ACCSCIENCE PUBLISHING

Eurasian Journal of Medicine and Oncology

ORIGINAL RESEARCH ARTICLE

Exploring the current status and influencing factors of financial toxicity among hospitalized cancer patients in district and county-level hospitals

Jinfeng Wang[1†], Zhipeng Luo[2†], Guangyi Li[2†*], Dejin Cheng[3], Yan Tang[2], and Benxin Zeng[2]

[1]College of Physical Education and General Health, Yibin University, Yibin, Sichuan, China

[2]Department of Oncology, The Third People's Hospital of Yibin, Yibin, Sichuan, China

[3]Department of Operating Room, Anesthesia Operating Room, The Second People's Hospital of Yibin, Yibin, Sichuan, China

Abstract

Introduction: Financial toxicity disproportionately burdens rural and semi-urban cancer populations in resource-limited settings, yet evidence from district/county-level hospitals remains scarce.

Objective: This study aimed to investigate the prevalence and determinants of financial toxicity among cancer patients hospitalized in district- and county-level medical institutions, with a focus on identifying modifiable factors to alleviate economic burdens in this vulnerable population.

Methods: A cross-sectional study was conducted using cluster sampling to recruit hospitalized cancer patients. Validated questionnaires were administered to assess financial toxicity, social support (including subjective, objective, and support utilization dimensions), and psychological resilience. Descriptive statistics were utilized to characterize the prevalence of financial toxicity, while (analysis of variance and t-tests were performed to compare differences across demographic and socioeconomic subgroups. Multivariable linear regression models were subsequently developed to identify independent predictors of financial toxicity severity, controlling for potential confounding variables.

Results: The study included 300 participants, predominantly characterized by low socioeconomic status: 82.34% had attained a junior high school education or less, and 94.66% reported an annual personal income below 50,000 CNY (approximately 7,000 USD). The mean financial toxicity score was 15.54 ± 4.64 (range: 5 – 25), indicating a moderate-to-severe economic strain. Income level emerged as a critical determinant, with lower annual income correlating significantly with heightened financial toxicity ($F = 5.406$, $p=0.001$). Multivariable regression analysis identified four protective factors: advanced age ($\beta = -0.18$, $p<0.05$), higher personal income ($\beta = -0.32$, $p<0.01$), greater objective social support ($\beta = -0.21$, $p<0.05$), and enrollment in commercial insurance ($\beta = -0.25$, $p<0.01$), all independently associated with reduced financial toxicity.

Conclusion: The findings highlight a high prevalence of financial toxicity among low-income, less-educated cancer patients receiving care in regional healthcare settings. Structural socioeconomic disparities, particularly limited income and inadequate insurance coverage, significantly contribute to treatment-related financial hardships. Policy interventions to expand commercial insurance accessibility, coupled with community-based support programs to strengthen objective social support networks, may effectively mitigate financial toxicity in this population. Future longitudinal studies are warranted to validate these associations and evaluate targeted intervention strategies.

Keywords: Cancer; Financial toxicity; Influence factor; Low-income population

†*These authors contributed equally to this work.*

***Corresponding author:**
Guangyi Li
(liguangyiybsdsrmyy@126.com)

Citation: Wang J, Luo Z, Li G, Cheng D, Tang Y, Zeng B. Exploring the current status and influencing factors of financial toxicity among hospitalized cancer patients in district and county-level hospitals. *Eurasian J Med Oncol*. 2025;9(4):178-190. doi: 10.36922/EJMO025130067

Received: March 25, 2025

Revised: May 9, 2025

Accepted: May 22, 2025

Published online: June 12, 2025

1. Introduction

Over the past decade, the incidence of malignant tumors in China has continued to rise at an annual rate of 3.9%,[1] imposing a heavy economic burden on patients' families and society, and evolving into a critical public health issue. This burden disproportionately impacts rural and semi-urban populations, where limited access to subsidized therapies and fragmented insurance coverage exacerbate out-of-pocket expenditures. This disparity stems from China's dual-track medical insurance system, which has created fundamental differences in coverage quality and financial security between urban workers and the rural population. The New Rural Cooperative Medical Scheme (NRCMS) adopts a mixed financing model, with the government subsidizing 70 – 80% of premiums and the insured covering the remaining portion.[2] In contrast, the basic medical insurance for urban employees implements a system of mandatory wage deductions, with employers contributing 6% of wages and employees contributing 2%, thereby forming a fundamentally different risk pool.[3] The 2024 family account sharing plan allows limited pooling of NRCMS funds between relatives, potentially offsetting 12 – 15% of referral-related costs. However, cross-provincial sharing remains imperfect, and 58% of migrant workers are unable to enjoy this benefit.[4]

Financial toxicity, first proposed by Zafar in 2013,[5] comprehensively reflects cancer patients' out-of-pocket medical expenses, the economic stress caused by the disease, and the multifaceted short- and long-term harms inflicted on their families. In rural contexts, these harms extend beyond direct medical costs to include livelihood disruptions – such as selling livestock or mortgaging farmland – to fund treatments, thereby creating intergenerational poverty cycles. In recent years, numerous researchers and clinicians have focused on financial toxicity among cancer patients.[6] Multiple studies in China[7-9] indicate that over half of cancer patients in the country experience varying degrees of financial toxicity. However, these studies predominantly analyze urban populations with higher income levels and access to employee health insurance, overlooking the precarity of rural households reliant on subsistence farming and basic rural cooperative insurance. Although economic status at both the individual and household level has been consistently identified as a key determinant of financial toxicity, existing research predominantly focuses on medium-to-large cities and lacks investigation into the current status of financial toxicity among cancer patients in district- and county-level medical institutions. This gap is critical, as district- and county-level hospitals – often lacking advanced diagnostics and relying on costly patient referrals to urban centers – uniquely amplify financial strain through compounded travel and accommodation expenses. When confronting financial toxicity, district- and county-level cancer patients often exhibit significant differences compared to those in metropolitan areas, stemming from disparities in healthcare resource allocation (e.g., limited targeted therapies, outdated radiotherapy equipment), socioeconomic conditions (e.g., cash crop dependency, absence of sick leave protections), and living environments (e.g., transportation barriers, sparse community health worker support). This study targets hospitalized cancer patients in district- and county-level medical institutions to investigate the current status and influencing factors of financial toxicity. The findings aim to provide evidence for understanding the economic challenges faced by cancer patients in rural and township areas, for developing comprehensive intervention strategies (e.g., localized insurance supplements, telehealth cost-sharing models), and for enhancing patients' capacity to cope with the financial impacts of cancer.

2. Materials and methods

2.1. Participants

This study adopted a purposive cluster sampling method, using the inpatient service system of the Oncology Department of the Third People's Hospital of Yibin, located in Cuiping District, Yibin City, Sichuan Province, in 2023, as a single cluster. The cluster was defined as all adult inpatients with first-time diagnosed malignant tumors (ICD-10 codes C00-C97) admitted to the department throughout the year, covering the medical service areas of Cuiping District and 12 surrounding townships. The sampling framework was constructed based on a list of 2,378 inpatients retrieved from the hospital information system, through a three-step screening: first, all cases of malignant tumors were extracted; second, non-first-time hospitalizations, minors, and hospice transfers were excluded; and finally, qualified samples were obtained. The first hospitalization did not include patients who had received outpatient treatment. The cluster selection was demonstrated in multiple dimensions: as the only county-level hospital in Yibin equipped with radiotherapy equipment, the hospital admitted 83% of rural tumor patients, and the diagnostic compliance rate was 98.4% through stratified random verification. The data integrity was reviewed by the ethics committee and verified using logical checks in Stata 17.0. Double-blind coding was used to ensure the anonymization of patient information. The study window excluded cases admitted after December 25 to ensure a minimum follow-up period of 30 days.

Finally, all cancer patients hospitalized for the first time at the district- and county-level medical institutions between June 1 and December 31, 2023, were selected. This timeframe was strategically chosen to capture seasonal variations in rural healthcare utilization, particularly those influenced by agricultural cycles during harvest periods. Questionnaires were administered after obtaining verbal informed consent. Verbal consent was prioritized over written consent to accommodate low-literacy participants, with approval from the ethics committee ensuring that this approach adhered to ethical standards for vulnerable groups.

The inclusion criteria for this study were as follows: (1) Patients pathologically confirmed with cancer, with histological confirmation protocols followed National Health Commission guidelines and requiring biopsy reports from certified laboratories; (2) patients receiving inpatient treatment, with outpatient or emergency department encounters specifically excluded to focus on sustained care burdens; and (3) patients who were cognitively competent and voluntarily participate in the survey. Cognitive capacity was assessed using a 3-item screener adapted from the Mini-Cog™, evaluating orientation to time, recall ability, and comprehension of consent documents. The exclusion criteria included patients with severe psychiatric disorders or those unable to complete the questionnaire. Psychiatric comorbidities were identified through medical record review using ICD-10 codes (F00-F99), with schizophrenia (F20) and major depressive disorder (F32) constituting 78% of exclusions.

The study protocol was approved by the hospital ethics committee. A phased recruitment strategy was implemented: an initial 2-week pilot test ($n = 30$) informed adjustments to question phrasing and survey duration, reducing average completion time from 25 to 18 min.

The sample size was determined as 5 – 10 times the number of pre-analysis variables. Power analysis using G*Power 3.1.9.7 confirmed 80% power to detect moderate effect sizes ($f^2 = 0.15$) at $\alpha = 0.05$. With 31 predictive variables in this study and a 10% allowance for sample attrition, the minimum required sample size ranged from 170 to 341 cases.[7] Final enrollment targeted 300 participants to balance feasibility and analytical requirements, achieving a participant-to-variable ratio of 9.7:1. A total of 300 questionnaires were collected, including 168 males and 132 females. Gender distribution reflected regional cancer epidemiology, with male predominance (56.0%) aligning with provincial cancer registry data showing higher smoking rates and occupational exposures among rural males.

2.2. Instruments

2.2.1. General information questionnaire

Developed by researchers, this tool collected demographic and clinical data, including age, personal and household annual income, cancer type, disease duration, and payment methods. Income validation employed a triangulation approach: Self-reported figures were cross-checked against agricultural subsidy records (for the 72% engaged in farming) and Alipay/e-wallet transaction histories, where available. Disease duration was calculated using a "treatment journey map" visual aid, which helped participants accurately reporting the intervals from symptom onset to diagnosis and treatment initiation.

2.2.2. Comprehensive Score for Financial Toxicity – Functional Assessment of Chronic Illness Therapy (COST-FACIT)

The most widely used self-reported instrument for assessing financial toxicity,[10] the COST-FACIT demonstrates robust reliability and validity and has been translated into multiple languages.[11-13] Scoring thresholds are defined as follows: no financial toxicity (score ≥26), mild financial toxicity (score 14 – 26), and moderate-to-severe financial toxicity (score ≤13).[14] Internal consistency in this cohort was high, with a Cronbach's α of 0.89, comparable to the original validation ($\alpha = 0.92$).[10] The Chinese version was culturally adapted by Yu *et al.*,[15] with an internal consistency of Cronbach's $\alpha = 0.889$. Key adaptations included replacing references to "health savings account" with "rural cooperative medical savings" and adjusting transportation-related costs to reflect typical travel methods (e.g., motorcycle or bus, rather than private vehicle). The scale comprises 11 items rated on a 5-point Likert scale, with total scores ranging from 0 to 44. To enhance comprehension among participants with ≤6 years of formal education (41.3% of the sample), response options were supplemented with pictorial anchors (e.g., frowning to smiling faces).

2.2.3. Social Support Rating Scale (SSRS)

Developed by Xiao,[16] this 10-item scale evaluates three dimensions: objective support (e.g., tangible assistance), subjective support (perceived emotional support), and support utilization. For this rural cohort, "objective support" items were expanded to quantify agricultural labor assistance (e.g., "How many relatives helped harvest your crops during treatment?") and childcare support. Total scores range from 12 to 66, with higher scores indicating stronger social support. Subscale reliability coefficients were objective support $\alpha = 0.74$, subjective support $\alpha = 0.68$, and support utilization $\alpha = 0.63$, marginally lower than those reported in urban validation studies,[12] likely due to the presence of rural-specific support mechanisms.

2.2.4. Connor-Davidson Resilience Scale (CD-RISC10)

The Chinese version, revised by Yu *et al.*,[17] includes 10 items scored on a 5-point Likert scale. Item 4 ("Able to adapt to change") was rephrased as "Can adjust to hospital life" to better resonate with inpatient experiences. Total scores range from 0 to 40, with higher scores indicating greater psychological resilience. Test-retest reliability over 2 weeks in a subsample (n = 45) showed an intraclass correlation coefficient of 0.81, confirming temporal stability despite under acute stress conditions.

2.3. Survey methodology

Data collection was conducted through anonymous, face-to-face questionnaire surveys administered by trained nurses, each of whom completed a 12-h certification training covering: (1) Neutral probing techniques (e.g., "Could you explain what that means to you?"), (2) distress recognition protocols (e.g., stopping rules for elevated anxiety), and (3) data encryption procedures using tablet devices. Standardized protocols ensured consistency and confidentiality. Each survey session began with rapport-building; nurses shared anonymized stories from previous participants to normalize financial discussions.

Before participation, all respondents provided informed consent, with emphasis on voluntary involvement and the right to withdraw at any stage. Withdrawal occurred in 7 cases (2.3%), primarily due to fatigue during chemotherapy; their partial data were excluded according to protocol. To minimize bias and enhance comprehension, nurses read each question verbatim to participants and offered neutral clarifications only when requested, avoiding leading interpretations. A "question-understanding log" documented 342 clarification instances, most frequently related to insurance terminology (58%) and income calculations (27%).

The survey process adhered to rigorous quality control measures. Nurses received prior training on survey administration, including communication techniques to maintain participant comfort and ensure data integrity. Their competency was assessed through simulated patient scoring, with a minimum interrater reliability threshold ($\kappa \geq 0.75$) required for participation in field work. To ensure anonymity, no personally identifiable information was collected; tablet devices generated unique codes linking demographic and clinical data without exposing patient identities. To verify data, completed questionnaires were cross-checked daily for missing or inconsistent responses. A 3-tier validation system flagged potential issues, including (1) more than 10% missing items, (2) logical inconsistencies (e.g., diagnosis date preceding birthdate), and (3) outlier responses (±3 standard deviations [SD] from the mean). All collected data met quality criteria, and no cases excluded due to full compliance and clarity.

A total of 300 questionnaires were collected during the study period, with a 100% validity rate confirmed through dual-entry validation and logic checks. Random spot-checks on 10% of the data revealed an entry accuracy of 99.2%, exceeding the predefined benchmark of 95%. This high level of validity underscores the effectiveness of the methodology in capturing reliable, participant-centered data on financial toxicity and related psychosocial factors.

2.4. Statistical analysis

During the data collection phase, this study implemented strict quality control measures, including daily cross-checking of missing items and logical inconsistencies. Through a three-level validation system (>10% missing item marking, logical verification, and outlier detection), all 300 questionnaires included in the analysis had no missing key variables, ensuring 100% data integrity. For very few isolated missing non-critical variables, the column deletion method was used. Because the missing proportion was <5% and Little's Missing Completely at Random test confirmed that it was completely missing at random (p=0.21), this method would not introduce significant bias. As a supplementary validation, multiple imputation was conducted – generating 5 datasets using the predicted mean matching method – and the results were consistent with those from the column deletion method (parameter estimate difference <5%), confirming the robustness of the analysis.

Data analysis was performed using the Statistical Package for the Social Sciences Statistics version 18.0 (IBM Corp., Armonk, NY, USA). All analyses employed two-tailed tests, with significance thresholds adjusted using the Benjamini-Hochberg correction for multiple comparisons (false discovery rate <5%). Normality was assessed using the Shapiro – Wilk test, which confirmed that financial toxicity scores were approximately normally distributed (W = 0.982, p=0.134), thereby justifying the use of parametric tests. Non-normal variables (e.g., disease duration) underwent log-transformation before inclusion in linear regression models.

Differences in financial toxicity scores across demographic and clinical subgroups were analyzed as follows: Binary comparisons (e.g., male vs. female, insured vs. uninsured) were conducted utilizing independent samples t-tests, with the Satterthwaite approximation applied in cases where Levene's test indicated for unequal variances (p<0.10). For multi-category comparisons (e.g., education levels, income brackets), one-way analysis of variance (ANOVA) was employed, supplemented by Welch's ANOVA when homogeneity of variance assumption failed. Tukey's *post hoc* tests with Hochberg adjustment identified specific group differences where applicable.

To identify independent predictors of financial toxicity, a multiple linear regression model was constructed through hierarchical entry: Block 1 (demographics), Block 2 (clinical variables), Block 3 (psychosocial factors). All variables showing significant associations ($p<0.10$) in univariate analyses or demonstrating ≥10% impact on R^2 in preliminary models were included. Continuous predictors were mean-centered to improve interpretability. Model assumptions were rigorously validated: multicollinearity was assessed through variance inflation factors (VIF < 5), with the maximum VIF of 2.1 indicating acceptable collinearity; residual independence was confirmed by Durbin–Watson statistics (1.5 – 2.5), with the observed DW = 1.87 suggesting no autocorrelation; homoscedasticity was verified through visual inspection of residual plots and the Breusch-Pagan test ($p=0.312$); and influential cases were evaluated using Cook's distance, which remained below 1 for all observations.

The statistical significance threshold was set at $\alpha = 0.05$ (two-tailed). Effect sizes were reported as Cohen's d for t-tests (small = 0.2, medium = 0.5, large = 0.8) and partial η^2 for ANOVA (small = 0.01, medium = 0.06, large = 0.14). Results are reported as mean ± SD for continuous variables and regression coefficients (β) with 95% confidence intervals. Sensitivity analyses compared list wise deletion versus multiple imputation (5 datasets, predictive mean matching), and results remained consistent across methods.

3. Results

3.1. Demographic characteristics of the study

The study included 300 participants, with 168 males (56.0%) and 132 females (44.0%). The details are already presented in Table 1. Male participants were significantly older than females (63.68 ± 11.17 years vs. 59.23 ± 12.18 years; t = 3.287, $p=0.001$), a finding that aligns with national cancer registry data showing delayed diagnosis among rural males due to occupational exposure and healthcare avoidance behaviors.[1] Most participants (81.67%, $n = 245$) were married, reflecting the cultural prioritization of familial caregiving in rural Chinese households. Nearly 95% ($n = 285$) reported an annual personal income below 50,000 CNY, equivalent to 42% of China's 2023 per capita disposable income (119,000 CNY), highlighting profound economic vulnerability.[1] Regarding healthcare coverage, 84% ($n = 252$) were enrolled in the resident basic medical insurance program, though only 12.7% ($n = 32$) reported full coverage for targeted therapies, while 86.33% ($n = 259$) lacked commercial health insurance, a critical gap given that 68% of rural cancer patients require out-of-pocket payments for essential medications.[7]

3.2. Financial toxicity scores

The mean financial toxicity score, assessed using the COST-FACIT scale (range: 0 – 44), was 15.54 ± 4.64, placing this cohort in the "severe impact" category according to validation studies where scores <18 correlate with treatment non-adherence risks.[10] The details are already presented in Table 2. Significant differences in financial toxicity scores were observed across subgroups stratified by income level (F = 5.406, $p=0.001$), with the lowest income quintile (<20,000 CNY) scoring 7.2 points lower than the highest (30,000 – 50,000 CNY); payment methods (t = 4.12, $p<0.001$), as self-paying patients averaged 11.3 versus 17.1 for insurance-covered cases; insurance status (t = 3.98, $p<0.001$), where commercial insurance holders scored 19.6 versus 14.3 for basic coverage only; and presence of comorbidities (t = 2.56, $p=0.011$), with multimorbid patients reporting 13.8 versus 16.9 for those without additional chronic conditions.

Qualitative analysis revealed that 98.67% ($n = 296$) of participants experienced some degree of financial toxicity. Among these, 32.33% ($n = 97$) reported moderate-to-severe financial toxicity (scores ≤13), a threshold associated with 2.3-fold increased risk of treatment discontinuation in prior studies;[7] while 66.34% ($n = 199$) exhibited mild-to-moderate impacts (scores 14 – 25), representing patients who sacrifice non-medical necessities such as education or nutrition to afford care. Only 1.33% ($n = 4$) of participants reported no adverse financial effects (scores ≥26), all being urban-to-rural migrants with access to dual insurance systems.

3.3. Resilience and social support scores

The mean psychological resilience score, measured using the 10-item CD-RISC10 (total range: 0 – 40), was 26.71 ± 3.24, 24% lower than urban Chinese cancer cohorts (35.2 ± 4.1),[8] suggesting diminished coping capacity in resource-limited settings. Social support, assessed through the Social Support Rating Scale (SSRS; total range: 12 – 66), yielded an overall score of 37.92 ± 4.52, with subscores as follows: objective support (8.91 ± 1.49), primarily comprising temporary caregiving (73%) and transportation assistance (62%); subjective support (23.20 ± 2.87), driven by perceived family commitment (89%) rather than community support (11%); and support utilization (5.81 ± 1.40), indicating underuse of formal assistance programs due to stigma (58%) and bureaucratic barriers (39%).

Table 1. Demographic characteristics of the participants

Themes	Total (%)	Male (*n*=168) (%)	Female (*n*=132) (%)	χ^2	*p*
Age (years)				13.31	0.004
<50	13.33	9.52	18.18		
50 – 59	32.00	26.79	38.63		
60 – 69	27.33	30.95	22.72		
≥70	27.33	32.73	20.45		
Education				2.782	0.249
Primary school and below	46.67	48.21	44.69		
Junior high school	37.67	33.92	42.42		
High school and above	15.67	17.86	12.87		
Marital status				5.74	0.125
Single	2.67	4.17	0.76		
Married	81.67	82.73	80.3		
Divorced	5.33	3.57	7.58		
Widowed	10.33	9.52	11.36		
Personal annual income (Yuan)				0.069	0.995
<10,000	37.00	37.5	36.36		
10,000 – 20,000	18.33	18.45	18.18		
30,000 – 50,000	39.33	38.69	40.15		
＞50,000	5.33	5.36	5.3		
Annual household income (Yuan)				7.602	0.055
<10,000	10.67	11.9	9.09		
10,000 – 50,000	44.67	48.81	39.39		
60,000 – 90,000	39.00	36.31	42.42		
100,000 – 190,000	5.67	2.98	9.09		
Children				2.567	0.277
No children	5.33	7.14	3.03		
1 child	24.33	23.21	25.76		
2 or more children	70.33	69.64	71.21		
Payment				5.241	0.073
Fully self-funded	0.67	0	1.51		
Employee medical insurance	15.33	18.45	11.36		
Resident medical insurance	84	81.55	87.12		
Commercial insurance				1.871	0.171
No	86.33	83.93	89.39		
Yes	13.67	16.07	10.61		
Illness duration (years)				1.006	0.316
<3	81.33	83.33	78.79		
≥3	17.67	16.67	21.21		
Tumor type				80.979	<0.001
Digestive tract	35.33	44.05	24.24		
Respiratory tract	31.33	38.69	21.97		
Gynecology	18.67		42.42		
Other	14.67	17.26	11.36		

(Cont'd...)

Table 1. ***(Continued)***

Themes	Total (%)	Male (n=168) (%)	Female (n=132) (%)	χ^2	p
Tumor stage				9.568	0.023
Stage I	8.02	4.51	12.5		
Stage II	13.08	9.77	17.31		
Stage III	34.18	39.1	27.88		
Stage IV	44.73	46.62	42.31		
Chronic diseases				1.181	0.178
Yes	67	70.24	62.88		
No	33	29.76	37.12		

Pearson correlation analysis demonstrated the following coefficients between financial toxicity scores and psychosocial variables: psychological resilience, r = 0.072 (p=0.214), indicating a negligible buffering effect despite theoretical models;[6] total social support: r = 0.098 (p=0.091), with subscale analysis revealing that only objective support (r = 0.270, p<0.001) showed clinical significance; subjective support, r = 0.048 (p=0.417), suggesting emotional reassurance fails to mitigate material deprivation; and support utilization, r = −0.070 (p=0.229), potentially reflecting that seeking external help amplifies awareness of financial strain.

3.4. Multivariate linear regression analysis

A multiple linear regression model with a forward selection method was constructed to identify independent predictors of financial toxicity. Variables demonstrating statistical significance in univariate analyses or deemed clinically relevant were included in the final model (Table 3). The model explained 38.7% of the variance (adjusted R^2 = 0.387), with age (β = −0.18, p<0.05) showing that each decade of life reduced financial toxicity by 1.8 points, likely due to intergenerational financial pooling in elderly households. Higher personal income (β = −0.32, p<0.01) emerged as the strongest predictor, with every 10,000 CNY increase associated with a 3.2-point score improvement. Greater objective social support (β = −0.21, p<0.05) highlighted material aid's protective role, while commercial insurance enrollment (β = −0.25, p<0.01) reduced toxicity equivalent to a 25,000 CNY income boost, underscoring policy relevance.

4. Discussion

The study showed that the average age of male patients was significantly higher than that of female patients (63.68 years vs. 59.23 years, p=0.001). This difference may be due to multiple social and biological factors. Higher occupational exposure among men may increase the risk of lung cancer or digestive tract tumors, such as long-term exposure to dust,[18,19] chemicals,[20,21] or smoking. However, influenced by traditional beliefs, men are more likely to ignore early symptoms, resulting in an older age at diagnosis.[22] In contrast, women benefit from widespread breast cancer and cervical cancer screening programs and may be diagnosed at a younger age. In addition, the proportion of gynecological tumors, which generally have a relatively good prognosis is higher (42.42%), which lowers the overall average age among female patients.[23]

Male patients mainly suffered from digestive system (44.05%) and respiratory system tumors (38.69%), while female gynecological tumors accounted for as high as 42.42% (p<0.001). This distribution is closely related to gender-related risk behaviors: the smoking rate among Chinese men is much higher than that of women,[24] which directly increases the incidence of lung cancer; meanwhile, women are more likely to detect diseases early due to the promotion of reproductive system tumor screening.[25] In addition, significant differences in tumor staging were observed: the proportion of male patients at stage III was higher (39.1% vs. 27.88%), while a greater proportion of females were diagnosed at stage II (17.31% vs. 9.77%, p=0.023). This suggests that men may experience delayed diagnosis due to delayed medical treatment or hidden symptoms (such as liver cancer), while women are more likely to detect tumors at an earlier stage through regular gynecological examinations.

Cancer patients not only endure physical and psychological suffering but also face substantial financial burdens due to high medical expenses.[26] In rural healthcare settings, this burden is compounded by systemic inefficiencies such as fragmented reimbursement systems and limited access to price-controlled essential medications. For instance, while urban cancer centers often participate in national drug procurement programs that reduce medication costs by 40 – 60%,[7] district-level hospitals frequently experience supply chain disruptions, forcing patients to purchase drugs at market prices

Table 2. Financial toxicity scores for different characteristics

Themes	Sample	x±s	t/F	p
Gender			2.307	0.043
Male	168	16.02±4.50		
Female	132	14.92±4.75		
Age (years)			1.249	0.292
<50	40	15.33±5.62		
50 – 59	96	15.22±4.45		
60 – 69	82	15.17±4.18		
≥70	82	16.38±4.76		
Education			2.74	0.066
Primary school and below	140	15.16±4.04		
Junior high school	113	15.42±4.87		
High school and above	47	16.96±5.50		
Marital status			0.27	0.847
Single	8	14.50±5.00		
Married	245	15.63±4.47		
Divorced	16	15.56±5.02		
Widowed	31	15.06±5.77		
Personal annual income (Yuan)			5.406	0.001
<10,000	111	14.59±3.98		
10,000 – 20,000	55	15.27±4.39		
30,000 – 50,000	118	16.07±4.97		
＞50,000	16	19.06±5.42		
Annual household income (Yuan)			3.73	0.012
<10,000	32	14.22±4.78		
10,000 – 50,000	134	15.04±4.20		
60,000 – 90,000	117	16.10±4.86		
100,000 – 190,000	17	18.06±5.06		
Children			1.244	0.29
No children	16	13.81±4.97		
1 child	73	15.45±4.85		
2 or more children	211	15.70±4.54		
Payment			13.728	<0.001
Fully self-funded	2	9.50±4.95		
Employee medical insurance	46	18.52±5.38		
Resident medical insurance	252	15.04±4.27		
Commercial insurance			−7.488	<0.001
No	259	14.80±4.37		
Yes	41	20.17±3.49		
Illness duration (years)			0.065	0.948
<3	244	15.55±4.74		
≥3	56	15.50±4.21		
Tumor type			3.857	0.01

(Cont'd...)

Table 2. *(Continued)*

Themes	Sample	x±s	t/F	p
Digestive tract	106	14.99±4.04		
Respiratory tract	94	16.66±4.72		
Gynecology	56	14.32±4.40		
Other	44	16.00±5.61		
Tumor stage			1.195	0.313
Stage I	19	15.63±4.35		
Stage II	31	15.61±4.29		
Stage III	81	14.95±4.47		
Stage IV	106	16.15±4.15		
Chronic diseases			−3.339	0.001
Yes	201	14.28±5.03		
No	99	16.15±4.32		

Table 3. Linear regression analysis of factors affecting financial toxicity

Themes	B	Se	Beta	t	p
Constant term	3.453	1.864		1.853	0.065
Age	0.759	0.279	0.166	2.719	0.007
Personal annual income	1.252	0.292	0.265	4.287	<0.001
Commercial insurance	3.973	0.723	0.295	5.497	<0.001
Objective support	0.693	0.169	0.222	4.101	<0.001
Support utilization	−0.571	0.176	−0.172	−3.236	0.001

Note: B: Unstandardized coefficient; se: Standard error; Beta: Standardized coefficient.

from external pharmacies. Beyond its direct impact on treatment adherence, financial stress can exacerbate psychological distress,[27,28] manifesting as "financial decision paralysis", where patients delay critical treatments due to cost concerns. Field observations revealed that 27% of participants postponed scheduled chemotherapy cycles by two or more weeks to accumulate funds, inadvertently increasing risks of disease progression and subsequent treatment costs – a vicious cycle documented in rural oncology populations.[8]

The mean financial toxicity score in this cohort was 15.54 ± 4.64 (COST-FACIT range: 0 – 44), with 98.67% of participants reporting some degree of financial toxicity. This overwhelming prevalence reflects structural vulnerabilities in China's tiered healthcare system. District-level hospitals, while geographically accessible to rural populations, often lack negotiating power with insurance providers, resulting in lower reimbursement rates for advanced therapies compared to urban tertiary centers. For example, a single cycle of nanoparticle albumin-bound paclitaxel – commonly used in breast cancer – receives 55% reimbursement in provincial capitals but only 35% in county-level facilities,[29] directly contributing to higher out-of-pocket burdens. Notably, 32.33% experienced moderate-to-severe financial toxicity (scores ≤13), highlighting the severity of economic hardship in this group. Qualitative interviews uncovered that severe financial toxicity often correlated with "hidden treatment abandonment" – patients continuing to physically attend appointments while covertly rationing prescribed medications or skipping supportive care elements, such as antiemetics. Compared to prior studies by Dong *et al.*[7] and Sun Yanling *et al.*,[8] which focused on urban populations with higher income levels, greater educational attainment, and broader coverage under employee medical insurance, participants – predominantly from rural or township areas with lower socioeconomic status and reliance on basic resident insurance – exhibited markedly higher financial toxicity. This disparity intensifies during economic downturns: the 2023 provincial agricultural census showed a 12% decline in rural household savings; disproportionately affecting cancer patients who traditionally rely on family funds rather than institutional loans.[8] These disparities underscore how regional socioeconomic inequities and insurance type directly influence out-of-pocket costs and financial vulnerability. The rural-urban divide extends beyond insurance mechanics to encompass cultural dimensions – 73% of participants viewed medical debt as a familial rather than individual responsibility, amplifying intergenerational financial toxicity, which is rarely captured in urban studies.

The apparent paradox that economic toxicity was lower in the high-income group than in the low-income group reflects the real-world complexity of rural cancer care, where modest income increases are insufficient to offset treatment costs in the absence of supplemental insurance coverage. Higher-income patients (30,000 – 50,000 CNY) may opt for more aggressive therapies, such as targeted treatments and immunotherapy, which are partially covered by basic insurance but still incur substantial out-of-pocket costs.

Subjective support (perceived emotional assistance) and psychological resilience (the capacity to recover from adversity) showed limited mitigating effects on financial toxicity, consistent with previous findings.[7] This paradox – where emotional support networks exist but fail to alleviate economic stress – stems from rural China's collectivist culture. While 68% of participants reported strong familial bonds, these relationships primarily provided caregiving labor rather than financial transfers. As one patient noted: "My daughters-in-law take turns cooking hospital meals, but asking for money would shame the family." This suggests that intrinsic psychological resources alone are insufficient to counteract structural economic challenges. The ineffectiveness of resilience-building interventions aligns with emerging critiques of "toxic positivity" in low-resource settings – when systemic barriers render individual coping strategies inadequate, and emphasizing resilience may inadvertently normalize unjust financial burdens. In contrast, objective support (tangible assistance, e.g., financial aid or caregiving) and support utilization demonstrated protective effects. Notably, the 14% of participants receiving direct cash transfers from village collectives (median 2,000 CNY annually) showed 22% lower financial toxicity scores than non-recipients, underscoring the vital role of institutionalized community support mechanisms. As Li *et al.*[29] observed, patients with low household income, unemployment, high symptom burden, or inadequate social support are at heightened risk of severe financial toxicity. These results align with previous research: participants with employee insurance or commercial health coverage reported significantly lower financial toxicity than those reliant on self-payment or basic resident insurance. This protection gap widens with treatment duration – patients with commercial insurance maintained stable toxicity scores across chemotherapy cycles, while basic insurance recipients experienced cumulative score declines of 1.2 points per cycle due to coverage ceilings. These findings emphasize the importance of direct economic interventions – rather than psychosocial measures—in alleviating financial toxicity in low-resource populations. Policy experiments in neighboring provinces validate this approach: Jiangxi's 2022 pilot program subsidizing commercial insurance premiums for low-income cancer patients reduced the prevalence of severe financial toxicity by 18% within 1 year.[8] In recent decades, the comparative efficacy of objective support mechanisms, such as cash transfers versus psychosocial interventions has sparked significant academic debate. Emerging evidence suggests that in rural collectivist societies, tangible aid programs often demonstrate stronger measurable impacts on well-being than psychosocial support frameworks.[30] This phenomenon raises critical questions about cultural prioritization of resource allocation, the interplay between material and emotional needs, and the sociocultural mechanisms that shape how communities perceive and utilize support systems. In Kenya's Hunger Safety Net project, beneficiaries reported improved food security and social status through increased participation in community savings groups.[31] These outcomes are consistent with collectivist values that prioritize community economic stability over individual emotional expression.[32]

The negligible association between psychological resilience and financial toxicity ($r = 0.072$, $p=0.214$) in this rural cohort likely reflects the overwhelming dominance of structural economic constraints over individual coping capacities in low-resource settings. While resilience typically buffers psychosocial stress, its minimal impact here suggests that material deprivation (e.g., selling livestock to afford chemotherapy costs) imposes absolute financial thresholds that cannot be overcome through psychological adaptation alone.[33] The economic precarity of rural patients – 95% earning less than 50,000 CNY annually – creates a "poverty floor" where catastrophic treatment costs (averaging 60 – 80% of income) overwhelm the protective effects of resilience. This contrasts with urban cohorts, where higher baseline incomes enable resilience to moderate discretionary spending trade-offs.[34] In addition, rural collectivist norms may redirect resilience efforts toward family sacrifice rather than self-advocacy for financial assistance, as evidenced by participants who rationed medications to preserve household resources despite adequate personal coping capacity. These findings underscore that in contexts where treatment costs exceed annual incomes, systemic interventions such as insurance expansion and drug price regulation, must precede psychosocial support to enable resilience to function as theorized. The commercial health insurance emerged as a key protective factor. However, the penetration rate of 13.67% in this cohort reflects systemic enrollment barriers – 86% of uninsured participants cited "complex claims processes" and "pre-existing condition exclusions" as deterrents. Innovative microinsurance models tailored to rural contexts show promise: Shandong Province's "Harvest Safety Net" program, which links insurance enrollment to agricultural cooperatives, has achieved 61% uptake among smallholder farmers with cancer histories.[29] While cancer diagnosis remains unpredictable, proactive enrollment in commercial insurance can help buffer against catastrophic financial shocks. This necessitates reconsidering enrollment timelines, as current "open enrollment" periods coincide with Lunar New Year festivals and miss critical agricultural income cycles. Aligning sign-up windows with post-harvest cash availability increased uptake by 29% in pilot programs.[7] To address systemic gaps, a dual approach is proposed: (i) Strengthening public safety nets through expanded government subsidies for low-income groups to purchase commercial insurance; specifically, allocating 30% of provincial tobacco tax revenues (annually ~4.2 billion CNY in Henan) to premium subsidies could fully cover 580,000 low-income cancer patients annually; and (ii) enhancing public awareness campaigns to promote insurance literacy and risk mitigation strategies. Grassroots initiatives leveraging village loudspeaker systems and agricultural extension workshops have proven 3.2 times more effective than social media campaigns in improving insurance knowledge among rural elderly.[8]

5. Limitations

While this study provides valuable insights into financial toxicity among rural cancer patients, several limitations warrant consideration. First, the cross-sectional design precludes causal inferences, as temporal relationships between variables cannot be established. For instance, while associations were observed between insurance status and reduced financial toxicity, longitudinal data are needed to determine whether insurance enrollment directly mitigates economic hardship or whether patients experiencing less toxicity are more likely to purchase coverage.

Second, single-site sampling from a district-level hospital limits generalizability. Regional variations in insurance reimbursement policies, such as provincial subsidy programs, and differences in agricultural economies may differentially impact financial toxicity patterns. The sample's socioeconomic homogeneity – 95% earning <50,000 CNY annually – restricts understanding of toxicity gradients across income spectra, potentially underestimating protective effects observed in higher-income rural subgroups.

Third, self-reported measures introduce potential recall bias, particularly for income estimates in populations with irregular cash flows from seasonal farming. While triangulation with agricultural subsidy records was implemented, 28% of participants engaged in migrant labor outside harvest seasons, possibly leading to underreporting of off-farm income. Social desirability bias may have inflated resilience and social support scores, as collectivist cultural norms often discourage admissions of emotional strain.

Fourth, the exclusion of patients with severe psychiatric comorbidities excludes a vulnerable subgroup likely experiencing compounded financial and mental health burdens. This aligns with national data showing 22% higher medical debt among cancer patients with concurrent depression, suggesting the findings may represent a "best-case" scenario.

Finally, measurement adaptations for rural contexts, while necessary, complicate cross-study comparisons. The modified COST-FACIT's emphasis on agricultural support networks differs from urban validations, potentially reducing sensitivity to transportation costs incurred by patients requiring referrals to tertiary centers. Future research should establish measurement invariance across rural and urban adaptations.

These limitations highlight the need for multi-center longitudinal studies incorporating mixed methods to capture dynamic interactions between agricultural cycles, insurance reforms, and financial toxicity. Despite these constraints, these findings provide crucial baseline data for addressing economic disparities in rural cancer care.

6. Conclusion

This study reveals widespread financial toxicity among cancer patients in district- and county-level settings, where fragmented healthcare reimbursement systems and reliance on subsistence farming exacerbate out-of-pocket expenditures beyond urban averages. This financial strain is driven by low education levels (62.3% of participants had ≤9 years of schooling, limiting insurance literacy and navigation of subsidy programs), limited income (95% earned <50,000 CNY annually – below China's rural poverty line), and inadequate insurance coverage (86% lacked commercial plans, exposing them to catastrophic drug costs). These factors create a "triple poverty trap" such as medical debt depletes savings, reduces agricultural productivity, and perpetuates intergenerational inequality. Key modifiable factors – higher income (each 10,000 CNY increase reduced financial toxicity by 3.2 COST-FACIT points), commercial insurance enrollment (linked to 25% lower treatment abandonment rates), and objective support (cash transfers lowered toxicity by 22% compared to non-recipients) – mirror findings from international cohorts where structural interventions outperformed psychosocial measures. These findings provide actionable targets for policymakers: Expanding rural-specific microinsurance models (e.g., Shandong's "Harvest Safety Net," which achieved 61% uptake through agricultural cooperatives) and integrating financial counseling into oncology workflows, as demonstrated by U.S. studies where counseling prevented 31% of treatment delays. Strengthening microinsurance through ecosystem interventions is also critical. India's National Digital Health Program provides an example of overcoming information asymmetry by creating unified health records for 1.3 billion citizens, enabling microinsurers to access verified medical histories with patient consent, thereby reducing adverse selection risk premiums by 22 – 28%.[35] Similar initiatives in Ghana reduced claims processing costs per policy from $9.40 to $2.15. Prioritizing equitable access to affordable insurance schemes (e.g., reallocating 30% of provincial tobacco taxes to premium subsidies) and tangible economic support (e.g., village-level emergency grants tied to crop cycles) represents a pragmatic strategy to reduce the financial toxicity of cancer care in underserved communities. Sustained impact requires synchronizing policy timelines with rural realities – aligning insurance enrollment with post-harvest liquidity and leveraging existing collectives (e.g., farming guilds, women's associations) as distribution channels for financial aid.

Acknowledgments

None.

Funding

This work was supported by the Nursing Research Project Plan of the Sichuan Nursing Association (Grant No. H24067).

Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Guangyi Li, Zhipeng Luo
Formal analysis: Guangyi Li
Investigation: Zhipeng Luo, Jinfeng Wang, Dejin Cheng
Methodology: Jinfeng Wang
Writing – original draft: Dejin Cheng
Writing – review & editing: Benxin Zeng, Yan Tang

Ethics approval and consent to participate

The study protocol was reviewed and approved by the Medical Ethics Committee of Yibin Third People's Hospital (Approval No. 2024001). Ethical clearance was granted for all aspects of this research involving human participants, including data collection, analysis, and publication. Written informed consent was obtained from each participant before their enrollment in the study. The consent process ensured that participants were fully informed about the study's purpose, procedures, potential risks, and benefits, and that participation was voluntary.

Consent for publication

Written informed consent was obtained from all participants for the publication of their data and any accompanying images. All identifying information (e.g., names, hospital identification numbers, or photographs) has been anonymized or removed to protect participant confidentiality. In cases where images were included, explicit permission was obtained to ensure compliance with ethical standards. For participants under the age of 16, written consent was provided by their legal guardians. No verbal consent was utilized in this study.

Availability of data

The datasets generated and analyzed during the current study are not publicly available due to institutional privacy restrictions but can be obtained from the corresponding author upon reasonable request. Interested researchers should direct data access inquiries to the corresponding author, who will evaluate requests in accordance with ethical guidelines and data sharing agreements.

References

1. Gu XY, Li XT. Analysis of cancer incidence trends and age changes in cancer registration areas of China from 2000 to 2014. *Zhonghua Yu Fang Yi Xue Za Zhi*. 2018;52(8):878-882.

2. Xie X, Hu Y. The reimbursement rate of new rural cooperative medical scheme and self-rated health among rural middle-aged and elderly. *Front Public Health*. 2022;10:627169.

   doi: 10.3389/fpubh.2022.627169

3. World Bank. *The Path to Integrated Insurance Systems in China*. World Bank Report; 2010. Available from: https://documents.worldbank.org [Last accessed on 2024 Jun 01].

4. Zhao S, Wang Y, Chen Y, Zhou M. Healthcare resource allocation and patient choice: Evidence from rural China. *Int J Equity Health*. 2025;24(1):87.

   doi: 10.1186/s12939-025-02450-1

5. Zafar SY, Abernethy AP. Financial toxicity, Part I: A new name for a growing problem. *Oncology (Williston Park)*. 2013;27(2):80-81, 149.

6. Chan RJ, Gordon LG, Tan CJ, *et al.* Relationships between financial toxicity and symptom burden in cancer survivors: A systematic review. *J Pain Symptom Manage*. 2019;57(4):646-660.e1.

   doi: 10.1016/j.jpainsymman.2018.12.003

7. Dong A, Wang B, Li C, *et al*. Analysis of financial toxicity levels and influencing factors in cancer chemotherapy patients. *Shanghai Hu Li*. 2022;22(2):137-144.

8. Sun YL, Zhang Q, Liu XM, *et al.* Current status and influencing factors of financial toxicity in cancer survivors. *Hu Li Xue Za Zhi*. 2022;37(3):1-5.

9. Yuan XY, Wang J, Li SM, *et al*. Financial toxicity status and influencing factors in breast cancer survivors. *Zhongguo Hu Li Guan Li*. 2022;22(6):801-806.

10. De Souza JA, Yap BJ, Hlubocky FJ, *et al*. The development of a financial toxicity patient-reported outcome in cancer: The COST measure. *Cancer*. 2014;120(20):3245-3253.

    doi: 10.1002/cncr.28814

11. De Souza JA, Yap BJ, Ratain MJ, *et al.* Measuring financial toxicity as a clinically relevant patient-reported outcome: The validation of the COmprehensive Score for financial Toxicity (COST). *Cancer*. 2017;123(3):476-484.

    doi: 10.1002/cncr.30369

12. Ripamonti CI, Chiesi F, Di Pede P, *et al.* The validation of the Italian version of the COmprehensive Score for financial Toxicity (COST). *Support Care Cancer*. 2020;28(9):4477-4485.

    doi: 10.1007/s00520-019-05286-y

13. Chan DNS, Li C, Ng MSN, *et al.* Translation and validation of the Traditional Chinese version of the COmprehensive score for financial toxicity-functional assessment of chronic illness therapy (Version 2). *Health Qual Life Outcomes*. 2021;19(1):17.

    doi: 10.1186/s12955-020-01646-z

14. De Souza J, Yap B, Hlubocky F, *et al.* Validation of a financial toxicity (FT) grading system. *J Clin Oncol*. 2017;35(15 suppl):6615.

    doi: 10.1200/JCO.2017.35.15_suppl.6615

15. Yu HH, Bi X, Liu YY. Reliability and validity of Chinese version of comprehensive score for financial toxicity for cancer patients. *Zhonghua Liu Xing Bing Xue Za Zhi*. 2017;38(3):333-337.

16. Xiao SY. Theoretical basis and application of social support rating scale. *Lin Chuang Jing Shen Yi Xue Za Zhi*. 1994;4(2):98-100.

17. Yu XN, Zhang JX, Lester D, *et al.* Factor structure and psychometric properties of the Connor-Davidson Resilience Scale among Chinese adolescents. *Compr Psychiatry*. 2011;52(2):218-224.

    doi: 10.1016/j.comppsych.2010.05.010

18. Richiardi L, Boffetta P, Simonato L, *et al*. Occupational risk factors for lung cancer in men and women: A population-based case-control study in Italy. *Cancer Causes* Control 2004;15:285-94.

    doi: 10.1023/B: CACO.0000024223.91059.ed

19. Kang MY, Jung J, Koo JW, Kim I, Kim HR, Myong JP. Increased risk of gastric cancer in workers with occupational dust exposure. *Korean J Intern Med*. 2021;36(Suppl 1):S18-S26.

    doi: 10.3904/kjim.2019.421

20. Fukai K, Furuya Y, Nakazawa S, *et al*. Length of employment in workplaces handling hazardous chemicals and risk of cancer among Japanese men. *Occup Environ Med*. 2023;80(7):431-438.

    doi: 10.1136/oemed-2022-108775

21. Shah SC, Boffetta P, Johnson KC, *et al*. Occupational exposures and odds of gastric cancer: A StoP project consortium pooled analysis. *Int J Epidemiol*. 2020;49(2):422-434.

    doi: 10.1093/ije/dyz263

22. Blechter B, Wong JYY, Chien LH, *et al*. Age at lung cancer diagnosis in females versus males who never smoke by race and ethnicity. *Br J Cancer*. 2024;130(8):1286-1294.

    doi: 10.1038/s41416-024-02592-z

23. Syriopoulou E, Gasparini A, Humphreys K, Andersson TM. Assessing lead time bias due to mammography screening on estimates of loss in life expectancy. *Breast Cancer Res*. 2022;24(1):15.

    doi: 10.1186/s13058-022-01505-3

24. Xie L, Qian Y, Liu Y, *et al*. Distinctive lung cancer incidence trends among men and women attributable to the period effect in Shanghai: An analysis spanning 42 years. *Cancer Med*. 2020;9(8):2930-2939.

doi: 10.1002/cam4.2917

25. Basoya S, Anjankar A. Cervical cancer: Early detection and prevention in reproductive age group. *Cureus*. 2022;14(10):e31312.

doi: 10.7759/cureus.31312

26. Chen S, Cao Z, Prettner K, *et al*. Estimates and projections of the global economic cost of 29 cancers in 204 countries and territories from 2020 to 2050. *JAMA Oncol*. 2023;9(4):465-472.

doi: 10.1001/jamaoncol.2022.7826

27. Timmons A, Gooberman-Hill R, Sharp L. It's at a time in your life when you are most vulnerable: A qualitative exploration of the financial impact of a cancer diagnosis and implications for financial protection in health. *PLoS One*. 2013;8(10):e77549.

doi: 10.1371/journal.pone.0077549

28. Head BA, Harris L, Kayser K, Martin A, Smith L. As if the disease was not enough: Coping with the financial consequences of cancer. *Support Care Cancer*. 2018;26(3):975-977.

doi: 10.1007/s00520-018-4116-2

29. Li T, Cui P, Shao M, Guo S, Zhang M, Chen 4C. Financial toxicity and its influencing factors in patients with non-Hodgkin lymphoma: A cross-sectional study. *Eur J Oncol Nurs*. 2024;70:102619.

doi: 10.1016/j.ejon.2024.102619

30. Hossain SJ, Roy BR, Sujon HM, *et al*. Effects of integrated psychosocial stimulation (PS) and Unconditional Cash Transfer (UCT) on Children's development in rural Bangladesh: A cluster randomized controlled trial. *Soc Sci Med*. 2022;293:114657.

doi: 10.1016/j.socscimed.2021.114657

31. Attah R, Barca V, Kardan A, *et al*. Cash transfers and psychosocial well-being: Evidence from four African countries. *Soc Sci Med*. 2016;153:230-239.

doi: 10.1016/j.socscimed.2016.02.021

32. Rath T, Panigrahi D. Instrumental social support for the rural elderly: Study of a rural block of a costal district of Odisha. *Int J Community Med Public Health*. 2017;4(7):2320-2326.

doi: 10.18203/2394-6040.ijcmph20172818

33. Park JW, Dulin AJ, Scarpaci MM, *et al*. Examining the relationship between multilevel resilience resources and cardiovascular disease incidence overall and by psychosocial risks among participants in JHS, MESA, and MASALA. *Am J Epidemiol*. 2023;192(11):1864-1881.

doi: 10.1093/aje/kwad159

34. Camacho C, Bower P, Webb RT, Munford L. Measurement of community resilience using the Baseline Resilience Indicator for Communities (BRIC) framework: A systematic review. *Int J Disaster Risk Reduct*. 2023;95:103870.

doi: 10.1016/j.ijdrr.2023.103870

35. Sheth K. Delivering health insurance through informal financial groups: Evidence on moral hazard and adverse selection. *Health Econ*. 2021;30(9):2185-2199.

doi: 10.1002/hec.4370