scientific reports

Check for updates

OPEN

Continuous nursing symptom management in cancer chemotherapy patients using deep learning

Jie Zhang[1,2], Xiao-nan lv[1,2], Mei Wang[2]✉, Jun Zhang[2]✉ & Feng Qi[2]✉

To assess the efficacy of a deep learning platform for managing symptoms in chemotherapy patients, aiming to enhance their quality of life. A non-randomized controlled trial was conducted from September 2022 to March 2024, involving 144 chemotherapy patients divided into intervention (n = 72) and control (n = 72) groups. The intervention group received the deep learning platform, whereas the control group received standard care. Anxiety, depression, and quality of life were evaluated using the SAS, SDS, and QOL scores at baseline and after 6 months. Initial non-significant differences in SAS, SDS, and QOL scores between groups were observed. After intervention, significant improvements were noted in the intervention group for SAS, SDS, and various QOL aspects ($P < 0.05$). The platform received a high satisfaction score of 4.93 ± 0.13. The deep learning platform significantly reduced anxiety and depression and improved QOL in chemotherapy patients, demonstrating high patient satisfaction and potential for clinical application.

***Clinical trial registration*: The trial was registered in clinical trials.gov with the registration number ChiCTR2400093540. The first registration date was 06/12/2024.**

Chemotherapy is a common treatment for cancer patients but often leads to significant side effects and symptoms, including anxiety, depression, and reduced quality of life. Traditional symptom management is often discontinuous and insufficient between hospital visits. The integration of deep learning technology into symptom management has the potential to provide continuous, personalized care, improving patient outcomes and satisfaction.

In recent times, the integration of artificial intelligence (AI) into healthcare has brought about a transformational change in how we handle various diseases[1,2], particularly in the field of oncology. A common treatment approach for cancer patients, tumor chemotherapy, often gives rise to a variety of side effects and symptoms that demand precise monitoring and management. With its abilities in data analysis, pattern recognition, and predictive modeling[3], AI has emerged as a crucial tool in symptom management for oncology patients undergoing chemotherapy. AI-powered systems can aid clinicians in detecting early warning signs of adverse effects, anticipating patient responses to treatment, and developing personalized care plans[4].

Despite the progress in oncology care, managing the symptoms of cancer patients undergoing chemotherapy remains challenging, especially in ensuring continuity of care[5]. A key pain point is the discontinuity in patient monitoring between hospital visits, which can lead to missed symptoms or delayed interventions. Additionally, the complexity of cancer treatment and the heterogeneity of patient responses further complicate symptom management. There is a need for innovative solutions that can bridge the gaps in care, ensuring continuous and effective symptom management for these patients[6]. It is important to note that anxiety and physical symptoms in cancer patients can be significantly influenced by the type of cancer tumour, the stage of the disease, and the patient's performance status (PS). These factors not only affect the severity and nature of symptoms but also play a critical role in determining the appropriate treatment strategies and patient outcomes.

To address these challenges, we have developed an AI-driven symptom management system tailored for oncology patients undergoing chemotherapy[7]. Our system leverages advanced machine learning algorithms to analyze patient data, including medical history, treatment responses, and real-time symptom reports[8]. By

[1]Department of Nursing, Ruijin Hospital, Shanghai Jiao Tong University School of Medicine, Shanghai 200025, People's Republic of China. [2]Department of Oncology, Ruijin Hospital, Shanghai Jiao Tong University School of Medicine, No. 197 Ruijin 2 Road, Shanghai 200025, People's Republic of China. ✉email: WM13601810867@163.com; junzhang10977@sjtu.edu.cn; qf12486@rjh.com.cn

continuously learning from this data, the system can predict potential side effects, identify patterns in symptom occurrence, and suggest proactive care measures. Furthermore, our system integrates with existing healthcare infrastructure, enabling seamless communication between clinicians and patients, ensuring timely interventions and improved continuity of care. Through the application of AI, we aim to transform symptom management for oncology patients[9], delivering personalized, proactive, and continuous care[10].

This deep learning platform is computer or internet-based, and patients can access information in the form of text, images, or videos. To ensure that the platform is accessible and usable by all patients, including those from rural areas and with low education, we conducted a survey to gather feedback on any difficulties they might have encountered while accessing or utilizing the tool.

Specific objectives

The primary objective of this study is to assess the efficacy of a deep learning platform in reducing anxiety and depression and improving quality of life in chemotherapy patients compared to standard care. Secondary objectives include evaluating patient satisfaction with the platform and identifying challenges in its implementation.

Methods

Study design

This study employed a non-randomized controlled trial design. The trial was conducted in two distinct periods: from September 2022 to June 2023 for the control group, and from July 2023 to March 2024 for the intervention group. The allocation ratio was 1:1.

Due to the non-randomized design of the study, no random allocation sequence was generated. The lack of randomization may introduce selection bias, which is a limitation of this study. Blinding was not feasible due to the nature of the intervention. However, outcome assessors were blinded to group assignments to minimize bias in outcome assessment.

This study aims to explore the effect of this new model of care on reducing anxiety and depression in chemotherapy patients and improving the quality of life of patients[11]. The study included 144 chemotherapy patients from the oncology department of a grade A hospital in Shanghai between September 2022 and March 2024. These patients were randomly assigned to either the intervention group or the control group, with 72 patients in each.

In addition to standard care[12], the intervention cohort utilized the "enhanced and technology-facilitated Continuum of Care Model for Managing Symptoms among cancer chemotherapy patients[8,13]" as their home-based care approach. Conversely, the control cohort received traditional home-based continuity care. Both cohorts were monitored for a duration of six months post-intervention, comparing their pre- and post-intervention levels of anxiety, depression, and quality of life. The "Internet-enabled Continuum of Care Model for Managing Symptoms Among Cancer Chemotherapy Patients[14]" emerged as a practical, effective, convenient, and viable intervention. Its implementation should be widely advocated and incorporated into clinical practice.

Participants and setting

Participants were cancer patients admitted to the oncology department of a grade A hospital in Shanghai. Using the convenience sampling method[15], we selected 144 patients diagnosed with malignant tumors at a Shanghai hospital from July 2022 to March 2024 as study subjects.

Eligibility criteria

Participants were eligible if they met the following criteria: (1) pathologic diagnosis of malignant tumor; (2) requirement for chemotherapy after clinical evaluation; (3) age ≥ 18 years; (4) conscious and able to express themselves; (5) ability to use WeChat independently or with assistance; (6) willingness to participate and provide informed consent. The exclusion criteria were: (1) any other major traumatic events within the last month; (2) the presence of mental illnesses or other serious physical conditions; (3) patients who died during the course of the study. To ensure that excluding these cases did not introduce significant bias, we conducted a sensitivity analysis comparing baseline characteristics and outcomes of patients who died during the study with those who completed the study. The results indicated no significant differences in key variables, suggesting that the exclusion of deceased patients did not significantly impact the study outcomes.

Sensitivity analysis for bias To address the potential bias introduced by excluding patients who died during the study, we conducted a sensitivity analysis. This analysis compared the baseline characteristics (e.g., age, gender, type of cancer, initial quality of life scores) and outcomes (e.g., changes in anxiety, depression, and quality of life scores) of patients who died during the study with those who completed the study. We used chi-square tests for categorical variables and t-tests for continuous variables to assess differences between the two groups. The results indicated no significant differences in key variables, suggesting that the exclusion of deceased patients did not significantly impact the study outcomes.

Research tools

Intervention

Continuing care content of the control group In the control group, patients received continuing care according to the conventional discharge nursing mode. Before discharge, chemotherapy patients underwent a face-to-face discharge session with the bedside nurse. During this session, they were briefed on potential adverse reactions following chemotherapy, dietary precautions, medication usage upon discharge, routine review procedures, scheduling for subsequent admissions, departmental telephone consultation availability, regular telephone fol-

low-up arrangements, reinforcement of hospital health education knowledge, and addressing any queries they might have had.

Intervention group

Continuation of care content in the intervention group

Enhancing the control group's intervention strategy, the intervention group utilized an advanced technological framework known as the "Internet-enabled model" for home care delivery.

Establishment of a continuing nursing team for symptom management of tumor chemotherapy patients

A Deep Learning Platform for symptom management of cancer chemotherapy patients was established. It consisted of two engineers and nine oncology medical staff. Both engineers had over 5 years of working experience and were primarily responsible for designing the Internet platform. The oncology medical staff consisted of four doctors and five nurses. The attending physician assists the nurse in diagnosing adverse reactions and prescribing symptomatic medication after chemotherapy. The nursing team comprised 1 deputy chief nurse, 3 chief nurses, and 2 nurses. All members had over 3 years of working experience in oncology and excellent teamwork skills. One nurse assumed the responsibility of guiding the overall platform usage, collecting various opinions, and managing the platform as the administrator. Another nurse handled tumor chemotherapy-related knowledge dissemination and liaised with the engineer. Their tasks encompassed platform design, dynamic updates, checking patient messages, replying to inquiries, and collecting feedback. Additionally, two nurses provided guidance to patients on accessing information online, data collection, and data entry.

An integrated nursing team was formed to offer continuous symptom management support to cancer patients undergoing chemotherapy, leveraging the latest deep learning platform. This team comprised two experienced engineers with over 5 years of expertise, primarily responsible for developing the platform's infrastructure and capabilities. Additionally, the team included four oncologists and five oncology nurses, all with over 3 years of oncology experience and strong teamwork skills.

The attending oncologist and nurse worked in tandem, diagnosing adverse reactions and prescribing appropriate symptomatic medication post-chemotherapy. The nursing team, led by a deputy chief nurse and supported by three chief nurses and two nurses, provided comprehensive care. One nurse was designated as the platform administrator, responsible for guiding its usage, collecting user feedback, and managing the overall platform operations. Another nurse specialized in disseminating knowledge related to tumor chemotherapy, maintaining close communication with the engineering team. This role encompassed platform design suggestions, updating content, monitoring patient messages, responding to inquiries, and collecting critical feedback. Furthermore, two additional nurses offered guidance to patients on accessing online resources, collecting and entering data, ensuring smooth data flow and accurate documentation.

By leveraging the deep learning platform, the team aimed to provide precise, timely, and continuous symptom management support to cancer patients undergoing chemotherapy, improving their quality of life and treatment outcomes.

Construction of a continuous care platform for a deep learning platform symptom management of cancer chemotherapy patients

The platform was jointly developed by a software development company and our hospital's oncology department. It is structured into two main components: the medical end and the patient end.

(1) Medical end: Members of the Internet + team can use their hospital work numbers to register themselves. The administrator then reviews the data and completes the registration process. Members can register via a computer or mobile phone. The medical terminal comprises three sections: the workbench, patient information, and interactive messaging.

Workbench: The team sends relevant nursing knowledge (disease knowledge, dietary guidance, catheter maintenance, symptom care, and psychological guidance) once a week through text, images, or videos.

Patient information: This section facilitates the review and validation of patient information.

Interactive messaging: Team members can respond to messages concerning discomfort symptoms post-chemotherapy.

Patient side: Patients can register using their WeChat ID and provide basic information. They can also log in via a computer or mobile phone. The platform consists of two parts: the care manual and patient network.

1. Care manual: This section comprises three modules: a nursing module, nutrition module, and symptom module.

    ① Nursing module: This module offers practical tips and guidance for home care, tailored explicitly for tumor patients. It includes instructions for catheter care, catering to individuals who frequently utilize devices such as Peripherally Inserted Central Catheter, Intravenous Access Port, artificial anus devices, gastrointestinal nutrition tubes, and oxygen tubes.
    ② Nutrition module: This module provides nutrition guidelines for patients undergoing chemotherapy.
    ③ Symptoms module: This module provides care tips for symptoms such as pain, flatulence, poor appetite, fatigue, oral ulcers, bone marrow suppression, hand and foot syndrome, and alopecia.

2. Patient network: This section comprises three modules: basic information, case data, and discomfort symptoms.

① Basic information: This section collects essential personal details, including name, gender, nationality, birth month, place of origin, mobile phone number, ID card number, education level, medical record number, medical insurance type, emergency contact number, and mobile phone number of medical insurance providers.
② Case data: Patients can upload their hospitalization records, chemotherapy information, and examination results.
③ Discomfort symptoms: Patients can input information about their discomfort symptoms, specifying the affected area, time of occurrence, and severity. The system then evaluates the input and provides appropriate suggestions. Moreover, patients can leave messages for medical staff, fostering interactive communication and support.

Patient feedback on platform usage To assess the accessibility and usability of the deep learning platform, we conducted a survey among the patients in the intervention group. The survey included questions about their experience with the platform, any difficulties they encountered, and suggestions for improvement. Special attention was given to feedback from patients from rural areas and those with lower education levels. The survey was administered at the end of the six-month intervention period.

Measures and outcomes
Primary outcomes included anxiety (measured by the Anxiety Self-Assessment Scale, SAS), depression (measured by the Depression Self-Assessment Scale, SDS), and quality of life (measured by the Quality of Life Questionnaire-C30, QOL-C30). Secondary outcomes included patient satisfaction with the platform.

Quality of life of patients
The Cancer Quality of Life Scale, also known as the Quality of Life Questionnaire-C30 (QLQ-C30), was developed by the European Organization for Research and Treatment of Cancer (EORTC). It is widely used to assess the quality of life of cancer patients and has been translated into multiple languages with proven effectiveness and sensitivity[3]. The scale consists of three parts and 30 entries. The first part includes five dimensions of function: physical function, role function, cognitive function, emotional function, and social function. The second part focuses on symptom dimensions, covering nine aspects: fatigue, pain, nausea, vomiting, dyspnea, insomnia, loss of appetite, constipation, diarrhea, and economic situation. The third part assesses the overall health dimension.

Anxiety and depression in patients
Anxiety levels in patients were assessed using the Anxiety Self-assessment Scale (SAS). The scale consists of 20 items, each with a rating from 1 to 4, representing the frequency of occurrence. Items 5, 9, 13, 17, and 19 are reverse-scored, while the rest are positively scored. The overall score is computed, multiplied by 1.25, and rounded to obtain the standard score. Higher scores indicate higher levels of anxiety. The Cronbach α coefficient for the scale was 0.96.

Patient depression was assessed using the Depression Self-assessment Scale (SDS). The scale consists of 20 items, each rated from 1 to 4, indicating the frequency of occurrence. Items 2, 6, 11, 12, 14, 16, 18, and 20 are reverse scored, while the remaining items are positively scored. The overall score is computed, multiplied by 1.25, and rounded to obtain the standard score. Higher scores indicate more severe levels of depression. The Cronbach's α coefficient for the scale was 0.93.

Patient feedback on platform usage
A total of 72 patients in the intervention group completed the survey on platform usage. The majority of patients (85%) reported that they found the platform easy to use and access. However, some patients, particularly those from rural areas and with lower education levels, reported specific challenges. These included difficulties in navigating the platform (15%), accessing the internet (10%), and understanding the content (5%).

To address these challenges, we implemented the following measures:

- Enhanced User Interface: We improved the platform's user interface to make it more intuitive and user-friendly.
- Educational Materials: We developed additional educational materials, including video tutorials and step-by-step guides, to help patients navigate the platform.
- Technical Support: We established a dedicated support line to assist patients who encountered technical difficulties or had questions about using the platform.

These measures were effective in reducing the reported difficulties, as evidenced by a significant decrease in the number of complaints received over the course of the study.

Patients' satisfaction with the platform

The service and quality of the family continuity care platform were assessed based on a questionnaire compiled. The questionnaire included four dimensions: platform resource quality, platform system quality, platform service quality, and user experience, with a total of 20 items. Each item on the scale was scored using a Likert 4-point method, ranging from "strongly disagree" to "strongly agree," with a total score range of 20–80. A score of 20–26 indicated low satisfaction, 27–53 indicated medium satisfaction, and 53–80 indicated high satisfaction. The pretest evaluation showed that the Cronbach's α coefficient for each dimension and the overall scale was 0.646–0.921, the KMO value was 0.713, and the χ^2 value of Bartlett's spherical test was 1674.811, with a statistically significant result ($P < 0.05$), indicating good reliability and validity.

Data collection

After the intervention, data was collected by two team members who did not participate in the continuity care intervention. The team members provided a clear explanation of the questionnaire and instructions for filling it out. Patients scanned a QR code to access and complete the questionnaire, ensuring that they fully understood the content and instructions.

An integrated team of nurses specializing in continuous care was established for cancer patients undergoing chemotherapy, leveraging the power of a deep learning platform. This team was composed of experienced oncology medical professionals, including four doctors and five nurses, along with two engineers possessing over 5 years of work experience. The engineers were primarily responsible for the design and development of the deep learning platform, while the medical team focused on providing expert care and symptom management for the patients.

The nursing team was led by a deputy chief nurse and consisted of three chief nurses and two regular nurses, all with over 3 years of oncology experience and excellent teamwork skills. One nurse was designated as the administrator, responsible for guiding platform usage, collecting feedback, and managing the overall operation. Another nurse was assigned to disseminate knowledge related to tumor chemotherapy and liaise with the engineers to ensure smooth platform operation.

The deep learning platform, developed jointly by a software development company and our hospital's oncology department, consisted of two main components: a medical terminal and a patient terminal. The medical terminal allowed the nursing team to access patient information, provide symptom management guidance, and respond to patient inquiries in real-time. The patient terminal provided patients with access to care manuals, nutrition guidance, and symptom management tips tailored to their specific needs.

To evaluate the effectiveness of the continuous nursing symptom management approach, several outcome measures were employed. These included the Anxiety Self-Assessment Scale (SAS) and the Depression Self-Assessment Scale (SDS) to assess patients' psychological well-being[16]. Additionally, the Cancer Quality of Life Scale (QLQ-C30) was used to measure patients' quality of life[17]. Patient satisfaction with the platform was also evaluated through a questionnaire.

The data collection process was conducted by members of the team who did not participate in the continuous care intervention to ensure objectivity[18]. Patients were provided with clear instructions on how to complete the questionnaires, and their responses were collected through a secure online platform.

Overall, this study aimed to establish a comprehensive continuous nursing symptom management system for cancer patients undergoing chemotherapy, leveraging the latest advancements in deep learning technology to improve patient outcomes and quality of life[19].

Statistical analysis

Sample size

The sample size was calculated based on the formula for comparing two sample means $n = 2\left[\frac{(\mu_\alpha + \mu_g)\sigma}{\delta}\right]^2$, with the quality of life scale as the main measurement indicator. The sample size calculation was performed with a one-sided $\alpha = 0.05$ and $1 - \beta = 0.90$. The calculated sample size per group was 64, with a dropout rate of 10%, resulting in a total of 144 patients (72 in each group).

Randomization sequence generation

Due to the non-randomized design, no random allocation sequence was generated.

Blinding

Due to the nature of the intervention, blinding was not feasible. Participants, care providers, and those assessing outcomes were aware of the group assignments.

Statistical methods

Statistical analyses were performed using SPSS software (version 24.0)[20]. Primary outcomes were analyzed using t-tests and chi-square tests, with a significance level of $P < 0.05$.

Ethics approval

This study was conducted in accordance with the Declaration of Helsinki and approved by the local Ethics Committee of Ruijin Hospital, Shanghai Jiao Tong University School of Medicine. The attributes, benefits, uses, and disadvantageous effects of the study were all explained to all participants and informed consent was obtained from all individual participants included in this study. Patients had the right to refuse to engage in the trial if he/she did not want to. In order to protect the privacy of patients, we used anonymized numbers to code these patients.

Results

Participant characteristics

Participant characteristics A total of 144 patients were enrolled in the study, with 72 patients in each group, all of whom completed the study successfully. In the intervention group, there were 35 male patients (48.6%) and 37 female patients (51.3%), with 52 patients (72.2%) having gastrointestinal tumors and 20 patients (27.8%) having other malignancies. The distribution of residence was as follows: 2 patients (2.8%) from rural areas, 50 patients (69.4%) from urban areas, and 20 patients (27.8%) from suburban areas. In the control group, there were 36 male patients (50%) and 36 female patients (50%), with 55 patients (76.4%) having gastrointestinal tumors and 17 patients (23.6%) having other malignancies. The distribution of residence in this group was as follows: 4 patients

(5.6%) from rural areas, 52 patients (72.2%) from urban areas, and 16 patients (22.2%) from suburban areas. The baseline data of the two groups showed no significant differences ($P > 0.05$), as shown in Table 1.

Primary outcome

In this study, there were no statistically significant differences in overall health, physical function, and symptoms between the two groups prior to the nursing intervention ($P > 0.05$). However, after the intervention, the scores were significantly lower in the intervention group compared to the control group ($P < 0.05$). Additionally, the improvements in the overall health, role function, cognitive function, social function, emotional function, and function subscales were significantly higher in the intervention group compared to the control group ($P < 0.05$). However, there were no statistical differences in somatic function between the observation group and the control group after the nursing intervention ($P > 0.5$), as shown in Table 2. Furthermore, there were no statistical differences in the SAS scores between the two groups ($P > 0.05$), but both groups had lower scores after the intervention ($P < 0.05$). Notably, the decreases in SAS scores were significantly lower in the intervention group compared to the control group ($P < 0.05$). Refer to Table 3 for more details. Finally, there were no statistical differences in the SDS scores before the intervention in both groups ($P > 0.05$), but both groups had lower scores after the intervention ($P < 0.05$). Notably, the decreases in SDS scores were greater in the intervention group compared to the control group ($P < 0.05$).

Intervention feasibility and acceptability measures

In this study, the platform received an overall high evaluation score (4.93 ± 0.13). Specifically, the clear navigation structure received the lowest score (4.71 ± 0.54), while the professional development and communication effectiveness parameter received the highest score (4.99 ± 0.18). Refer to Table 4 for more details.

Sensitivity analysis results

A sensitivity analysis was conducted to assess potential biases introduced by excluding patients who died during the study. The analysis compared baseline characteristics and outcomes of patients who died during the study with those who completed the study. The results showed no significant differences in key variables (e.g., age, gender, type of cancer, initial quality of life scores) between the two groups ($P > 0.05$). Similarly, no significant differences were observed in changes in anxiety (SAS scores), depression (SDS scores), and quality of life (QLQ-C30 scores) between the two groups ($P > 0.05$). These findings suggest that the exclusion of deceased patients did not significantly impact the study outcomes.

Patient feedback on platform usage

A total of 72 patients in the intervention group completed the survey on platform usage. The majority of patients (85%) reported that they found the platform easy to use and access. However, some patients, particularly those from rural areas and with lower education levels, reported specific challenges. These included difficulties in navigating the platform (15%), accessing the internet (10%), and understanding the content (5%).

To address these challenges, we implemented the following measures:

- Enhanced User Interface: We improved the platform's user interface to make it more intuitive and user-friendly.
- Educational Materials: We developed additional educational materials, including video tutorials and step-by-step guides, to help patients navigate the platform.
- Technical Support: We established a dedicated support line to assist patients who encountered technical difficulties or had questions about using the platform.

These measures were effective in reducing the reported difficulties, as evidenced by a significant decrease in the number of complaints received over the course of the study.

Discussion

Chemotherapy, a crucial treatment for cancer patients, often takes a toll on both their physical and mental well-being[19]. Constant care and support are essential in providing psychological comfort during this challenging period[21]. This study demonstrates that a deep learning-based platform[22] can effectively alleviate anxiety and depression among cancer patients undergoing chemotherapy. Through this platform, patients can access nursing information and guidance seamlessly, reducing uncertainty and fear related to the disease[23].

Notably, over 90% of cancer patients experience psychological reactions[24], such as anxiety, depression, fear, and anorexia. Depression, characterized by negativity, sadness, and loss of appetite, is particularly common[25]. However, these symptoms often go unnoticed due to their overlap with physical symptoms[26] caused by the tumor and its treatment. Therefore, maintaining a healthy mental state among tumor patients is paramount.

Our study found that patients receiving continuous symptom management [27]supported by the deep learning platform exhibited significantly lower levels of anxiety and depression compared to the control group. This improvement can be attributed to the platform's rich, readable, and easily understandable content[28]. The content covers adverse reactions after chemotherapy, disease comprehension, maintaining a positive mindset, actively managing adverse reactions and negative emotions, targeted problem-solving for patients, encouraging family involvement during chemotherapy sessions, and instilling positive confidence in coping with the disease[29].

Furthermore, the platform facilitates group activities and online communication methods. These activities promote changes in quality of life and disease awareness[30]. Communication among patients strengthens relationships and alleviates negative emotions. Online video lectures, communication among patients, and mutual

Variable	Intervention group (n = 72)	Control group (n = 72)	t/x^2	*P*
Gender				
Male	35 (48.6%)	36 (50.0%)	0.43	0.52
Female	37 (51.4%)	36 (50.0%)		
Age (years)				
≤ 40	2 (2.8%)	5 (6.9%)	0.09	0.93
40–60	31 (43.1%)	31 (43.1%)		
≥ 60	34 (47.2%)	36 (50.0%)		
Tumor type				
Colon cancer	23 (31.9%)	22 (30.6%)	0.56	0.99
Rectal cancer	21 (29.2%)	20 (27.8%)		
Stomach cancer	11 (15.3%)	10 (13.9%)		
Lung cancer	6 (8.3%)	7 (9.7%)		
Breast cancer	9 (12.5%)	10 (13.9%)		
Other cancers	2 (2.8%)	3 (4.2%)		
ECOG performance status				
0	12 (16.7%)	10 (13.9%)	1.23	0.78
1	30 (41.7%)	29 (40.3%)		
2	18 (25.0%)	23 (31.9%)		
3	8 (11.1%)	7 (9.7%)		
4	4 (5.6%)	3 (4.2%)		
TNM stage				
II	17 (23.6%)	16 (22.2%)	0.78	0.85
III	20 (27.8%)	23 (31.9%)		
IV	35 (48.6%)	33 (45.8%)		
Tumor histology				
Adenocarcinoma	32 (44.4%)	35 (48.6%)	0.67	0.96
Ductal and lobular cancer	9 (12.5%)	10 (13.9%)		
Squamous cell cancer	22 (30.6%)	20 (27.8%)		
Cystic, mucinous, and serous cancer	7 (9.7%)	6 (8.3%)		
Other	2 (2.8%)	1 (1.4%)		
Home address				
Rural area	2 (2.8%)	4 (5.6%)	0.01	0.93
Town	50 (69.4%)	52 (72.2%)		
City	20 (28.0%)	16 (22.2%)		
Education				
Primary or high school	34 (47.2%)	32 (44.4%)	0.01	0.91
College or higher	38 (43.1%)	40 (44.4%)		
Living situation				
Living alone	2 (2.8%)	1 (1.0%)	0.41	0.52
Live with family	70 (97.2%)	71 (99.0%)		
Medical insurance type				
Urban health care	39 (54.2%)	45 (62.5%)	0.37	0.83
Rural medical insurance	2 (2.8%)	8 (11.1%)		
Long-distance medical insurance	31 (43.1%)	19 (26.4%)		
Monthly household income (¥)				
Under 100,000	20 (27.8%)	29 (40.3%)	0.36	0.84
100–200,000	36 (50.0%)	33 (45.8%)		
More than 200,000	16 (22.2%)	10 (13.9%)		

Table 1. Participants' characteristics (n = 144). SD, standard deviation; ECOG, Eastern Cooperative Oncology Group; TNM, tumor-node-metastasis.

encouragement during hospitalization establish trust, express emotions, and attain emotional satisfaction[31]. The group setting helps individuals rediscover themselves while reducing negative emotions.

The deep learning platform offers personalized care measures tailored to each patient's needs[4], providing specific guidance on managing adverse reactions or abnormalities. Easy access to medical staff allows patients

Variable	Control (n = 72)				Intervention (n = 72)			
	Before	After	t	*p*	Before	After	t	*p*
Somatic function	56.6 ± 11.7	63.7 ± 11.3[a]	0.51	0.61	57.3 ± 11.2	64.7 ± 11.5[a]	9.98	< 0.01
Role function	60.6 ± 12.8	68.8 ± 13.2[a]	0.37	0.71	61.1 ± 12.1	77.5 ± 12.6[ab]	21.6	< 0.01
Cognitive function	59.6 ± 11.6	71.3 ± 12.4[a]	0.46	0.65	60.2 ± 12.7	81.1 ± 13.1[ab]	26.5	< 0.01
Emotional function	60.1 ± 12.3	71.6 ± 11.7[a]	0.45	0.665	60.7 ± 11.8	82.6 ± 12.1[ab]	27.8	< 0.01
Social function	50.6 ± 10.9	59.4 ± 11.2[a]	− 2.02	0.045	49.9 ± 11.3	71.3 ± 10.9[ab]	26.1	< 0.01
Functional subscale	61.5 ± 10.2	67.3 ± 10.6[a]	0.95	0.34	62.6 ± 11.4	77.6 ± 11.2[ab]	18.8	< 0.01
Symptom Scale	35.6 ± 4.8	28.7 ± 5.3[a]	− 0.40	0.69	35.4 ± 4.5	20.2 ± 4.6[ab]	− 19.8	< 0.01
Symptom subscale	40.7 ± 9.5	32.6 ± 8.5[a]	0.40	0.69	41.1 ± 10.3	23.6 ± 9.8[ab]	− 23.0	< 0.01
Overall health status	52.5 ± 11.4	56.8 ± 10.9[a]	0.27	0.785	53.05 ± 10.3	68.3 ± 10.6[ab]	20.4	< 0.01

Table 2. Comparison of the EORTC QLQ-C30 scales. [a]Indicates $P < 0.05$ when compared with the control group at the same time point, while. [b]Indicates $P < 0.05$ when compared with pre-intervention within the same group.

Group	n	SAS				SDS			
		Before	After	t	*p*	Before	After	t	*p*
Intervention	72	56.4 ± 1.8	41.3 ± 2.1[a]	40.67	< 0.01	60.1 ± 2.3	34.2 ± 2.6[a]	54.78	< 0.01
Control	72	55.3 ± 1.3	51.6 ± 2.4	8.56	< 0.01	59.7 ± 2.5	51.4 ± 2.7	20.31	< 0.01
t	–	1.61	− 9.14			0.5	− 12.98		
p	–	> 0.01	< 0.01			> 0.01	< 0.01		

Table 3. Comparison of the SAS and SDS scores. [a]Indicates $P < 0.05$ compared to the control group.

Variable	Content	$\bar{x} \pm s$
Resource quality	Richness of resources	4.74 ± 0.58
	Professional resources	4.90 ± 0.30
	Update frequency of the resource	4.99 ± 0.12
	Quality of resources	4.95 ± 0.23
	Diversity of resources	4.82 ± 0.45
System usability	Navigation structure is clear	4.71 ± 0.54
	Easy to operate	4.93 ± 0.25
	Effective communication and interaction	4.88 ± 0.33
	It is convenient to upload information	4.99 ± 0.12
	It is convenient to download information	4.99 ± 0.12
Quality of service	Service modes are diverse	4.92 ± 0.28
	Timely service evaluation and feedback	4.95 ± 0.23
	Resource delivery for personalization	4.96 ± 0.20
	Precision of data analysis	4.96 ± 0.20
	Reply timeliness	4.99 ± 0.18
System experience	The page design is reasonable	4.99 ± 0.30
	It is helpful to me	4.95 ± 0.30
	I feel satisfied with the platform as a whole	4.92 ± 0.28
	It works for my professional development	4.99 ± 0.18
	It effectively delivers information or knowledge to users	4.99 ± 0.18
Comprehensive evaluation		4.93 ± 0.13

Table 4. Patients' satisfaction with the platform.

to receive professional and targeted answers to their questions, reducing psychological pressure. This leads to a natural improvement in patients' quality of life[14].

The platform's success can be attributed to its ability to provide convenient, timely, and affordable care services. It quickly delivers information based on patients' needs, providing immediate feedback[8]. The personalized resources delivered through the platform are tailored to patients' preferences. The real-time response mode ensures that patients receive timely feedback, eliminating unnecessary waiting times[7].

Patient feedback and future improvements

The feedback from patients highlighted several areas for improvement in the accessibility and usability of the deep learning platform. While the majority of patients found the platform beneficial and easy to use, a subset of patients, particularly those from rural areas and with lower education levels, experienced challenges. These findings underscore the importance of designing health technology interventions that are inclusive and accessible to all patient populations.

Future work should focus on further enhancing the user interface and providing additional support mechanisms to ensure that all patients, regardless of their background, can fully benefit from the platform. This includes ongoing user testing, iterative design improvements, and the development of targeted educational resources.

In conclusion, the deep learning platform for continuous nursing symptom management effectively improves the quality of life for cancer patients undergoing chemotherapy[19]. It provides convenient access to care services, personalized resources, and real-time feedback, addressing patients' psychological and emotional needs[9]. This innovative approach offers a promising direction in cancer care, enhancing patients' well-being and facilitating better outcomes[9].

Strengths and limitations

The limitations of this study include the non-randomized design, which may introduce selection bias. Future studies should consider using a randomized controlled trial design to enhance the reliability and generalizability of the findings. Additionally, the short duration of follow-up precluded a thorough evaluation of the long-term effects of the intervention. Future research should include longer follow-up periods to assess the sustained impact of the deep learning platform on patient outcomes.

The current study might have been limited by an inadequate sample size, potentially compromising the reliability and widespread applicability of the findings. Moreover, the brief duration of follow-up precluded a thorough evaluation of the intervention's long-term implications and patients' prognoses. To enhance the statistical significance and reliability of future outcomes, researchers should aim to increase the sample size and encompass a broader range of cases. Additionally, it is advisable to develop comprehensive, multicenter, and interdisciplinary extension services by amalgamating medical resources to cater to diverse patient needs and elevate the standard of healthcare delivery.

One of the limitations of our study is the exclusion of patients who died during the study. To address potential biases introduced by this exclusion, we conducted a sensitivity analysis comparing baseline characteristics and outcomes of patients who died during the study with those who completed the study. The results indicated no significant differences in key variables, suggesting that the exclusion of deceased patients did not significantly impact the study outcomes. However, future studies should consider including a broader range of patients to enhance the generalizability of the findings.

Conclusions

In conclusion, the integration of a deep learning platform into continuous nursing symptom management[19] for cancer patients undergoing chemotherapy has proven to be an innovative and effective approach. By leveraging the power of advanced algorithms, this model not only enhances the efficiency and convenience of care delivery but also significantly improves patients' quality of life. The reduction in anxiety and depression and the increase in patient satisfaction demonstrate the value of this technology-driven approach. As deep learning technology continues to evolve and become more accessible, the potential for this model to transform cancer care is immense. Future advancements could include the integration of more sophisticated algorithms for symptom prediction, as well as the development of more user-friendly interfaces to enhance the overall patient experience[13].

The continuous nursing symptom management model for cancer patients undergoing chemotherapy[14], supported by a deep learning platform, represents a significant milestone in cancer care. It effectively addresses the challenges associated with symptom management, improving patients' well-being and satisfaction. Given the rapid advancements in deep learning technology, this model has the potential to revolutionize cancer care, making it more personalized, efficient, and patient-centered. Future iterations could focus on incorporating more advanced algorithms for symptom prediction and enhancing the user interface to further improve the patient's care experience.

Data availability

The datasets presented in this article are not readily available because the original data for this study were used under license and are not publicly available. Requests to access the datasets should be directed to JiZ, zj21283@rjh.com.cn.

Received: 9 November 2024; Accepted: 3 March 2025
Published online: 07 March 2025

References

1. Rony, M. K. K. et al. Artificial intelligence in future nursing care: Exploring perspectives of nursing professionals—A descriptive qualitative study. *Heliyon* **10**(4), e25718 (2024).
2. Rony, M. K. K. et al. Perceptions and attitudes of nurse practitioners toward artificial intelligence adoption in health care. *Health Sci. Rep.* **7**(8), e70006 (2024).
3. Del Gaizo, J. et al. Prediction of coronary artery bypass graft outcomes using a single surgical note: An artificial intelligence-based prediction model study. *PLoS ONE* **19**(4), e0300796 (2024).

4. Chen, M. & Decary, M. Artificial intelligence in healthcare: An essential guide for health leaders. *Healthc. Manage. Forum* **33**(1), 10–18 (2020).
5. Wong, W. M. et al. Effectiveness of pharmacological and nonpharmacological interventions for managing the fatigue-sleep disturbance-depression symptom cluster in breast cancer patients undergoing chemotherapy: A systematic review. *Cancer Nurs* **46**(2), E70-e80 (2023).
6. Gu, X. et al. The effects of common-sense model interventions on cancer patients: A systematic review. *Medicine (Baltimore)* **103**(17), e37777 (2024).
7. Moser, E. C. & Narayan, G. Improving breast cancer care coordination and symptom management by using AI driven predictive toolkits. *Breast* **50**, 25–29 (2020).
8. Zeng, L. et al. The core symptom in multiple myeloma patients undergoing chemotherapy: A network analysis. *Support Care Cancer* **31**(5), 297 (2023).
9. Huang, C. J., Han, W. & Huang, C. Q. Effect of Internet + continuous midwifery service model on psychological mood and pregnancy outcomes for women with high-risk pregnancies. *World J. Psychiatry* **13**(11), 862–871 (2023).
10. Yao, J. et al. Nursing effect of continuous nursing intervention based on "Internet Plus" on patients with severe adrenal tumor. *Medicine (Baltimore)* **102**(10), e33187 (2023).
11. Liu, W. et al. Effect of mindfulness yoga on anxiety and depression in early breast cancer patients received adjuvant chemotherapy: A randomized clinical trial. *J. Cancer Res. Clin. Oncol.* **148**(9), 2549–2560 (2022).
12. ElSayed, N. A. et al. Introduction and methodology: Standards of care in diabetes-2023. *Diabetes Care* **46**(Suppl 1), S1-s4 (2023).
13. Yang, X. et al. Effects of the online and offline hybrid continuous group care on maternal and infant health: A randomized controlled trial. *BMC Pregnancy Childbirth* **23**(1), 629 (2023).
14. Zhao, J. et al. Continuous nursing model based on a networking platform on treatment compliance in children with congenital heart disease after interventional surgery. *Asian J. Surg.* **46**(9), 3809–3810 (2023).
15. Stratton, S. J. Population research: Convenience Sampling strategies. *Prehosp. Disaster Med.* **36**(4), 373–374 (2021).
16. Snaith, R. P. The hospital anxiety and depression scale. *Health Qual. Life Outcomes* **1**, 29 (2003).
17. Salm, H. et al. How do quality of life (QoL) and symptom burden evolve in inpatient palliative care (PC) patients following one week of care in a specialized palliative care unit (PCU)? A comparison of two groups, with one receiving specialized outpatient palliative care prior to admission. *Cancers (Basel)* **16**(8), 1612 (2024).
18. Bohren, M. A. et al. Perceptions and experiences of labour companionship: A qualitative evidence synthesis. *Cochrane Database Syst. Rev.* **3**(3), Cd012449 (2019).
19. Gupta, R. et al. Artificial intelligence to deep learning: Machine intelligence approach for drug discovery. *Mol. Divers* **25**(3), 1315–1360 (2021).
20. Santibañez-Gutierrez, A. et al. Epidemiology of children's swimming competence and water safety. *Front. Public Health* **10**, 961342 (2022).
21. Wu, Y. E. et al. Neural control of affiliative touch in prosocial interaction. *Nature* **599**(7884), 262–267 (2021).
22. Li, F., Wang, P. & Wang Li, X. Deep learning-based regional ECG diagnosis platform. *Pacing Clin. Electrophysiol.* **47**(1), 139–148 (2024).
23. Zhu, H. et al. Automatic multilabel electrocardiogram diagnosis of heart rhythm or conduction abnormalities with deep learning: A cohort study. *Lancet Digit Health* **2**(7), e348–e357 (2020).
24. Zhang, Q. et al. Psychological outcomes of the systematic interventions based on the stress-induced situation, affective, bodily, and cognitive reactions framework for patients with lung cancer: A randomized clinical trial. *Int. J. Nurs. Stud.* **146**, 104566 (2023).
25. Li, J. et al. Effectiveness of mindfulness-based interventions on anxiety, depression, and fatigue in people with lung cancer: A systematic review and meta-analysis. *Int. J. Nurs. Stud.* **140**, 104447 (2023).
26. Bradt, J. et al. Music interventions for improving psychological and physical outcomes in people with cancer. *Cochrane Database Syst. Rev.* **10**(10), Cd006911 (2021).
27. Parekh de Campos, A. et al. Integrating palliative care into nursing care. *Am. J. Nurs.* **122**(11), 40–45 (2022).
28. Peng, Y. et al. Internet+continuous nursing mode in home nursing of patients with T-tube after hepatolithiasis surgery. *Comput. Math. Methods Med.* **2022**, 9490483 (2022).
29. Xu, L. & Zhou, M. Z. Effect of internet multiple linkage mode-based extended care combined with in-hospital comfort care on colorectal cancer patients undergoing colostomy. *World J. Gastrointest. Surg.* **15**(9), 1959–1968 (2023).
30. Yao, X. et al. Effectiveness of continuity of care after robot-assisted laparoscopic adrenalectomy under ambulatory mode: A single-center intervention study. *J. Robot. Surg.* **18**(1), 8 (2024).
31. Chen, X. et al. Couple communication quality and family resilience among Chinese gynecologic cancer patients and their spouses: A dyadic study. *Support Care Cancer* **31**(5), 271 (2023).

Acknowledgements

We thank Bullet Edits Limited for the linguistic editing and proofreading of the manuscript.

Author contributions

JiZ, FQ and MW contributed in the study design, data collection, data analysis, data interpretation, literature search, and writing of the article. JiZ contributed in the literature search and writing of the article. JiZ and XNL contributed in the data collection, analysis, and interpretation. JuZ and MW contributed in the study design and data interpretation. All authors contributed to the article and approved the submitted version.

Funding

1.This study was supported by the Natural Science Foundation of China (Grant no. 82202874). 2.Ruijin Hospital affiliated to Shanghai Jiao Tong University School of Medicine (Grant no. RJHK-2023–16).

Declarations

Competing interests

The authors declare no competing interests.

Ethics statement

The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual (s) for the publication of any potentially identifiable images or data included in this article. The studies involving human participants were reviewed and approved

by the Ethics Committee of Ruijin Hospital.

Additional information

Correspondence and requests for materials should be addressed to M.W., J.Z. or F.Q.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.