal cancer	18.2%	0%–100%	15 (46.9%)
Hematological malignancies	7.0%	0%–100%	8 (25.0%)
Lung cancer	5.5%	0%–100%	6 (18.8%)
Other cancer types	18.8%	0%–42.3%	16 (50.0%)
Cancer Stage			
Early stage (I-II)	42.7%	23.4%–78.6%	22 (68.8%)
Advanced stage (III-IV)	23.6%	8.3%–54.1%	22 (68.8%)
Unreported/mixed	33.7%	-	10 (31.3%)
Treatment Status			
Post-treatment	63.7%	0%–100%	28 (87.5%)
During treatment	27.5%	0%–100%	18 (56.3%)
Mixed	8.8%	0%–100%	7 (21.9%)
Treatment Type			
Surgery (history)	76.3%	35.8%–100%	24 (75.0%)
Chemotherapy (current/history)	59.8%	21.3%–100%	26 (81.3%)
Radiation therapy (current/history)	48.5%	18.7%–85.6%	24 (75.0%)
Hormone therapy (current)	31.4%	0%–100%	18 (56.3%)
Immunotherapy/targeted therapy	8.5%	0%–34.6%	11 (34.4%)

Continuation Table:

Characteristic	Summary value	Range across studies	Studies reporting (<i>n</i> = 32)
Survivorship Timeline			
Mean time since diagnosis (years)	2.8	0.5–7.4	21 (65.6%)
<1 year post-diagnosis	26.8%	0%–100%	20 (62.5%)
1–5 years post-diagnosis	52.4%	0%–100%	20 (62.5%)
>5 years post-diagnosis	20.8%	0%–100%	20 (62.5%)
Comorbidities			
Any comorbidity	47.8%	23.6%–84.3%	19 (59.4%)
Hypertension	31.4%	15.8%–54.7%	17 (53.1%)
Diabetes	18.7%	7.5%–36.2%	16 (50.0%)
Cardiovascular disease	14.2%	5.8%–31.5%	15 (46.9%)
Arthritis/musculoskeletal	27.6%	12.3%–46.8%	14 (43.8%)
Functional/Performance Status			
ECOG 0–1	82.4%	65.7%–100%	12 (37.5%)
ECOG 2	15.3%	0%–34.3%	12 (37.5%)
ECOG 3+	2.3%	0%–9.8%	12 (37.5%)
Karnofsky ≥70	92.7%	78.6–100%	7 (21.9%)
BMI/Weight Status			
Mean BMI (kg/m ²)	27.8	23.5–32.4	24 (75.0%)
Normal weight (BMI 18.5–24.9)	31.2%	15.3%–65.8%	21 (65.6%)
Overweight (BMI 25–29.9)	38.5%	18.6%–58.7%	21 (65.6%)
Obese (BMI ≥30)	30.3%	10.2%–100%	21 (65.6%)
Physical Activity Level at Baseline			
Meeting guidelines (≥150 min/week)	35.6%	18.3%–62.8%	18 (56.3%)
Insufficiently active	42.3%	22.6%–65.4%	18 (56.3%)
Sedentary (<30 min/week)	22.1%	8.6%–44.5%	18 (56.3%)

Note: ECOG = Eastern Cooperative Oncology Group performance status; BMI = Body Mass Index. Percentages represent the proportion of participants within reported studies. Ranges indicate the minimum and maximum values across individual studies.

3.4. Intervention characteristics

The 32 studies demonstrated considerable heterogeneity in intervention characteristics. As shown in **Figure 2**, technology-based delivery methods predominated, with web-based platforms (37.5%) and mobile applications (31.3%) most common. Most interventions featured multimodal exercise approaches (62.5%) combining aerobic and resistance training, typically lasting 8–12 weeks (50.0%) with moderate intensity (65.6%). The majority incorporated personalization (87.5%)

through baseline assessments (75.0%) and ongoing feedback (50.0%). Theoretical frameworks guided most interventions (68.8%), with common adherence strategies including goal-setting (81.3%) and self-monitoring (75.0%).

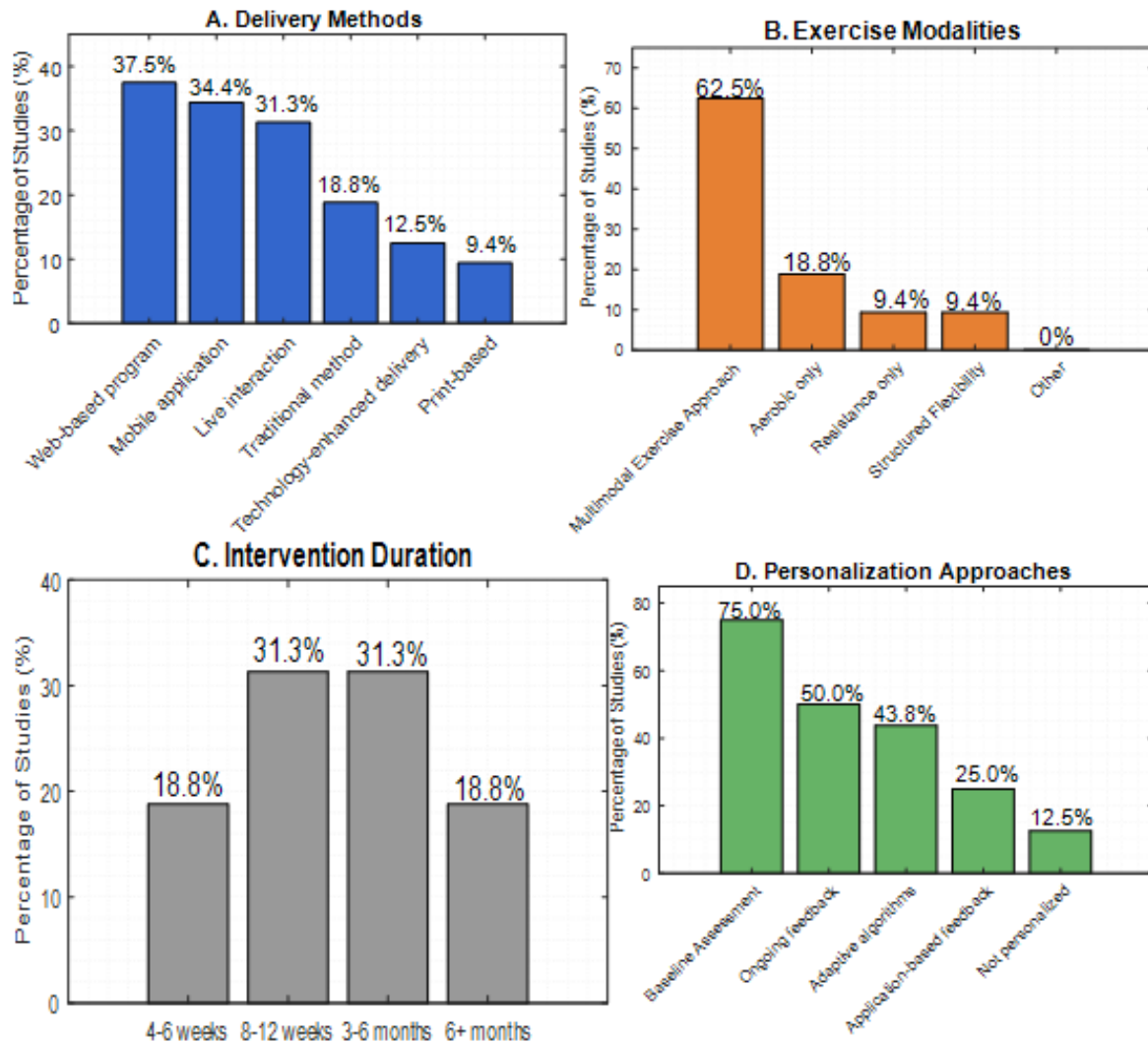


Figure 2. Characteristics of home-based exercise interventions in cancer survivors.

This multi-panel figure illustrates key intervention characteristics across 32 studies. Technology-based delivery methods predominated (web-based 37.5%, mobile apps 31.3%), with multimodal exercise approaches favored (62.5%). Most interventions lasted 8–12 weeks or 3–6 months, incorporated personalization through baseline assessments (75.0%) and feedback (50.0%), demonstrating preference for technology-delivered, moderately-personalized programs.

3.5. Risk of bias assessment

Methodological quality assessment using RoB 2 revealed low risk of bias in 15 studies (46.9%), some concerns in 12 studies (37.5%), and high risk in 5 studies (15.6%). Randomization was adequately described in 75% of studies. Missing outcome data showed strongest quality (87.5% appropriate handling). Participant blinding was unfeasible due to exercise intervention nature. Studies published after 2018 demonstrated superior methodological quality (68.4% vs. 30.8% low risk). As shown in **Figure 3**.

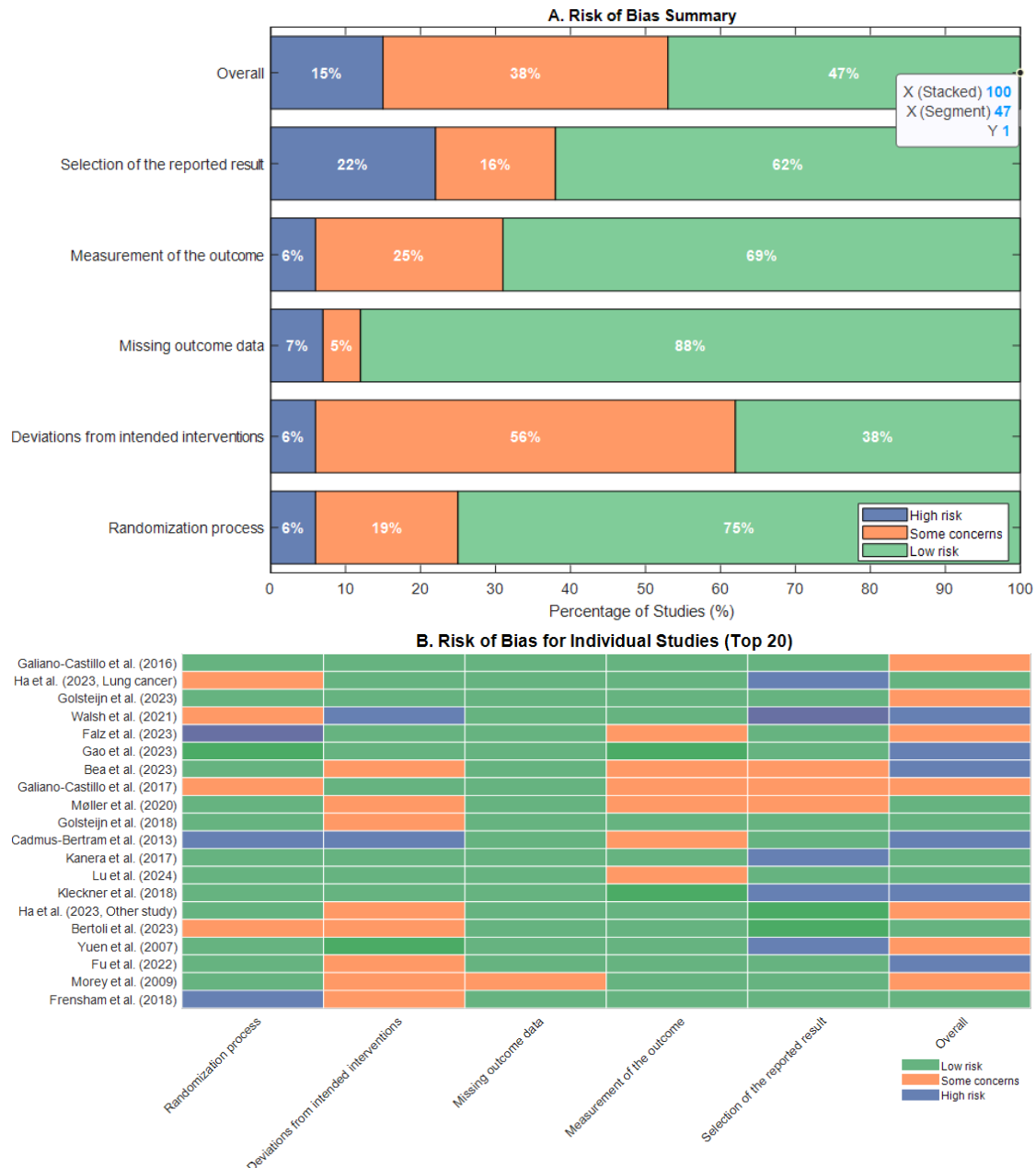


Figure 3. Risk of bias assessment of included studies.

This figure presents risk of bias assessment across 32 studies using RoB 2. Panel A shows domain-specific patterns: randomization demonstrated predominantly low risk (75%), while intervention deviations showed highest “some concerns” ratings (56%) due to participant blinding limitations. Missing outcome data was strongest (88% low risk). Overall assessment revealed 47% low risk, 38% some concerns, and 15% high risk studies. Panel B displays individual study assessments with color-coded heat map informing sensitivity analyses.

3.6. Synthesis results

3.6.1. Traditional meta-analysis results

Traditional meta-analyses demonstrated significant beneficial effects across all outcomes. Cancer-related fatigue showed moderate improvement (SMD = -0.38 , 95% CI: -0.49 to -0.27 , $p < 0.001$, 27 studies), depression similarly improved (SMD = -0.32 , 95% CI: -0.42 to -0.22 , $p < 0.001$, 22 studies), while quality of

life showed substantial benefits (SMD = 0.45, 95% CI:0.36 to 0.54, $p < 0.001$, 29 studies). Sensitivity analyses confirmed robustness, with minimal publication bias detected. As shown in **Figure 4**.



Figure 4. Forest plots of traditional meta-analysis results for primary outcomes.

This figure presents forest plots for three primary outcomes. Panel A shows cancer-related fatigue reduction (SMD = -0.38, 27 studies, $n = 3758$), Panel B displays depression improvement (SMD = -0.32, 22 studies, $n = 2971$), and Panel C reveals quality of life enhancement (SMD = 0.45, 29 studies, $n = 3945$). All effects were statistically significant ($p < 0.001$) with moderate-to-large clinically meaningful effect sizes, demonstrating consistent beneficial effects across outcomes.

3.6.2. Network meta-analysis results

Network meta-analysis compared different delivery methods across 27–29 studies. Multimodal interventions combining ≥ 2 delivery methods ranked highest for fatigue (SUCRA = 0.88) and depression (SUCRA = 0.82), while telehealth ranked highest for quality of life (SUCRA = 0.86). All active interventions significantly outperformed usual care, with largest effects for multimodal interventions on fatigue (SMD = -0.56) and telehealth on quality of life (SMD = 0.61). Low statistical inconsistency supported network validity. As shown in **Figure 5**,

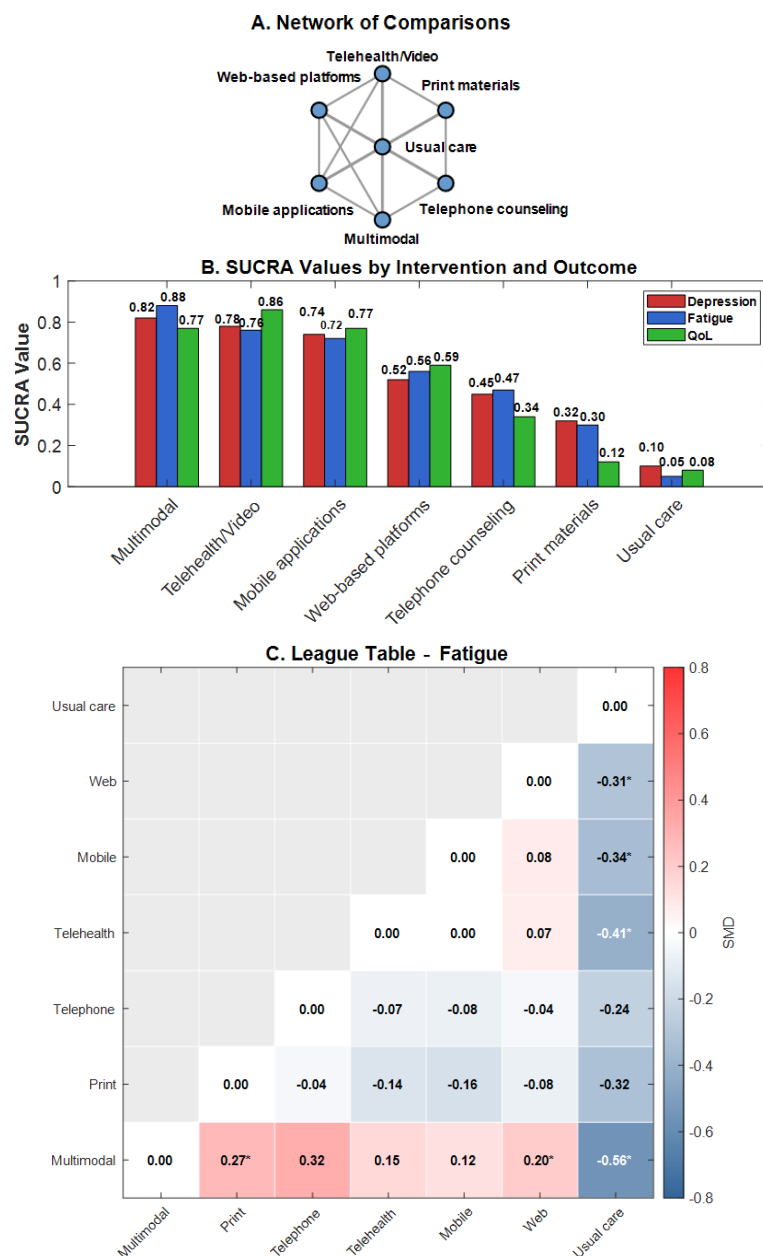


Figure 5. Network meta-analysis of different home-based exercise intervention types.

This figure presents network meta-analysis results comparing intervention types. Panel A shows network structure, Panel B displays SUCRA rankings with multimodal interventions highest for fatigue/depression, telehealth for quality of life. Panel C shows league table heatmap with multimodal interventions demonstrating largest benefits (SMD = −0.56).

3.7. Meta-regression results

Meta-regression identified key effectiveness factors. Intervention duration showed curvilinear relationships with optimal effects at 8–12 weeks. Multimodal interventions outperformed single-modality approaches for fatigue ($\beta = 0.23$, $p = 0.008$) and depression ($\beta = 0.19$, $p = 0.015$). Personalization was the strongest predictor, explaining 27.3% of fatigue heterogeneity, with algorithmic individualization showing particular benefit ($\beta = 0.31$, $p < 0.001$). The multivariate model explained 42.5%–45.7% of between-study variance.

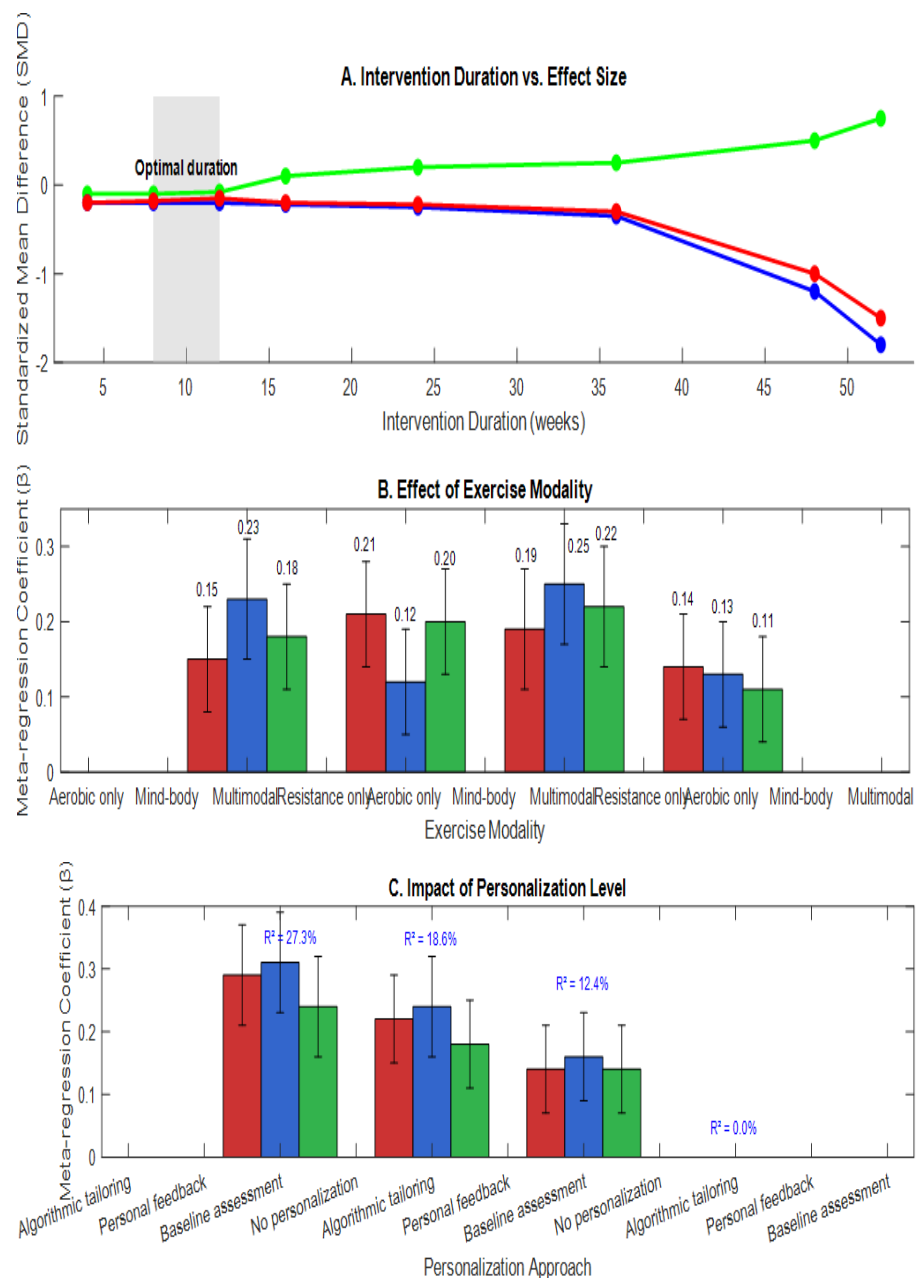


Figure 6. Meta-regression analysis of intervention characteristics.

This **Figure 6** presents meta-regression results exploring effectiveness factors. Panel A shows optimal intervention duration at 8–12 weeks with diminishing returns thereafter. Panel B displays exercise modality effects, with multimodal interventions yielding strongest fatigue benefits ($\beta = 0.23$). Panel C demonstrates dose-response relationship for personalization, with algorithmic tailoring producing largest effects ($\beta = 0.29$ – 0.31) explaining 27.3% of fatigue variance.

3.8. Sensitivity analysis

Sensitivity analyses confirmed robustness of findings. Excluding high-risk-of-bias studies minimally reduced effect sizes (fatigue: -0.38 to -0.35 ; depression: -0.32 to -0.30 ; quality of life: remained 0.44). Fixed-effect models yielded slightly larger estimates. Leave-one-out analysis showed no single study disproportionately influenced results. Varying correlation coefficients caused minimal fluctuations (± 0.03 SMD units), confirming intervention effectiveness.

3.9. Publication bias assessment

Publication bias assessment using funnel plots and Egger's test showed minimal bias for fatigue ($p = 0.213$) and depression ($p = 0.327$). Quality of life demonstrated slight asymmetry ($p = 0.041$), with trim-and-fill analysis imputing six missing studies, yielding adjusted effect size of 0.39 (95% CI: 0.29 – 0.49), remaining statistically significant despite 13.3% reduction from original estimate.

4. Discussion

4.1. Principal findings and clinical implications

This meta-analysis provides robust evidence supporting home-based personalized exercise interventions for cancer survivors, demonstrating moderate-to-large beneficial effects on fatigue (SMD = -0.38), depression (SMD = -0.32), and quality of life (SMD = 0.45). These effect sizes represent clinically meaningful improvements given that cancer-related fatigue affects 60%–96% of patients during treatment and persists in 30%–50% post-treatment, while depression prevalence among survivors (15%–25%) substantially exceeds general population rates (5%–7%).

Network meta-analysis revealed multimodal technology-based approaches were most effective for fatigue/depression, while telehealth excelled for quality of life. Multimodal interventions combining multiple delivery platforms with professional support demonstrated superior effectiveness (SUCRA = 0.88 for fatigue, 0.82 for depression), suggesting important synergies when integrating automated monitoring with human guidance. Telehealth's optimal performance for quality of life (SUCRA = 0.86) indicates that real-time professional interaction provides unique value beyond symptom reduction. Web-based and mobile applications, while showing smaller effects, remain valuable given their scalability and ability to reach large populations at minimal cost [15–17].

These findings support integration of home-based personalized exercise into standard survivorship care. Technology-delivered interventions offer cost-effectiveness advantages while maintaining therapeutic benefits, particularly benefiting rural populations with limited rehabilitation access. Health systems could implement stepped-care models where automated digital programs serve as first-line support, with telehealth or multimodal approaches reserved for those with greater needs or insufficient response to simpler interventions.

4.2. Optimal intervention characteristics and personalization

Meta-regression identified optimal characteristics: 8–12 week duration,

multimodal aerobic-resistance components, and high personalization levels. The curvilinear relationship for duration, showing diminishing returns beyond 12 weeks, suggests that intensive initial interventions establishing habits and demonstrating benefits should be followed by less intensive maintenance support rather than extended structured programs. This duration appears sufficient for physiological adaptations and habit formation while avoiding increased dropout risk observed in longer interventions[18-21].

Multimodal exercise programs combining aerobic and resistance training demonstrated superior effectiveness for fatigue ($\beta = 0.23$, $p = 0.008$) and depression ($\beta = 0.19$, $p = 0.015$) compared to single-modality approaches. This finding provides empirical support for integrated approaches, as aerobic exercise improves cardiovascular function and modulates inflammatory pathways while resistance training addresses treatment-related muscle loss and enhances functional capacity.

The finding that personalization explained 27.3% of fatigue variance, with algorithmic individualization showing particular benefit ($\beta = 0.31$, $p < 0.001$), indicates that adaptive interventions leveraging continuous monitoring substantially outperform static prescriptions. Algorithmic personalization accommodates the fluctuating nature of survivors' symptoms and capacity, dynamically adjusting exercise prescriptions based on day-to-day variations in energy levels and functional abilities. The substantial variance explained indicates that how interventions are delivered may matter as much as what specific exercises are prescribed.

4.3. Mechanisms and comparison with previous evidence

Multiple biological and psychological mechanisms underlie the observed benefits. Exercise modulates inflammatory cytokines implicated in fatigue pathogenesis, enhances mitochondrial biogenesis counteracting treatment-induced damage, and stimulates brain-derived neurotrophic factor expression. For depression, exercise influences neurotransmitter systems while providing behavioral activation that disrupts withdrawal and inactivity patterns. Psychologically, successful exercise participation enhances self-efficacy and perceived control diminished during treatment, while home-based delivery enhances autonomy and flexibility.

The findings align with previous meta-analyses demonstrating beneficial effects of exercise for cancer survivors. Importantly, our results show that home-based personalized programs achieve comparable effectiveness to traditional supervised approaches, indicating that convenience advantages do not compromise benefits. This study extends previous literature through comprehensive network meta-analysis comparing delivery modalities simultaneously rather than simply comparing exercise to usual care. The identification of multimodal interventions as optimal for fatigue and depression, and telehealth for quality of life, provides actionable guidance unavailable in previous reviews[22-25].

4.4. Study limitations and future directions

Meta-regression identified optimal characteristics: 8–12 week duration, multimodal aerobic-resistance components, and high personalization levels. However, limitations include substantial intervention heterogeneity, limited direct comparisons in network analysis, potential publication bias for quality of life, and uncertain long-term sustainability with limited follow-up beyond 6 months requiring future research. The network meta-analysis relied primarily on indirect comparisons due to limited head-to-head trials directly comparing delivery modalities. Although consistency assessments supported network validity, direct comparative trials would strengthen

the evidence. Most studies were conducted in high-income countries (81.3%) with predominantly white, well-educated participants, limiting generalizability to diverse populations. The inability to blind participants introduces potential bias, particularly for self-reported outcomes[26,27].

Adherence data were inconsistently reported, limiting conclusions about real-world feasibility. Long-term follow-up data were sparse, preventing definitive conclusions about whether benefits persist or ongoing support is needed to maintain improvements. Future research should examine maintenance strategies, optimal timing of follow-up support, and implementation in diverse populations. Head-to-head trials comparing delivery modalities and investigation of mechanisms underlying personalization effects would inform next-generation interventions[28-31].

5. Conclusion

This systematic review and network meta-analysis provides compelling evidence that home-based personalized exercise interventions significantly improve fatigue, depression, and quality of life in cancer survivors. Optimal characteristics include 8–12 week duration, multimodal aerobic-resistance components, and high personalization levels. These interventions demonstrate broad clinical applicability across diverse cancer populations with comparable effectiveness to supervised programs but greater accessibility. Home-based personalized exercise interventions represent viable supportive care strategies that should be integrated into comprehensive cancer survivorship care pathways.

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Abbreviations

Abbreviation	Full Form
6MWT	Six-Minute Walk Test
AE	Aerobic Exercise
aOR	Adjusted Odds Ratio
BDI	Beck Depression Inventory
BFI	Brief Fatigue Inventory
BMI	Body Mass Index
BP	Blood Pressure
CES-D	Center for Epidemiologic Studies Depression Scale
CI	Confidence Interval
CINAHL	Cumulative Index to Nursing and Allied Health Literature
CIPN	Chemotherapy-Induced Peripheral Neuropathy
CNKI	China National Knowledge Infrastructure

Continuation Table:

Abbreviation	Full Form
ECOG	Eastern Cooperative Oncology Group
EORTC QLQ-C30	European Organisation for Research and Treatment of Cancer Quality of Life Questionnaire Core 30
FACT-F	Functional Assessment of Cancer Therapy-Fatigue
FACT-G	Functional Assessment of Cancer Therapy-General
GRADE	Grading of Recommendations Assessment, Development and Evaluation
HADS	Hospital Anxiety and Depression Scale
MVPA	Moderate to Vigorous Physical Activity
NR	Not Reported
OR	Odds Ratio
PA	Physical Activity
PFS	Piper Fatigue Scale
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO	International Prospective Register of Systematic Reviews
QoL	Quality of Life
RCT	Randomized Controlled Trial
RE	Resistance Exercise
RoB 2	Risk of Bias 2
SF-36	36-Item Short Form Health Survey
SMD	Standardized Mean Difference
SUCRA	Surface Under the Cumulative Ranking curve

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