

Original Article

Patterns and associated factors of online health information seeking behaviors among young women diagnosed with breast cancer in China

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ABSTRACT

Objective: This study aimed to identify latent classes of online health information seeking (OHIS) behaviors among young women diagnosed with breast cancer in China and examine associated personal characteristics to support tailored health education strategies.

Methods: Young women diagnosed with breast cancer were recruited from a cancer center in China between April and September 2024. Participants completed questionnaires on demographic and clinical characteristics, OHIS behaviors, psychosocial and cognitive factors, trust, social norms, communication, and information seeking experience. Latent class analysis (LCA) identified OHIS patterns, and multivariate logistic regression explored associated characteristics.

Results: Among the 398 patients, the median number of topics sought was 5 (4–7). The most frequently sought topics related to breast cancer included basic knowledge (89.7%), treatment plans (77.6%), and lifestyle (75.4%). Nearly half sought information only a few times a month or less. Social media (82.7%) and official accounts/websites (71.1%) were the most frequently used sources. LCA revealed three OHIS behavior classes: Class 1 “information explorers” (26.4%), Class 2 “occasional seekers” (49.2%), and Class 3 “information experts” (24.4%). Patients in adjuvant or other treatment phases were more likely to belong to Class 2 than Class 1. Those with a longer time since diagnosis were also more likely to be classified into Class 2 or Class 3. Conversely, stage I patients and those who trusted online health information were more likely to belong to Class 1, while higher eHealth literacy was associated with Class 3 membership.

Conclusions: Young women diagnosed with breast cancer display diverse OHIS patterns influenced by demographic and clinical factors. Recognizing these differences is vital for delivering tailored online health information services.

Introduction

Breast cancer is one of the most prevalent cancers worldwide,¹ with an increasing incidence among young women.² According to the international consensus of the European School of Oncology and European Society of Medical Oncology, young women diagnosed with breast cancer are defined as those under the age of 40.³ While young breast cancer cases constitute a small proportion globally, such as 4.9% in the United States,⁴ the incidence is notably higher in China at 16.4%.⁵ Compared to

older patients, young breast cancer cases often exhibit more aggressive tumor characteristics and poorer prognoses,^{6–8} imposing substantial physical, psychological, and social burdens.^{9–11} Given their diverse and complex needs, traditional medical information sources often fail to provide sufficient support,^{12,13} leading many young patients to increasingly rely on online health information.^{14,15}

Research indicates that online health information seeking (OHIS) plays a crucial role in the health management of cancer patients,^{16,17} particularly among younger individuals.¹⁸ By providing both

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informational and emotional support, OHIS enhances informed decision-making and promotes self-management,^{19–21} ultimately leading to better health outcomes.²² However, the accuracy of online information remains uncertain,²³ and exposure to misinformation may result in inappropriate health decisions, increased anxiety, and impaired doctor-patient relationships.^{20,24} Therefore, understanding the OHIS patterns of young women diagnosed with breast cancer is critical for developing targeted health education strategies and enabling health care professionals (HCPs) to guide patients in navigating online health information safely and effectively.^{25,26}

Most existing research on OHIS primarily focuses on single-dimensional analyses, such as its prevalence and preferred sources.^{27–29} However, these approaches fail to capture the diverse and complex information needs. Limited studies, such as Marcu et al.,³⁰ has categorized information seeking attitudes in older women, but the heterogeneity of OHIS patterns in young women diagnosed with breast cancer remains unexplored. To address this gap, this study employs latent class analysis (LCA), a statistical method used to identify latent classes of OHIS patterns based on response patterns to observed variables.³¹

Additionally, studies have shown that OHIS willingness is influenced by individual characteristics and competencies,^{32,33} such as age, education level, and eHealth literacy, which determine one's ability to seek, evaluate, and apply digital health information effectively.³⁴ However, the relationship between diverse OHIS patterns and their associated individual characteristics remains underexplored, despite its importance in helping HCPs identify and support different patient groups. Therefore, This study aims to use LCA to identify different OHIS patterns and their related individual characteristics among young women diagnosed with breast cancer in China, providing a theoretical basis for optimizing information provision. Based on these findings, tailored health information interventions and personalized communication strategies can be developed to enhance patients' health information acquisition and decision-making participation, ultimately improving their health care experience and satisfaction.

Methods

Research design

A cross-sectional descriptive design was used. This study received ethical approval from the Ethics Committee of Fudan University Shanghai Cancer Centre (Approval No. 2401290-34). Written informed consent was obtained from all participants before data collection began.

Sample and recruitment

Participants were recruited from a cancer center between April and September 2024. Inclusion criteria were: (1) a confirmed diagnosis of breast cancer, (2) aged 18–40 years, (3) had sought online health information, and (4) provided signed informed consent. Patients with cognitive or psychiatric impairments were excluded.

Measurements

Demographic and clinical characteristics

Demographic data were collected using self-administered questionnaires, including age, education level, employment status, marital status, number of children, and annual personal income. Clinical information, including cancer stage, tumor pathology, age at diagnosis, and treatment stage, were retrieved from electronic medical records. Ten questions were used to assess treatment-related symptom clusters, such as gastrointestinal, skin-mucosal, and peripheral nerve symptoms.

OHIS behaviors

OHIS behaviors were assessed using a structured questionnaire developed based on a literature review. The questionnaire included three

closed-ended questions to evaluate three dimensions of OHIS behaviors: (1) Information topics: Participants were asked to select all topics they had previously sought from the following options: basic knowledge about breast cancer, treatment plans, prognosis, treatment-related side effects, and other relevant topics. (2) Information sources: Participants selected their primary online health information sources from multiple-choice options, including search engines, social media platforms, official accounts/websites, professional medical Q&A platforms, and video-sharing platforms. (3) Information seeking frequency: A single-choice question assessed participants' recent information-seeking frequency, categorized as multiple times a day, multiple times a week, or a few times a month or less.

eHealth literacy scale

The eHealth literacy scale (eHEALS), developed by Norman,³⁵ was used to measure participants' ability to access, evaluate, and apply online health information. The scale consists of 8 items rated on a five-point Likert scale, with higher scores indicating higher eHealth literacy. Guo et al.³⁶ translated and adapted the scale into Chinese. The Chinese version of eHEALS demonstrated good reliability and validity, with a Cronbach's α coefficient of 0.913 and factor loadings ranging from 0.692 to 0.869.

Information needs questionnaire

To assess participants' perceived adequacy of knowledge, two questions adapted from Link et al.³⁷ were used. The first question asked participants to self-rate their current knowledge about breast cancer, while the second question evaluated their perceived knowledge gaps. To measure unmet health information needs, the Patient-provider communication scale (PPCS) used by Oh et al.³⁸ was adapted to assess patient-provider communication and unmet information needs. Responses were rated on a five-point Likert scale, where 1 = strongly disagree and 5 = strongly agree.

Emotional response questionnaire

Emotional responses were measured using the Patient-reported outcomes measurement information system (PROMIS) anxiety and depression 8a short forms. These short forms are among the most widely used tools under the PROMIS mental health module for assessing patients' negative emotions.³⁹ Each short form consists of 8 items, asking participants to rate their experiences of anxiety and depression over the past week. Each item is scored on a five-point Likert scale (1 = never, 5 = always), with higher total scores indicating more severe anxiety or depression symptoms. The Chinese version of the scale has demonstrated excellent reliability and validity among breast cancer patients, with Cronbach's α coefficients of 0.958 and 0.961 for anxiety and depression, respectively, and standardized factor loadings all exceeding 0.7, indicating strong construct validity.⁴⁰

Information seeking attitudes questionnaire

Based on previous research, information seeking attitudes were assessed across two dimensions: social norms and patient-provider communication. Social norms related to health information seeking were measured using 4 items adapted from Kahlor,⁴¹ focusing on the attitudes of family, friends, and HCPs toward OHIS. Each item was rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Additionally, to evaluate patients' communication with HCPs regarding online health information, a single-choice question was used to ask whether participants had discussed the information they obtained online with their HCPs. Response options included: (1) Discussion - explicitly mentioned: The patient discussed the online health information with their HCPs and explicitly stated that the information was obtained from the internet. (2) Discussion - implicitly mentioned: The patient discussed the online health information with their HCPs but did not explicitly disclose its online source, possibly due to concerns such as avoiding disagreements with the provider. (3)

Non-discussed: The patient did not discuss the online health information with their HCPs.

Trust questionnaire

To assess participants' trust in online health information, they were asked to rate 14 different information sources. These sources covered a variety of online health information channels commonly used in China, including search engines (e.g., Baidu, Google), social media platforms (e.g., Rednote, WeChat), official accounts/websites, professional medical Q&A platforms (e.g., Haodf.com), and video-sharing platforms (e.g., TikTok). Ratings ranged from 1 (not trustworthy) to 5 (very trustworthy), with higher scores indicating greater trust. A score of 0 was also included to indicate that the participant was unfamiliar with the information source. The average trust level was calculated by summing all scores and dividing by the number of information sources rated.

Information seeking experience questionnaire

The Information seeking experience (ISEE) scale was used to assess patients' experiences with information seeking.⁴² Four items from the original scale were used,³⁸ each scored on a five-point Likert scale using reverse scoring, with higher scores indicating a more positive information seeking experience.

Data collection

Data collection for this study was conducted between April and September 2024. After obtaining written informed consent from eligible participants, they were provided with paper questionnaires. If participants had difficulty reading the questionnaire, the researchers assisted by reading the questions aloud and recording the responses. Participants did not receive compensation.

Data analysis

Data analysis was performed using Stata 17.0, R 4.3.3, and Python 3.10.11. Missing data were handled using the multiple imputation method implemented in the "mice" package in R. Descriptive statistics for categorical variables were presented as frequencies and percentages, while normally distributed continuous variables were expressed as mean \pm standard deviation, and non-normally distributed continuous variables were reported as median (interquartile range).

LCA was conducted using the "poLCA" package in R⁴³ to identify distinct patterns of OHIS behaviors among young women diagnosed with breast cancer.³¹ A set of behavioral features, including information topics, sources, and information seeking frequency, were used as observed variables to capture the heterogeneity of OHIS behaviors. Based on these dimensions, different types of OHIS behavior patterns were identified, and sociodemographic and clinical characteristics were included as covariates to analyze their associations with the identified patterns.

The goodness-of-fit of the LCA models was evaluated using several statistical indices, including log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), and entropy.⁴⁴ Higher LL values indicate better model fit, while lower AIC and BIC values reflect a better balance between model fit and complexity. Entropy ranges from 0 to 1, with values closer to 1 indicating higher classification accuracy; an entropy value ≥ 0.80 is considered indicative of high classification accuracy.⁴⁴

Univariate analyses were conducted in Stata, and significant categorical variables were visualized using the "WordCloud" library in Python to illustrate OHIS behavior patterns and patient characteristics.⁴⁵ After assessing multicollinearity among these significant variables in R, they were included in a multivariate logistic regression model with latent classes as the dependent variable. A significance level of $P < 0.05$ was used for all analyses.

Results

Sample characteristics

The demographic and clinical characteristics of the participants across latent classes are presented in Table 1. A total of 398 young women diagnosed with breast cancer were included in the study. The median age was 36 (33–38) years, with an age range of 21–39 years. The majority of the patients were married (79.9%), and most had a college or associate degree (63.1%). A large proportion of the patients were from the southeastern region of China, accounting for 82.2% of the sample. Nearly half of the patients had one child (42.0%), and a significant percentage were corporate employees (42.5%). The personal annual income of most participants ranged from 100,000 to 199,900 yuan (29.4%). In terms of clinical characteristics, most patients were at stage II breast cancer (48.2%) and had luminal subtypes (58.0%). The majority were in the adjuvant therapy phase (49.5%) and reported a median of 4 (1–6) treatment-related symptom clusters.

OHIS behaviors

Among the 398 patients who used the internet to seek health information, their information topics, information sources, and frequency of information seeking are shown in Table 2. The vast majority sought information on basic knowledge (89.7%), followed by treatment plans (77.6%), lifestyle (75.4%), and prognosis (75.1%). Patients sought information on a median of 5 topics (4–7). In terms of information seeking frequency, nearly half (50.5%) reported seeking information several times a month or less. Social media was the most popular source (82.7%), followed by official accounts and websites (71.1%), and search engines (63.6%). Patients used a median of 3 (2–4) different information sources.

Model selection and class descriptions

Model selection

By comparing the goodness-of-fit indices of latent class models with 1–5 classes (Table 3), the 3-class model was ultimately selected as the best-fitting model. As the number of classes increased, the LL gradually improved, indicating a continuous enhancement in model fit. Both the AIC and BIC showed a decreasing trend, with the AIC decreasing more notably than the BIC, reflecting the trade-off between model fit and complexity as the number of classes increased. The entropy value for the 3-class model exceeded 0.8, indicating high classification accuracy. Additionally, the 3-class model demonstrated balanced class probability distributions, avoiding the issue of small classes observed in models with 4 or more classes, thereby enhancing the model's stability and interpretability. Therefore, after comprehensive consideration, the 3-class model was selected as the optimal classification solution. Fig. 1 presents the distribution of information topics, information sources, and frequency of information seeking by latent classes.

Class descriptions

Class 1 "information explorers" ($n = 105$, 26.4%) – These patients sought a broad range of topics of health information with relatively high information seeking frequency, typically several times a week. They demonstrated an active but relatively generalized approach to information seeking.

Class 2 "occasional seekers" ($n = 196$, 49.2%) – These patients displayed more sporadic and infrequent information seeking behaviors, focusing on a limited range of topics and relying more on search engines than professional platforms. The majority (81.6%) sought information only several times a month, indicating that their information seeking was incidental and driven by specific needs.

Class 3 "information experts" ($n = 97$, 24.4%) – These patients extensively sought information across all categories, frequently using professional platforms and official sources. They exhibited a high

Table 1Demographic and clinical characteristics of young women diagnosed with breast cancer between latent classes ($N = 398$).

Demographic and clinical variables	Total ($n = 398$)	Class 1 ($n = 105$)	Class 2 ($n = 196$)	Class 3 ($n = 97$)	χ^2/H	P-value
Age [years, M (P_{25}–P_{75})]	36 (33–38)	35 (33–38)	36 (34–37)	36 (32–37)	0.433 ^b	0.806
Marital status [n (%)]					16.524 ^a	0.002*
Single/Never married	65 (16.3)	15 (14.3)	22 (11.2)	28 (28.9)		
Married	318 (79.9)	87 (82.9)	164 (83.7)	67 (69.1)		
Divorced	15 (3.8)	3 (2.9)	10 (5.1)	2 (2.1)		
Number of children [n (%)]					10.386 ^a	0.034*
0	85 (21.4)	20 (19.0)	34 (17.3)	31 (32.0)		
1	167 (42.0)	41 (39.0)	87 (44.4)	39 (40.2)		
≥ 2	146 (36.7)	44 (41.9)	75 (38.3)	27 (27.8)		
Education level [n (%)]					25.253 ^a	< 0.001*
High school or below	97 (24.4)	22 (21.0)	64 (32.7)	11 (11.3)		
College/Associate degree	251 (63.1)	74 (70.5)	113 (57.7)	64 (66.0)		
Postgraduate or above	50 (12.6)	9 (8.6)	19 (9.7)	22 (22.7)		
Employment status [n (%)]					22.785 ^a	0.001*
Public sector employees	75 (18.8)	27 (25.7)	23 (11.7)	25 (25.8)		
Corporate employees	169 (42.5)	38 (36.2)	84 (42.9)	47 (48.5)		
Unemployed	91 (22.9)	23 (21.9)	58 (29.6)	10 (10.3)		
Self-employed	63 (15.8)	17 (16.2)	31 (15.8)	15 (15.5)		
Annual personal income [CNY, n (%)]					15.332 ^a	0.018*
$\leq 49,900$	90 (22.6)	23 (21.9)	53 (27.0)	14 (14.4)		
50,000–99,900	100 (25.1)	23 (21.9)	58 (29.6)	19 (19.6)		
100,000–199,900	117 (29.4)	36 (34.3)	46 (23.5)	35 (36.1)		
$\geq 200,000$	91 (22.9)	23 (21.9)	39 (19.9)	29 (29.9)		
Place of residence [n (%)]					6.648 ^a	0.036*
Urban	335 (84.2)	89 (84.8)	157 (80.1)	89 (91.8)		
Rural	63 (15.8)	16 (15.2)	39 (19.9)	8 (8.2)		
Province [n (%)]					12.507 ^a	0.130
Shanghai	122 (30.7)	28 (26.7)	53 (27.0)	41 (42.3)		
Jiangsu	97 (24.4)	24 (22.9)	54 (27.6)	19 (19.6)		
Zhejiang	43 (10.8)	15 (14.3)	21 (10.7)	7 (7.2)		
Anhui	65 (16.3)	21 (20.0)	33 (16.8)	11 (11.3)		
Others	71 (17.8)	17 (16.2)	35 (17.9)	19 (19.6)		
Cancer stage [n (%)]					22.490 ^a	0.004*
0	13 (3.3)	5 (4.8)	4 (2.0)	4 (4.1)		
I	88 (22.1)	28 (26.7)	32 (16.3)	28 (28.9)		
II	192 (48.2)	45 (42.9)	101 (51.5)	46 (47.4)		
III	67 (16.8)	24 (22.9)	31 (15.8)	12 (12.4)		
IV	38 (9.5)	3 (2.9)	28 (14.3)	7 (7.2)		
Molecular subtype [n (%)]					7.548 ^a	0.110
LuminalA/B	231 (58.0)	71 (67.6)	103 (52.6)	57 (58.8)		
HER2+	52 (13.1)	13 (12.4)	26 (13.3)	13 (13.4)		
TNBC	115 (28.9)	21 (20.0)	67 (34.2)	27 (27.8)		
Duration since diagnosis [years, M (P_{25}–P_{75})]	0 (0–1)	0 (0–0)	0 (0–1)	0 (0–1)	20.546 ^b	< 0.001*
Treatment stage [n (%)]					29.099 ^a	< 0.001*
NAC	73 (18.3)	31 (29.5)	23 (11.7)	19 (19.6)		
Surgery	49 (12.3)	15 (14.3)	23 (11.7)	11 (11.3)		
NAC + surgery	23 (5.8)	7 (6.7)	10 (5.1)	6 (6.2)		
Adjuvant	197 (49.5)	47 (44.8)	98 (50.0)	52 (53.6)		
Others	56 (14.1)	5 (4.8)	42 (21.4)	9 (9.3)		
Number of symptom clusters [M (P_{25}–P_{75})]	4 (1–6)	4 (1–5)	4 (1.75–7)	5 (1–7)	5.664 ^b	0.059

*Significant at $P < 0.05$. HER2, Human epidermal growth factor receptor 2; TNBC, triple-negative breast cancer; NAC, neoadjuvant chemotherapy; M, mean.^a Chi-square test.^b Kruskal–Wallis H test.

frequency of information seeking, often weekly or daily, indicating a thorough and sustained engagement with breast cancer-related information.

Associated factors

Bivariate analysis showed that 14 variables were significantly associated with class membership. Fig. 2 visualizes the portraits of OHIS patterns and personal characteristics across latent classes. Further analysis indicated that multicollinearity among the continuous variables was within acceptable ranges, but the Cramer's V value between child status and marital status exceeded 0.5, suggesting a strong association between these two variables. To avoid unnecessary complexity in the subsequent multivariate analysis, the marital status variable was removed, leaving child status as part of the analysis. Ultimately, 13

variables significant at $P < 0.05$ were included in the multivariate logistic regression model.

The results of the multivariable logistic regression analysis are presented in Table 4. Compared to Class 2, patients undergoing adjuvant treatment stages ($OR = 0.341$, 95% CI [0.159–0.732], $P = 0.006$) or other treatment stages ($OR = 0.238$, 95% CI [0.060–0.947], $P = 0.042$) were less likely to belong to Class 1. In terms of occupation, company employees were also less likely to be categorized as Class 1 compared to Class 2 ($OR = 0.404$, 95% CI [0.192–0.850], $P = 0.017$). Regarding time since diagnosis, patients in both Class 2 ($OR = 0.490$, 95% CI [0.253–0.950], $P = 0.035$) and Class 3 ($OR = 0.467$, 95% CI [0.231–0.944], $P = 0.034$) had significantly longer durations since diagnosis than those in Class 1, suggesting that a longer time since diagnosis is associated with higher likelihood of being in Class 2 or Class 3. In addition, compared to Class 2, patients diagnosed at stage I were

Table 2Information topics, information sources, and frequency of information seeking between latent classes of young women diagnosed with breast cancer ($N = 398$).

OHIS variables	Total ($n = 398$)	Class 1 ($n = 105$)	Class 2 ($n = 196$)	Class 3 ($n = 97$)
Information topics [n (%)]				
Basic knowledge	357 (89.7)	90 (85.7)	171 (87.2)	96 (99.0)
Treatment plan	309 (77.6)	77 (73.3)	135 (68.9)	97 (100.0)
Lifestyle	300 (75.4)	75 (71.4)	134 (68.4)	91 (93.8)
Prognosis	299 (75.1)	73 (69.5)	129 (65.8)	97 (100.0)
Side effects	286 (71.9)	73 (69.5)	121 (61.7)	92 (94.8)
Medical institutions or doctors	190 (47.7)	44 (41.9)	51 (26.0)	95 (97.9)
Others' experiences	162 (40.7)	35 (33.3)	54 (27.6)	73 (75.3)
Genetics or offspring	150 (37.7)	38 (36.2)	53 (27.0)	59 (60.8)
CAM	109 (27.4)	24 (22.9)	27 (13.8)	58 (59.8)
Number of topics [M (P_{25}–P_{75})]	5 (4–7)	5 (4–6)	5 (3–6)	8 (7–9)
Information sources [n (%)]				
Medical Q and A platforms	103 (25.9)	23 (21.9)	34 (17.3)	46 (47.4)
Video sharing platforms	197 (49.5)	54 (51.4)	98 (50.0)	45 (46.4)
Search engines	253 (63.6)	56 (53.3)	143 (73.0)	54 (55.7)
Official accounts or websites	283 (71.1)	72 (68.6)	122 (62.2)	89 (91.8)
Social media	329 (82.7)	85 (81.0)	150 (76.5)	94 (96.9)
Number of sources [M (P_{25}–P_{75})]	3 (2–4)	3 (2–4)	3 (2–3)	3 (3–4)
Frequency of information seeking [n (%)]				
≤ several times a month	201 (50.5)	0 (0.0)	160 (81.6)	41 (42.3)
Several times a week	131 (32.9)	105 (100.0)	0 (0.0)	26 (26.8)
≥ several times a day	66 (16.6)	0 (0.0)	36 (18.4)	30 (30.9)

CAM, complementary and alternative medicine; M, mean.

more likely to belong to Class 1 ($OR = 2.226$, 95% CI [1.162–4.262], $P = 0.016$). With respect to information seeking characteristics, patients who reported lower trust in online health information were more likely to be classified as Class 3 rather than Class 1 ($OR = 1.656$, 95% CI [1.177–2.331], $P = 0.004$). Furthermore, patients with higher eHealth literacy were less likely to be categorized as Class 2 than Class 3 ($OR = 0.590$, 95% CI [0.354–0.985], $P = 0.044$).

Discussion

This study revealed diverse OHIS behavior patterns among young women diagnosed with breast cancer and explored factors associated with these patterns. The results showed that the majority of patients actively sought information on basic knowledge and treatment plans, followed by lifestyle information. This finding aligns with the results of Mallmann et al.,¹⁵ confirming the broad scope of OHIS topics among breast cancer patients. However, it is noteworthy that previous studies often emphasized side effect information as a primary concern for cancer patients.^{46,47} In contrast, this study found that young patients were more inclined to use online resources to fill knowledge gaps and support treatment decision-making, while their seeking rates for side effect information were relatively low. This reflects their urgent need to enhance disease understanding and a sense of control during treatment.

The study also found that although official websites and accounts remain important sources of health information for breast cancer patients, young patients increasingly rely on social media platforms. Their usage rates of platforms such as Rednote and WeChat far exceed the 66.7% reported in 2015.²³ This shift highlights the dual value of social media in meeting both emotional and informational needs of young patients. However, research indicates that breast cancer-related information on platforms like Twitter and Facebook is heavily commercialized,

with more content focused on fundraising and product promotion than health education, and insufficient advocacy for individual health actions.⁴⁸ Given that the inaccurate health information may alter or delay health behavior intentions, ultimately impacting medical decision-making,⁴⁹ future research should further evaluate the accuracy of breast cancer-related information on social media, particularly on platforms like Rednote and WeChat, which have become primary information sources for young women diagnosed with breast cancer in China.

Using LCA, this study identified three classes of patients: Class 1 “information explorers”, Class 2 “occasional seekers”, and Class 3 “information experts”. Among these, “occasional seekers” accounted for the largest proportion, characterized by lower information seeking frequency and limited topic coverage. In contrast, “information experts” exhibited in-depth information seeking behaviors across multiple channels and topics. Multivariate analysis revealed that employment status, cancer stage, time since diagnosis, treatment phase, eHealth literacy, and trust in information sources were key factors influencing OHIS behavior patterns.

Class 1 “information explorers” had a shorter time since diagnosis and engaged in information seeking multiple times per week. This finding aligns with the study by Melhem et al.,⁵⁰ which reported that cancer patients' information needs peak during the initial diagnosis, with most patients seeking disease-related information online daily or weekly. Compared to Class 2, patients with stage I breast cancer were more likely to belong to Class 1. This trend may stem from the more treatment options available to stage I patients, such as different surgical approaches and adjuvant therapy regimens.⁵¹ The increased number of treatment options elevates decision-making complexity, driving more frequent OHIS behaviors to weigh the advantages and disadvantages of different treatments and address uncertainty and decision-making needs. Given the high information needs and greater trust in online information among

Table 3

Comparison of fit indices for latent class models.

Model	LL	AIC	BIC	Entropy	Class proportions
1-Class	−3961.288335	7956.576669	8024.346353	–	–
2-Class	−3808.822427	7687.644854	7827.170674	0.688385616	0.44/0.56
3-Class	−3692.791914	7491.583827	7702.865784	0.855370532	0.26/0.49/0.24
4-Class	−3567.596750	7277.193501	7560.231593	0.924129440	0.26/0.42/0.14/0.18
5-Class	−3497.749639	7173.499278	7528.293507	0.901214615	0.17/0.22/0.15/0.18/0.28

LL, Log Likelihood; AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion.

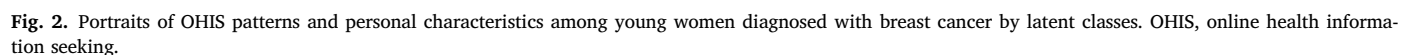
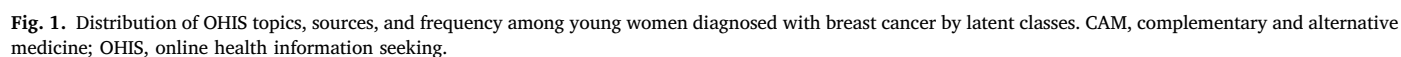


Table 4

Multivariate logistic regression analysis between latent classes.

Variables	Class 1 vs. Class 2			Class 1 vs. Class 3			Class 2 vs. Class 3		
	OR	95% CI	P	OR	95% CI	P	OR	95% CI	P
(Intercept)	1.184	0.218–6.436	0.845	0.379	0.056–2.567	0.320	0.320	0.025–4.119	0.382
Number of children									
1	0.792	0.377–1.662	0.537	1.191	0.542–2.615	0.664	1.504	0.510–4.432	0.460
≥ 2	1.131	0.518–2.469	0.758	1.567	0.670–3.665	0.300	1.386	0.437–4.395	0.579
Education level									
College/Associate degree	1.570	0.678–3.633	0.292	1.327	0.454–3.878	0.605	0.846	0.217–3.300	0.809
Postgraduate or above	0.895	0.239–3.357	0.870	0.669	0.151–2.955	0.596	0.747	0.102–5.456	0.774
Employment									
Corporate employees	0.404	0.192–0.850	0.017*	0.824	0.376–1.807	0.628	2.036	0.691–6.004	0.197
Unemployed	0.489	0.177–1.348	0.167	2.068	0.605–7.070	0.247	4.227	0.859–20.803	0.076
Self-Employed	0.605	0.226–1.623	0.318	0.718	0.246–2.097	0.545	1.186	0.277–5.089	0.818
Annual personal income (CNY)									
50,000–99,900	0.671	0.284–1.587	0.364	1.369	0.460–4.078	0.573	2.041	0.508–8.194	0.315
100,000–199,900	1.006	0.411–2.462	0.989	1.608	0.548–4.719	0.387	1.599	0.394–6.480	0.511
≥ 200,000	0.768	0.285–2.073	0.603	1.862	0.574–6.040	0.300	2.424	0.520–11.299	0.260
Place of residence									
Rural	0.872	0.398–1.914	0.733	1.103	0.388–3.133	0.854	1.264	0.342–4.671	0.725
Duration since diagnosis (years)	0.490	0.253–0.950	0.035*	0.467	0.231–0.944	0.034*	0.954	0.363–2.503	0.923
Cancer stage									
I	2.226	1.162–4.262	0.016*	1.082	0.530–2.207	0.828	0.486	0.185–1.275	0.143
III–IV	1.278	0.619–2.638	0.508	1.658	0.704–3.902	0.247	1.298	0.423–3.984	0.649
Treatment stage									
Surgery	0.478	0.201–1.133	0.094	0.697	0.257–1.889	0.478	1.459	0.390–5.458	0.575
Adjuvant	0.341	0.159–0.732	0.006*	0.659	0.283–1.536	0.334	1.930	0.618–6.029	0.258
Others	0.238	0.060–0.947	0.042*	1.024	0.189–5.558	0.978	4.308	0.485–38.287	0.190
eHealth literacy	1.259	0.913–1.737	0.161	0.743	0.500–1.106	0.144	0.590	0.354–0.985	0.044*
Information need	0.994	0.746–1.324	0.967	0.942	0.679–1.307	0.721	0.948	0.613–1.465	0.809
Social norms	1.067	0.803–1.417	0.656	0.769	0.556–1.064	0.113	0.721	0.468–1.110	0.138
Information communication									
Discussion - implicit mentioned	1.865	0.793–4.383	0.153	1.864	0.750–4.629	0.180	0.999	0.287–3.482	0.999
Non-discussed	1.260	0.621–2.557	0.522	1.744	0.806–3.776	0.158	1.384	0.485–3.946	0.543
Reliability evaluation	1.217	0.902–1.641	0.199	1.656	1.177–2.331	0.004*	1.361	0.864–2.144	0.183

* Significant at $P < 0.05$.

Class 1 patients, this group may be more susceptible to misinformation or information overload. Therefore, it is recommended that HCPs proactively provide authoritative information during the initial diagnosis phase to promote informed decision-making and enhance medical satisfaction.⁵² For example, hospitals could use official websites or accounts to deliver personalized information on disease introduction and treatment options, helping patients quickly understand their condition and available treatments.

This study found that Class 2 “occasional seekers” exhibited lower information seeking frequency, and patients in the adjuvant or other treatment phases were more likely to belong to this category, reflecting changes in information needs across different treatment stages. Elbarazi et al.⁵³ demonstrated that cancer patients have higher information needs during the diagnosis phase, while these needs fluctuate during the treatment phase. During adjuvant therapy, patients are typically diagnosed and have begun receiving established treatment plans, with their information needs primarily triggered by symptoms related to periodic treatments. In other treatment phases, such as palliative care, patients’ OHIS behaviors also exhibited low-frequency characteristics, which may be related to barriers to information access caused by cancer progression, including the lack of specific information, insufficient peer support, and emotional withdrawal due to sensitive topics like palliative care.^{54,55}

Additionally, corporate employees were more likely to belong to Class 2, suggesting that time and energy constraints limit their frequency of actively seeking health information, leading them to prefer concise and direct information channels. However, the use of search engines for quick information access has limitations, further restricting this group’s ability to obtain information. For example, in Baidu search results for breast cancer-related content, commercial and personal websites account for 78.8%, while treatment-related content constitutes only 4.3%.⁵⁶ Therefore, to meet the health information needs of Class 2, the presentation of

search engine results should be optimized to prioritize authoritative information and reduce patients’ exposure to low-quality information. Furthermore, delivering information on side effect prevention and intervention could help compensate for these patients’ limited active OHIS behaviors, enhancing their ability to access effective health information within limited time.

Notably, Class 1 and Class 2 patients showed a preference for short video platforms such as TikTok, a trend that aligns with findings from a Spanish study on breast cancer patients’ preferences for video-based information.⁵⁷ However, the quality of content on TikTok is uneven, and only a small proportion (less than 5%) of accounts are affiliated with health institutions.^{58,59} This phenomenon highlights the need to improve the quality of health education resources on short video platforms by strengthening content regulation and increasing the engagement of HCPs and health institutions to better meet patients’ demand for visual health information.

Class 3 “information experts” primarily consisted of patients with longer time since diagnosis and higher eHealth literacy. They extensively accessed breast cancer-related information through multiple channels, such as official websites and professional medical Q&A platforms, demonstrating systematic disease understanding and sustained engagement. Saffarzadeh⁶⁰ also highlighted the critical role of eHealth literacy in accessing high-quality medical information. However, this group rated the credibility of online information lower and emphasized the integration of information from multiple sources. This finding aligns with previous studies indicating that eHealth literacy not only influences information-seeking behaviors but also serves as a mediator in the process by which health-related information leads to changes in health-related behaviors.⁶¹ Given their higher eHealth literacy, the limited time for patient-provider communication in clinical settings may hinder their efficient use of the information obtained. To optimize

decision support and enhance shared decision-making efficiency, it is recommended that HCPs guide patients to access high-quality medical evidence, such as the latest treatment options and clinical guidelines, thereby enhancing the credibility of online information and strengthening patients' confidence in using it for informed decision-making.

Practice implications

This study highlights the need for personalized online health information strategies that address distinct patterns of OHIS behaviors among young women diagnosed with breast cancer. Based on the identified patient classifications, HCPs and health care institutions should consider implementing tailored health information support strategies according to patients' engagement levels, preferences, and eHealth literacy. Specifically, for Class 1 "information explorers", information intervention strategies should focus on providing foundational guidance and high-quality information support during the early stages of the disease to enhance their health literacy and optimize decision-making experiences. For Class 2 "occasional seekers", whose OHIS behaviors are influenced by treatment phase, occupational factors, and information environment, it is recommended to improve their access to accurate and authoritative health information by optimizing information accessibility and implementing interventions based on recommended system. The widespread use of short video platforms offers new opportunities for health communication, and HCPs should actively participate in content creation to optimize patients' information seeking experiences. For Class 3 "information experts", who exhibit high autonomy in information acquisition, strategies should focus on supporting the evaluation and integration of information from multiple sources, enhancing their confidence in applying health information and aligning it with clinical recommendations. By addressing the diverse information needs of patients, this study offers a theoretical foundation for developing tailored health information strategies. These strategies, when aligned with patients' behavioral patterns and individual characteristics, can enhance decision-making engagement and improve overall health care experiences.

Limitations

This study has several limitations. First, the sample is geographically limited and predominantly highly educated, which may affect the generalizability of findings to the broader young breast cancer population in China. Future research should aim for more diverse and representative sampling, including patients from different educational backgrounds and geographic regions, to better understand variations in OHIS behaviors. Second, as a cross-sectional study, it cannot capture changes in OHIS behaviors, such as variations across different stages of the information seeking process. Longitudinal follow-up studies are needed to track the evolution of OHIS behaviors—from the initial information need to information acquisition and decision-making. Additionally, the reliance on self-reported data may introduce recall or social desirability bias. Future studies could incorporate objective tracking methods to improve accuracy.

Conclusions

This study comprehensively analyzed the OHIS behaviors of young women diagnosed with breast cancer, identifying three distinct categories: "information explorers", "occasional seekers", and "information experts". Key factors such as employment status, cancer stage, duration since diagnosis, treatment stage, eHealth literacy, and reliability evaluation significantly influenced these behavior patterns. These findings provide a scientific foundation for optimizing online health information services tailored to the unique characteristics of young women diagnosed with breast cancer, emphasizing the need for personalized support strategies to enhance health literacy and encourage positive health behaviors.

CRedit authorship contribution statement

Jialin Chen: Conceptualization, Data curation, Writing – original draft, Writing – review and editing. **Yang Yang:** Data curation, Resources. **Haozhi Xia:** Conceptualization, Methodology. **Yiwen Duan:** Data curation. **Chaojin Da:** Methodology. **Tingting Cai:** Conceptualization, Methodology, Writing – review and editing, Funding acquisition. **Changrong Yuan:** Conceptualization, Funding acquisition, Supervision. All authors have read and approved the final manuscript.

Ethics statement

The study was approved by the Ethics Committee of Fudan University Shanghai Cancer Centre (Approval No. 2401290-34) and was conducted in accordance with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. All participants provided written informed consent.

Data availability statement

The datasets generated during and analyzed during the current study are available from the corresponding author, TC, on reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4.0 in order to check spelling, grammar, and sentence structure to enhance readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare no conflict of interest. The corresponding author, Dr. Tingting Cai, is an editorial board member of *Asia-Pacific Journal of Oncology Nursing*. The article was subject to the journal's standard procedures, with peer review handled independently of Dr. Cai and their research groups.

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