



Comorbidity patterns and their associations with performance status and treatment receipt in breast and colorectal cancers in a multiethnic Asian setting: a latent class analysis

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Abstract

Purpose Comorbidity is usually summarised as a count or index, which treats different combinations of conditions equally. Whether distinct comorbidity patterns have different implications for management decisions in cancer is unclear. We applied latent class analysis (LCA) to identify comorbidity patterns and examined their associations with performance status and cancer treatment in individuals with breast or colorectal cancer.

Methods Data from two Malaysian cohorts comprising adults with breast or colorectal cancer were analysed. Comorbidities, verified against medical records, were grouped into 20 categories. LCA was used to identify comorbidity patterns. Outcomes included ECOG performance status (0–1 vs ≥ 2) and receipt of treatment (surgery, chemotherapy, radiotherapy, immunotherapy, anti-HER2, CDK4/6 inhibitors, hormone therapy).

Results Among 1117 individuals, 695 (62.2%) had ≥ 1 comorbidity. Hypertension, dyslipidaemia, diabetes and obesity were most prevalent. LCA identified three classes: low ($n = 723$), cardiovascular-kidney-metabolic (CKM) ($n = 368$) and multisystem ($n = 26$). All in the multisystem group and half in the CKM group had modified Charlson Comorbidity Index ≥ 3 . The CKM group was older than the low-comorbidity group (62 vs 51 years) but did not differ in performance or treatment status. The multisystem group however had poorer performance status (adjusted odds ratio [aOR] = 4.04, 95%CI = 1.50–10.84), lower odds of receiving chemotherapy (aOR = 0.10, 95%CI = 0.04–0.25) and anti-HER2 therapy (aOR = 0.14, 95%CI = 0.02–0.86).

Conclusion Comorbidity patterns revealed differences that counts alone would have missed. The CKM class had similar performance status and treatment receipt to the low-comorbidity class despite cardiovascular and renal comorbidity, highlighting risks not reflected by performance status. The multisystem class requires validation.

Keywords Comorbidity pattern · Cardiovascular-kidney-metabolic · Multimorbidity · Cancer treatment patterns · Performance status (ECOG)

Highlights

- Two comorbidity classes with high index scores differed in performance status and treatment receipt.
- Individuals with clustered cardiovascular-kidney-metabolic conditions were as functionally fit at diagnosis and as likely to receive standard cancer treatment as those with low comorbidity.

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Introduction

Cancer remains a leading cause of morbidity and mortality worldwide, with over 19 million new diagnoses in 2020 and a projected 26 million by 2030 [1]. Amid this rise in cancer incidence, ageing populations and longer post-diagnosis survival are likely to make multimorbidity a routine challenge in oncology [2]. Southeast Asia, which is home to many low- and middle-income countries (LMICs) and diverse, multiethnic populations, recorded 1.1 million new cancer cases in 2022. Cancer incidence in the region is projected to

double by 2050, and the convergence of cancer and chronic disease is expected to intensify [3].

Despite this, integration of comorbidities and broader health needs into multidisciplinary cancer care and survivorship services remains limited particularly in LMICs [4]. Clinical practice guidelines, trials and electronic health records typically capture comorbidity using a single index score or disease count, treating all multimorbidity as equivalent [5], which can obscure important differences. Patients with cardiometabolic disease for instance may differ clinically from those with organ failure or frailty even when assigned the same index score [6]. The Charlson Comorbidity Index (CCI) remains widely used in research and administrative settings due to its simplicity and validation [7]. However, like other indices, it reduces complex comorbidity patterns to a single score [7]. Studies conducted in LMICs including our prior work have also largely employed index-based measures and focused on single cancer site [8, 9].

Performance status is a central determinant of treatment eligibility, toxicity, survival and care planning in oncology [10]. However, its association with patterned multimorbidity remains insufficiently studied and is especially under investigated in LMICs. Distinct clusters of conditions are likely to have different functional footprints that may not be captured by conventional comorbidity indices. Furthermore, conditions such as cardiometabolic disease and kidney impairment may influence treatment tolerance and decisions regarding surgery and systemic therapies [11, 12]. They may also alter drug metabolism, increase toxicity risk and become important causes of non-cancer death in individuals with cancer [11, 13, 14].

Given these gaps, understanding how comorbidity patterns relate to performance status and treatment is important for guiding individualised care in diverse settings. This study aimed to identify patterns of comorbidity in individuals with breast or colorectal cancer in a multiethnic Asian population using latent class analysis (LCA) and examine their associations with performance status and treatment receipt.

Methods

Study design, study sites and study population

This cross-sectional analysis used baseline data from two ongoing prospective cohort studies of supportive care needs and patient-centred outcomes among individuals with breast cancer (BC) and colorectal cancer (CRC) in Malaysia, a multiethnic upper-middle-income country [15]. Participants were recruited from nine centres across East and West Malaysia comprising Ministry of Health (MOH), academic and private hospitals, and non-governmental organisations.

The BC and CRC cohorts were derived from the multicentre Happiness Registry and Living Well with CRC cohort, respectively. The Happiness Registry included a substantial proportion of individuals with advanced disease. Eligible participants were adults (≥ 18 years) with a confirmed breast or colorectal cancer diagnosis who could converse in Malay or English. Participants were recruited consecutively from participating clinics through face-to-face and online approaches. Ethics approval was obtained from the relevant institutional review boards and all participants provided informed consent.

Study variables

Comorbidity

Comorbidities documented at or before baseline (first or recurrent cancer diagnosis, before systemic treatment initiation) were verified against available medical records, with self-report used when records were unavailable. Comorbidities were coded using the International Classification of Diseases 10th Revision and grouped into 20 categories. Diabetes, dyslipidaemia, hypertension, ischaemic heart disease, heart failure and cerebrovascular disease were coded separately, with other endocrine/metabolic and circulatory conditions grouped within their respective categories. Obesity was defined as BMI > 30 kg/m².

LCA identified comorbidity patterns across 20 predefined conditions, while modified Charlson Comorbidity Index (mCCI) scores described comorbidity burden within each class. The mCCI excluded cancer (weight = 2) and distant metastasis (weight = 6), with age scores starting at one point for 50–59 years and increasing by one point per decade thereafter [16]. The included conditions and weights are shown in Supplementary Table 1. Comorbidity-only CCI scores excluding age were also calculated for clarity. Both measures were derived from baseline comorbidity data for the full study cohort.

Performance status

Performance status was assessed using the Eastern Cooperative Oncology Group (ECOG) scale and dichotomised as 0–1 versus ≥ 2 [17].

Cancer treatment receipt

Receipt of surgery, radiotherapy, chemotherapy and immunotherapy was assessed in the full cohort and classified as yes or no. Receipt of anti-HER2 targeted therapy, cyclin-dependent kinase 4/6 inhibitors (CDK4/6i) and hormone therapy was assessed among participants with the relevant indication, namely HER2-positive BC, hormone

receptor-positive (HR-positive) HER2-negative BC and HR-positive BC, respectively.

Other variables

Other variables included age, gender, ethnicity, household income, highest attained education and treatment centre, as well as cancer site and stage at diagnosis. Household income was classified according to national statistics as low (< USD 1045/< RM 4850), middle (USD 1045–2366/ RM 4850–10,959) or high (> USD 2366/≥ RM 10,960) [20]. Cancer stage was classified as early-stage (colon cancer stages I–IIIC, rectal cancer stages I–III and BC stages I–IIIA) [18–20] or advanced-stage (CRC stage IV and BC stages IIIB–IV) [18–20].

Statistical analysis

Descriptive statistics included frequencies and percentages for categorical variables and medians with interquartile ranges for non-normally distributed continuous variables. LCA was used to identify comorbidity classes [21, 22], with model selection guided by the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), bootstrap likelihood ratio test (BLRT), average posterior probabilities, model parsimony and clinical interpretability [21, 22]. For each comorbidity, observed-to-expected (O/E) ratios were calculated and ratios > 1.5 were used to label the latent classes, consistent with prior methodology [23]. Baseline sociodemographic and clinical characteristics were compared across LCA classes using chi-square test, Fisher's exact test or Kruskal-Wallis test.

Associations between comorbidity classes and (i) ECOG performance status and (ii) cancer treatment receipt were examined using multivariable binary logistic regression. Covariates were selected a priori using directed acyclic graphs (Supplementary Figure 1–2), informed by clinical knowledge and published literature [24]. ECOG models were adjusted for age, cancer type and stage at diagnosis. Treatment models were adjusted for age, ethnicity, household income, cancer type, stage at diagnosis and ECOG. Although ECOG may lie on the pathway from comorbidities to treatment receipt [25], it was adjusted for to compare treatment receipt across comorbidity classes among individuals with similar performance status.

Adjusted odds ratios (aORs) with 95% confidence intervals (CIs) were reported with the low-comorbidity class as reference. Missing values were imputed using multiple imputation by chained equations with five imputations and estimates pooled using Rubin's rules. Multicollinearity was assessed using variance inflation factors and tolerance values. Statistical analyses were conducted using SPSS version

29. LCA and Firth penalised logistic regression were performed in Python 3.13.

Sensitivity analyses

Nine sensitivity analyses assessed cohort composition (comparison of BC and CRC cohorts and restriction to incident first cancer cases), LCA robustness (cancer-specific LCAs), model specification (alternative confounder selection using a data-driven approach, stage-stratified ECOG analyses, alternative ECOG categorisation and treatment models without ECOG adjustment) and outcome-specific analyses (assessment of potential differences in immunotherapy indication and Firth penalised logistic regression for anti-HER2 therapy).

Results

Cohort characteristics

The study included 1117 individuals with BC or CRC from a multiethnic background (Malay = 53.3%, Chinese = 32.4%, Indians = 10.4%, others = 3.9%), with a median age of 55 years (Q1–Q3 = 47–63) (Table 1). Most were female (83.5%), from low-income households (67.0%) and treated in MOH-owned public hospitals (62.2%). Breast cancer accounted for 64.7% and CRC for 35.3%, with 52.3% having early-stage disease. Nearly three-quarters underwent surgery and 83.9% received chemotherapy (not mutually exclusive). For 21.2% ($n = 237$), comorbidity data were self-reported because medical records were unavailable. Missing data ranged from 0.6 to 5.6% (Supplementary Table 2).

Overall, 62.2% ($n = 695$) had ≥ 1 of the 20 LCA comorbidity categories, while 764 participants had $mCCI \geq 1$ (Table 1); the higher $mCCI$ count reflects the inclusion of age points. Excluding age, 326 participants had a comorbidity-only $CCI \geq 1$. Among participants with comorbidity, hypertension was most common (60.7%), followed by dyslipidaemia (41.7%), diabetes (39.6%) and obesity (33.5%). Across ethnic groups, comorbidity prevalence was highest among Indians (73.3%), followed by Malays (63.7%), Chinese (56.9%) and other ethnicities (56.8%) ($p = 0.009$).

Latent class analysis

Models with two to six classes were evaluated, and the three-class solution was selected based on the lowest BIC (8634.16) (Supplementary Table 3), high classification accuracy (average posterior probabilities 0.93–1.00; Supplementary Table 4), parsimony and clinical interpretability. The classes were labelled low-comorbidity, cardiovascular-kidney-metabolic (CKM) and multisystem. Although the

Table 1 The comparison of baseline characteristics by LCA classes

Variables		Total cohort <i>N</i> = 1117	Class 1 (low comorbidity) (<i>n</i> = 723)	Class 2 (cardio- vascular-kidney- metabolic) (<i>n</i> = 368)	Class 3 (multisystem comorbidity) (<i>n</i> = 26)	<i>p</i> -value ^a	Effect size ^b (Cramer's <i>V</i> / <i>ε</i> ²)
		<i>n</i> (%)	<i>n</i> (%)	<i>n</i> (%)	<i>n</i> (%)		
Sociodemographic characteristics							
Age	Median (IQR)	55.0 (47, 63)	51.0 (43, 59)	62.0 (55, 68)	55 (46, 66)	<0.001 ^c	0.163 (L)
Gender	Male	184 (16.5)	120 (16.6)	64 (17.4)	0 (0.0)	0.038 ^c	0.069 (S)
	Female	933 (83.5)	603 (83.4)	304 (82.6)	26 (100.0)		
Ethnicity	Malay	595 (53.3)	367 (50.8)	214 (58.2)	14 (53.8)	<0.001 ^c	0.117 (S)
	Chinese	362 (32.4)	269 (37.2)	89 (24.2)	4 (15.4)		
	Indian	116 (10.4)	60 (8.3)	49 (13.3)	7 (26.9)		
	Others	44 (3.9)	27 (3.7)	16 (4.3)	1 (3.8)		
Highest educa- tion level attained	None and primary education	136 (12.2)	66 (9.1)	68 (18.5)	2 (7.7)	<0.001 ^c	0.132 (S)
	Secondary educa- tion	538 (48.2)	330 (45.6)	196 (53.3)	12 (46.2)		
	Tertiary education	443 (39.7)	327 (45.2)	104 (28.3)	12 (46.2)		
Income group ^d	Low	748 (67.0)	454 (62.8)	277 (75.3)	17 (65.4)	<0.001 ^c	0.094 (S)
	Middle	238 (21.3)	171 (23.7)	59 (16.0)	8 (30.8)		
	High	131 (11.7)	98 (13.6)	32 (8.7)	1 (3.8)		
Centre for treatment	Academic hos- pital	274 (24.5)	178 (24.6)	89 (24.2)	7 (26.9)	<0.001 ^c	0.095 (S)
	Ministry of health hospital	695 (62.2)	428 (59.2)	253 (68.8)	14 (53.8)		
	Private hospital	148 (13.2)	117 (16.2)	26 (7.1)	5 (19.2)		
Disease-related characteristics							
Cancer type	Breast cancer	723 (64.7)	443 (61.3)	254 (69.0)	26 (100.0)	<0.001 ^c	0.137 (S)
	Colorectal cancer	394 (35.3)	280 (38.7)	114 (31.0)	0 (0.0)		
Current cancer status	First cancer	992 (88.8)	641 (88.7)	337 (91.6)	14 (53.8)	<0.001 ^c	0.177 (S)
	Recurrent cancer	125 (11.2)	82 (11.3)	31 (8.4)	12 (46.2)		
Cancer staging	Early	584 (52.3)	390 (53.9)	193 (52.4)	1 (3.8)	<0.001 ^c	0.150(S)
	Advanced	533 (47.7)	333 (46.1)	175 (47.6)	25(96.2)		
ECOG score	0	737 (66.0)	502 (69.4)	233 (63.3)	2 (7.7)	<0.001 ^c	0.145 (S)
	1	267 (23.9)	149 (20.6)	100 (27.2)	18 (69.2)		
	2 and above	113 (10.1)	72 (10.0)	35 (9.5)	6 (23.1)		
Modified CCI (mCCI) score ^e	0	353 (31.6)	334 (46.2)	19 (5.2)	0 (0.0)	<0.001 ^c	0.430 (M)
	1	258 (23.1)	195 (27.0)	63 (17.1)	0 (0.0)		
	2	235 (21.0)	135 (18.7)	100 (27.2)	0 (0.0)		
	3 and above	271 (24.3)	59 (8.2)	186 (50.5)	26 (100.0)		
Treatment-related characteristics							
Treatment modalities ^f		Total cohort <i>N</i> = 1117 <i>n</i> (%)	Class 1 (low Comorbidity), <i>n/N</i> (%)	Class 2 (cardio- vascular-kid- ney-metabolic), <i>n/N</i> (%)	Class 3 (multisystem comorbid- ity), <i>n/N</i> (%)	<i>p</i> -value ^a	Effect size ^b (Cramer's <i>V</i> / <i>ε</i> ²)
Surgery		837 (74.9)	540/723 (74.7)	286/368 (77.7)	11/26 (42.3)	<0.001 ^c	0.121 (S)
Radiotherapy		634 (56.8)	407/723 (56.3)	217/368 (59.0)	10/26 (38.5)	0.116	0.062 (S)
Chemotherapy		937 (83.9)	611/723 (84.5)	315/368 (85.6)	11/26 (42.3)	<0.001 ^c	0.175 (S)
Immunotherapy		37 (3.3)	11/723 (1.5)	5/368 (1.4)	21/26 (80.8)	<0.001 ^c	0.668 (L)
Anti-HER2 targeted therapy		282 (25.2)	171/202 (84.7)	107/122 (87.7)	2/7 (28.6)	0.002 ^c	0.232 (S)
CDK4/6 inhibitors		74 (6.6)	36/173 (20.8)	28/92 (30.4)	4/18 (22.2)	0.221	0.104 (S)
Hormone therapy		437 (39.1)	269/296 (90.9)	141/151 (93.4)	22/24 (91.7)	0.655	0.042 (S)

Table 1 (continued)

Footnotes:

^a*p*-values were calculated using chi-square or Fisher's exact tests, with Fisher's test used when expected cell counts were < 5, Kruskal-Wallis test for age (not normally distributed). Comparison across comorbidity classes was descriptive only; *p*-values are presented for exploratory purposes and should be interpreted with caution due to non-probabilistic sampling

^bCramer's *V* values of 0.1, 0.3 and 0.5 were interpreted as small (S), medium (M) and large (L), respectively, while epsilon-squared (ϵ^2) values of 0.01, 0.06 and 0.14 representing small (S), medium (M) and large (L) effects

^cStatistically significant *p* < 0.05

^dIncome group: low: < RM 4850, middle (RM 4851–10,959), high ($\geq$ RM 10,960)

^eModified CCI (mCCI) score excluded cancer (weight = 2) and distant metastasis (weight = 6) from scoring; age scores start at one point for 50–59 years and increase by one point per decade thereafter

^fThe total cohort values indicate the number and percentage of participants who received the therapy among all 1117 participants. The indication-eligible subgroup and class-specific columns are restricted to participants meeting the prespecified receptor-based eligibility criteria; therefore, these counts may differ from the total cohort treatment counts

^gBreast cancer survivors with HER2 receptor-positive disease

^hBreast cancer survivors with hormone receptor-positive, HER2-negative disease

ⁱBreast cancer survivors with hormone receptor-positive disease

four-class model had a lower AIC and significant BLRT, it produced smaller, less interpretable classes without a distinct clinical pattern. O/E ratios are presented in Supplementary Table 5.

The low-comorbidity class showed no excess prevalence of any condition, whereas the CKM class clustered hypertension, dyslipidaemia, diabetes, obesity, cardiovascular disease and chronic kidney disease, the latter accounting for 44.5% of genitourinary conditions. In the CKM class, 41.0%, 40.2% and 12.2% had two, three or ≥ 4 of these conditions. The multisystem class comprised only females with BC, of whom 25 (96.2%) had advanced-stage disease and 12 (46.2%) had recurrent disease, and showed elevated comorbidity prevalence across multiple organ systems, with all having ≥ 4 comorbidities (Fig. 1, Supplementary Table 6). All individuals in the multisystem group and approximately half in the CKM group had mCCI ≥ 3 (Table 1). After excluding age, all individuals in the multisystem group remained at CCI ≥ 3 , whereas most participants in other groups moved to lower categories (Supplementary Table 7).

Class characteristics

Median age was highest in the CKM group (62 years; Q1–Q3 = 55–68), followed by the multisystem (55 years; Q1–Q3 = 45–66) and low-comorbidity groups (51 years; Q1–Q3 = 43–59) (Table 1). Participants from low-income households accounted for 75.3% and 65.4% of the CKM and multisystem groups, respectively. Approximately half of the low-comorbidity (53.9%) and CKM (52.4%) groups had early-stage disease, whereas advanced-stage disease predominated in the multisystem group (96.2%; *p* < 0.001). Poor performance status (ECOG ≥ 2) was most common in the multisystem group (23.1%), versus about 10% in the other groups. The multisystem group had lower receipt of surgery

(42.3%; *p* < 0.001), chemotherapy (42.3%; *p* < 0.001) and anti-HER2 therapy (28.6%; *p* = 0.002), but higher immunotherapy receipt (80.8%; *p* < 0.001). Radiotherapy was numerically lower (38.5%, *p* = 0.116), while CDK4/6i and hormone therapy did not differ significantly.

Association between comorbidity classes and ECOG performance status

Compared with the low-comorbidity group, the CKM group was not significantly associated with ECOG ≥ 2 (aOR = 1.11, 95%CI = 0.70–1.79), whereas the multisystem group was associated with higher odds of ECOG ≥ 2 (aOR = 4.04, 95%CI = 1.50–10.84; Table 2).

Association between comorbidity classes and cancer treatment receipt

Compared with the low-comorbidity group, the CKM group showed no significant associations with any treatment modality (Table 3). The multisystem group had lower odds of receiving chemotherapy (aOR = 0.10, 95%CI = 0.04–0.25) and anti-HER2 therapy (aOR = 0.14, 95%CI = 0.02–0.86). Immunotherapy receipt was higher in the multisystem group (21/26, 80.8%) than in the low-comorbidity (11/723, 1.5%) and CKM groups (5/368, 1.4%). No adjusted estimate is presented because nearly all multisystem participants had advanced-stage disease and the association could not be separated from stage. Although lower odds were also observed for surgery, radiotherapy and CDK4/6i, and higher odds for hormone therapy, the corresponding CI included the null. No multicollinearity was observed (Supplementary Table 8).

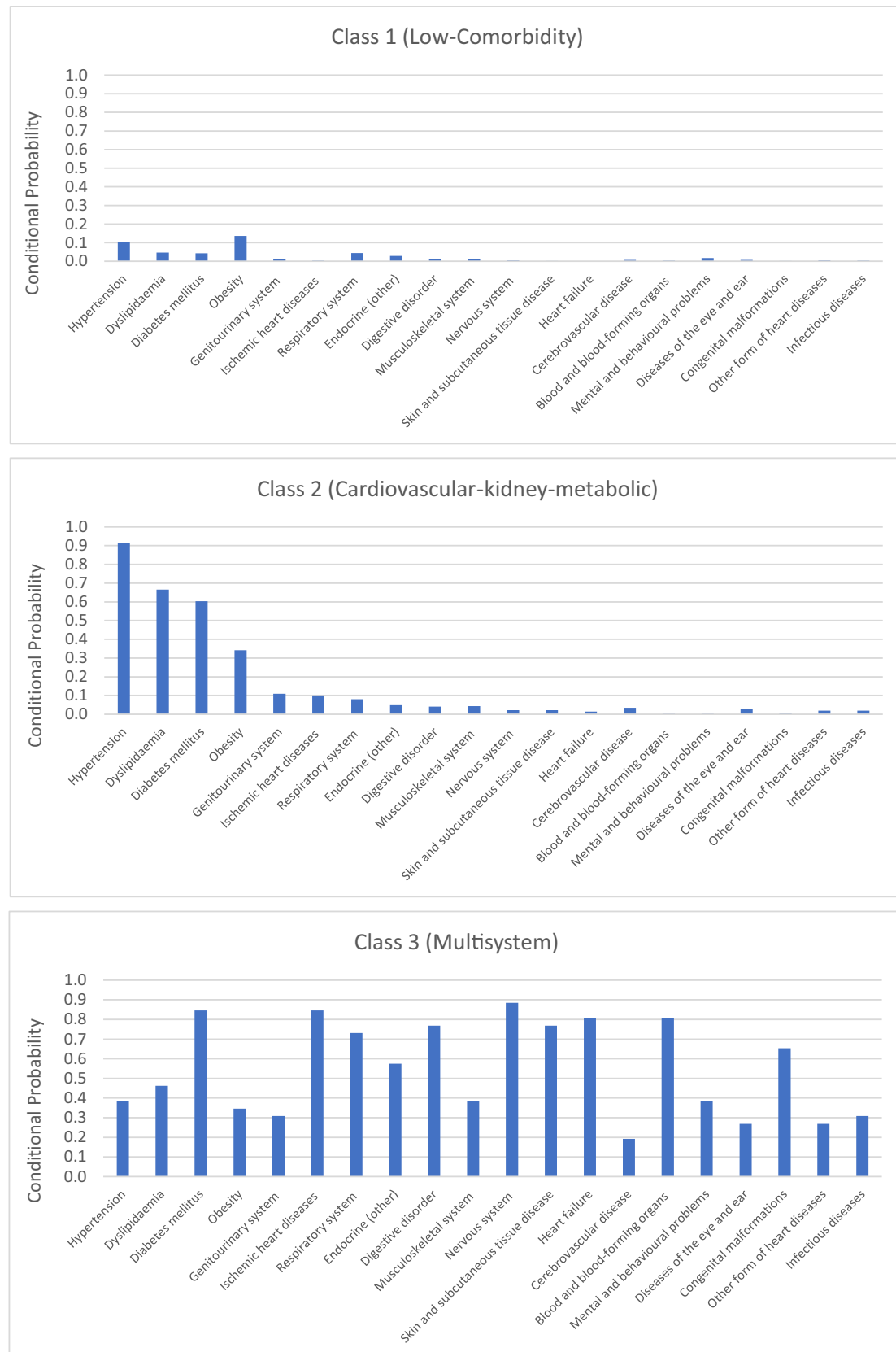


Fig. 1 Conditional probabilities of comorbidities across the three latent classes: low comorbidity ($n=723$), cardiovascular-kidney-metabolic ($n=368$) and multisystem comorbidity ($n=26$). Comorbidities are presented in the same order across classes

Table 2 Multivariable analysis of ECOG performance status (ECOG 0–1 vs ≥ 2) across LCA comorbidity classes

Cancer stage	Comorbidity class	ECOG ≥ 2 , n/total	Adjusted OR	95%CI	p-value
Overall ($n = 1117$) ^a	Low	72/723	1.00	–	–
	CKM	35/368	1.11	0.70–1.79	0.654
	Multisystem	6/26	4.04	1.50–10.84	0.006 ^d
Early-stage ($n = 584$) ^b	Low	46/390	1.00	–	–
	CKM	16/193	0.87	0.45–1.70	0.689
	Multisystem	0/1	N/A	N/A	N/A
Advanced-stage ($n = 533$) ^c	Low	26/333	1.00	–	–
	CKM	19/175	1.40	0.70–2.78	0.338
	Multisystem	6/25	3.87	1.38–10.82	0.010 ^d

OR odds ratio, CI confidence interval, CKM cardiovascular-kidney-metabolic

Footnotes:

^aMultivariable logistic regression was used to analyse the association between LCA comorbidity class and ECOG functional status, adjusting for age, cancer type, cancer stage

^bIn early-stage cancer, multivariable logistic regression was used to analyse the association between LCA comorbidity class and ECOG functional status, adjusting for age, cancer type. The adjusted OR for the multisystem group in early-stage cancer was not reported because no events were observed in this group (0 cases), resulting in complete separation and a non-estimable odds ratio

^cIn advanced-stage cancer, multivariable logistic regression was used to analyse the association between LCA class and ECOG functional status, adjusting for age, cancer type

^dStatistically significant $p < 0.05$

Sensitivity analysis

Cohort composition

Baseline characteristics were similar between the BC and CRC cohorts, although cancer stage and gender showed moderate and large between-cohort differences, respectively (Supplementary Table 9). Restriction to incident first cancer cases ($n = 992$) produced broadly similar treatment patterns, although estimates for anti-HER2 and hormone therapy in the multisystem class were limited by the small sample size (Supplementary Table 10–11).

LCA robustness

Cancer-specific LCAs identified three-class solutions in both BC (Supplementary Tables 12–13) and CRC (Supplementary Tables 14–15), including a multisystem class in each. Multisystem involvement was broader in BC (18/20 ICD categories) than CRC (9/20).

Model specification

Findings were largely unchanged with alternative confounder selection (Supplementary Table 16). CKM remained not associated with ECOG ≥ 2 across stages, whereas multisystem was associated with ECOG ≥ 2 in advanced-stage disease (aOR = 3.87, 95%CI = 1.38–10.82; Table 2). Reliable estimation in early-stage

disease was precluded by the small multisystem group. Alternative ECOG categorisation (0 vs ≥ 1) yielded consistent findings (Supplementary Table 17). Treatment models excluding ECOG adjustment yielded broadly similar estimates (Supplementary Table 18).

Outcome-specific analyses

Given the high immunotherapy receipt in the multisystem class, potential differences in treatment indication were explored. The multisystem class had a higher proportion of advanced-stage disease than the low-comorbidity and CKM classes, while HER2 and triple-negative status did not differ significantly across classes (Supplementary Table 19). Firth penalised logistic regression yielded a similar estimate for anti-HER2 therapy (aOR = 0.17, 95%CI = 0.03–0.89).

Discussion

In this multiethnic Malaysian cancer cohort, over 60% of participants had at least one comorbidity and LCA identified three classes comprising low-comorbidity, CKM and multisystem patterns. Although the CKM and multisystem classes both carried a high comorbidity burden, they differed substantially in performance status and treatment receipt. The CKM class had performance status and treatment receipt comparable to the low-comorbidity class, while the

Table 3 Multivariable analysis of receipt of cancer therapy across LCA comorbidity classes

Treatment received	Comorbidity class ^a	n/N	Adjusted OR ^a	95%CI ^a	p-value
Surgery ^a	Low	540/723	1.00	–	–
	CKM	286/368	1.44	1.00–2.07	0.052
	Multisystem	11/26	0.78	0.33–1.85	0.578
Radiotherapy ^a	Low	407/723	1.00	–	–
	CKM	217/368	1.18	0.87–1.59	0.293
	Multisystem	10/26	0.43	0.19–1.01	0.053
Chemotherapy ^a	Low	611/723	1.00	–	–
	CKM	315/368	1.23	0.82–1.85	0.324
	Multisystem	11/26	0.10	0.04–0.25	<0.001 ^e
Immunotherapy ^a	Low	11/723	1.00	–	–
	CKM	5/368	0.90	0.27–2.99	0.867
	Multisystem	21/26	NE	NE	NE ^f
Anti-HER2 targeted therapy ^b	Low	171/202	1.00	–	–
	CKM	107/122	2.06	0.94–4.52	0.071
	Multisystem	2/7	0.14	0.02–0.86	0.033 ^e
CDK4/6 inhibitors ^c	Low	36/173	1.00	–	–
	CKM	28/92	1.99	0.98–4.04	0.058
	Multisystem	4/18	0.53	0.14–1.96	0.337
Hormone therapy ^d	Low	269/296	1.00	–	–
	CKM	141/151	1.74	0.75–4.04	0.200
	Multisystem	22/24	1.53	0.30–7.78	0.610

LCA latent class analysis, OR odds ratio, CI confidence interval, CKM cardiovascular-kidney-metabolic, NE-not estimable

Footnotes:

^aMultivariable logistic regression was used to analyse the association between comorbidity class and receipt of surgery, radiotherapy, chemotherapy and immunotherapy adjusting for age, cancer type, stage, ECOG, ethnicity, income

^bMultivariable logistic regression was used to analyse the association between comorbidity class and receipt of anti-HER2 therapy in women with HER2-positive breast cancer, adjusting for age, stage, ECOG, ethnicity, income

^cMultivariable logistic regression was used to analyse the association between comorbidity class and receipt of CDK4/6i in women with hormone receptor-positive and HER2 receptor-negative breast cancer, adjusting for age, stage, ECOG, ethnicity, income

^dMultivariable logistic regression was used to analyse the association between comorbidity class and receipt of hormone therapy in women with hormone receptor-positive breast cancer, adjusting for age, stage, ECOG, ethnicity, income

^eStatistically significant $p < 0.05$

^fAdjusted estimates for immunotherapy are not presented because nearly all multisystem participants had advanced-stage disease and the association could not be separated from stage; receipt is described in the text

multisystem class had poorer performance status and lower receipt of chemotherapy and anti-HER2 therapy. Cancer-specific analyses identified the same three classes in both BC and CRC, although multisystem involvement was broader in BC. Taken together, these findings suggest that the pattern of comorbidity may convey clinical information that is not apparent from a count or index alone.

Notably, performance status and treatment receipt were comparable between the CKM and low-comorbidity classes. Comparable treatment receipt however does not mean that the cardiovascular and renal considerations surrounding

treatment are also comparable. Kidney function influences treatment selection, dosing and monitoring [26], while advanced kidney disease has been associated with reduced chemotherapy use [27]. Cardiovascular disease is also a leading cause of non-cancer death among people with cancer [14].

The CKM pattern is hence particularly relevant because cardiovascular, kidney and metabolic conditions commonly coexist and interact [28]. The American Heart Association CKM framework recognises the interrelationship between metabolic risk factors, chronic kidney disease and

cardiovascular disease [28], while CKM syndrome stage has been shown to predict cardiovascular outcomes following cancer [29]. In our study, the CKM group indeed carried cardiovascular, metabolic and renal conditions relevant to treatment safety and longer-term outcomes. Several commonly used cancer treatments may add to these risks. Anthracyclines and anti-HER2 therapies for instance have recognised cardiovascular effects, while renal function influences the use and dosing of several systemic agents [30]. Performance status is therefore useful in assessing treatment eligibility but does not necessarily reflect these underlying risks.

This distinction becomes important when treatment is first planned. In a cohort of 2127 Asian women with newly diagnosed breast cancer, modifiable cardiovascular risk factors were common at diagnosis and nearly two-thirds of those receiving adjuvant therapy were estimated to be at high or very high risk of cardiotoxicity [31]. International cardio-oncology guidelines already recommend baseline cardiovascular risk assessment using approaches such as HFA-ICOS [32]. Such assessment however requires ECG, cardiac imaging, biomarkers and specialist expertise depending on baseline risk and planned treatment. As the CKM pattern identified in our study draws on conditions that are routinely recorded in clinical care, it may provide a useful starting point for deciding who warrants more comprehensive cardiovascular and renal assessment, particularly where such assessment cannot readily be offered to everyone. This would not replace formal risk assessment but may allow assessment and monitoring to be tailored more prudently according to underlying comorbidity.

The potential value of risk factor control is also supported by prospective data from 14,466 individuals with cancer, where each additional cardiovascular risk factor within the target range was associated with a 12% lower risk of heart failure [33]. In settings where access to imaging, high-cost biomarkers and specialist services is constrained [34], recognition of comorbidity patterns from routine clinical information may therefore be particularly useful in prioritising patients for closer cardiovascular and renal assessment, monitoring and risk factor control. Whether the CKM pattern provides additional prognostic value beyond existing risk stratification tools and whether pattern-based assessment can be delivered within routine cancer care warrants prospective evaluation.

The multisystem class presented a different clinical picture. Poor ECOG performance status was substantially more common in this group. This is clinically relevant because performance status is a key determinant of treatment eligibility and prognosis, but reflects current functional ability rather than the conditions contributing to its decline [10]. The multisystem class also had lower receipt of chemotherapy and anti-HER2 therapy. This is in keeping with previous evidence showing that multimorbidity is associated with a

lower likelihood of receiving cancer treatment even after adjustment for relevant factors [35].

Unlike the CKM class, the multisystem class involved comorbidities across several organ systems and nearly all its participants had advanced-stage disease. It is therefore conceivable that lower treatment receipt reflects greater clinical complexity and treatment-related toxicity concerns [31]. Symptomatic heart failure for instance may limit the use of anthracyclines and anti-HER2 therapies because of their cardiotoxic potential [32]. Importantly, estimates for treatment receipt changed only modestly when ECOG was omitted from the models, suggesting that the observed associations were not explained by performance status alone. The small number of participants in this class however limits further interpretation and these findings should be considered exploratory.

Immunotherapy receipt was concentrated in the multisystem class. Nearly all participants in this group had advanced-stage disease where immunotherapy is mainly used [36], and the association could not be separated from stage. In contrast, hormone therapy receipt did not differ significantly across the comorbidity classes, consistent with guidance that endocrine therapy can be given to most women with an indication including older women and those with comorbidity [37]. CDK4/6 inhibitor use was also modest, potentially reflecting cost, access and reimbursement policies [38].

Several limitations should be considered. The multisystem class was small and findings for this class require validation in larger disease-specific cohorts, although the direction of the findings remained consistent across sensitivity analyses including Firth penalised regression. The parent cohorts differed in eligibility criteria and funding sources, which may have influenced participant selection and stage distribution. Clinic-based recruitment may also have under-represented severely unwell patients, including those with CKM conditions who were too unwell to receive treatment, which may partly explain the comparable treatment receipt in the CKM and low-comorbidity classes. We also acknowledge that the findings may not apply to rarer cancers where comorbidity burden and treatment pathways may differ [39]. Comorbidities were assessed at baseline before systemic treatment. Among individuals with recurrent cancer however, the cross-sectional design could not always distinguish pre-existing comorbidity from morbidity arising from previous cancer treatment. Reverse causation is therefore possible. Nonetheless, findings were broadly similar after restriction to incident first cancers, suggesting that reverse causation does not fully explain the observed associations.

Strengths include a large multiethnic population with two common cancers recruited across public, academic and private healthcare settings. The same three broad comorbidity patterns were identified when BC and CRC were analysed

separately and the main findings remained broadly stable across sensitivity analyses. This supports the pooled analysis and suggests that these patterns are not confined to a single cancer type. Furthermore, access to standard cancer therapies is substantially subsidised in Malaysia. Differences in treatment receipt across comorbidity classes are therefore less likely to be explained by affordability alone, although access to targeted agents remains dependent on cost and reimbursement.

Longitudinal evidence is now needed particularly for the CKM group. Changes in performance status, quality of life, cardiovascular and renal events, treatment interruptions and mortality will help determine whether the pattern identified here has prognostic value beyond conventional comorbidity indices. It will also be important to establish whether comorbidity patterns add value to existing clinical assessment and identify individuals who may benefit from earlier cardio-oncology [32], nephrology input or more coordinated management of multimorbidity [40]. Ultimately, how such care is best shared between oncology, primary care and specialist services will depend on the health system and warrants investigation alongside clinical outcomes.

Conclusion

Our findings suggest that the pattern of comorbidity rather than its count alone may be clinically informative in routine oncology care. The CKM and multisystem classes had high comorbidity index scores but differed substantially in performance status and treatment receipt, distinctions that a simple comorbidity count would not have captured. One in three participants had CKM conditions. Their receipt of standard cancer therapies was similar to that of patients with low comorbidity, while performance status did not reflect the cardiovascular, metabolic and renal risks they carried into treatment. In settings where access to imaging, high-cost biomarkers and specialist care is limited, comorbidity patterns derived from routinely available clinical information may offer a pragmatic way to identify patients who warrant more detailed risk factor assessment and closer monitoring from diagnosis onward. The multisystem pattern requires validation in larger cohorts.

Abbreviations aOR: Adjusted odds ratio; BC: Breast cancer; CDK4/6i: CDK4/6 inhibitors; CCI: Charlson Comorbidity Index; CKD: Chronic kidney disease; CRC: Colorectal cancer; CI: Confidence intervals; ECOG: Eastern Cooperative Oncology Group; HR: Hormone receptor; LCA: Latent class analysis; LMICs: Low- and middle-income countries; mCCI: Modified Charlson Comorbidity Index; O/E: Observed to expected; OR: Odds ratios

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Data availability Data are available on reasonable request from the corresponding author. Restrictions apply due to ongoing data collection and ethical requirements related to participant privacy.

Declarations

Ethics approval National Medical Research Registry and Medical Research and Ethics Committee (NMRR ID 21-1757-60381(IIR); NMRR-21-1758-61030(IIR); NMRR-21-1153-58621(IIR)), University of Malaya Research Ethics Committee (20181016-6757, 202183-10444, 2021722-10405), SJMC (202112.01, 202203.2, 202204.1), KPJ (kpj_004/2002), PHKL (PHKL-EC-2022-0002, PHKL-EC-2022-0004).

Consent to participate Informed consent was obtained from all individual participants included in the study.

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References

- Sung H, Ferlay J et al (2021) Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA Cancer J Clin* 71(3):209–249. <https://doi.org/10.3322/caac.21660>
- Bluthmann SM, Mariotto AB, Rowland JH (2016) Anticipating the “silver tsunami”: prevalence trajectories and comorbidity burden among older cancer survivors in the United States. *Cancer Epidemiol Biomarkers Prev* 25(7):1029–1036. <https://doi.org/10.1158/1055-9965.Epi-16-0133>
- Dee EC, Laversanne M et al (2022) Cancer incidence and mortality estimates in 2022 in Southeast Asia: a comparative analysis. *Lancet Oncol*. [https://doi.org/10.1016/s1470-2045\(25\)00017-8](https://doi.org/10.1016/s1470-2045(25)00017-8)
- Bhoo-Pathy N, Taylor C, Unger-Saldana K (2024) Operationalizing patient-centered cancer care in low- and middle-income countries. *Cell Rep Med* 5(5):101517. <https://doi.org/10.1016/j.xcrm.2024.101517>
- Sarfati D (2012) Review of methods used to measure comorbidity in cancer populations: no gold standard exists. *J Clin Epidemiol* 65(9):924–933. <https://doi.org/10.1016/j.jclinepi.2012.02.017>
- McAlister FA, Savu A et al (2020) The hospital frailty risk score in patients with heart failure is strongly associated with outcomes but less so with pharmacotherapy. *J Intern Med* 287(3):322–332. <https://doi.org/10.1111/joim.13002>
- Leong JE, Tan BJW et al (2024) Comparative analysis of clinical comorbidity assessment tools in cancer. *Cancer Surviv Res Care* 2(1):2407969. <https://doi.org/10.1080/28352610.2024.2407969>
- Subramaniam S, Kong YC et al (2023) Association between pre-existing cardiometabolic comorbidities and the pathological profiles of breast cancer at initial diagnosis: a cross sectional study. *Ecancer-medicalscience* 17:1512. <https://doi.org/10.3332/ecancer.2022.1512>
- Wadasadawala T, Datta D et al (2023) Prospective study of incidence and impact of comorbidities on breast cancer survival from India. *Asian Pac J Cancer Prev* 24(11):3805–3814. <https://doi.org/10.31557/apjcp.2023.24.11.3805>
- Scott JM, Stene G et al (2020) Performance status in cancer: not broken, but time for an upgrade? *J Clin Oncol* 38(25):2824–2829. <https://doi.org/10.1200/jco.20.00721>
- George M, Smith A et al (2021) Physical comorbidities and their relationship with cancer treatment and its outcomes in older adult populations: systematic review. *JMIR Cancer* 7(4):e26425. <https://doi.org/10.2196/26425>
- Edwards MJ, Campbell ID et al (2017) Influence of comorbidity on chemotherapy use for early breast cancer: systematic review and meta-analysis. *Breast Cancer Res Treat* 165(1):17–39. <https://doi.org/10.1007/s10549-017-4295-4>
- Launay-Vacher V, Oudard S et al (2007) Prevalence of renal insufficiency in cancer patients and implications for anticancer drug management: the renal insufficiency and anticancer medications (IRMA) study. *Cancer* 110(6):1376–84. <https://doi.org/10.1002/cncr.22904>
- Ng HS, Meng R et al (2024) Cardiovascular mortality in people with cancer compared to the general population: a systematic review and meta-analysis. *Cancer Med* 13(15):e70057. <https://doi.org/10.1002/cam4.70057>
- Bank, W. *Malaysia: overview*. 2025 19 November 2025]; Available from: <https://www.worldbank.org/en/country/malaysia/overview>.
- Charlson ME, Carrozzino D et al (2022) Charlson comorbidity index: a critical review of clinimetric properties. *Psychother Psychosom* 91(1):8–35. <https://doi.org/10.1159/000521288>
- Simcock R, Wright J (2020) Beyond performance status. *Clin Oncol (R Coll Radiol)* 32(9):553–561. <https://doi.org/10.1016/j.clon.2020.06.016>
- Costas-Chavarri A, Nandakumar G et al (2019) Treatment of patients with early-stage colorectal cancer: ASCO resource-stratified guideline. *J Glob Oncol* 5:1–19. <https://doi.org/10.1200/jgo.18.00214>
- Cardoso F, Costa A et al (2014) ESO-ESMO 2nd international consensus guidelines for advanced breast cancer (ABC2). *Breast* 23(5):489–502. <https://doi.org/10.1016/j.breast.2014.08.009>
- Cardoso F, Paluch-Shimon S et al (2024) 6th and 7th international consensus guidelines for the management of advanced breast cancer (ABC guidelines 6 and 7). *Breast* 76:103756. <https://doi.org/10.1016/j.breast.2024.103756>
- Sinha P, Calfee CS, Delucchi KL (2021) Practitioner’s guide to latent class analysis: methodological considerations and common pitfalls. *Crit Care Med* 49(1):e63–e79. <https://doi.org/10.1097/ccm.0000000000004710>
- Naldi L, Cazzaniga S (2020) Research techniques made simple: latent class analysis. *J Invest Dermatol* 140(9):1676–1680.e1. <https://doi.org/10.1016/j.jid.2020.05.079>
- Ng HS, Woodman R et al (2025) Comorbidity patterns and mortality in atrial fibrillation: a latent class analysis of the EUROpean study of older subjects with atrial fibrillation (EUROSOF). *Ann Med* 57(1):2454330. <https://doi.org/10.1080/07853890.2025.2454330>
- Hernán MA, Hernández-Díaz S et al (2002) Causal knowledge as a prerequisite for confounding evaluation: an application to birth defects epidemiology. *Am J Epidemiol* 155(2):176–184. <https://doi.org/10.1093/aje/155.2.176>
- Datta SS, Ghosal N et al (2019) How do clinicians rate patient’s performance status using the ECOG performance scale? A mixed-methods exploration of variability in decision-making in oncology. *ecancermedsci* 13:913. <https://doi.org/10.3332/ecancer.2019.913>
- Sandhu G, Adattini J et al (2025) Integrating international consensus guidelines for anticancer drug dosing in kidney dysfunction (ADDIKD) into everyday practice. *eClinicalMedicine* 82:103161. <https://doi.org/10.1016/j.eclinm.2025.103161>
- Hong YW, Kuo IM et al (2024) The influence of chronic renal insufficiency on multi-therapeutic modalities for breast cancer: a single-center experience. *Breast Cancer (Auckl)* 31(2):252–262. <https://doi.org/10.1007/s12282-023-01530-w>
- Ndumele CE, Rangaswami J et al (2023) Cardiovascular-kidney-metabolic health: a presidential advisory from the American Heart Association. *Circulation* 148(20):1606–1635. <https://doi.org/10.1161/cir.0000000000001184>
- Ko T, Suzuki Y et al (2025) Cardiovascular-kidney-metabolic syndrome stage predicts cardiovascular outcomes in cancer patients: a real-world data analysis of a nationwide epidemiological dataset. *Eur Heart J Open* 5(5):oeaf115. <https://doi.org/10.1093/ehjopen/oeaf115>
- Yang H, Bhoo-Pathy N et al (2022) Risk of heart disease following treatment for breast cancer - results from a population-based cohort study. *Elife*. <https://doi.org/10.7554/eLife.71562>

31. Subramaniam S, Kong YC et al (2021) Baseline cardiovascular comorbidities, and the influence on cancer treatment decision-making in women with breast cancer. *Ecancermedalscience* 15:1293. <https://doi.org/10.3332/ecancer.2021.1293>
32. Lyon AR, López-Fernández T et al (2022) 2022 ESC guidelines on cardio-oncology developed in collaboration with the European Hematology Association (EHA), the European Society for Therapeutic Radiology and Oncology (ESTRO) and the International Cardio-Oncology Society (IC-OS). *Eur Heart J* 43(41):4229–4361. <https://doi.org/10.1093/eurheartj/ehac244>
33. Cai YW, Gao JW et al (2026) Comprehensive multiple risk factor control in cancer survivors to mitigate heart failure risk: insights from a prospective cohort study. *Eur J Prev Cardiol* 33(4):578–586. <https://doi.org/10.1093/eurjpc/zwaf711>
34. Alizadehasl A, Amin A et al (2020) Cardio-oncology discipline: focus on the necessities in developing countries. *ESC Heart Fail* 7(5):2175–2183. <https://doi.org/10.1002/ehf2.12838>
35. Pham TT, Connor AE, Rositch AF (2026) Multimorbidity and cancer treatment among the older patients in the United States. *PLoS ONE* 21(1):e0338721. <https://doi.org/10.1371/journal.pone.0338721>
36. Smith A, Boby JM et al (2024) Immunotherapy in older patients with cancer: a narrative review. *Int J Gen Med* 17:305–313. <https://doi.org/10.2147/ijgm.S435001>
37. Sautter-Bühl ML, Souchon R, Gerber B (2011) Adjuvant therapy for women over age 65 with breast cancer. *Dtsch Arztebl Int* 108(21):365–371. <https://doi.org/10.3238/arztebl.2011.0365>
38. Jaya-Prakason S, Kong Y-C et al (2024) Trends in presentation, management, and survival of women with breast cancer in a multiethnic, middle-income Asian setting. *JCO Glob Oncol* 10:e2400054. <https://doi.org/10.1200/go.24.00054>
39. Abravan A, Faivre-Finn C et al (2024) Comorbidity in patients with cancer treated at The Christie. *Br J Cancer* 131(8):1279–1289. <https://doi.org/10.1038/s41416-024-02838-w>
40. Jeon S, Sikorskii A et al (2019) Latent transition analysis of the symptom experience of cancer patients undergoing chemotherapy. *Nurs Res* 68(2):91–98. <https://doi.org/10.1097/nnr.0000000000000332>

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