

Chatbot for Self-Management Education in Osteoporosis - An RCT Study

Jinling Huang, Xiaolian Xin, Chunyan He, HaoYan Xiong, Wenjun Pang, Shaobo Pang

Submitted to: Journal of Medical Internet Research
on: October 08, 2025

Disclaimer: © The authors. All rights reserved. This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on its website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressly prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Original Manuscript.....	5
Supplementary Files.....	17

Preprint
JMIR Publications

Chatbot for Self-Management Education in Osteoporosis - An RCT Study

Jinling Huang^{1,2} MD; Xiaolian Xin¹; Chunyan He¹; HaoYan Xiong³ MD; Wenjun Pang¹; Shaobo Pang¹

¹ Affiliated Hospital of Guangdong Medical University Zhanjiang CN

² University of Glasgow Scotland GB

³ Affiliated hospital of Guangdong medical university Zhanjiang CN

Corresponding Author:

HaoYan Xiong MD

Affiliated hospital of Guangdong medical university
No. 57, Renmin Avenue South, Xiashan District
Zhanjiang
CN

Abstract

Background: Chronic conditions cause over two-thirds of global deaths. Effective self-management is vital but often hindered by limited patient knowledge and skills. Osteoporosis (OP) leads to fragility fractures and high healthcare costs, yet many patients remain unaware of necessary lifestyle modifications. While online education provides flexibility, usability issues reduce engagement. Chatbots, offering interactive and personalized communication, show promise for health education and behavior support. However, evidence on their effectiveness in improving OP self-management remains scarce.

Chatbots

Self-Management Education Osteoporosis

ABSTRACT

Objective: This study evaluated the effectiveness of a chatbot (OPBot) for self-management education (SME) in osteoporosis patients.

Design: This study conducted a single-blind randomized controlled trial.

Setting: Participants were recruited from inpatients in the affiliated hospital of Guangdong Medical University, Guangdong, China.

Method: We conducted an RCT to compare the effectiveness of an OPBot versus traditional health education methods for patient SME. Participants were diagnosed with osteoporosis. We assessed osteoporosis knowledge, the time nurses invest in health education, adherence to disease management at 1, 3 and 6 months, and the reliability of the OPBot responses in free conversations.

Result: A total of 100 participants were randomized; 12 were excluded from the final analysis due to loss to follow-up, refusal to complete the second knowledge assessment, or death, leaving 88 participants included in the analysis (45 in the intervention group and 43 in the control group). Knowledge scores improved significantly in the OPBot group compared with the control group (mean difference (MD): 6.069; 95% CI: 0.894 to Inf, PNI = 0.048). Nurses in the OPBot group spent less time on verbal education than those in the control group (MD: -12.848, 95% CI: -Inf to -10.007, PNI < 0.001). OPBot also demonstrated better patient self-management adherence at 1 month (MD: 7.733, 95% CI: 0.177 to Inf, PNI = 0.029) and 6 months (MD: 17.765, 95% CI: 8.911 to Inf, PNI < 0.001), but not at 3 months (MD: 2.694, 95% CI: -5.463 to Inf, PNI = 0.227). In the Q&A module, the reliability of OPBot responses was as follows: highly reliable, 89.4%; mostly reliable, 1.2%; partly reliable, 1.2%; unreliable, 1.2%; and unable to respond, 7.0%.

Conclusion: Chatbots are suitable for basic SME, but further research and exploration are needed in the area of personalized education.

(JMIR Preprints 08/10/2025:85475)

DOI: <https://doi.org/10.2196/preprints.85475>

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain visible to all users.

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in [http://www.jmir.org/](#)

No. Please do not make my accepted manuscript PDF available to anyone. I understand that if I later pay to participate in [https://www.jmir.org/](#)

Original Manuscript

Chatbot for Self-Management Education in Osteoporosis - An RCT Study

1

ARTICLE INFO

Keywords:

Chatbots

Self-Management

Education

Osteoporosis

ABSTRACT

Objective: This study evaluated the effectiveness of a chatbot (OPBot) for self-management education (SME) in osteoporosis patients.

Design: This study conducted a single-blind randomized controlled trial.

Setting: Participants were recruited from inpatients in the affiliated hospital of Guangdong Medical University, Guangdong, China.

Method: We conducted an RCT to compare the effectiveness of an OPBot versus traditional health education methods for patient SME. Participants were diagnosed with osteoporosis. We assessed osteoporosis knowledge, the time nurses invest in health education, adherence to disease management at 1, 3 and 6 months, and the reliability of the OPBot responses in free conversations.

Result: A total of 100 participants were randomized; 12 were excluded from the final analysis due to loss to follow-up, refusal to complete the second knowledge assessment, or death, leaving 88 participants included in the analysis (45 in the intervention group and 43 in the control group). Knowledge scores improved significantly in the OPBot group compared with the control group (mean difference (MD): 6.069; 95% CI: -0.894 to Inf, $P_{NI} = 0.048$). Nurses in the OPBot group spent less time on verbal education than those in the control group (MD: -12.848, 95% CI: -Inf to -10.007, $P_{NI} < 0.001$). OPBot also demonstrated better patient self-management adherence at 1 month (MD: 7.733, 95% CI: 0.177 to Inf, $P_{NI} = 0.029$) and 6 months (MD: 17.765, 95% CI: 8.911 to Inf, $P_{NI} < 0.001$), but not at 3 months (MD: 2.694, 95% CI: -5.463 to Inf, $P_{NI} = 0.227$). In the Q&A module, the reliability of OPBot responses was as follows: highly reliable, 89.4%; mostly reliable, 1.2%; partly reliable, 1.2%; unreliable, 1.2%; and unable to respond, 7.0%.

Conclusion: Chatbots are suitable for basic SME, but further research and exploration are needed in the area of personalized education.

Highlight:

(1) Providing new insights into chronic disease SME.

(2) chatbot-based SME can significantly reduce nurses' time burden while maintaining the effectiveness of traditional education methods, thereby achieving more efficient resource allocation in healthcare settings;

(3) OPBot improved short-term adherence to disease management, suggesting that chatbot interventions can enhance patient engagement and self-care behaviors in the early stages of treatment.

(4) The chatbot's responsiveness inpatient interactions, supports the integration of AI-driven tools into clinical practice to provide scalable, accessible, and interactive health education.

1. Introduction

The global prevalence of chronic conditions is an increasing concern. In 2024, WHO reported that chronic conditions accounted for over two-thirds of deaths worldwide (World Health Organization, 2024). Alongside healthcare services, self-management plays a crucial role in addressing these conditions, involving an individual's ability to manage symptoms, treatments, physical and psychosocial impacts, and necessary lifestyle changes (Allegrante et al., 2019). Self-management Education (SME) equips individuals with the essential knowledge and skills to manage their conditions effectively (Hassan et al., 2013), making it an increasingly vital component of healthcare (Weiss, 2003). Without adequate education, individuals may struggle to understand their condition and lack management skills (Chodosh et al., 2005). Traditionally, SME has been delivered by healthcare staff in medical settings such as hospitals or clinics, primarily through face-to-face lectures (Farley, 2020). However, this approach demands substantial time from healthcare staff, a resource often strained in modern healthcare systems.

Osteoporosis (OP) is a skeletal condition characterized by low bone density and impaired bone metabolism, leading to fragile bones and an increased risk of fractures (Sabri et al., 2023). Globally, OP accounts for 70% of fragility fractures, which often result in chronic pain, reduced physical activity, and significant levels of disability and dependence (Cappelle et al., 2017; Borgström et al., 2020). The economic burden is substantial, with fragility-related hip fractures costing approximately €20 billion annually in Europe and £3 billion in the UK (Mitchell et al., 2019). Thankfully, OP can be managed proactively to prevent fractures, and even after an initial fracture, interventions can reduce the likelihood of subsequent fractures (Eisman et al., 2012). The International Osteoporosis Foundation (IOF) highlights that preventive strategies often include lifestyle modifications. Without this, the risk of a second fracture within two years is notably high. However, many patients lack awareness of the importance of lifestyle changes, often relying solely on medical treatments or struggling to effectively manage the disease (Barker et al., 2016).

Online education allows patients to learn at their convenience, in a more relaxed state, without being restricted by time or location (Win et al., 2016). However, usability challenges and a lack of interactive features contribute to high abandonment rates and pose obstacles to their broader adoption (Hall et al., 2012; Hanson et al., 2008; Paris et al., 2019). Unlike traditional web and mobile applications, chatbots engage with users through natural and familiar conversations, enhancing their usability and appeal (Atiyah et al., 2019; Svenningsson and Faraon, 2019). With their interactive form of conversation, chatbots have been explored for providing mental health therapies (Greer et al., 2019; Hunt et al., 2021; Fitzpatrick et al., 2017), disease monitoring (Echeazarra et al., 2021; Gong et al., 2020), and symptom analysis and treatment recommendations (Rosruen and Samanchuen, 2018). In addition, the development of artificial intelligence (AI) and digital psychotherapy has provided new support for such applications. A series of studies by Beg and colleagues have highlighted the potential of AI tools (including chatbots) in emotion recognition, dynamic feedback, and remote interventions, while also noting ongoing challenges related to ethics, trust, and human-AI collaboration (Beg, 2025; Beg & Verma, 2024; Beg et al., 2025). Overall, chatbots have garnered significant attention for their potential and impact in the healthcare field, particularly in applications related to self-management. However, research on whether chatbots can effectively enhance OP patients' disease knowledge and positively influence their self-management behaviors was limited.

1.1. Education Chatbot- OPBot

There are three modules of the OPBot. Among them, a knowledge base module was added to deliver structured OP and self-management resources. Further, a knowledge assessment module was introduced. This module is designed to elicit learners' beliefs and theories, promoting the integration of new and refined concepts

into their belief systems (Ko, 2013). The knowledge assessment module provides educational feedback based on users' responses, enabling the recommendation of more tailored learning content and enhancing the effectiveness of health education. This also addresses the limitation in Chinese clinical practice where time constraints often hinder pre-education assessments. It uses content adapted from the Osteoporosis Knowledge Test (Gendler et al., 2015) and translated for Chinese. The user-friendly design mirrors real-world clinical assessments.

Finally, the Q&A module is designed to provide an efficient and convenient solution to address patients' concerns during hospitalization and offer ongoing support after discharge. OPBot's training materials were sourced from the IOF and clinical consultation records. The IOF content was reviewed, translated, and adapted by orthopedic nursing experts to align with the Chinese healthcare context. The clinical consultation records initially included 361 entries related to OP. After removing duplicates and irrelevant content, 128 refined entries were ultimately selected to train OPBot. Clinical evaluation by two nurses assessed Q&A module responses to ensure practical relevance. The final suitability rate was 86.7%, which has reached a moderately high level, the healthcare field demands precision. While OPBot was still considered as suitable as a tool for SME, providers will need to be involved by reviewing patient queries and OPBot's responses daily to deliver timely interventions if needed.

1.2. Purpose of Study

This study aims to determine whether a chatbot can improve OP patients' disease knowledge and impact their self-management behaviors.

2. Method

2.1. Study Design and Setting

A single-blind randomized controlled trial was conducted in an affiliated hospital of Guangdong Medical University, Guangdong, China, from February 2024 to March 2025. This study was approved by the ethics committee of Affiliated Hospital of Guangdong Medical University (no. KT2024-216-01).

2.2. Participants Recruitment

The study began recruiting patients from February 2024 to September 2024, with follow-up ending in March 2025. The inclusion criteria were: (1) were aged ≥ 18 years; and (2) were diagnosed with OP. The exclusion criteria were as follows: (1) unwilling or unable to use smartphones; (2) hearing impairment; (3) impaired consciousness; (4) Critically ill patients; (5) paralyzed in bed; (6) language barrier.

2.3. Sample Size

Using the sample size calculator from the PASS tool for the non-inferiority trial and a significance (α) level of 0.025, power of 90%, a standard deviation of the outcome from the pilot study of 1, and a non-inferiority limit of -1 , a minimum of 49 subjects per group (allocation ratio 1:1) was required for this study.

2.4. Randomization, Concealment, and Blinding

This study was designed as a single-blind randomized controlled trial. Researcher A assessed participants' eligibility, obtained written informed consent, and collected baseline data. Researcher B, who was not involved in recruitment, generated the random sequence using Excel. To ensure allocation concealment, the sequence was placed in sequentially numbered opaque envelopes. Prior to the start of the intervention, participants were randomly assigned in a 1:1 ratio to either the intervention group or the control group, according to their enrollment order and the random code indicated on the envelope. Each group included 50 participants. It should be noted that the intervention coordinator was aware of the group assignments, as blinding was not feasible in this role. However, to minimize potential bias, both participants and the data analyst remained blinded to group allocation.

2.5. Intervention

During hospitalization, participants in the intervention group learned about OP knowledge by using the OPBot. Specifically, after the participants were enrolled, nurses provided detailed instructions on how to use the OPBot. During hospitalization, participants could consult nurses during working hours if they had any questions regarding OP management during hospitalization or home care. Additionally, the specialist nurse and the case manager monitored the OPBot's backend daily to identify issues requiring manual intervention and provided personalized support to participants either face-to-face or online. Before discharge, participants will undergo a second knowledge assessment.

2.6. Comparison

The control group received traditional health education, which included face-to-face communication and written materials. After the participants were enrolled, nurses provided health education and distributed an OP health handbook for participants to read. Additionally, during hospitalization, participants could consult nurses during working hours regarding OP treatment, either during hospitalization or for home care. Before discharge, participants underwent a second knowledge assessment.

2.7. Outcomes

The changes in knowledge score: In this study, the OP Knowledge Assessment Test (OKAT) which has been conducted in Chinese, was used to assess the participants' OP knowledge score. The OKAT consists of 20 items and the overall Cronbach's coefficient is 0.821. Before the implementation of the intervention or control group measures, the first OP knowledge score assessment was conducted as the baseline value. On the day of discharge, participants underwent a second knowledge assessment.

The working hours of nurses: The intervention group: nurse' time spent on health education, consultation, and operational guidance; The control group: nurse' time spent on health education, and consultation.

Participants' adherence: At 1, 3 and 6 months after discharge, researchers contacted the participants by phone to inquire in detail and collect information on their dietary habits, exercise routines, sunlight exposure, and medication adherence during this period.

The reliability of OPBot: During the study, participants asked all questions and received corresponding answers through the Q&A module of OPBot. The specialist nurse and the case manager assessed the reliability of each response, categorizing them as follows: Highly Reliable, Mostly Reliable, Partially Reliable, Unreliable, and Unable to Respond.

2.8. Statistical Analysis

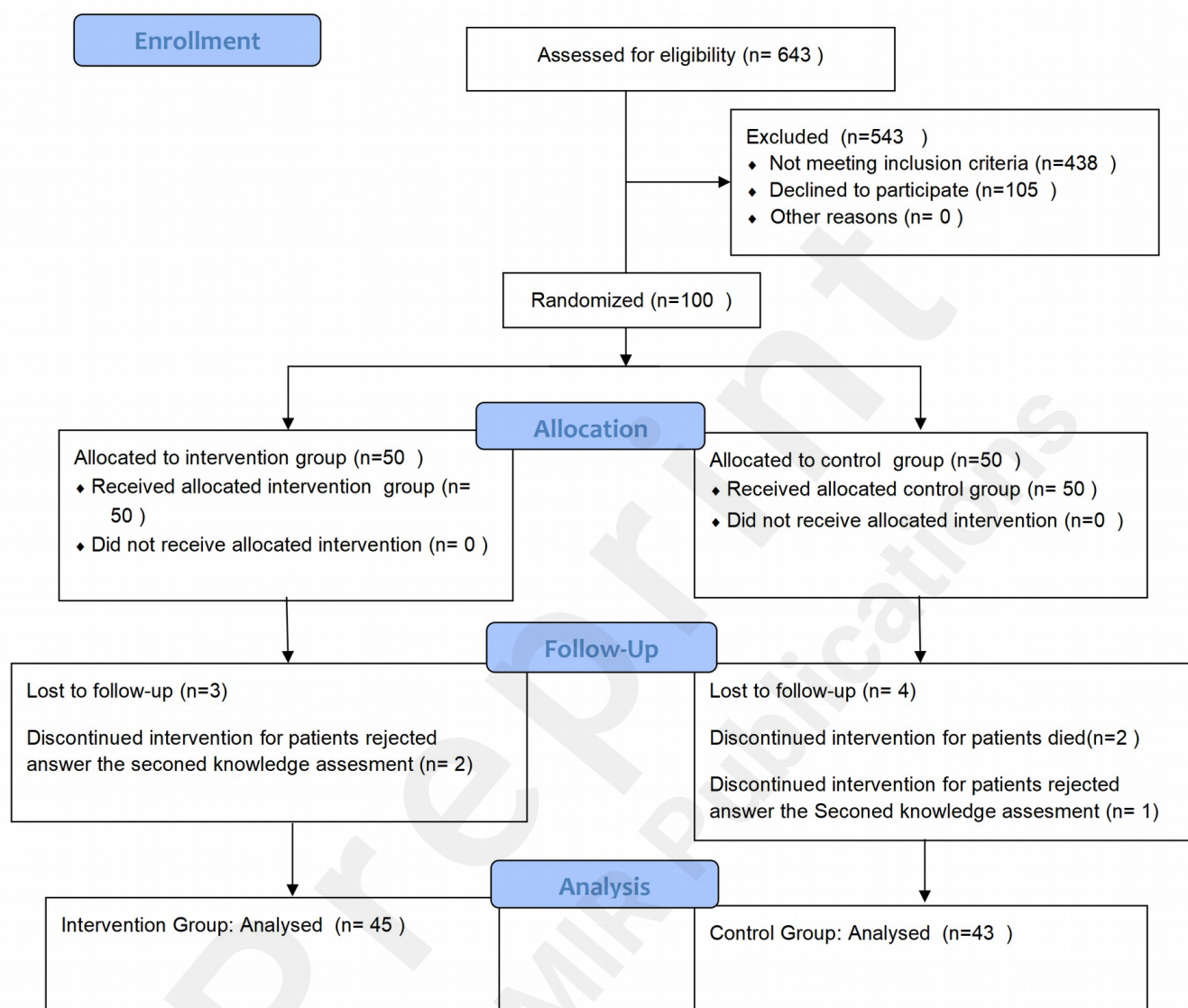
Non-inferiority of the intervention group versus control group was assessed using a margin of -1 for continuous variables and -1% for categorical variables, with a one-sided $\alpha = 0.025$.

3. Results

3.1. Study Population and Characteristics

A total of 643 participants were screened before the study, and the 100 who met the study's criteria and volunteered were included and randomized into the intervention (50) or control (50) group. In the end, 45 patients in the experimental group and 43 patients in the control group completed the trial, with an overall dropout rate of 12%. In the experimental group, 2 participants did not complete the second knowledge assessment, and 3 participants were lost to follow-up. In the control group, 1 participant did not complete the second knowledge assessment, 2 participants died, and 4 participants were lost to follow-up (Fig.1). At baseline, no significant differences were observed in gender distribution, education level and age between the two groups.

CONSORT 2010 Flow Diagram



3.2. Knowledge Score

Table 1 revealed that the difference in the distribution of baseline values between the experimental and control groups was not statistically significant, A1 scores (54.22 vs. 52.86, $P_{NI} = 0.278$). The intervention group improved patients' disease knowledge significantly more than the control group, with higher A2 scores (78.73 vs. 71.30, MD: 7.431, 95% CI: 2.955 to Inf, $P_{NI} = 0.001$), and a greater improvement from baseline ($A3 = A2 - A1$: 24.51 vs. 18.44, MD: 6.069, 95% CI: -0.894 to Inf, $P_{NI} = 0.048$).

3.3. The Working Hours of Nurses

The intervention group resulted in a significantly lower amount of nurse education time compared to the control group (9.73 vs. 22.58, MD: -12.848, 95% CI: -Inf to -10.007, $P_{NI} < 0.001$), indicating that the use of the chatbot substantially reduced the time nurses spent on patient education (Table 1).

3.4. Adherence of Disease Management

Patient adherence, as measured by the total score (higher score indicating better adherence), was compared between the intervention and control groups at 1, 3, and 6 months. At 1 month, the intervention group had a significantly higher mean total score than the control group (77.50 vs. 69.77; MD: 7.733, 95% CI: 0.177 to Inf, $P_{NI} = 0.029$). At 3 months, the difference between groups was not statistically significant (73.33 vs. 70.64; MD: 2.694, 95% CI: -5.463 to Inf, $P_{NI} = 0.227$). However, at 6 months, the intervention group demonstrated a substantially higher total score (80.56 vs. 62.79; MD: 17.765, 95% CI: 8.911 to Inf, $P_{NI} < 0.001$), indicating significantly better long-term adherence.

Table 1:

	Group		Between-group difference [95% CI]	P non-inferior
	Intervention	control		
Gender				
Female	29 (64.44%)	34 (79.07%)	-14.625% (-32.651% ~ 4.305%)	0.922
Male	16 (35.56%)	9 (20.93%)		
Age	67.76 (10.68)	73.30 (11.11)	-5.547 [-9.413 ~ Inf]	0.973
Education				
Illiteracy	9 (20.00%)	7 (16.28%)	3.721% (-12.931% ~ 20.161%)	0.283
Primary school/Secondary school	35 (77.78%)	34 (79.07%)	-1.292% (-18.615% ~ 16.252%)	0.513
College/Undergraduate	1 (2.22%)	2 (4.65%)	-2.429% (-13.531% ~ 7.471%)	0.646
Knowledge Score				
A1 ^a	54.22 (20.30)	52.86 (17.07)	1.362 [-5.276 ~ Inf]	0.278
A2 ^b	78.73 (12.42)	71.30 (12.81)	7.431 [-2.955 ~ Inf]	0.001
A3=A2-A1 ^c	24.51 (23.87)	18.44 (14.37)	6.069 [-0.894 ~ Inf]	0.048
Working Hours				
Working Hours (min)	9.73 (9.53)	22.58 (6.20)	-12.848 [-Inf ~ -10.007]	<0.001
The First Month				
Taking Calcium Supplements				
0 (None)	8 (17.78%)	5 (11.63%)	6.150% (-9.332% ~ 21.611%)	0.173
25 (Always)	37 (82.22%)	38 (88.37%)		
Consume Calcium-rich Foods				
0 (None)	6 (13.33%)	18 (41.86%)	-28.527% (-45.627% ~ -10.240%)	0.998
12.5 (Sometimes)	9 (20.00%)	4 (9.30%)	10.698% (-4.504% ~ 26.079%)	0.062
25 (Always)	30 (66.67%)	21 (48.84%)	17.829% (-2.797% ~ 37.075%)	0.037
Sun Exposure (average daily)				
0 (None)	3 (6.67%)	5 (11.63%)	-4.961% (-18.843% ~ 8.013%)	0.742
12.5 (Sometimes)	17 (37.78%)	19 (44.19%)	-6.408% (-26.320% ~ 13.950%)	0.697
25 (Always)	25 (55.56%)	19 (44.19%)	11.370% (-9.436% ~ 31.222%)	0.123
Weekly Frequency of Exercise (≥ 30 min per session)				
0 (None)	8 (17.78%)	9 (20.93%)	-3.152% (-20.129% ~ 13.647%)	0.601
12.5 (Sometimes)	5 (11.11%)	8 (18.60%)	-7.494% (-23.254% ~ 7.782%)	0.805
25 (Always)	32 (71.11%)	26 (60.47%)	10.646% (-9.132% ~ 29.797%)	0.125
Total	77.50 (21.09)	69.77 (21.52)	7.733 [0.177 ~ Inf]	0.029
The Third Month				

Taking Calcium Supplements

0 (None)	8 (17.78%)	9 (20.93%)	-3.152% (-20.129% ~ 13.647%)	0.601
25 (Always)	37 (82.22%)	34 (79.07%)		

Consume Calcium-rich Foods

0 (None)	15 (33.33%)	14 (32.56%)	0.775% (-18.730% ~ 20.114%)	0.430
12.5 (Sometimes)	10 (22.22%)	9 (20.93%)	1.292% (-16.252% ~ 18.615%)	0.397
25 (Always)	20 (44.44%)	20 (46.51%)	-2.067% (-22.379% ~ 18.385%)	0.540

Sun Exposure (average daily)

0 (None)	4 (8.89%)	6 (13.95%)	-5.065% (-19.760% ~ 8.962%)	0.726
12.5 (Sometimes)	15 (33.33%)	15 (34.88%)	-1.550% (-21.112% ~ 18.011%)	0.522
25 (Always)	26 (57.78%)	22 (51.16%)	6.615% (-13.989% ~ 26.702%)	0.237

Weekly Frequency of Exercise (≥ 30 min per session)

0 (None)	6 (13.33%)	8 (18.60%)	-5.271% (-21.355% ~ 10.476%)	0.708
12.5 (Sometimes)	5 (11.11%)	3 (6.98%)	4.134% (-9.119% ~ 17.649%)	0.203
25 (Always)	34 (75.56%)	32 (74.42%)	1.137% (-16.970% ~ 19.366%)	0.408
Total	73.33 (24.51)	70.64 (21.46)	2.694 $\square$ -5.463~Inf $\square$	0.227

The Sixth Month

Taking Calcium Supplements

0 (None)	5 (11.11%)	15 (34.88%)	-23.773% (-40.587% ~ -6.527%)	0.995
25 (Always)	40 (88.89%)	28 (65.12%)		

Consume Calcium-rich Foods

0 (None)	9 (20.00%)	14 (32.56%)	-12.558% (-30.588% ~ 5.881%)	0.891
12.5 (Sometimes)	12 (26.67%)	11 (25.58%)	1.085% (-17.394% ~ 19.355%)	0.412
25 (Always)	24 (53.33%)	18 (41.86%)	11.473% (-9.318% ~ 31.291%)	0.121

Sun Exposure (average daily)

0 (None)	2 (4.44%)	9 (20.93%)	-16.486% (-31.493% ~ -3.004%)	0.987
12.5 (Sometimes)	16 (35.56%)	19 (44.19%)	-8.630% (-28.356% ~ 11.700%)	0.768
25 (Always)	27 (60.00%)	15 (34.88%)	25.116% (4.261% ~ 43.862%)	0.007

Weekly Frequency of Exercise (≥ 30 min per session)

0 (None)	2 (4.44%)	8 (18.60%)	-14.160% (-28.896% ~ -1.020%)	0.975
12.5 (Sometimes)	6 (13.33%)	6 (13.95%)	-0.620% (-15.967% ~ 14.454%)	0.479
25 (Always)	37 (82.22%)	29 (67.44%)	14.780% (-3.382% ~ 32.516%)	0.044
Total	80.56 (18.18)	62.79 (29.94)	17.765 $\square$ 8.911~Inf $\square$	<0.001

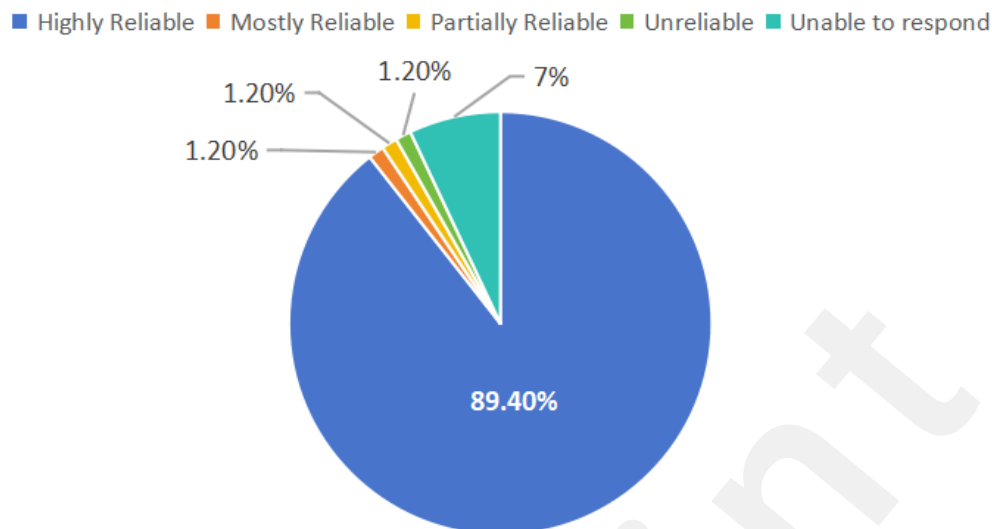
a: The baseline of knowledge score about Osteoporosis.

b: Post-intervention osteoporosis knowledge score.

c: The change in osteoporosis knowledge scores from pre- to post-intervention.

3.5. Reliability of OPBot

In the Q&A module, there were a total of 85 questions' records. In these records, 76 records have been confirmed highly reliable(89.4%), 1 record has been confirmed mostly reliable (1.2%), 1 record has been confirmed partially reliable(1.2%), 1 record has been confirmed unreliable(1.2%), 6 records have been confirmed unable to respond(7%) (Fig.2)

Fig 2: Reliability of Chatbot

4. Discussion

SME for diseases has become a widely used non-pharmacological approach in disease management and continues to play a significant role. Chatbots provide a promising solution by enabling interactive, dialogue-based learning. As demonstrated in this study, OPBot allows learners to identify their knowledge gaps simply by responding with "yes" or "no." Additionally, it supports multiple learning formats, including text, images, and videos, catering to different learning preferences and enhancing engagement. To evaluate the effectiveness of this approach, we designed an educational chatbot and conducted a randomized trial with a 6-month follow-up among OP patients. Previous studies have confirmed that face-to-face health education can significantly improve patients' disease knowledge and self-management ability (Dehkordi and Heydarnejad, 2008; Zhao and Potter, 2016). In addition, in recent years, chatbots, have also been gradually applied to the field of health education and have shown certain advantages in imparting psychological skills (Greer et al., 2019), improving self-care behaviors, and reducing chemotherapy side effects in cancer patients (Tawfik et al., 2023). The results of this study are consistent with the above studies, indicating that participants who used OPBot for health education had a significant improvement in disease knowledge and showed higher self-management compliance in the long-term.

It is noteworthy that the differences in adherence between the two groups were mainly time-dependent. At 1 and 6 months, adherence in the intervention group was significantly higher than in the control group, whereas no significant difference was observed at 3 months. This phenomenon may be related to patients' shifting priorities at different stages as well as the timing of outpatient follow-ups. Previous study have shown that most hospitalized patients are primarily concerned with perioperative issues, and traditional health education is usually delivered during hospitalization (Huang and Ding, 2024). Combined with the limitations of memory, this results in lower adherence in the control group during the first month after discharge compared with the robot group, which allowed patients to review and learn at any time. By the first-month outpatient follow-up, nurses or physicians reinforced the importance of long-term osteoporosis management, and patients gradually shifted their attention toward rehabilitation and chronic care. As a result, the difference between the two groups was no longer significant at 3 months. However, because the next outpatient follow-up was scheduled one year later, patients in the control group lacked further reminders, and memory decay led to a decline in adherence by the sixth month, whereas the robot group maintained a relatively stable level.

Possible mechanisms include personalized interaction and immediate feedback provided by chatbots, which may enhance patients' learning interest and information retention. In addition, OPBot may facilitate self-

management by providing readily accessible health information when patients need it. However, the reasons for the decline in long-term compliance need further exploration, which may involve patients' fading novelty of chatbots or the lack of sustained behavioral reinforcement strategies. Future research can further optimize the chatbot's interaction methods, such as increasing personalized push notifications, combining social support, or incorporating behavioral incentives to improve long-term compliance. In addition, larger-scale, long-term follow-up studies are needed to evaluate whether chatbot-based health education can maintain patients' self-management behaviors for a longer period of time, and further compare it with different types of traditional education methods.

Integrating OPBot into the healthcare system, especially in-hospital clinical education, can significantly enhance the effectiveness of SME. Although there have been studies on chatbots in education, there is still a lack of research on their use scenarios within hospitals. Typically, SME starts when a patient is admitted to the hospital and runs through the entire treatment and follow-up process. However, the introduction of OPBot has redefined this traditional process. Based on our study, OPBot could serve as a knowledge coach, mainly responsible for providing patients with general OP knowledge and answering questions. Although chatbots have shown great potential in personalized guidance (Aggarwal et al., 2023), the accuracy and reliability of information are still key issues that must be addressed, especially in the medical field, where any misinformation may have a negative impact on patients. Therefore, current chatbots cannot completely replace the role of human providers (Alowais et al., 2023). In actual applications, neither nurses nor patients rely on OPBot alone but rather regard it as an auxiliary tool, which aligns with the findings of (Acharya et al., 2024).

Further, Beg (2025) emphasized that AI research should establish clear standards for ethical review and transparency to safeguard participants' rights and mitigate potential risks. While AI shows great promise in emotion recognition, dynamic feedback, and remote intervention, it also faces challenges related to trust, ethical responsibility, and role coordination. Accordingly, this study strengthened data privacy protection, information traceability, and mechanisms for human oversight. For instance, nurses reviewed OPBot's responses daily and proactively contacted patients when necessary to provide personalized guidance, reflecting the ethical principle of human-AI collaboration.

Moreover, although chatbots can provide real-time feedback and personalized learning based on patients' needs, a lack of transparency in algorithmic logic and information sources may lead to bias or misinformation. As Beg and Verma (2024) further highlighted, personalization and clinical interpretability are essential in AI-driven digital interventions. Therefore, this study implemented safety mechanisms within OPBot. For example, any inquiry related to medication or treatment automatically triggered the response "Please consult your doctor." This design ensured that patients made medical decisions under professional supervision, embodying the importance of ethical risk control.

However, this study still has certain limitations. First, the participants were recruited from a single tertiary hospital in China, which may limit the generalizability of the findings. Future studies should conduct multi-center, large-sample randomized controlled trials to provide higher-quality evidence. Second, the reliance on self-reported adherence data prone to recall and social-desirability bias. Extending the follow-up duration in future research would allow for a more comprehensive evaluation of the long-term effectiveness of chatbot-based self-management education, such as its impact on patients' bone density.

5. Conclusion

OPBot effectively enhances patients' self-management knowledge of their disease. In healthcare settings with limited human resources, leveraging educational chatbots to share part of the educational workload and provide patients with basic self-management guidance is a viable strategy. Furthermore, to provide better personalized guidance to patients, continuously expanding the chatbot's corpus is essential to improving its accuracy and credibility. Finally, this study offers valuable insights for the education of other chronic diseases.

References

- Acharya, P.C., Alba, R., Krisanapan, P., Acharya, C.M., Suppadungsuk, S., Csongradi, E., Mao, M.A., Craici, I.M., Miao, J., Thongprayoon, C., et al., 2024. Ai-driven patient education in chronic kidney disease: evaluating chatbot responses against clinical guidelines. *Diseases* 12, 185.
- Aggarwal, A., Tam, C.C., Wu, D., Li, X., Qiao, S., 2023. Artificial intelligence-based chatbots for promoting health behavioral changes: Systematic review. *Journal of medical Internet research* 25, e40789.
- Allegre, J.P., Wells, M.T., Peterson, J.C., 2019. Interventions to support behavioral self-management of chronic diseases. *Annual review of public health* 40, 127–146.
- Alowais, S.A., Alghamdi, S.S., Alsuhebany, N., Alqahtani, T., Alshaya, A.I., Almohareb, S.N., Aldaire, A., Alrashed, M., Bin Saleh, K., Badreldin, H.A., et al., 2023. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC medical education* 23, 689.
- Atiyah, A., Jusoh, S., Alghanim, F., 2019. Evaluation of the naturalness of chatbot applications, in: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), IEEE. pp. 359–365.
- Barker, K., Toye, F., Lowe, C.M., 2016. A qualitative systematic review of patients' experience of osteoporosis using meta-ethnography. *Archives of osteoporosis* 11, 1–13.
- Beg, M. J. (2025). Qualitative Methods in Mental Health Research: Standards for Ethical Inquiry, Research Practice, and Peer Review. *Indian Journal of Psychological Medicine*, 02537176251363817.
- Beg, M. J., & Verma, M. K. (2024). Exploring the potential and challenges of digital and AI-driven psychotherapy for ADHD, OCD, schizophrenia, and substance use disorders: A comprehensive narrative review. *Indian Journal of Psychological Medicine*, 02537176241300569.
- Beg, M. J., Verma, M., M, V. C. K., & Verma, M. K. (2025). Artificial intelligence for psychotherapy: a review of the current state and future directions. *Indian Journal of Psychological Medicine*, 47(4), 314–325.
- Borgström, F., Karlsson, L., Orsäter, G., Norton, N., Halbout, P., Cooper, C., Lorentzon, M., McCloskey, E.V., Harvey, N.C., Javaid, M.K., et al., 2020. Fragility fractures in europe: burden, management and opportunities. *Archives of osteoporosis* 15, 1–21.
- Cappelle, S., Ramon, I., Dekelver, C., Rozenberg, S., Baleanu, F., Karmali, R., Rubinstein, M., Tondeur, M., Moreau, M., Paesmans, M., et al., 2017. Distribution of clinical risk factors for fracture in a brussels cohort of postmenopausal women: the frisbee study and comparison with other major cohort studies. *Maturitas* 106, 1–7.
- Chodosh, J., Morton, S.C., Mojica, W., Maglione, M., Suttrop, M.J., Hilton, L., Rhodes, S., Shekelle, P., 2005. Meta-analysis: chronic disease self-management programs for older adults. *Annals of internal medicine* 143, 427–438.
- Clynes, M.A., Harvey, N.C., Curtis, E.M., Fuggle, N.R., Dennison, E.M., Cooper, C., 2020. The epidemiology of osteoporosis. *British medical bulletin* 133, 105–117.
- Dehkordi, A.H., Heydarnejad, M.S., 2008. The impact of problem-based learning and lecturing on the behavior and attitudes of iranian nursing students. *Danish medical bulletin* 55, 224–226.
- Echeazarra, L., Pereira, J., Saracho, R., 2021. Tensiobot: a chatbot assistant for self-managed in-house blood pressure checking. *Journal of medical systems* 45, 54.
- of Economic, U.N.D., Social Affairs, P.D., 2022. *World population prospects 2022: Summary of results*.
- Eisman, J.A., Bogoch, E.R., Dell, R., Harrington, J.T., McKinney Jr, R.E., McLellan, A., Mitchell, P.J., Silverman, S., Singleton, R., Siris, E., et al., 2012. Making the first fracture the last fracture: Asbmr taskforce report on secondary fracture prevention. *Journal of bone and mineral research* 27, 2039–2046.
- Farley, H., 2020. Promoting self-efficacy inpatients with chronic disease beyond traditional education: A literature review. *Nursing open* 7, 30–41.
- Fitzpatrick, K.K., Darcy, A., Vierhile, M., 2017. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): a randomized controlled trial. *JMIR mental health* 4, e7785.
- Gendler, P.E., Coviak, C.P., Martin, J.T., Kim, K.K., Dankers, J.K., Barclay, J.M., Sanchez, T.A., 2015. Revision of the osteoporosis knowledge test: Reliability and validity. *Western journal of nursing research* 37, 1623–1643.
- Gong, E., Baptista, S., Russell, A., Scuffham, P., Riddell, M., Speight, J., Bird, D., Williams, E., Lotfaliany, M., Oldenburg, B., 2020. My diabetes coach, a mobile app-based interactive conversational agent to support type 2 diabetes self-management: randomized effectiveness- implementation trial. *Journal of medical Internet research* 22, e20322.
- Greer, S., Ramo, D., Chang, Y.J., Fu, M., Moskowitz, J., Haritatos, J., et al., 2019. Use of the chatbot “vivibot” to deliver positive psychology skills and promote well-being among young people after cancer treatment: randomized controlled feasibility trial. *JMIR mHealth and uHealth* 7, e15018.
- Ha, P., Hean, R., Tang, P., Choy, A., Thakur, U., Dev, A., 2019. Implementation of an educational ipad application for patients with chronic hepatitis b. *Frontiers in Public Health* 7, 372.
- Hall, A.K., Stellefson, M., Bernhardt, J.M., 2012. Healthy aging 2.0: the potential of new media and technology. *Preventing chronic disease* 9.
- Hanson, C., Thackeray, R., Barnes, M., Neiger, B., McIntyre, E., 2008. Integrating web 2.0 in health education preparation and practice. *American Journal of Health Education* 39, 157–166.
- Hassan, N.M., Win, K.T., Hyland, P., 2013. Exploring design features and benefits of online patient education (ope) sites for chronic diseases, in: 2013 46th Hawaii International Conference on System Sciences, IEEE. pp. 2454–2463.
- Huang, J., & Ding, X. (2025). Self-Management Support (SMS) in Transition: The Case of Osteoporosis Management Support in a Chinese Hospital. *Computer Supported Cooperative Work (CSCW)*, 34(1), 1–39.
- Hunt, M., Miguez, S., Dukas, B., Onwude, O., White, S., et al., 2021. Efficacy of zemedi, a mobile digital therapeutic for the self-management of irritable bowel syndrome: crossover randomized controlled trial. *JMIR mHealth and uHealth* 9, e26152.
- Jacobs, A., 2021. 'nursing is in crisis': Staff shortages put patients at risk. *International New York Times*, NA–NA.
- Kim, J.J., Mohammad, R.A., Coley, K.C., Donihi, A.C., 2015. Use of an ipad to provide warfarin video education to hospitalized patients. *Journal of Patient Safety* 11, 160–165.
- Ko, D.A., 2013. The process of experiential learning. *Culture and Processes of Adult Learning* 138.
- McGowan, P.T., 2012. Self-management education and support in chronic disease management. *Primary Care: Clinics in Office Practice* 39, 307–325.
- Miranda, F.D., Salomé, G.M., Costa, M.G.d., Alves, J.R., 2022. Mobile app for patient education about breast cancer surgical treatment. *Fisioterapia em Movimento* 35, e35128.
- Mitchell, P.J., Cooper, C., Fujita, M., Halbout, P., Åkesson, K., Costa, M., Dreinhöfer, K.E., Marsh, D.R., Lee, J.K., Chan, D.C., et al., 2019. Quality improvement initiatives in fragility fracture care and prevention. *Current osteoporosis reports* 17, 510–520.
- Mohd Azmi, N.F.I., Aznul Hisham, M.H., Jamil, N.A., 2023. Development and evaluation of an e-book for bone health and osteoporosis education in adolescents. *Nutrients* 15, 1899.

- Østbye, T., Yarnall, K.S., Krause, K.M., Pollak, K.I., Gradison, M., Michener, J.L., 2005. Is there time for management of patients with chronic diseases in primary care? *The Annals of Family Medicine* 3, 209–214.
- Paris, L., Duclos, M., Fillol, F., Rousset, S., 2019. Acceptance of ict for health and/or physical activity monitoring inpatients with chronic diseases. *Journal of Advances in Sports and Physical Education* 2, 50–58.
- Rosruen, N., Samanchuen, T., 2018. Chatbot utilization for medical consultant system, in: 2018 3rd technology innovation management and engineering science international conference (TIMES-iCON), IEEE, pp. 1–5.
- Sabri, S.A., Chavarria, J.C., Ackert-Bicknell, C., Swanson, C., Burger, E., 2023. Osteoporosis: an update on screening, diagnosis, evaluation, and treatment. *Orthopedics* 46, e20–e26.
- Svenningsson, N., Faraon, M., 2019. Artificial intelligence in conversational agents: A study of factors related to perceived humanness in chatbots, in: Proceedings of the 2019 2nd Artificial Intelligence and Cloud Computing Conference, pp. 151–161.
- Tawfik, E., Ghallab, E., Moustafa, A., 2023. A nurse versus a chatbot—the effect of an empowerment program on chemotherapy-related side effects and the self-care behaviors of women living with breast cancer: a randomized controlled trial. *BMC nursing* 22, 102.
- Valero-Ramon, Z., Louro, P., Irio, L., Dimitriadis, I., Poiitis, M., Toliopoulos, T., Lagakis, P., Petridis, G., Papachristou, N., Núñez-Benjumea, F.J., et al., 2022. A collective intelligence platform to support older cancer survivors: Towards the definition of lifechamps system and big data reference architecture, in: MEDINFO 2021: One world, one health—global partnership for digital innovation. IOS Press, pp. 1008–1009.
- Weiss, B.D., 2003. Health literacy. American Medical Association 253.
- Win, K.T., Hassan, N.M., Oinas-Kukkonen, H., Probst, Y., 2016. Online patient education for chronic disease management: consumer perspectives. *Journal of medical systems* 40, 1–13.
- Winkley, K., Upsher, R., Keij, S., Chamley, M., Ismail, K., Forbes, A., 2018. Healthcare professionals' views of group structured education for people with newly diagnosed type 2 diabetes. *Diabetic Medicine* 35, 911–919.
- World Health Organization, 2024. Who search results on death. <https://www.who.int/home/search-results?indexCatalogue=genericsearchindex1&searchQuery=death&wordsMode=AnyWord>. Accessed: 2024-07-31.
- Zhao, B., Potter, D.D., 2016. Comparison of lecture-based learning vs discussion-based learning in undergraduate medical students. *Journal of surgical education* 73, 250–257.
- Guo Qiyun, Guo Mujie, Zhang Lin, et al. Reliability and validity test of the Chinese version of osteoporosis knowledge assessment tool[J]. *Chinese Journal of Practical Nursing*, 2015, 31(7): 512-515.

Supplementary Files