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Mobile Health in the Self-Management of Patients with Lung Cancer: A Scoping Review

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Abstract: Mobile health has been widely applied in the self-management of patients with lung cancer, yet its forms, functions and outcome measures have not been systematically mapped. This scoping review therefore characterized how mobile health is used in lung cancer self-management, with the aim of informing future research and clinical practice. Following the JBI methodological framework for scoping reviews, we systematically searched CNKI, Wanfang Data, the VIP Database, SinoMed, PubMed, Embase, Web of Science, the Cochrane Library, and EBSCOhost from database inception to August 2026 and synthesized the included studies descriptively. Fourteen studies were included. Mobile health was delivered primarily through mobile applications, websites, WeChat mini-programs, WeChat group chats, and telephone follow-up. Core functions comprised symptom self-reporting, personalized symptom-management advice, high-risk alerting, patient health-data transmission, individualized exercise programs, psychological support, peer interaction platforms, personalized reminders and notifications, and clinician feedback and consultation. Outcome measures covered quality of life, feasibility and satisfaction, anxiety and depression, pulmonary function, physical symptoms, knowledge, physical activity, sleep, and self-efficacy. Mobile health shows promising potential for alleviating symptom burden and promoting postoperative recovery in lung cancer self-management, although its application formats remain heterogeneous. Future research should strengthen theory-driven study designs, promote the integration of artificial intelligence with mobile health platforms, establish stratified intervention frameworks and a core outcome set, and incorporate age-friendly design and humanistic care to extend the value and sustainability of these interventions.

Keywords: Lung cancer; Mobile health; Self-management; Scoping review; Nursing

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1. Introduction

Lung cancer is the most common malignancy of the respiratory system and has the highest incidence and mortality among all cancers worldwide [1]. Its treatment includes surgery, radiochemotherapy, targeted therapy

and immunotherapy, which are individualized according to disease stage and molecular subtype at diagnosis [2]. Owing to the disease itself and treatment-related complications, patients experience multiple symptoms such as dyspnoea, cancer-related fatigue, pain, cough, anxiety, and depression, which persistently impair their health status and quality of life [3]. Patients treated surgically require long-term postoperative pulmonary rehabilitation to reduce the incidence of complications and accelerate recovery [4]. Against this background, active participation of patients in the day-to-day management of their disease can effectively alleviate symptom burden, standardize rehabilitation training and improve quality of life [5]. Mobile health (mHealth), a branch of telemedicine, refers to a mode of medical practice that provides medical information, health management and public health services by means of mobile communication technologies and mobile terminal devices [6]; it is characterized by freedom from time and space constraints, efficient information transmission, and traceable data [7]. In this review, mobile health is understood broadly to encompass the various forms that support patient self-management through mobile communication or remote technologies, including mobile applications, websites, WeChat mini-programs, WeChat group chats, and telephone follow-up. Mobile health can help patients manage their condition more independently and exerts a positive influence on physical function and quality of life [8]. Research on the application of mobile health in lung cancer self-management is growing, yet existing reviews have largely focused on a single intervention format or a single outcome and have not systematically examined the relationships among functional characteristics, application formats and outcome instruments. Following the JBI scoping review framework [9] and in accordance with the PRISMA-ScR reporting guideline, this review scopes studies on the application of mobile health in lung cancer self-management, so as to inform subsequent research.

2. Materials and methods

2.1. Research questions

The specific research questions were as follows:

(1) What are the core functions and format characteristics of mobile health interventions?

(2) What outcome measures and measurement instruments are used in relation to self-management?

2.2. Inclusion and exclusion criteria

Inclusion and exclusion criteria were established according to the PCC (Population, Concept, Context) principle. Population (P): patients with lung cancer. Concept (C): the application of mobile health in the self-management of patients with lung cancer. Context (C): the various settings of lung cancer self-management, including hospitalization, postoperative home rehabilitation, and treatment intervals, without restriction on the type of healthcare institution or geographical region.

2.2.1. Inclusion criteria

(1) Participants were patients with lung cancer;

(2) The intervention involved the application of mobile health for self-management;

(3) The publication was an original study.

2.2.2. Exclusion criteria

(1) Non-Chinese/English publications;

(2) Conference abstracts, study protocols, or reviews;
(3) Full texts that could not be obtained.

2.3. Literature search

A systematic search was conducted in CNKI, Wanfang Data, the VIP Chinese Science and Technology Periodical Database, SinoMed, PubMed, Embase, Web of Science, the Cochrane Library, and EBSCOhost. On the EBSCOhost platform, the search covered three sub-databases, namely CINAHL, MEDLINE, and Education Source. The search period ranged from database inception to August 2026. A combination of subject headings and free-text terms was used; the Chinese search terms included lung cancer, pulmonary malignancy, mobile health, mHealth, digital health, smartphone, and application. In addition, the reference lists of the included studies were screened to identify further eligible literature. Taking PubMed as an example for the English-language databases, the search strategy was as follows:

(1) "lung neoplasms"[MeSH] OR "lung cancer"[Title/Abstract] OR "lung carcinoma"[Title/Abstract] OR "non-small cell lung cancer"[Title/Abstract] OR NSCLC [Title/Abstract]
(2) "telemedicine"[MeSH] OR "mobile health"[Title/Abstract] OR "mHealth"[Title/Abstract] OR "eHealth"[Title/Abstract] OR "mobile application"[Title/Abstract] OR "mobile app"[Title/Abstract] OR "smartphone"[Title/Abstract] OR "digital health"[Title/Abstract]
(3) (1) AND (2)

2.4. Study selection and data extraction

All retrieved records were imported into EndNote X9. After removal of duplicates, two researchers independently screened titles and abstracts to exclude irrelevant studies, and then read the full texts to determine eligibility according to the inclusion and exclusion criteria. Any disagreement was resolved by discussion with a third researcher. Extracted data included author, year of publication, country, study design, type of mobile health, sample size, intervention duration, and outcome measures. Data extraction was performed independently by two researchers, and disagreements were resolved by discussion or adjudicated by a third researcher.

3. Results

3.1. Search results and characteristics of the included studies

The initial search retrieved 1,486 records; after removal of 295 duplicates,1,191 records remained. Following title and abstract screening,1,148 records were excluded, and 43 proceeded to full-text screening, of which 29 were excluded (inconsistent content,n = 24; inconsistent study design, n = 4; inconsistent context, n = 1). Finally, 14 studies were included. The screening process is shown in **Figure 1**, and the basic characteristics of the included studies are presented in Table 1.

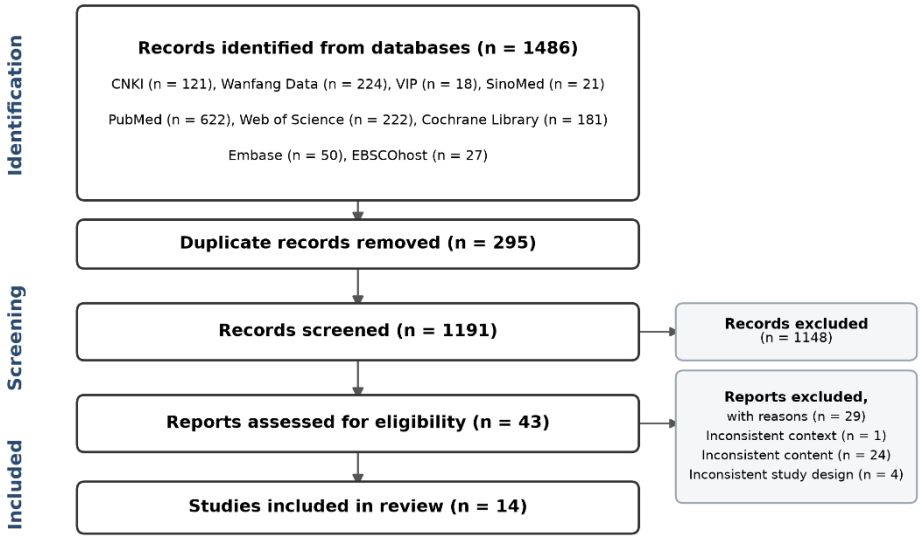


Figure 1. Flowchart of literature screening.

Table 1. Basic characteristics of the included studies

Author	Year	Country	Study design	Sample size	mHealth format	Functions	Duration (months)	Outcomes
Redd[y[10]]	2026	UK	Single-arm	43	eRAPID	①②③④⑨	12	ABCE
Curry[11]	2026	UK	Mixed-methods	18	Exercise GuideUK	②④⑤⑧	2	ABCG
Tang[12]	2026	China	Single-arm	250	Dignio APP	③④	6	D
Pongiglione[13]	2025	Italy	RCT	48/52	LuCApp	①③④	6	ABCE
Boulanger[14]	2025	USA	RCT	61/59	THRIVE App	①⑥	3	ABCE
Liang[15]	2025	China	Quasi-experimental	45/45	WeChat group	①②③④⑥⑦⑧⑨	6	AEI
Granger[16]	2024	Australia	RCT	58/58	Telephone	⑤	3	AGI
Zhang[17]	2024	China	RCT	50/51	ACT platform	⑥⑧	2	ABCH
Ha[18]	2023	USA	RCT	14/14	6WT App	④⑤	3	ABCEGH
Janssen[19]	2023	Australia	Mixed-methods	23	Microlearning platform	⑧	2	BFI
Qu[20]	2022	China	RCT	60/60	WeChat mini-program	④⑤⑥⑦⑧⑨	3	ABCE
Ji[21]	2019	South Korea	RCT	32/32	Eil breath App	④⑤⑧	3	ABDG
Park[22]	2019	South Korea	Single-arm	100	Smart Aftercare App	①②③④⑤⑥⑧⑨	3	ABCEG
Huang[23]]	2019	China	RCT	27/28	Website, SMS	④⑨	3	AE

Note: ①symptom self-reporting; ②personalised symptom-management advice; ③high-risk alerting; ④patient health-data transmission; ⑤individualised exercise programs; ⑥psychological support; ⑦peer interaction platforms; ⑧personalised reminders and notifications; ⑨clinician feedback and consultation. A quality of life; B feasibility and satisfaction; C anxiety and depression; D pulmonary function; E physical symptoms; F knowledge; G physical activity; H sleep; I self-efficacy.

3.2. Formats of mobile health

Six studies [12-14,18,21,22] used self-developed mobile applications, which represent the predominant format of mobile health at present. Five studies [10,11,17,19,23] used websites; one study [15] used WeChat group chats to deliver health information; one study [20] developed a WeChat-based mini-program; and one study [16] delivered mobile health by telephone.

3.3. Functions and intervention content

3.3.1. Symptom self-reporting

Five studies [10,13-15,22] provided patients with a symptom self-reporting function. Patients completed online symptom reports at preset intervals, mainly by ticking standardized symptom items [10,13,22]. In one study, healthcare professionals communicated with patients through a mobile application to collect symptom information [15], thereby achieving symptom self-reporting. Another study combined patient self-reported symptoms with wearable-device data to record more comprehensive health data [22]. The reporting frequency ranged from every other day to once every two weeks, depending on clinical needs and the purpose of the intervention.

3.3.2. Personalized symptom-management advice

Four studies [10,11,15,22] provided personalized symptom-management advice through mobile health. Advice was generated either automatically by algorithms [10,11,22] or manually by healthcare professionals [15]. In the study by Reddy et al. [10], the algorithm was based on CTCAE severity grading and matched content to the patient-reported symptom. Park et al. [22] did not specify the underlying algorithm and provided management advice for pain and skin-related adverse reactions according to the symptom data entered by patients. In the study by Liang et al. [15], nurses manually assessed patients and guided the WeChat platform.

3.3.3. High-risk alerting

Five studies [10,12,13,15,22] set up a high-risk alerting function for patients. Of these, four used automatic judgment based on preset thresholds [10,12,13,22] and one relied on remote manual judgment by nurses [15]. The alert content covered symptoms and vital signs. Symptom-based alerting could be anchored to the CTCAE standardized grading [10]: patients were given management advice for mild grade 1-2 reactions, whereas warnings were issued and healthcare professionals notified from grade 3 onwards. In the study by Pongiglione et al. [13], two additional conditions, namely a temperature ≥ 38°C and a weight loss ≥ 5% over two weeks, were added on top of symptoms, so that either abnormality triggered an alert on the physician-facing app.

3.3.4. Patient health-data transmission

In ten studies [10-13,15,18,20-23], patient data were uploaded to the clinician-facing end or the cloud through mobile platforms or wearable devices for real-time review and tracking by healthcare professionals. Automatic upload by wearable devices required no patient involvement; for example, in Tang et al. [12], vital signs were automatically uploaded to the cloud daily via Bluetooth devices. Some studies combined both approaches: Park et al. [22] uploaded patient-reported symptoms together with step counts and heart rate automatically captured by IoT devices for comprehensive clinical judgment. With regard to the clinician-facing receiving format, a few studies achieved direct integration with the hospital electronic medical record system [10],

whereas most relied on standalone platforms or dedicated websites for clinician review [13,21,22], and WeChat-based interventions relied mainly on manual collection [15].

3.3.5. Individualized exercise programs

Six studies [11,16,18,20-22] provided patients with individualized exercise programs. Curry et al. [11] used a conditional-matching logic algorithm that automatically generated a tailored exercise program, including exercise type, frequency, intensity, and weekly schedule, according to predefined decision rules combined with the patient-reported assessment questionnaire. The remaining five studies [16,18,20-22] formulated programs after remote assessment by healthcare professionals, with assessment comprising objective functional tests,wearable-device monitoring, and patient self-reports; the adjustment cycle was either fixed or event-triggered.

3.3.6. Psychological support

Five studies [14,15,17,20,22] provided psychological support through mobile health. Some studies embedded structured psychological intervention courses, such as standardized modules of acceptance and commitment therapy and cognitive behavioral therapy, into the platform for independent learning [14],[17]. Some programs included emotion management as a standalone science education section with daily push notifications, such as articles on emotion management [20] and audio clips for psychological adjustment [15]. Patients experiencing psychological distress could also seek psychological counselling from healthcare professionals through the in-app chat service [22].

3.3.7. Peer interaction platforms

Two studies [15,20] incorporated a peer interaction platform, both of which were China-localized mobile health interventions based on the WeChat ecosystem. The main forms of the peer interaction platform were patient WeChat groups and online forums. Liang et al[15] established a patient WeChat group comprising patients undergoing treatment and those in recovery, enabling open question-and-answer, exchange of treatment experience, and mutual encouragement among patients, as well as open clinician-patient interaction, thereby forming a community model that combined peer-to-peer support with professional guidance. Zhai et al. [20] set up a public communication module within the mini-program, where patients could post questions or share experiences to form an open community; group members took turns answering forum questions, and common questions were addressed collectively through live streaming.

3.3.8. Personalized reminders and notifications

Seven studies [11,15,17,19-22] incorporated personalized reminders and notifications, which were delivered either by automatic system push or by proactive contact from healthcare professionals. Mobile health devices could automatically send reminders for medication, exercise, and follow-up visits based on patient information or preset times [21,22], and send supervisory notifications when patients had been inactive for a long time. Alternatively, healthcare professionals sent reminders manually through WeChat groups, telephone, or text messages [15,17,20].

3.3.9. Clinician feedback and consultation

Five studies [10,15,20,22,23] incorporated clinician feedback and consultation, allowing patients to communicate

with healthcare professionals through the mobile platform. Some studies embedded a real-time chat service in the app, through which patients could ask questions at any time and nurses replied online [22]; others enabled real-time communication through WeChat groups, with video consultations initiated directly for moderate-to-severe symptoms [15],[20]. Other studies used a message-based consultation model, in which research nurses and thoracic surgeons replied within 24 hours after patients submitted open-ended questions in the website Q&A module [23]. Reddy et al. [10] combined a passive response mechanism triggered by system alerts: after patients submitted severe symptom reports, the system automatically notified nurses,who then proactively contacted patients for assessment and guidance, thereby linking alerting with consultation.

3.4. Frequency and duration

Among the 14 studies, the intervention lasted 2 months in three studies [11,17,19],3 months in seven studies [14,16,18,20-23],6 months in three studies [12,13,15], and 12 months in one study [10]. With regard to frequency, among the studies with explicit frequency requirements, six studies [12,13,15,18,20,22] required daily or every-other-day use, three studies [10,16,17] required a fixed weekly frequency, and one study [23] required use every two weeks; the remaining four studies [11,14,19,21] did not specify a frequency, allowing patients to use the intervention flexibly according to their own circumstances.

3.5. Outcome measures and measurement instruments

3.5.1. Quality of life

Twelve studies [10,11,13-18,20-23] evaluated quality of life, covering dimensions such as global health status, physical function, role function,emotional function, cognitive function, social function, and lung cancer-specific symptoms. The instruments used included the EORTC QLQ-C30 [10,11,16,22,23], the FACT-L [13-15,17], the EQ-5D-5L and EQ-VAS [10,13,21], the SGRQ [18], and the GQOLI-74 [20]. The EORTC QLQ-C30 is suitable for cross-sectional comparison across cancer types; the FACT-L is a lung cancer-specific instrument and is more focused on the lung cancer population; the EQ-5D-5L emphasizes the assessment of health utility values; and the SGRQ specifically targets respiratory diseases.

3.5.2. Feasibility and satisfaction

Ten studies [10,11,13,14,17-22] evaluated feasibility and satisfaction. Feasibility indicators included recruitment rate, retention rate, and intervention adherence; satisfaction and usability were assessed with the SUS [10,11,14], the CSUQ [13], the TSUQ [18], the PGA [21], and self-developed satisfaction questionnaires [17,20,22]. Semi-structured interviews were used to explore patients' subjective experience of the intervention and to elicit suggestions for improvement [10,11,13,14,18,19].

3.5.3. Anxiety and depression

Eight studies [10,11,13,14,17,18,20,22] evaluated anxiety and depression. The instruments included the HADS [10,11,13,14,17], the GAD-7 [18,22], the PHQ-9 [22], and the SAS/SDS [20]. This dimension relied mainly on standardized psychological scales with good reliability and validity, among which the HADS was the most widely used. The HADS is designed specifically for patients with physical illness and can effectively avoid the interference of somatic symptoms with emotional assessment.

3.5.4. Pulmonary function

Two studies [12,21] evaluated pulmonary function. The indicators included FEV1, FVC, FEV1/FVC, PEF, and FEF25-75, all measured by spirometry as auxiliary indicators of the effect of exercise interventions.

3.5.5. Physical symptoms

Eight studies [10,13-15,18,20,22,23] evaluated physical symptoms, with symptom severity as the sole indicator. The instruments included the CTCAE symptom report [10,13], the MDASI [14], the EORTC QLQ-C30 symptom scales and the NRS [22], the SDS [23], the UCSD SOBQ [18], the EGFR-TKI adverse-reaction grading [15] and the Brief Fatigue Inventory (BFI) [20]. The instruments for this dimension were heterogeneous. The CTCAE and MDASI are standardized patient-reported outcome measures with good reliability and validity; the UCSD SOBQ specifically assesses dyspnoea; and the EGFR-TKI adverse-reaction grading is based on expert consensus and is less standardized.

3.5.6. Knowledge

One study [19] evaluated knowledge. The indicator was patients' mastery of the chemotherapy side-effect management knowledge delivered by the microlearning platform. The instrument was a knowledge-retention assessment embedded in semi-structured interviews, which explored patients' memory and understanding of the learning content.

3.5.7. Physical activity

Five studies [11,16,18,21,22] evaluated physical activity, covering functional exercise capacity and daily physical-activity level. The instruments comprised objective functional tests,wearable-device monitoring, and subjective activity questionnaires. The 6-minute walk test was the most widely used instrument [16,21,22], measuring walking distance under standardized conditions to reflect overall functional exercise capacity. Wearable devices included smart bands [18], pedometers [16] and wearable pulse oximeters [21,22]. Subjective activity questionnaires included the CHAMPS physical-activity questionnaire [11] and the short form of the International Physical Activity Questionnaire [11,16,18].

3.5.8. Sleep

Two studies [17,18] evaluated sleep, covering sleep quality and insomnia severity. The instruments were the Insomnia Severity Index [17] and the Pittsburgh Sleep Quality Index [18]. The Insomnia Severity Index assesses the severity of insomnia and its impact on daytime function, whereas the Pittsburgh Sleep Quality Index comprehensively evaluates sleep quality over the past month across multiple dimensions such as sleep duration, sleep latency, and sleep efficiency.

3.5.9. Self-efficacy

Three studies [15,16,19] evaluated self-efficacy, covering cancer self-management self-efficacy [15], exercise self-efficacy [16], and chronic-disease self-management self-efficacy [19]. The instruments were the Chinese version of the Cancer Self-management Self-efficacy Scale [15], the Exercise Self-efficacy Scale [16] and the Chronic Disease Self-efficacy Scale [19], respectively.

4. Discussion

4.1. Advantages of mobile health in lung cancer self-management and remaining challenges

The self-management needs of patients with lung cancer span two critical stages, namely the postoperative rehabilitation period and the intervals between systemic therapies. Most patients have a relatively high level of disease awareness but insufficient skills [24]. This cognition-action gap can be explained by the Common-Sense Model of self-regulation: patients' coping behaviors are not driven directly by medical advice but are generated by their own illness representations, namely what the disease is, what causes it, how long it will last, and whether it can be controlled [32]. In other words, knowing what to do and being able to do it in a specific context are two distinct capabilities, and the role of mobile health lies precisely between them: it does not change patients' illness perceptions but translates cognition into executable, feedback-driven, and correctable daily actions. This also explains why theory-driven interventions are more likely to produce behavioral effects. Liang et al. [15] constructed a stratified intervention based on Orem's Self-Care Theory, covering universal, developmental, and health-deviation self-care requisites; its underlying logic is that when patients' self-care capability is insufficient, nurses provide partial compensation according to the size of the deficit. The data-upload supervision and complication-grading management in Zhai et al. [20] follow the same mechanism. The application of mobile health in nursing has been reviewed previously [7]; however, based on the evidence of this review, it should not be positioned merely as an information-dissemination tool but rather as a dynamic compensation system for self-care deficits, in which the timing, dose, and escalation pathway of compensation are what nursing science needs to design and validate.

Within this framework, the functions of the included studies concentrated on four aspects.

(1) Specialized remote health education: platforms delivered disease knowledge, symptom-management strategies, and exercise-rehabilitation guidance through knowledge modules, periodic push notifications, and auxiliary manuals; the microlearning platform of Janssen et al. [19] and the daily science-education push of Zhai et al. [20] both used sustained knowledge delivery as an intervention component. (2) Proactive symptom monitoring and alerting: patients reported symptoms proactively through the platform, and the system automatically matched management advice according to CTCAE severity grading [10], notifying the clinical team when severe symptoms or abnormal device-monitored parameters were reported, thereby shifting symptom management from passive follow-up to proactive response; high-risk alerting and closed-loop management were observed in five studies [10,12,13,15,22], of which four [10,13,15,22] also evaluated symptom burden or quality of life.

(3) Scientific exercise-rehabilitation guidance: individualised aerobic, resistance or respiratory training plans were developed according to patients' own activity levels and delivered through apps or wearable devices, with telephone or video guidance in some studies; six studies provided this function [11,16,18,20-22], of which five [11,16,18,21,22] evaluated exercise capacity or physical activity, and the follow-up of Granger et al. [16] extended to 12 months postoperatively beyond the 3-month intervention.

(4) Multidimensional psychological and behavioral support: structured emotion-management courses, emotional science education, and peer support provided sustained emotional support; five studies provided psychological support [14,15,17,20,22], of which four [14,17,20,22] evaluated anxiety, depression, or psychological distress; personalized reminders and notifications (seven studies [11,15,17,19-22]) promoted self-management through both psychological counseling and behavioral supervision, delivered by system push or proactive clinician contact.

It should be noted that the coverage of the above functions was unbalanced: symptom data transmission, reminders and symptom monitoring were the most prevalent, whereas psychological support, peer interaction platforms and clinician feedback were relatively limited. Moreover, the basis on which exercise programs were formulated varied considerably across studies, ranging from automatic algorithm generation to manual clinician assessment, and their degree of standardization and generalisability remains to be validated. This imbalance itself deserves attention: the most frequently designed function is not necessarily the function most needed by patients during rehabilitation.

Among the nine functions, clinician feedback and consultation differs in nature from the other eight: whereas the remaining functions are patient-side self-help tools, this is the only bidirectional function, directly reconnecting patients to the healthcare system. The five studies providing this function [10,15,20,22,23] all reported positive evaluations; however, the response mechanisms described varied greatly. Only Liang et al. [15] specified a clear time limit (response by healthcare professionals within 2 h, with graded management according to a protocol and immediate video consultation for moderate-to-severe symptoms); Reddy et al. [10] adopted a passive response in which system alerts triggered nurses to contact patients proactively; Zhai et al. [20] stipulated that failure to upload data on time would trigger a telephone call; and the remaining studies merely stated “online reply” or “reply within 24 h”, with none reporting the response arrangement outside working hours. From the perspective of nursing safety, response time is not a service-experience indicator but a safety parameter: it determines whether symptom deterioration can be intercepted in time and how much staffing is required. Future research should therefore report who responds, within what time frame, and under what circumstances escalation occurs as design variables, rather than dismissing them as service details.

The peer interaction platform appeared only in two China-localized studies based on the WeChat ecosystem [15,20], and its applicability outside Chinese-speaking cultural contexts should not be dismissed as unclear. What is non-transferable lies not in technology but in three cultural parameters: the density of patients’ existing relationship networks, the acceptability of openly discussing one’s condition, and the convention of open clinician-patient question-and-answer. All three are embedded in specific healthcare cultures and cannot be replaced by technical adaptation at the platform level,so they need to be examined through multinational studies rather than assumed to be transferable.

The evidence structure of the existing studies is itself a finding: of the 14 studies, eight were randomized controlled trials, one [15] was a quasi-experimental design assigned by admission time, three were single-arm studies, and two were mixed-methods studies. Only Granger et al. [16] and Zhang et al. [17] adopted assessor blinding; the comparators were mostly usual care or waiting lists, without active controls; and five studies had a total sample size of fewer than 60 participants. This composition is not coincidental but reflects the fact that mobile-health oncology research as a whole remains at the feasibility and acceptability exploration stage. Correspondingly, the effective operation of the above functions depends on the human input and organizational workflow behind them, and their sustainability depends on whether this human cost can be made explicit, which is both a design question for future research and a determinant of whether mobile health can move from the research setting into routine nursing.

Compared with previous reviews, the contributions of this review are threefold. First, the literature review by Sereno et al. [6] focused on the formats and feasibility of mobile health in lung cancer, and the systematic review by Kirkpatrick et al. [8] focused on the effects of supportive eHealth technologies on physical function and quality of life, but neither examined the qualitative differences among functions; this

review identified that only clinician feedback is bidirectional among the nine functions and accordingly proposed that response time should be treated as a safety parameter. Second, previous reviews did not discuss the cross-study comparability of outcome instruments, whereas this review found marked dispersion of instruments within the same outcome category, which is the direct reason why effects are difficult to pool. Third, this review elevated the nursing response model from an implementation detail to a design variable, thereby defining a specific research position for nursing science in this field.

4.2. Profile of the outcome measures used

In terms of outcome measures, the 14 studies reported nine categories of outcomes. Quality of life and feasibility and satisfaction were the most widely used, followed by anxiety and depression, physical symptoms, physical activity and self-efficacy, with patient-reported outcomes predominating overall, which is consistent with the emphasis of modern nursing science on both functional recovery and quality of life. This distribution is itself informative: the most widely used outcomes were precisely those most easily collected, namely scale-based self-report, questionnaires, and platform back-end data, whereas outcomes requiring clinical interpretation or objective measurement were markedly fewer, with pulmonary function [12,21] and knowledge [19] evaluated in only two studies and one study, respectively. In other words, what the literature measures is determined to a large extent by what the platform can collect, rather than entirely by what patients most need during rehabilitation.

More noteworthy is the dispersion of instruments within the same outcome category. Quality of life involved six instruments (EORTC QLQ-C30, FACT-L, EQ-5D-5L, EQ-VAS, SGRQ, GQOLI-74) targeting the general cancer population, the lung cancer-specific population, health utility values, and respiratory diseases, respectively, with different measurement purposes. The three studies on self-efficacy used the Cancer Self-management Self-efficacy Scale [15], the Exercise Self-efficacy Scale [16], and the Chronic Disease Self-efficacy Scale [19], respectively; the three share the label of "self-efficacy" but not the underlying construct being measured. Feasibility and satisfaction used five instruments (SUS, CSUQ, TSUQ, PGA, and self-developed questionnaires), and physical symptoms involved eight instruments. This heterogeneity means that even when all studies report "improvement", the improvements cannot be combined into a single conclusion; what this review characterizes is research activity rather than a poolable effect.

With regard to feasibility, qualitative feedback and usage indicators suggest that patients with lung cancer show good acceptance of mobile health, but two points warrant attention. First, recruitment and retention rates were not benchmarked against a control in most studies, and the relevant data were scattered across the methods and results sections, limiting cross-study comparison. Second, the included studies used usual care or waiting lists as comparators; only two used assessor blinding [16,17], and only two reported formal sample-size calculations [13,14]; notably, Granger et al. [16] explicitly stated that the study was not powered for between-group differences in secondary outcomes. Therefore, the direction of the "effect" is determined to a large extent by the instruments and comparators chosen by each study, and effect sizes still require validation in more high-quality randomized controlled trials.

Finally, the boundary of the evidence should be made explicit. No study used clinical events such as symptom deterioration, treatment interruption, or unplanned hospitalization as the primary outcome; all focused on patient-reported symptom burden, quality of life, and feasibility indicators. Current evidence therefore supports the claim that mobile health can improve self-reported symptom burden and quality of life

in patients with lung cancer, but is insufficient to support the claim that it can reduce acute events, alter the treatment trajectory, or confer survival benefit. Likewise, a platform being shown to be usable and accepted does not equate to being shown to be beneficial, which is a limitation that this review should convey clearly to readers.

4.3. Limitations of existing research and future directions

This review has several limitations. At the methodological level, grey literature was not included, and only Chinese- and English-language publications were searched, which may introduce language and publication bias. At the evidence level, the included studies mostly used usual care as the comparator; only two used assessor blinding [16,17], five had a total sample size of fewer than 60 participants; and only four [10,12,13,15] had an intervention period of six months or longer, so evidence on long-term effects is insufficient; these characteristics reflect the stage of the field rather than the shortcomings of individual studies. At the resource level, only Pongiglione et al. [13] reported an economic evaluation (a per-patient cost of €2,900 versus €3,720,with no statistically significant difference, and cost data from a single hospital); the remaining studies did not characterize resource consumption and staffing costs, leaving a gap between "effective" and "generalizable". At the geographical level, the samples of the included studies were predominantly from high-income and upper-middle-income countries and regions; this distribution is directly related to the infrastructure of the mobile-health industry, reimbursement models, and the entry threshold for digital health, and represents a structural feature of the field rather than a retrieval bias of this review.

To further improve the effectiveness of mobile health, future research should proceed in the following directions.

(1) Stratified intervention and the integration of artificial intelligence. Early postoperative patients prioritize exercise rehabilitation [4], patients on maintenance therapy for advanced disease prioritize symptom control, and patients receiving targeted therapy or immunotherapy need to cope with specific adverse reactions [25]. Future research may stratify patients according to clinical stage and treatment phase, and develop mobile products with clinical-grade specialized functions for each scenario. Preliminary evidence supports the integration of generative artificial intelligence with mobile health: a recent scoping review showed that multi-turn large-language-model-based conversational systems have been used for continuous communication with patients with cancer and their caregivers, extending beyond protocolized symptom lists to answering additional questions [29]. Notably, in the studies included in this review, this function is currently performed by nurses under research conditions [10,15,20,22,23]. The core question for the next step is therefore not technical feasibility but whether such systems can take over part of the response function while guaranteeing response quality and without weakening the nurse-patient relationship itself. Future research should further introduce large language models and multimodal artificial intelligence technologies to build intelligent interactive systems capable of understanding patients' semantic context, dynamically assessing the trajectory of symptom evolution, and generating individualized management advice.

(2) Strengthening age-friendly design and humanistic care. Patients with lung cancer are predominantly middle-aged and older adults, for whom the digital divide is a major barrier to intervention participation. Qualitative research on the adoption of digital health technologies by older patients with cancer indicates that the barriers center on device access, the availability of family assistance, and patients' self-assessment of their own technical competence [26]; the last suggests that the barrier

is partly self-perceived and can be alleviated through guidance and companionship rather than being a purely technical threshold. Studies show that patients with lung cancer prefer real-time one-to-one communication, which could be incorporated [27]. Domestic patient groups are highly familiar with and attached to the WeChat ecosystem, making the WeChat public account a highly feasible and acceptable intervention vehicle [28]. Humanistic care is key to helping patients understand and trust mobile health effectively [30]; future research should deeply integrate the concept of humanistic care into technology development, and embed it throughout product design, service delivery, health intervention and outcome evaluation.

(3) Information-quality building and long-term effect validation. The quality of the health information carried by a platform underpins its sustainable development; attention should be paid to the standardization of health information, the establishment of content-review mechanisms and reputation-evaluation systems, so as to ensure that platforms do not sacrifice information quality while expanding coverage and thus achieve sustainable development [31]. Future research should extend follow-up to six months or longer, establish multicentre, large-sample randomized controlled trials, and promote the construction of a core outcome set to accumulate high-quality evidence on the long-term effects of mobile health.

(4) Nurse-led implementation models. Whether the above functions can be truly implemented depends on the position of the nursing team. In this review, alert judgment, data verification, and consultation replies were undertaken by nurses in five studies [10,15,20,22,23], of which two delegated the response threshold to clinical judgment rather than to an algorithm [15,23]. A systematic review supports the effect of nurse-led mHealth interventions on symptom outcomes in the oncology population [33], and individualized nurse-led programs for post-discharge patients have been validated in a randomized controlled trial [34]. On this basis, future research is advised to report the implementation model itself as an intervention variable: who responds, within what time, what threshold triggers escalation, and how online and offline components are connected; and to incorporate the concordance between patient-reported symptoms and nurse assessment as a nursing-specific outcome measure. Only in this way can an intervention shown to be effective in a single-center trial be judged in terms of the staffing required and its potential to enter routine nursing.

5. Conclusion

This review included 14 studies and mapped the application formats, core functions and outcome measures of mobile health in lung cancer self-management. Existing interventions are dominated by mobile applications and websites, with functions covering symptom monitoring, exercise rehabilitation, psychological support, and clinician consultation. This review draws three conclusions. First, among the nine functions, only clinician feedback and consultation are bidirectional, yet no study reported its response arrangement outside working hours; response time thus becomes a safety parameter that has not yet been reported. Second, the nine categories of outcome measures are dispersed across six quality-of-life instruments, three self-efficacy scales, and multiple symptom-assessment tools, and cannot be combined within the same category; current evidence supports an improvement in self-reported symptom burden and quality of life,but is insufficient to support clinical endpoints such as survival benefit. Third, the value of mobile health in nursing practice should be understood as the dynamic compensation of self-care deficits, the sustainability of which depends on whether the human and organizational workflow can be made explicit. Future research should first unify outcome-measurement instruments and treat the nursing response model and response time as essential

design and reporting variables, before undertaking long-term, multicentre effect validation.

Disclosure statement

The authors declare no conflict of interest.

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