Research Square

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Identifying risk factors for adverse cancer-related fatigue trajectories after endometrial cancer surgery: A longitudinal study

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Abstract

Objective: To identify distinct longitudinal trajectories of cancer-related fatigue in postoperative endometrial cancer patients and determine the multidimensional predictors of adverse trajectory membership, with the aim of informing person-centered risk-stratified nursing care.

Methods:A prospective longitudinal study was conducted in 145 endometrial cancer patients with assessments at 1, 3, and 5 months after surgery. Cancer-related fatigue was measured using the Cancer Fatigue Scale. Latent class growth modeling identified fatigue trajectories, and binary logistic regression examined predictors from physiological, psychological, and environmental domains guided by the Theory of Unpleasant Symptoms.

Results: Two distinct trajectories were identified: a fatigue-decreasing group (78.62%) and a fatigue-increasing group (21.38%). Postoperative complications (OR = 8.60, 95% CI: 1.10–67.02), depressive symptoms (OR = 1.31, 95% CI: 1.10–1.55), self-perceived burden (OR = 1.22, 95% CI: 1.05–1.40), and low social support (OR = 1.39, 95% CI: 1.10–1.77) independently predicted membership in the fatigue-increasing group.

Conclusions: Postoperative cancer-related fatigue exhibits heterogeneous trajectories. The four identified modifiable biopsychosocial factors can be used by nurses to screen for high-risk patients and to deliver person-centered, targeted interventions (e.g., enhanced recovery for complications, psychological support for depressive symptoms and self-perceived burden, and family involvement for low social support). These findings provide an evidence base for developing a risk-stratified nursing management pathway that aligns with the principles of person-centered care.

Keywords: Endometrial cancer; Cancer-related fatigue; Person-centered care; Longitudinal study; Risk factors; Nursing

Clinical trial number: Not applicable.

1. Introduction

Endometrial cancer is one of the most common gynecologic malignancies globally, with an increasing incidence [1, 2]. Surgery remains the cornerstone of curative treatment; however, the postoperative recovery period is often accompanied by various distressing symptoms that impair patients' quality of life [3].

Among these, cancer-related fatigue is the most prevalent and debilitating symptom, characterized by a persistent, subjective sense of physical, emotional, and cognitive exhaustion related to cancer or its treatment that is not proportional to recent activity and interferes with usual functioning[4]. Cancer-related fatigue affects over 50% of cancer patients during treatment and can persist for years, leading to poor treatment adherence and diminished quality of life [5, 6]. Importantly, cancer-related fatigue is not a static phenomenon; its severity fluctuates throughout the disease trajectory[7]. Therefore, cross-sectional assessments, which capture cancer-related fatigue at a single time point, are insufficient to understand its

dynamic development. Longitudinal studies that track individual changes over time are urgently needed to identify distinct patterns of cancer-related fatigue progression [8].

The Theory of Unpleasant Symptoms provides a valuable framework for investigating the complex, multidimensional nature of cancer-related fatigue [9]. The theory posits that symptoms like fatigue are influenced by the interplay of physiological (e.g., disease stage, complications), psychological (e.g., depression, self-perceived burden), and situational (e.g., social support) factors. Despite this, current research on cancer-related fatigue in endometrial cancer patients has several limitations. Most studies are cross-sectional, focusing on prevalence and associated factors at a single time point, thus failing to capture the heterogeneity of cancer-related fatigue development over time [10, 11]. Furthermore, the specific influence of key psychological factors, such as self-perceived burden—the feeling of being a burden to caregivers—and its interaction with other multidimensional determinants on the long-term trajectory of cancer-related fatigue, remains largely unexplored in this population [12].

To address these gaps, we conducted a prospective longitudinal study guided by the Theory of Unpleasant Symptoms framework. Our objectives were (1) to identify distinct trajectories of cancer-related fatigue in patients during the first five months after endometrial cancer surgery using latent class growth modeling, and (2) to determine the predictive effects of physiological, psychological, and situational factors on trajectory group membership. We hypothesize that cancer-related fatigue follows heterogeneous patterns and that modifiable factors, particularly psychological distress and social support, are key determinants of an adverse fatigue trajectory. Identifying these factors and their associated trajectories is a critical first step toward developing a clinically applicable, risk-stratified management pathway. This approach breaks away from the traditional “one-size-fits-all” intervention model by providing person-centered care at the earliest possible stage to high-risk patients whose fatigue continues to worsen or deteriorate, ultimately improving their postoperative recovery outcomes and enhancing their quality of life.

2. Methods

This study was conducted and reported in accordance with the STROBE guidelines for cohort studies.

2.1 Sampling and Participants

Convenience sampling was employed. This prospective longitudinal study was conducted at the Department of Gynecology, the First Hospital of China Medical University, Shenyang, China, between January 2021 and December 2025. Patients with newly diagnosed endometrial cancer who underwent surgical treatment were consecutively enrolled. Eligible participants were: (1) aged ≥ 18 years; (2) histopathologically confirmed primary endometrial cancer; (3) underwent surgery; (4) able to communicate independently and complete questionnaires; (5) provided written informed consent. Exclusion criteria were: (1) tumor recurrence or metastasis during follow-up; (2) other malignant tumors; (3) severe physical or mental comorbidities that might interfere with participation.

2.2 Research Design and Data Collection

Patients were recruited by their attending physicians at the preoperative visit. After providing informed consent, participants completed a baseline questionnaire 1 month after surgery (time point 1). Follow-up assessments were conducted at 3 months (time point 2) and 5 months (time point 3) postoperatively. Time point 1 questionnaires were completed via face-to-face interviews, while time point 2 and time point 3 assessments were primarily conducted through telephone interviews. Sample size was calculated using G*Power (v 3.1.9.7). The parameters were set as follows: effect size = 0.1, power = 0.95, and significance level α = 0.05[13]. For three repeated measurements, a minimum of 92 participants was required. Accounting for an anticipated 20% attrition rate, a minimum of 115 participants needed to be enrolled initially.

At time point 1, 170 valid questionnaires were collected. The subsequent number of participants lost to follow-up was as follows: 13 participants at time point 2, and 12 participants at time point 3. Consequently, 145 participants successfully completed the entire follow-up protocol; 25 participants (14.71%) were lost to follow-up throughout the study period. Participants were lost to follow-up for the following reasons: incomplete data (n = 7), withdrawal from the study (n = 14), and loss to follow-up (n = 4). A flow diagram of participant enrollment and follow-up is shown in Fig. 1.

2.3 Measures

2.3.1 Sociodemographic and Clinical Characteristics

A self-designed questionnaire collected baseline sociodemographic and clinical data, including age (< 50, 50–60, > 60 years), marital status (married/cohabited vs. divorced/separated/widowed), educational level (junior high school or below, senior high/secondary vocational, college diploma or above), monthly household income (< 3000 Chinese Yuan, 3000–5000 Chinese Yuan, > 5000 Chinese Yuan), residence (urban vs. rural), passive smoking exposure (yes vs. no; defined as exposure to secondhand smoke at least once a week for ≥ 15 minutes per occasion), disease stage (I, II, III/IV) according to the 2023 International Federation of Gynecology and Obstetrics staging system, and presence of postoperative complications (yes vs. no) [14].

2.3.2 Cancer-Related Fatigue

Cancer-related fatigue was measured using the Cancer Fatigue Scale, a 15-item self-rating instrument developed by Okuyama and colleagues. [15]. It comprises three subscales: physical, affective, and cognitive fatigue. Each item is scored from 1 to 5, with total scores ranging from 0 to 60; higher scores indicate greater fatigue severity. In this study, Cronbach's alpha coefficients for the Cancer Fatigue Scale were 0.858 at time point 1, 0.892 at time point 2, and 0.867 at time point 3.

2.3.3 Depressive Symptoms

Depressive symptoms were assessed using the Self-rating Depression Scale [16], a 20-item scale with a 4-point Likert format. The raw sum score is converted to a standardized score (range 25–100) by multiplying by 1.25. Higher scores represent more severe depression, with cutoffs: <53 normal, 53–62 mild, 63–72 moderate, ≥ 73 severe. Cronbach's alpha for the Self-rating Depression Scale in this sample was 0.830.

2.3.4 Self-Perceived Burden

The Self-Perceived Burden Scale [12] was used to evaluate patients' feelings of being a burden to others. This 10-item scale uses a 5-point Likert scale (1 = none of the time to 5 = all of the time), with total scores ranging from 10 to 50. Higher scores indicate greater self-perceived burden (0–25 low, 26–33 moderate, 34–50 high). Cronbach's alpha was 0.948 in this study.

2.3.5 Social Support

Social support was measured using the Perceived Social Support from Family scale [17], a 9-item self-report instrument. Each item is rated on a 4-point scale (1 = strongly disagree to 4 = strongly agree), with total scores ranging from 9 to 36. Higher scores reflect lower perceived family support. The scale demonstrated good internal consistency (Cronbach's alpha = 0.901).

2.4 Statistical Analysis

Descriptive statistics were computed for sociodemographic and clinical variables. Continuous data were tested for normality using the Shapiro–Wilk test; normally distributed variables were expressed as mean ± standard deviation, and non-normally distributed variables as median with interquartile range. Categorical variables were presented as frequencies and percentages.

To identify distinct trajectories of cancer-related fatigue from time point 1 to time point 3, we performed latent class growth modeling using Mplus version 8.7 (Muthén & Muthén, Los Angeles, CA, USA). Latent class growth modeling is a specialized form of finite mixture modeling that identifies unobserved subpopulations following similar developmental trajectories. Models with one to five latent classes were fitted sequentially, specifying a linear functional form for each trajectory. The optimal number of classes was determined based on a combination of statistical fit indices and substantive interpretability. Lower values of the Akaike information criterion, Bayesian information criterion, and sample-size adjusted Bayesian information criterion indicated better model fit. Classification accuracy was assessed using entropy, with values > 0.8 considered indicative of high precision in class assignment. The Lo-Mendell-Rubin likelihood ratio test and bootstrapped likelihood ratio test were used to compare nested models; a significant *P*-value (< 0.05) indicated that a model with *k* classes provided a superior fit compared to a model with *k* − 1 classes[18]. Posterior class membership probabilities > 0.9 were interpreted as reflecting reliable individual assignment to the identified trajectory groups.

Following trajectory identification, differences in baseline characteristics between the latent classes were examined. Given the modest sample size and the exploratory nature of the analysis, the chi-square test and Fisher’s exact test were used for categorical variables, and the Mann-Whitney U test was used for continuous variables due to their non-normal distribution. Variables that demonstrated significant differences at $P < 0.05$ in the univariate analyses were subsequently entered into a binary logistic regression model to identify independent predictors of trajectory group membership. The "fatigue-decreasing group" was set as the reference category. Odds ratios with 95% confidence intervals were calculated. All statistical tests were two-tailed, and $P < 0.05$ was considered statistically significant. All descriptive and regression analyses were conducted using SPSS version 21.0 (IBM, Asia Analytics Shanghai).

2.5 Ethics approval

This study was formally approved by the Institutional Review Board of China Medical University Ethics Review Committee (approval number: 2025 – 181), with retrospective review of anonymized clinical data collected as part of routine clinical practice. All procedures adhered to the principles of the Declaration of Helsinki, and all participants provided written informed consent prior to enrollment.

3. Results

3.1 Participant Characteristics

A total of 145 patients with endometrial cancer were included in the final analysis. Baseline sociodemographic and clinical characteristics are summarized in Table 1. The majority of participants were aged 50–60 years (53.10%, n = 77), married or cohabiting (89.66%, n = 130), and resided in urban areas (82.07%, n = 119). Approximately half had a junior high school education or below (55.17%, n = 80), and a monthly household income of 3000–5000 Chinese Yuan (55.86%, n = 81). Passive smoking exposure was reported by 23.45% (n = 34) of participants. Regarding clinical characteristics, 58.62% (n = 85) were diagnosed with stage I disease according to the 2023 International Federation of Gynecology and Obstetrics staging system [14], and 39.31% (n = 57) experienced postoperative complications.

Table 1
The general information of participants(n = 145)

Variables	**Participants N(%)**
Age(years)	
< 50	33(22.76)
50–60	77(53.10)
> 60	35(24.14)
Marital status	
Divorced/separated/ widowed	15(10.34)
Married/cohabited	130(89.66)
Education level	
Junior high school education or below	80(55.17)
Senior high / Secondary vocational	40(27.59)
College diploma or above	25(17.24)
Monthly income (yuan)	
< 3000	34(23.45)
3000–5000	81(55.86)
> 5000	30(20.69)
Place of residence	
Urban	119(82.07)
Rural	26(17.93)
Passive smoking exposure	
Yes	34(23.45)
No	111(76.55)
Stage of disease	
Stage □	85(58.62)
Stage □	26(17.93)
Stage □/□	34(23.45)
Complication	

Variables	Participants N(%)
Yes	57(39.31)
No	88(60.69)

3.2 Identification of Cancer-Related Fatigue Trajectories

Latent class growth modeling was performed to identify distinct developmental trajectories of cancer-related fatigue from time point 1 to time point 3. Fit indices for models with one to five classes are presented in Table 2. The two-class solution demonstrated the best fit, with significantly lower Akaike information criterion, Bayesian information criterion, and sample-size adjusted Bayesian information criterion values compared to the one-class model, and a significant Lo-Mendell-Rubin likelihood ratio test *P*-value (< 0.001). Although the three-class model showed further reduction in information criteria, the Lo-Mendell-Rubin likelihood ratio test was non-significant (*P* = 0.33), indicating that the two-class model was more parsimonious and statistically preferable. Entropy for the two-class model was 0.826, indicating high classification accuracy. Posterior class membership probabilities were 0.961 for Class 1 and 0.935 for Class 2 (Table 3), reflecting reliable individual assignment.

Table 2
Model fit information for cancer-related fatigue trajectories in participants

Class	AIC	BIC	aBIC	Entropy	LMR	BLRT	Class proportions(%)
1	3292.09	3306.97	3291.15				
2	3272.19	3296.00	3270.68	0.83	< 0.001	< 0.001	78.62/21.38
3	3270.37	3303.12	3268.31	0.74	0.33	0.12	65.47/14.48/20.05
4	3273.12	3314.80	3270.50	0.81	0.76	0.42	5.54/15.08/20.04/59.34
5	3278.52	3329.13	3275.33	0.65	0.35	0.90	12.36/15.08/20.04/46.22/6.30

Note. AIC, Akaike Information Criteria; BIC, Bayesian Information Criterion; aBIC, sample-size adjusted BIC; LMR, Lo-Mendell-Rubin; BLRT, Bootstrapped-Likelihood Ratio Test.

Table 3
Posterior probabilities of each latent class of cancer-related fatigue in participants

Class	Posterior probabilities	
	C1	C2
C1	0.961	0.039
C2	0.065	0.935

The two identified cancer-related fatigue trajectories are illustrated in Fig. 2. Class 1, designated the **"fatigue-decreasing group"**, comprised 78.62% (n = 113) of the sample. This group exhibited a relatively high initial fatigue level (intercept estimate = 24.91, standard error = 0.879, $P < 0.001$) followed by a significant linear decrease over time (slope estimate = -4.65, standard error = 0.569, $P < 0.001$), indicating gradual symptom improvement during the postoperative period. Class 2, designated the **"fatigue-increasing group"**, comprised 21.38% (n = 32) of the sample. This group showed a lower initial fatigue level (intercept estimate = 22.49, standard error = 1.181, $P < 0.001$) but a significant linear increase over time (slope estimate = 7.79, standard error = 1.093, $P < 0.001$), representing a progressively worsening fatigue trajectory. Detailed parameter estimates for both trajectory groups are provided in Table 4.

Table 4
Latent variable means of each latent class group of cancer-related fatigue

Class	Parameter	Mean Estimate	*SE*	*t*	*P*
C1	intercept	24.909	0.879	28.349	< 0.001
	slope	-4.652	0.569	-8.175	< 0.001
C2	intercept	22.491	1.181	19.048	< 0.001
	slope	7.792	1.093	7.128	< 0.001

3.3 Factors Associated with Cancer-Related Fatigue Trajectory Membership

Univariate analyses comparing baseline characteristics between the two trajectory groups are presented in Table 5. Significant differences were observed for residence ($P = 0.002$), passive smoking exposure ($P < 0.001$), disease stage ($P < 0.001$), postoperative complications ($P < 0.001$), depressive symptoms ($P < 0.001$), self-perceived burden ($P < 0.001$), and social support ($P < 0.001$). No significant differences were found for age, marital status, education level, or monthly income.

Table 5
Univariate analysis of cancer-related fatigue trajectories in participants

Variables	C1	C2	χ^2/U	*P*
	n(%)			
Age(years)			1.312	0.519
< 50	25(22.12%)	8(25.00%)		
50–60	62(54.87%)	15(46.88%)		
> 60	26(23.01%)	9(28.13%)		
Marital status			0.019[a]	0.891
Divorced/separated/ widowed	12(10.62%)	3(9.38%)		
Married/cohabited	101(89.38%)	29(90.63%)		
Education level			0.133	0.936
Junior high school education or below	61(53.98%)	19(59.38%)		
Senior high / Secondary vocational	32(28.32%)	8(25.00%)		
College diploma or above	20(17.70%)	5(15.63%)		
Monthly income (yuan)			4.115[a]	0.128
< 3000	24(21.24%)	10(31.25%)		
3000–5000	62(54.87%)	19(59.38%)		
> 5000	27(23.89%)	3(9.38%)		
Place of residence			9.523	0.002
Urban	98(86.73%)	21(65.63%)		
Rural	15(13.27%)	11(34.48%)		
Passive smoking exposure			14.016	<0.001
Yes	13(11.50%)	21(65.63%)		
No	100(88.50%)	11(34.48%)		
Stage of disease			15.180	<0.001
Note.[a] Fisher's exact test				
Variables that were significant in univariate analyses were entered into a binary logistic regression model, with the fatigue-decreasing group serving as the reference category. Variable assignments are shown in Table 6. The final model (Table 7) identified four independent predictors of belonging to the fatigue-increasing group:				

Variables	C1	C2	χ^2/U	*P*
	n(%)			
Stage □	76(67.26%)	9(28.13%)		
Stage □	17(15.04%)	9(28.13%)		
Stage □/□	20(17.70%)	14(43.75%)		
Complication			24.003	<0.001
Yes	32(28.32%)	25(78.13%)		
No	81(71.68%)	7(21.88%)		
Depressive symptoms [points,M(P25,P75)]	40(33,46)	60(53,66)	327.5	< 0.001
Self-Perceived Burden [points,M(P25,P75)]	16(14,18)	30(28,34)	69.5	< 0.001
Social support [points,M(P25,P75)]	9(9,10)	22(18,24)	102.5	< 0.001
Note.[a] Fisher's exact test				
Variables that were significant in univariate analyses were entered into a binary logistic regression model, with the fatigue-decreasing group serving as the reference category. Variable assignments are shown in Table 6. The final model (Table 7) identified four independent predictors of belonging to the fatigue-increasing group:				

- **Postoperative complications**: Patients with complications had significantly higher odds of being in the fatigue-increasing group compared to those without complications (odds ratio = 8.595, 95% confidence interval: 1.102–67.019, *P* = 0.040).
- **Depressive symptoms**: Higher Self-rating Depression Scale scores were associated with increased odds of unfavorable trajectory membership (odds ratio = 1.305, 95% confidence interval: 1.103–1.545, *P* = 0.002).
- **Self-perceived burden**: Greater self-perceived burden (higher Self-Perceived Burden Scale scores) significantly predicted inclusion in the fatigue-increasing group (odds ratio = 1.216, 95% confidence interval: 1.054–1.403, *P* = 0.007).
- **Social support**: Lower perceived family support (higher Perceived Social Support from Family Scale scores) was associated with increased odds of belonging to the fatigue-increasing group (odds ratio = 1.393, 95% confidence interval: 1.096–1.771, *P* = 0.007).

Table 6
Assignment of each variable

Variables	Assignment
Place of residence	Urban = 1;Rural = 2
Passive smoking exposure	Yes = 1;No = 2
Stage of disease	Stage □=1;Stage □=2□Stage □/□=3
Complication	Yes = 1;No = 2
Depressive symptoms	Original Value
Self-Perceived burden	Original Value
Social support	Original Value
Note.Reference group:C1: fatigue-decreasing group;C2: fatigue-increasing group	

Table 7
Logistic regression analysis of influencing factors for different latent classes

Variables	Reference	B	Wald	*P*	OR	95% CI	
						LL	UL
Complication							
Yes	No	2.151	4.215	0.040	8.595	1.102	67.019
Depressive symptoms		0.267	9.627	0.002	1.305	1.103	1.545
Self-Perceived burden		0.195	7.155	0.007	1.216	1.054	1.403
Social support		0.332	7.348	0.007	1.393	1.096	1.771
Note.Reference group:C1: fatigue-decreasing group;C2: fatigue-increasing group							

4. Discussion

This prospective longitudinal study identified two distinct trajectories of cancer-related fatigue in patients with endometrial cancer during the first five months after surgery: a fatigue-decreasing group (78.62%) and a fatigue-increasing group (21.38%). Guided by the Theory of Unpleasant Symptoms [9], we further demonstrated that the adverse fatigue-increasing trajectory was independently predicted by postoperative complications (physiological factor), depressive symptoms and self-perceived burden (psychological factors), and low social support (environmental factor). These findings provide actionable insights for clinical practice by identifying a high-risk subgroup and delineating modifiable targets for early intervention, thereby supporting the development of a stratified management pathway for postoperative cancer-related fatigue in endometrial cancer patients.

4.1 Prevalence and Heterogeneity of Postoperative Cancer-related Fatigue Trajectories

In our cohort, cancer-related fatigue was highly prevalent, with 98.6% of patients reporting fatigue at one-month post-surgery (time point 1), consistent with previous reports in gynecologic cancer populations where cancer-related fatigue affects up to 90% of patients during active treatment [5, 6]. More importantly, we identified two distinct trajectory patterns, revealing that cancer-related fatigue does not follow a uniform course. This heterogeneity aligns with findings from other cancer populations: in lung cancer patients undergoing surgery, 19.51% were classified into a “severe group” [19]; in esophageal cancer, 36% followed a high-level increasing fatigue trajectory over five years [20]. The proportion of patients in our fatigue-increasing group (21.38%) is consistent with the range reported in these studies (15–36%), confirming that a consistent minority of cancer patients experience worsening symptom trajectories across diverse cancer types.

Notably, despite the smaller sample size of this subgroup, the high classification accuracy (entropy = 0.826) and robust posterior probabilities (> 0.93) support the reliability of the identified subgroups. From a clinical perspective, identifying this smaller but high-risk subgroup is of particular importance, as these patients may derive the greatest benefit from targeted, early interventions to prevent symptom deterioration.

4.2 Physiological Factors: Postoperative Complications

Among the physiological factors examined, postoperative complications emerged as a significant independent predictor of membership in the fatigue-increasing group (odds ratio = 8.595, 95% confidence interval: 1.102–67.019, $P = 0.040$), consistent with prior research demonstrating that complications are associated with greater symptom burden and prolonged recovery in cancer patients [21, 22]. This association has been specifically documented in esophageal cancer, where medical and pulmonary complications were linked to elevated cancer-related fatigue levels for up to two years after surgery [23], and in colorectal cancer patients undergoing chemotherapy [24].

The mechanisms linking complications to persistent fatigue are multifactorial. Complications such as infection, bleeding, or prolonged hospitalization increase systemic inflammatory responses, a well-established pathway in cancer-related fatigue pathophysiology [25]. A recent qualitative synthesis further underscores that cancer-related fatigue encompasses physical, emotional, and cognitive exhaustion, with physiological stressors amplifying its severity [26]. Moreover, complications may delay recovery, limit physical activity, and exacerbate psychological distress, creating a cascade of adverse effects that sustain fatigue [27, 28].

From a clinical perspective, these findings suggest that preventing and promptly managing postoperative complications may serve as a critical upstream intervention to mitigate cancer-related fatigue progression. Enhanced recovery protocols, early mobilization, and vigilant perioperative monitoring could potentially reduce the risk of patients entering an adverse fatigue trajectory.

4.3 Psychological Factors: Depressive Symptoms and Self-Perceived Burden

Psychological factors played a pivotal role in differentiating cancer-related fatigue trajectories. Higher depressive symptom scores were independently associated with increased odds of belonging to the fatigue-increasing group (odds ratio = 1.305, 95% confidence interval: 1.103–1.545, *P* = 0.002), consistent with evidence demonstrating a bidirectional relationship between depression and fatigue in cancer patients [29, 30]. This association has been observed longitudinally in breast cancer survivors and cross-sectionally in myelodysplastic syndrome [31, 32], and is underpinned by neurobiological mechanisms involving hypothalamic-pituitary-adrenal axis dysregulation, altered monoamine neurotransmission, and pro-inflammatory cytokine activity [33].

Self-perceived burden was also an independent predictor of adverse trajectory membership (odds ratio = 1.216, 95% confidence interval: 1.054–1.403, *P* = 0.007). Patients who feel a burden often experience guilt and social withdrawal, which deplete psychological resources and amplify exhaustion [12]. The adverse impact of self-perceived burden on health outcomes has been demonstrated in older adult inpatients, where higher self-perceived burden was associated with poorer health-related quality of life [34]. Cognitively, self-perceived burden may foster rumination and anticipatory anxiety, leading to sustained sympathetic activation and energy depletion [33]; behaviorally, it may reduce help-seeking and promote social isolation, limiting access to supportive resources [35]. Importantly, self-perceived burden is modifiable, and interventions such as cognitive behavioral therapy and family support have shown promise in reducing self-perceived burden and improving quality of life [36]. Integrating routine self-perceived burden assessment into postoperative care could help identify patients at risk for adverse fatigue trajectories and enable timely psychosocial support.

4.4 Environmental Factors: Social Support

Low perceived social support from family was the environmental factor independently associated with an increased risk of belonging to the fatigue-increasing group (odds ratio = 1.393, 95% confidence interval: 1.096–1.771, *P* = 0.007). This finding aligns with the Theory of Unpleasant Symptoms, which posits that environmental factors modulate symptom experience [9]. Social support has been consistently identified as a protective factor against cancer-related fatigue across various cancer types [37, 38]. In a meta-analysis of 84 studies including 144,813 cancer patients, Ma and colleagues found that higher social support was associated with lower cancer-related fatigue severity [5].

The protective effect of social support may operate through multiple pathways. Social support can buffer stress by providing emotional reassurance, practical assistance, and informational resources, thereby reducing the psychological burden of illness [39]. It may also promote health behaviors such as physical activity and treatment adherence, which indirectly improve fatigue [40]. In the Chinese cultural context, where family plays a central role in patient care, the absence of adequate family support may be particularly detrimental. These findings underscore the importance of incorporating family members into the care plan and proactively assessing patients' support systems. Nurses and clinicians should encourage family

involvement, facilitate open communication between patients and caregivers, and connect patients with community resources when family support is limited.

4.5 Nursing Implications

The findings of this study have direct implications for nursing practice. First, nurses are ideally positioned to conduct routine screening for the four identified predictors during postoperative follow-up visits. A brief assessment tool incorporating these factors could be integrated into existing nursing assessment protocols.

Second, for patients with postoperative complications, nurses should implement enhanced recovery protocols and early mobilization strategies. For those with elevated depressive symptoms or self-perceived burden, nurses can provide psychosocial support, facilitate referrals to mental health services, and engage in therapeutic communication techniques. For patients with limited family support, nurses can actively involve family members in care planning and provide education on the importance of social support during recovery.

Third, the finding that psychological and environmental factors are as influential as physiological factors supports the adoption of a biopsychosocial nursing assessment model. Nurses should consider these multidimensional factors holistically rather than focusing solely on physical symptoms.

4.6 Strengths and Limitations

This study has several strengths. The prospective longitudinal design with three repeated assessments captured the dynamic evolution of cancer-related fatigue during the critical early recovery period. The use of latent class growth modeling enabled identification of distinct trajectory subgroups, moving beyond traditional approaches that assume population homogeneity. The study was guided by a well-established theoretical framework—the Theory of Unpleasant Symptoms—providing a systematic basis for selecting and interpreting multidimensional predictors.

Several limitations should be acknowledged. First, this was a single-center study conducted at a tertiary referral hospital in northeastern China. While the institution serves a large and diverse population, the generalizability of our findings to other settings or populations may be limited. Future multi-center studies are needed to validate our findings across diverse geographic and cultural settings. Second, the sample size was modest (N = 145), with the fatigue-increasing group comprising only 32 patients. Although model fit indices (entropy = 0.826, posterior probabilities > 0.93) support classification reliability, findings from smaller subgroups warrant cautious interpretation. Larger studies are needed to confirm trajectory stability. Third, the follow-up period was limited to five months after surgery. Longer-term follow-up is needed to determine whether identified trajectories persist beyond the first year. Fourth, the use of self-report measures may introduce reporting bias, though self-report remains the gold standard for assessing the subjective experience of fatigue. Additionally, despite theoretically guided predictor selection, unmeasured factors such as pain, insomnia, physical activity, and treatment regimens may contribute to cancer-related fatigue trajectories and warrant investigation in future research [7, 11].

4.7 Future Research

Building on these actionable insights, future research should focus on three key areas. First, multi-center, large-scale longitudinal studies are needed to externally validate the trajectory patterns and predictors identified in this study. Second, intervention studies targeting the four modifiable predictors—postoperative complications, depressive symptoms, self-perceived burden, and social support—should be developed to test whether modifying these factors can alter cancer-related fatigue trajectories. Third, longer-term follow-up studies are needed to explore whether the identified trajectories persist beyond the first year and to examine associations between fatigue trajectories and clinically meaningful outcomes such as treatment adherence, recurrence, and survival.

5. Conclusions

In conclusion, this prospective longitudinal study identified two distinct cancer-related fatigue trajectories after endometrial cancer surgery (a fatigue-decreasing group and a fatigue-increasing group), with postoperative complications, depressive symptoms, self-perceived burden, and low social support independently predicting the adverse trajectory, thereby supporting the development of a risk-stratified, multidimensional nursing management pathway.

6. Relevance for Person-Centered Clinical Practice

This study identified two distinct cancer-related fatigue trajectories in endometrial cancer patients, highlighting the heterogeneity of patient experiences. The identification of four independent, modifiable predictors—postoperative complications, depressive symptoms, self-perceived burden, and low social support—provides nurses with a practical, evidence-based framework for early risk stratification. This framework directly supports person-centered care by enabling the tailoring of interventions to each patient's unique risk profile. Specifically, findings support targeted nursing actions—such as enhanced recovery protocols, psychological support, and family involvement—to improve fatigue management, accelerate postoperative recovery, and ultimately enhance patient quality of life in alignment with the principles of person-centered care.

Declarations

Ethics approval and consent to participate

This study was performed in line with the principles of the Declaration of Helsinki (Approval Number: 2025 – 181). Approval was granted by the Ethics Committee of China Medical University.The procedures of this study were reviewed and approved. All participants provided written informed consent. We protected personal privacy when handling personal data and kept personal records confidential.

Consent for publication

Written informed consent was obtained from all participants included in the study.

Competing interests

The authors declare no competing interests.

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Author Contribution

Yani Liu: Conceptualization, Methodology, Formal analysis, Writing – original draft.Ke Zhang: Conceptualization, Methodology, Formal analysis, Writing – review & editing.Lei Dou: Conceptualization, Methodology, Formal analysis, Writing – review & editing.Zhihui Gu: Methodology, Formal analysis.Miao Lin: Validation, Visualization.Yan Yan: Data curation, Software.Huayang Li: Investigation, Project administration.Yi Zhang: Supervision, Writing – review & editing.Hui Wu: Supervision, Writing – review & editing, Funding acquisition.

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Data Availability

The data supporting the conclusions of this research will be made available from the corresponding authors upon reasonable request.

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Figures

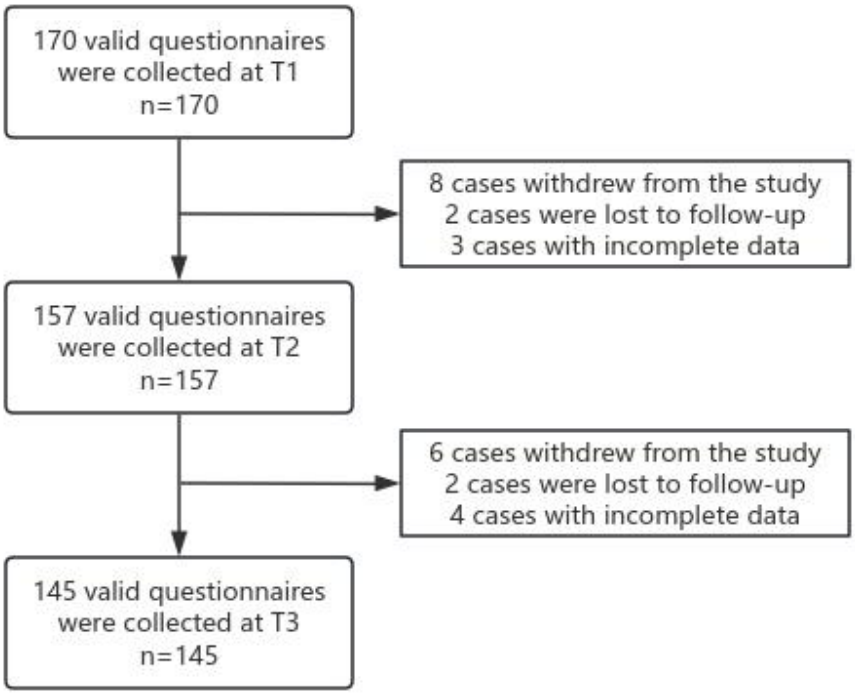


Figure 1

Flow chart of follow-up completion status of included participants

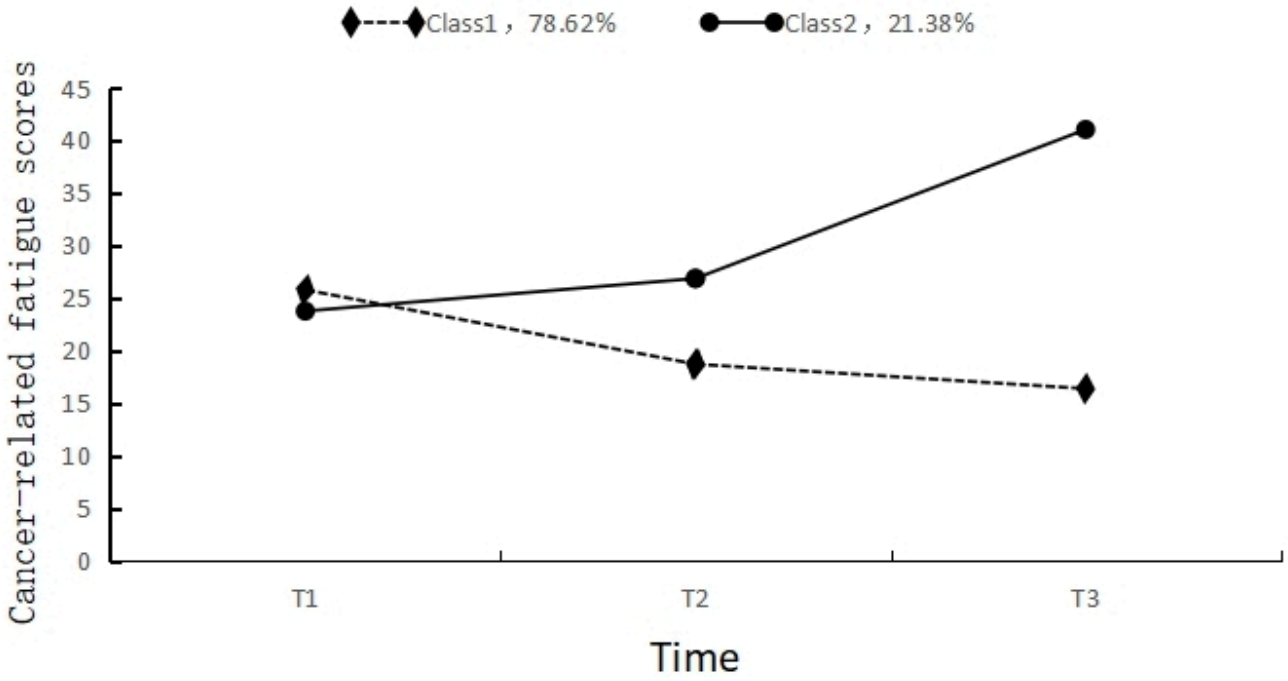


Figure 2

Two latent trajectories of cancer-related fatigue among endometrial cancer patients