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Co-Occurring Depressive Symptoms, Malnutrition Risk and Fall-Related Mobility Risk Among Community-Dwelling Older Adults in Maha Sarakham Province, Thailand: A Latent Class Analysis

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Highlights

What are the main findings?

- Among 12,115 community-dwelling older adults in 39 purposively selected subdistricts of Maha Sarakham Province, Thailand, depressive symptoms, malnutrition risk and fall-related mobility risk were mutually associated, and all three co-occurred about six times more often than expected by chance, largely because of their pairwise associations.
- Latent class analysis identified an exploratory, model-dependent complex multidomain profile (6.5% in the main model; 0.9–11.7% across indicator specifications), characterised mainly by gait impairment and malnutrition risk (only about one-quarter of its members were expected to have all three conditions) and associated with older age, not working, household debt, multimorbidity, study-defined polypharmacy (>3 medications/day) and home hazards.

What are the implications of the main findings?

- Jointly interpreting depression, nutrition and fall-risk screening results already collected in Thai primary care to prompt a fuller integrated assessment is a hypothesis that requires prospective validation; classification of individuals was uncertain, and a simple two-or-more-conditions rule agreed only partly with class membership.
- Many older adults with co-occurring risks may fall outside dependency-focused long-term care, so coordinated health, social welfare and home-modification support at the subdistrict level should be tested in prospective studies.

Abstract

Background/Objectives: Depressive symptoms, malnutrition and falls are common geriatric syndromes with shared risk factors, yet they are usually studied separately. We aimed to identify latent subgroups defined by their co-occurrence among older adults in 39 subdistricts of Maha Sarakham Province, Thailand, and the factors associated with membership. **Methods**: In this cross-sectional survey (October–December 2025), 12,115 community-dwelling adults aged ≥60 years were interviewed. Latent class indicators were the Thai 9-item depression scale, Mini Nutritional Assessment Short-Form (MNA-SF), calf circumference, recent falls and gait impairment or walking-aid use. Associated factors were estimated

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with bias-adjusted three-step models and small-sample-corrected cluster-robust inference. **Results**: Depressive symptoms affected 8.4%, malnutrition risk (MNA-SF ≤ 11) 24.5% and fall-related mobility risk 17.0% (recent fall 3.7%; gait impairment or walking aid 14.9%); all three co-occurred in 2.2%, 6.2 times more often than expected under independence, mainly reflecting pairwise associations. Three classes emerged: low-burden (77.3%), nutritional risk (16.2%) and complex multidomain (6.5%; 0.9–11.7% across specifications). The complex multidomain class featured gait impairment (78.2%) and malnutrition risk (70.2%), with elevated depressive symptoms (40.9%) and recent falls (26.8%); an estimated one-quarter of members had all three conditions. Membership was associated with age ≥ 80 years (adjusted odds ratio 4.39, 95% CI 2.57–7.48), not working (4.23, 2.45–7.29), high household debt (2.45, 1.22–4.91), ≥2 chronic conditions (3.54, 2.17–5.78), study-defined polypharmacy (2.45, 1.69–3.55) and per additional home hazard (1.44, 1.28–1.62). **Conclusions**: A small, model-dependent subgroup characterised mainly by mobility impairment, malnutrition risk and socioeconomic disadvantage was identified. Because class size and individual assignment were uncertain, the classes describe population-level patterns; whether jointly interpreting existing screening results improves the targeting of integrated care requires prospective evaluation.

Keywords: latent class analysis; depressive symptoms; malnutrition; accidental falls; older adults; Thailand

1. Introduction

Thailand is one of the most rapidly ageing middle-income countries. Adults aged 60 years or older made up about one-fifth of the population in 2024, and this proportion is projected to reach 28% within the next decade, when Thailand becomes a super-aged society [1]. In Maha Sarakham, a predominantly agricultural province in the Northeast, 20.3% of residents are aged 60 years or older [2]. Among the health problems that accompany this transition, depressive symptoms, malnutrition and falls are common and consequential. Falls are the second leading cause of unintentional injury death worldwide; adults aged over 60 years sustain the greatest number of fatal falls, and more than 80% of fall-related deaths occur in low- and middle-income countries [3]. In Thailand, a meta-analysis estimated that 37.8% of older adults are at risk of malnutrition on the Mini Nutritional Assessment Short-Form [4]; depression was identified in 18.5% of older adults in a rural community study [5] and in 17.7% of rural older adults in Southeast Asian studies pooled in a regional meta-analysis [6]; and 34.5% of rural older adults in Maha Sarakham reported a fall in the previous six months [7].

These three conditions are unlikely to occur independently. They are geriatric syndromes: multifactorial conditions that share risk factors such as older age, functional and mobility impairment and multimorbidity, and that converge on common outcomes including disability and loss of independence [8]. Malnutrition is associated with approximately twice the odds of depression in older adults (pooled odds ratio 2.03, 95% CI 1.47–2.81) [9], and both depression and malnutrition have been associated with a higher risk of falls [10], although reviews have not consistently found an association between depression and falls [11]. Reflecting this interdependence, the World Health Organization's Integrated Care for Older People (ICOPE) approach frames declines in mobility, vitality (including nutrition) and psychological capacity as related domains of intrinsic capacity that should be assessed and managed together in the community rather than condition by condition [12].

Despite this, most epidemiological studies examine these conditions one at a time or in pairs. Such variable-centred analyses estimate average associations across the population,

but they cannot show how conditions combine within individuals, which subgroups carry the greatest combined burden, or whom integrated care should prioritise. Person-centred methods such as latent class analysis (LCA) address these questions by identifying unobserved subgroups with distinct patterns of co-occurring conditions, which can then inform targeted interventions [13]. Studies that have applied LCA to intrinsic capacity in China have identified subgroups with concurrent declines in several domains, including locomotion, psychological function and vitality; in one community sample, a small class with declines in locomotion, psychological function, cognition and vitality had more disability and more hospitalisation over one year [14], and in a rural sample, class membership was associated with living alone, lower household income, work participation and use of multiple medications, among other factors [15]. This evidence, however, comes from relatively small samples of about 600–760 participants in China, has rarely examined socioeconomic and home-environment factors that local governments can act on, and has seldom accounted for the clustering of older adults within communities. Co-occurring geriatric syndromes, including depressive symptoms, malnutrition and falls, have also been described in community-dwelling older adults in China, but with counts and regression models rather than latent subgroups [16], and latent class analyses of older adults in Southeast Asia have addressed other outcomes, such as physical limitations in Viet Nam [17]. Our search of the literature did not identify any study that has applied a person-centred approach to depressive symptoms, malnutrition risk and fall-related mobility risk among older adults in Thailand or elsewhere in Southeast Asia.

This gap has practical consequences. Thailand's community-based long-term care programme, introduced in 2016 under the Universal Coverage Scheme and delivered through local administrative organisations, care managers and trained caregivers, focuses on older people who are already dependent [18]. Older adults who remain independent but have co-occurring psychological, nutritional and mobility-related risks, among whom prevention might delay dependency, fall largely outside its core services. Although depressive symptoms, nutritional status and fall risk are screened in Thai primary care, the resulting data are held in separate information systems and are rarely combined to identify people with multiple risks. Identifying a subgroup with co-occurring risks, and the social and environmental factors associated with belonging to it, could show how existing screening data might be used to target integrated prevention at the subdistrict level.

This study used data from 12,115 community-dwelling older adults in 39 subdistricts of Maha Sarakham Province to (1) estimate the prevalence of depressive symptoms, malnutrition risk and fall-related mobility risk and the extent to which they co-occur beyond chance; (2) identify latent classes of older adults defined by these conditions; (3) examine the demographic, socioeconomic, health, behavioural and home-environment factors associated with class membership, accounting for clustering within subdistricts; and (4) examine concurrently measured external correlates of the classes (self-rated health relative to peers, self-reported ability to look after oneself and difficulty eating) to aid the descriptive interpretation of the classes, because these items were measured at the same interview and with the same instrument as the nutritional indicators, they were not intended as independent criterion measures. We hypothesised that a distinct subgroup with co-occurring depressive symptoms, malnutrition risk and fall-related mobility risk would be identifiable and that membership would be socially patterned.

2. Materials and Methods

2.1. Study Design and Setting

Maha Sarakham is a predominantly agricultural province in which 190,402 residents (20.32%) were aged 60 years or older in 2025, meeting the definition of a fully aged society [2].

Care for older people in the province is provided through subdistrict health-promoting hospitals, local administrative organisations (LAOs), village health volunteers and trained community caregivers under the Older Persons Act and the national long-term care programme [19,20]. The study is reported in accordance with the STROBE statement for cross-sectional studies [21]; the completed checklist is provided as Supplementary File S2.

2.2. Data Source

Data were collected between October and December 2025 through face-to-face interviews at participants' homes. In each subdistrict, 7–12 interviewers were nominated by the subdistrict health-promoting hospital and trained by the research team in October 2025 in the study procedures, administration of the questionnaire, anthropometric measurement and use of the electronic data-collection form. Training lasted one day: the morning covered research ethics and the components of the instrument, and the afternoon covered the questionnaire item by item, with demonstration and supervised practice of the anthropometric measurements, including the use of the measuring tape. The validated paper questionnaire was converted into an online form (Google Forms), on which interviewers recorded responses directly during the interview; this avoided paper forms and repeated data entry. The research team supplied measuring equipment, including digital weighing scales and measuring tapes. Identifying information was removed before the dataset was released for this analysis.

2.3. Sampling and Sample Size

Forty subdistricts, each corresponding to one LAO, were selected purposively from the research network on the basis of data-system readiness—an established older-adult database and ongoing systematic community health activities. The sites were distributed across 12 of the province's 13 districts and ranged from rural subdistrict administrative organisations to the provincial municipality (Talat subdistrict, Mueang District). The target sample size for each subdistrict was calculated with Yamane's formula [22], $n = N/(1 + \mathrm{Ne2})$ with e = 0.05, using the number of residents aged ≥60 years registered with the Department of Provincial Administration on 30 April 2025 (60,478 in total), giving a planned sample of 12,039 (240–383 per subdistrict) (Table S1). One subdistrict (Khwao, Mueang District; planned $n = 354$) was not surveyed. In the remaining 39 subdistricts, 12,115 older adults from 527 villages were interviewed, 103.7% of the planned 11,685; the target was exceeded in 27 subdistricts (by up to 44.2%, in Ku Santarat; 478 interviews beyond the targets in total), met exactly in seven and 93.2–99.7% reached in the other five. The overall sampling fraction was 21.1% (range 4.0% in the municipality to 48.5%). The study protocol specified the calculated sample size as the minimum number of participants required in each subdistrict rather than as a fixed quota. Within each subdistrict, older adults were selected at random from the registry of older residents; interviewers then confirmed eligibility at the home visit and invited each selected person to participate. Because the calculated number was a minimum, data collection was not stopped once it had been reached: in 27 subdistricts, interviewers continued to invite older residents of the same subdistrict who met the eligibility criteria during the scheduled data-collection period, using the same consent procedure and questionnaire, which yielded 478 interviews beyond the minimum. The order in which these additional residents were approached was not documented, so we cannot confirm that they were selected at random, and they may have been more accessible to interviewers than other residents. In total, at least 12,125 older adults were invited to participate, against a required minimum of 11,685 in the 39 surveyed subdistricts: 12,115 were interviewed and 10 declined (their subdistricts were not recorded), a participation rate of 99.9% among those whose invitation was recorded. Interviewers and local coordinators reported no older

adults who could not be contacted, who were found ineligible at the visit or who were replaced by another resident; however, these events were not recorded systematically on the data-collection form, so their numbers may be underestimated, and the participation rate should be regarded as an upper bound. Within-subdistrict selection should therefore be regarded as approximating, rather than strictly following, simple random sampling with a fixed sample size. The 478 additional interviews made up 3.9% of the analysed sample; if more accessible residents were healthier or more mobile, their inclusion would bias prevalence estimates slightly downwards. Because these interviews were conducted with the same eligibility criteria, consent procedure and questionnaire, they were retained in all analyses; their possible influence was examined in a bounding analysis (see Sensitivity analyses in the Methods and Between-subdistrict heterogeneity and sensitivity analyses in the Results). The participant flow is shown in Figure 1.

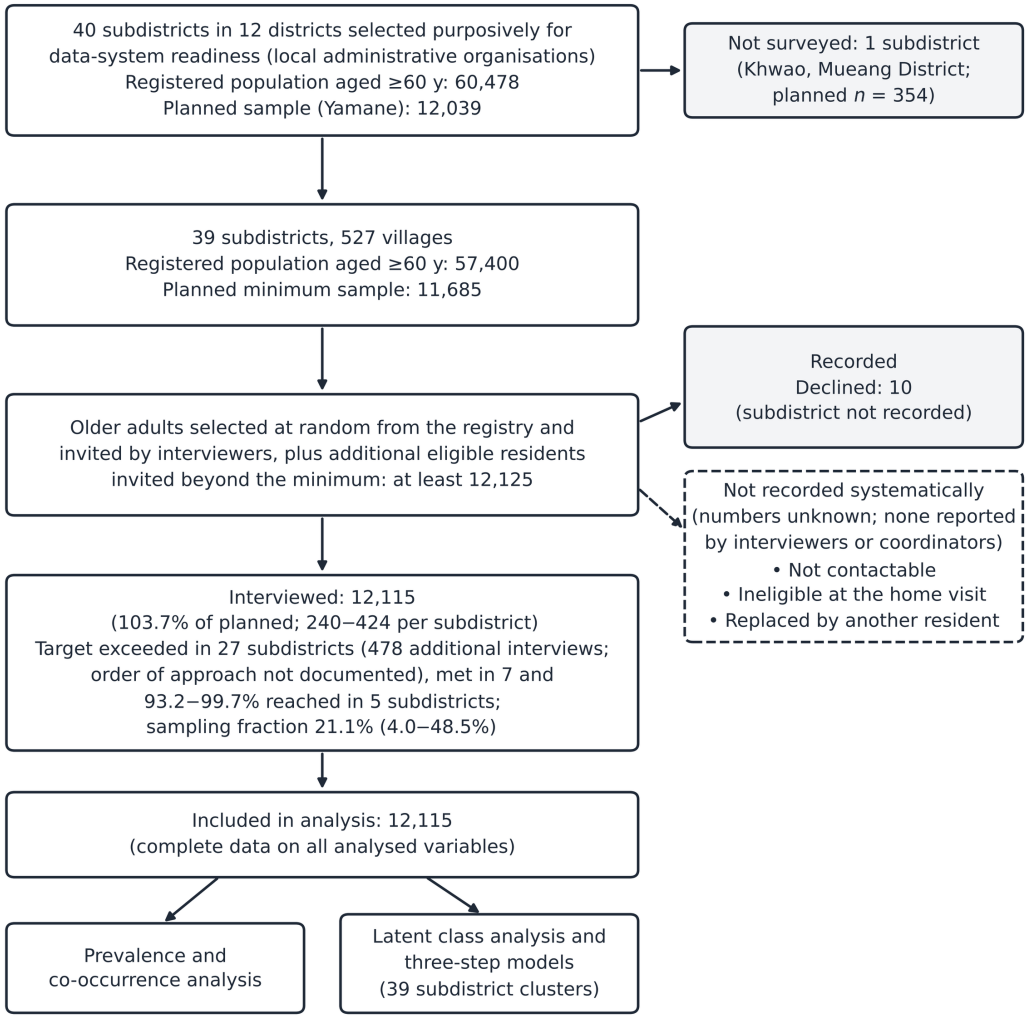

Figure 1. Flow of subdistricts and participants.

Because selection of subdistricts was purposive and sampling fractions differed markedly between subdistricts, we treated subdistricts as clusters in all inferential analyses and reported estimates weighted to the registered older population of the study subdistricts as a sensitivity check (see Section 2.8). The target population for inference is therefore the registered older population of the 39 study subdistricts, not the province or rural Northeast Thailand as a whole. Cluster-robust inference treats the subdistricts as clusters from a

hypothetical population of similar subdistricts; it accounts for within-subdistrict correlation but does not correct for their purposive selection.

2.4. Participants

Eligible participants were aged 60 years or older on the date of interview, had lived in the study area for at least six months, were able to communicate and provide information themselves (or with an authorised assistant) and gave informed consent. An authorised assistant could help participants who had difficulty communicating. The electronic form did not record whether, or on which items, assistance was given, so the number of assisted interviews cannot be reported; the implications are considered under Strengths and limitations in the Discussion. Older adults with severe dementia or neurological disorders that prevented an interview, those who declined or could not consent, and those who were acutely ill or hospitalised during data collection were excluded. People who met an exclusion criterion at the home visit were not interviewed (Figure 1). All 12,115 interviewed participants had complete data for the variables analysed, and no records were excluded from the analysis.

2.5. Survey Instrument

The interviewer-administered structured data-collection instrument ("Health and well-being interview for people aged 60 years and over") comprised three parts: (1) socioeconomic characteristics (17 items); (2) health, in five sections—health screening and medical history (7 items), health behaviours according to the Thai "3A–2S–1F" framework (healthy eating, physical activity, emotional management, smoking cessation, alcohol avoidance, and oral and dental health care) (23 items), depression screening with the 2Q and 9Q (11 items), the full Mini Nutritional Assessment (MNA; 18 items including anthropometry) and a fall-risk assessment based on the Morse Fall Scale (6 items); and (3) the home and surrounding environment (15 items). Standardised instruments were used in their official Thai versions: the 9Q of the Department of Mental Health [23], the MNA (validated in Thai older adults [24]) and the health-behaviour assessment developed by the Health Education Division, Department of Health Service Support [25]. The home-environment checklist was developed by the project team from fall-prevention literature, including evidence from rural Thailand on the association between the living environment and fall risk [26]. The content validity of the complete questionnaire, including the home-environment checklist, was assessed by five experts using the index of item–objective congruence (IOC) [27]; the IOC for the instrument as a whole was 0.991, which indicates expert agreement on the relevance of the items rather than the validity of any single measure. Item-level and scale-level content validity indices (I-CVI and S-CVI) were not calculated. Before data collection, the questionnaire was tried out with 34 older adults in Kham Riang Subdistrict, Kantharawichai District, an area outside the study sites. Because the instrument combines heterogeneous socioeconomic, health, behavioural, nutritional, fall-related and environmental items, it is not a single scale, and the internal-consistency coefficient computed for the instrument as a whole in the pilot (Cronbach's α 0.897) does not indicate the reliability of its component measures. Reliability was therefore considered instrument by instrument: the 9Q is a unidimensional symptom scale validated in Thai [23], with an internal consistency in the present sample of Cronbach's $\alpha = 0.921$ (95% CI 0.919–0.923; $n = 12{,}115$); the MNA-SF and the Morse items are clinical screening indices whose items are not expected to be internally consistent, so their validity rests on published validation studies [24]; and the home hazard score is a count of observed hazards rather than a reflective scale. Separate IOC coefficients for the home-environment checklist are not available. Weight, height, mid-arm circumference and

calf circumference were measured by the trained interviewers using a digital weighing scale and a measuring tape supplied by the research team.

2.6. Measures

2.6.1. Latent Class Indicators

Five indicators representing three interrelated domains—depressive symptoms, nutritional vulnerability, and fall-related mobility risk—were used to identify latent subgroups of community-dwelling older adults. These indicators comprised depressive symptom severity assessed using the Thai 9-item depression scale (9Q), nutritional status assessed using the Mini Nutritional Assessment Short-Form (MNA-SF), calf circumference, recent fall history, and gait impairment or walking-aid use. The indicators were selected based on their clinical relevance to geriatric health, availability in the community health survey, and potential applicability to integrated screening in Thai primary healthcare settings.

Depressive symptoms. Depressive symptoms were assessed using the Thai 9Q developed by the Department of Mental Health [23]. The instrument evaluates nine depressive symptoms experienced during the preceding two weeks, with each item scored from 0 (never) to 3 (every day), yielding a total score ranging from 0 to 27. Although the national screening protocol generally administers the 9Q following a positive two-question depression screen (2Q), all participants in this study completed the 9Q. Scores were categorised according to the Department of Mental Health thresholds as no depressive symptoms (0–6), mild depressive symptoms (7–12), and moderate-to-severe depressive symptoms (≥13). For descriptive and co-occurrence analyses, depressive symptoms were operationally defined as a 9Q score ≥ 7. These categories reflect screening-based symptom severity rather than a clinical diagnosis of depressive disorder.

Nutritional status. Nutritional vulnerability was assessed using the MNA-SF, a screening instrument comprising six components: reduced food intake, recent weight loss, mobility, acute illness or psychological stress, neuropsychological problems, and body mass index (BMI). The total score ranges from 0 to 14, with established categories of normal nutritional status (12–14), risk of malnutrition (8–11), and malnutrition according to the screening classification (0–7) [28]. For the co-occurrence analyses, an MNA-SF score ≤11 was used to identify participants with nutritional risk, combining those classified as at risk of malnutrition and those screening positive for malnutrition. Importantly, the MNA-SF is a screening rather than a diagnostic instrument; consequently, these categories should not be interpreted as confirming clinical malnutrition without further assessment using established diagnostic criteria. Calf circumference was included as an additional anthropometric indicator of nutritional and physical vulnerability. It was derived from item R of the full MNA and dichotomised as <31 cm or ≥31 cm. This threshold reflects the original MNA scoring system but is lower than the sex-specific thresholds recommended for identifying low muscle mass in Asian populations (34 cm for men and 33 cm for women) [29]. Because calf circumference was recorded only as a categorical MNA item score rather than as a continuous measurement in centimetres, alternative thresholds could not be applied retrospectively. Accordingly, calf circumference <31 cm was interpreted as an anthropometric marker of nutritional and physical vulnerability rather than a diagnostic measure of reduced muscle mass or sarcopenia. Its inclusion provided complementary information to the MNA-SF, although the two indicators may share underlying nutritional and functional characteristics.

Fall-related mobility risk. Fall-related mobility risk was assessed using selected items from the Morse Fall Scale [30], which includes six components: recent fall history, secondary medical diagnoses, ambulatory aid use, intravenous therapy, gait characteristics, and mental status. Because the original scale was developed primarily for hospitalised patients, its total score may not be directly applicable to community-dwelling older adults. Therefore,

the primary LCA used two indicators considered relevant to community settings [31]: (1) a self-reported fall during the preceding three months and (2) gait impairment or walking-aid use, defined as a non-zero score on the corresponding Morse items. For descriptive and co-occurrence analyses, fall-related mobility risk was defined as the presence of either indicator. These measures were intended to capture complementary aspects of mobility-related vulnerability rather than to estimate the probability of future falls. Recent fall history represents an observed event, whereas gait impairment and walking-aid use indicate potential functional limitations. Because gait impairment or walking-aid use was more prevalent than recent falls, the composite measure primarily reflected mobility-related limitations. It should therefore not be interpreted as a validated community fall-risk prediction score or as a direct measure of fall incidence. The two components were retained separately in the LCA to preserve their distinct clinical meanings. The conventional Morse Fall Scale categories (<25, 25–44, and ≥45) were examined in a sensitivity analysis to evaluate the influence of alternative fall-risk specifications.

Indicator overlap and local independence. An important methodological consideration was the potential conceptual and measurement overlap among the selected indicators. The MNA-SF includes a mobility component (item C), which overlaps with gait impairment and walking-aid use, and a neuropsychological component (item E), which may overlap with depressive symptoms. In the Thai questionnaire, item E was administered in terms of memory problems, potentially reducing, but not eliminating, this overlap. In addition, calf circumference and MNA-SF scores represent related aspects of nutritional vulnerability, although calf circumference was not directly incorporated into the BMI-based MNA-SF score used in the primary analysis. Such overlap may introduce residual associations between indicators within latent classes, potentially violating the conditional local independence assumption of conventional LCA. Consequently, the resulting classes may partly reflect shared measurement content rather than entirely distinct underlying health profiles. To evaluate this possibility, bivariate residuals were examined, and several sensitivity analyses were conducted. These included removing calf circumference (SA1), recalculating nutritional risk using four MNA-SF components excluding mobility and neuropsychological items (SA7), and combining MNA-SF and calf circumference into a single categorical indicator (SA10). The primary model retained the original screening indicators and established scoring thresholds to reflect the information available through routine community health assessments in Thai primary care. However, particular emphasis was placed on SA7 when evaluating the robustness of the multidomain profiles because this specification reduced conceptual overlap while retaining information from the three principal health domains. Differences in class prevalence, indicator-response probabilities, and classification agreement across specifications were considered when interpreting the stability and clinical relevance of the identified classes. Overall, the selected indicators were intended to characterise population-level patterns of co-occurring psychological, nutritional, and mobility-related vulnerabilities. The resulting latent classes were interpreted as exploratory statistical profiles rather than clinically validated diagnostic categories or instruments for individual risk classification.

2.6.2. Covariates

Covariates were specified a priori within a social-determinants framework and grouped into four blocks. (i) Demographic: age group (60–69, 70–79, ≥80 years) and sex. (ii) Socioeconomic and social: marital status (married; widowed; single, divorced or separated), education (no schooling or primary vs. secondary or higher), main occupation (agriculture; not working; other), personal monthly income (≤1000; 1001–3000; 3001–5000; >5000 baht), self-reported insufficiency of monthly income, level of current household debt (none, low,

moderate, high), living alone, having no main family caregiver, holding a community role (e.g., village head, village health volunteer, village committee member, local sage) and participation in an elderly school, community welfare fund, religious activity or community club. (iii) Health and behaviour: number of self-reported physician-diagnosed chronic conditions (14 in total: diabetes, hypertension, chronic obstructive pulmonary disease, cancer, cardiovascular disease, dyslipidaemia, stroke, kidney disease, liver disease, genetic disease, metabolic syndrome, thyroid disease, gout and musculoskeletal disorders; categorised 0, 1, ≥2), study-defined polypharmacy (>3 medications per day, the threshold used in MNA item H [32]; this is lower than the commonly used threshold of ≥5 medications [33] and therefore identifies a broader group) and five health behaviours from the 3A–2S–1F assessment. Items are rated for the past week on a five-point frequency scale (every day, 5–6, 3–4, 1–2 days, never) and scored 1–5, with 5 representing the most favourable behaviour; we defined vigorous physical activity on ≥3 days, consumption of at least five handfuls (400 g) of fruit and vegetables on ≥5 days, any smoking, any alcohol use and tooth-brushing with fluoride toothpaste at least twice daily every day. (iv) Home environment: a home hazard score counting 11 hazards observed or reported—structurally unsound house, door thresholds, uneven floor levels, sleeping on the floor, toilet outside the house, squat toilet, no bathroom grab bar, a built-in cement water tank in the bathroom (a bending, syncope and drowning hazard), hazardous walkway around the house, clutter of unused items and hazardous materials—and cooking with charcoal. The hazard score is a simple count rather than a validated scale, and two items were very common (no grab bar, 83.7%; door thresholds, 66.9%); a nine-item score excluding them was used in a sensitivity analysis. Body mass index was not used as a covariate because it is a component of the MNA-SF.

2.6.3. Measurement of Concurrent External Correlates

To further characterise the clinical and functional profiles of the identified latent classes, three concurrently measured variables from the Mini Nutritional Assessment (MNA) were examined as external correlates. These variables were not included as indicators in the latent class models and comprised (1) self-rated health compared with that of peers (MNA item P; question 16 of the Thai questionnaire), (2) perceived ability to look after oneself (MNA item G; question 7), and (3) difficulty eating or requiring assistance with eating (MNA item N; question 14). These measures were selected to provide supplementary descriptive information on perceived health, self-care ability, and eating-related functional difficulties across the latent classes. Self-rated health was operationalised as reporting poorer health than peers, providing a subjective assessment of overall health status. Perceived self-care ability was assessed using MNA item G. Although the standard MNA asks whether an individual lives independently rather than in a nursing home or hospital, the Thai questionnaire asks whether the respondent is able to look after himself or herself. Consequently, responses may reflect perceived self-care capacity as well as residential circumstances. This variable was therefore interpreted as a self-reported indicator of perceived self-care ability rather than an objective measure of functional dependence or limitations in activities of daily living (ADL), which were not independently assessed in this study. Eating-related functional difficulty was assessed using MNA item N and reflected self-reported difficulty eating or the need for assistance during meals. Class-specific prevalences of these three variables were estimated to describe differences in concurrent health and functional characteristics across the latent profiles. Because all three variables were obtained during the same interview and originated from the MNA instrument, their associations with latent class membership may be influenced by shared-method variance, correlated measurement content, and common underlying health characteristics. In particular, eating-related difficulties may be conceptually associated with the nutritional indicators used to define the latent classes. Accordingly,

these variables were treated as concurrent external correlates for descriptive interpretation, rather than independent distal outcomes or criterion measures for validating the latent class solution. Differences between classes were interpreted as cross-sectional associations and were not considered evidence of temporal relationships, causal effects, predictive validity, or external validation of the identified classes.

2.7. Data Management and Quality Control

The raw dataset was not modified; all cleaning and derivation steps were scripted and logged. There were no missing values or duplicate records. Body mass index was recomputed from weight and height because the stored value was inconsistent with them; the MNA body-mass-index item score agreed with the recomputed value in all records. Coding of marital status and of five home-environment items was verified with the data owner; for two environment items (bathroom grab bar and walkway hazard), the value labels initially supplied were reversed. The reversal was first suspected from internal-consistency checks (e.g., a lower reported prevalence of walkway hazards on soil or stone surfaces than on concrete walkways), and the correct coding (e.g., grab bar: 1 = present, 2 = absent) was then re-confirmed by the data owner against the questionnaire before analysis; no values were changed on the basis of the plausibility checks alone. Community role and social participation were derived from free-text fields where these conflicted with the coded item (109 and 88 records, respectively). Inconsistencies that could not be resolved (e.g., personal income exceeding household income in 344 records) were retained, as the affected variables were not central to the analysis.

2.8. Statistical Analysis

2.8.1. Descriptive Analysis and Co-Occurrence

Participant characteristics were summarised as *n* (%) or mean (SD), overall and by the number of conditions present (depressive symptoms, 9Q $\geq$ 7; malnutrition risk, MNA-SF $\leq$ 11; fall-related mobility risk, a fall in the previous 3 months or gait impairment/walking-aid use). Because participants were nested within 39 subdistricts, prevalence estimates are reported with 95% confidence intervals (CIs) based on Taylor-linearised cluster-robust standard errors on the logit scale; design effects and intraclass correlation coefficients (ICCs, one-way ANOVA estimator) quantify clustering. Estimates weighted to the older population of the study subdistricts (weight = registered population/sample size per subdistrict) are also presented. Pairwise associations between the three conditions were estimated with logistic regression adjusted for age group and sex and, additionally, for the third condition, with cluster-robust standard errors. Co-occurrence beyond chance was assessed by comparing the observed frequency of each combination with that expected under statistical independence (product of the marginal prevalences); 95% CIs for the observed-to-expected (O/E) ratios were obtained from 2000 subdistrict-level cluster-bootstrap replicates. Observed-to-expected ratios are displayed in Figure 2B. Because expectations under independence ignore the pairwise associations between the conditions, a large O/E ratio for the triad can arise from pairwise associations alone. We therefore also fitted hierarchical log-linear (Poisson) models to the 2 × 2 × 2 table and compared the observed frequency of the triad with that expected under the homogeneous-association model, which contains all pairwise terms but no three-way term; the three-way interaction was expressed as a ratio of odds ratios [34], with 95% CIs from 2000 subdistrict cluster-bootstrap replicates. Because the likelihood-ratio test assumes independent observations, the three-way term was tested with a Wald test using the cluster-bootstrap standard error and with a Rao–Scott first-order corrected likelihood-ratio test, in which the likelihood-ratio statistic is divided by the design effect of the three-way coefficient (cluster-bootstrap variance divided by

model-based variance) [35]; the unadjusted likelihood-ratio test is reported for comparison. The analysis was repeated with age group, sex and their interactions with each condition included. To examine how closely a simple count of conditions reproduced the latent classification, the number of conditions was cross-tabulated with modal class assignment, and the agreement of a rule of two or more conditions with complex multidomain membership was summarised with sensitivity, specificity and predictive values, using posterior class probabilities as fractional membership (modal assignment as a secondary comparison). Because the latent classes were derived from the same indicators, these quantities measure agreement with the latent classification, not diagnostic accuracy against an independent reference standard.

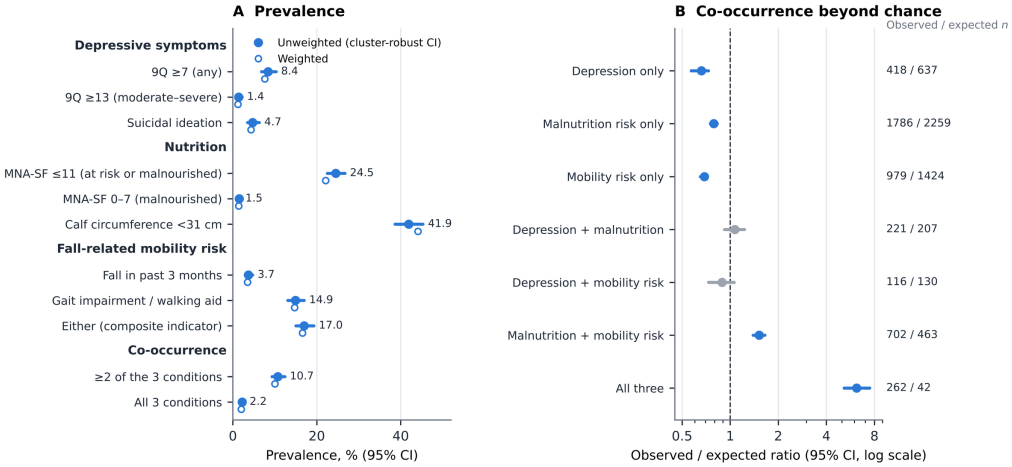

Figure 2. Prevalence and co-occurrence of depressive symptoms, malnutrition risk and fall-related mobility risk (N = 12,115). (**A**) Prevalence with 95% CIs from cluster-robust standard errors (39 subdistricts); open circles show estimates weighted to the registered older population. (**B**) Ratio of observed to expected frequency of each combination under independence, with 95% CIs from 2000 subdistrict cluster-bootstrap replicates (log scale); grey = CI includes 1. Numbers at right are observed/expected counts. Fall-related mobility risk = a fall in the past 3 months or gait impairment/walking-aid use.

2.8.2. Latent Class Analysis

Latent class analysis (LCA) was used to identify subgroups with distinct patterns of the three conditions. The primary model used five indicators: 9Q category (three levels), MNA-SF category (three levels), low calf circumference, a recent fall and gait impairment. Retaining polytomous categories rather than binary indicators increased the information available for model identification (72 response patterns). Models with one to six classes were estimated by maximum likelihood with the expectation–maximisation algorithm, using 500 random starting values per model; the 10 best solutions were iterated to convergence (relative change in log-likelihood $< 10^{-9}$) and replication of the best log-likelihood was checked to avoid local maxima; the selected model was then re-estimated with 1000 random starting values, of which the 20 best were iterated to convergence.

The number of classes was selected on the basis of the Bayesian information criterion (BIC), with the Akaike information criterion (AIC), sample-size-adjusted BIC (SABIC), the parametric bootstrap likelihood ratio test (BLRT; 100 bootstrap samples) comparing K − 1 with K classes, the likelihood-ratio chi-square (L2), relative entropy, average posterior probabilities (AvePP), the size of the smallest class and substantive interpretability considered jointly [13,36]. Because the BIC can be conservative and L2 is sensitive to large samples, no single index was used alone. The local independence assumption was examined with bivariate residuals (BVR; Pearson X2/df), with values > 3.84 indicating residual association.

2.8.3. Accounting for the Multilevel Structure

To account for the nesting of participants within subdistricts, nonparametric multilevel LCA [37] was fitted, in which subdistricts belong to M latent clusters that differ in class proportions while item parameters are held equal. Following Lukočienė et al. [38], K was first chosen from single-level models, M was then chosen using the BIC based on the number of level-2 units ($n = 39$), and K was re-examined given M. Because the multilevel solutions replicated poorly and substantially altered the class structure (see Results), the single-level model was retained as the primary model; clustering was accounted for in all subsequent inference by cluster-robust (sandwich) standard errors or cluster bootstrap with subdistricts as clusters, and the multilevel model is reported as a sensitivity analysis. Between-subdistrict heterogeneity in class prevalence was described with subdistrict-level class proportions weighted by the Bolck–Croon–Hagenaars (BCH) method [39].

2.8.4. Factors Associated with Class Membership and External Correlates

Associations between covariates and latent class membership were estimated with the bias-adjusted maximum-likelihood three-step approach [40], which corrects for classification error when regressing modal class assignment on covariates, using multinomial logistic regression with the low-burden class as reference. Covariate blocks were entered sequentially (Model 1, demographic; Model 2, +socioeconomic and social; Model 3, +health and behaviour; Model 4, +home environment); Model 4 is presented as the main model. Because Model 4 adjusts each covariate for all others, including factors that may lie on pathways from upstream determinants (e.g., chronic conditions and polypharmacy for income and debt), its aORs are conditional associations and should not be interpreted as total effects [41]; estimates for socioeconomic factors before adjustment for health and behavioural factors are shown for Model 2 (Table S5). Results are reported as adjusted odds ratios (aORs) with 95% CIs. Because there were only 39 clusters of unequal size, the primary 95% CIs for the fully adjusted model (Model 4) are based on leave-one-subdistrict-out jackknife (CR3-type) standard errors with t-distribution critical values with 38 degrees of freedom, a small-sample correction that is more conservative than the conventional sandwich estimator [42]; conventional cluster-robust (sandwich) CIs are shown alongside them in Table S9, and the sequential Models 1–3 (Table S5) use cluster-robust standard errors; interpretation focused on the magnitude and precision of estimates rather than on p values. Multicollinearity was assessed with variance inflation factors (VIFs). The urban municipality comprised a single subdistrict and therefore could not be modelled as a covariate with cluster-robust standard errors; its influence was examined by exclusion. Class-specific prevalences of the external correlates were estimated with the bias-adjusted maximum-likelihood three-step approach for distal outcomes [43], with 95% CIs and differences from the low-burden class obtained from 1000 cluster bootstrap replicates.

2.8.5. Sensitivity Analyses

The robustness of the class solution was examined by (SA1–SA2) removing calf circumference; (SA3) adding multimorbidity and polypharmacy as indicators; (SA4) applying design weights; (SA5) excluding the urban municipality; (SA6) replacing the fall indicators with Morse Fall Scale categories; (SA7) redefining nutritional risk using the four MNA-SF items that exclude mobility and neuropsychological problems, which overlap conceptually with the fall and depression indicators; (SA8) a four-class solution; (SA9) the nonparametric multilevel model; and (SA10) relaxing the local dependence between the MNA-SF and calf circumference by combining them into a single six-category item. Classes in each three-class specification were matched to those of the main model by maximal agreement of modal assignments, unless this conflicted with the item-response profiles (SA3), in which case the

class with the highest combined probability of depressive symptoms and gait impairment was matched to the complex multidomain class. Agreement was summarised as percentage agreement and Cohen's κ, and the item-response probabilities of all sensitivity solutions are reported (Table S8). Associations with covariates were additionally re-estimated with the nine-item home hazard score and after omitting tooth-brushing (Table S10). All 12,115 participants were retained in the main analyses. Because the 478 interviews conducted beyond the minimum sample could not be identified in the dataset, their potential influence was bounded in a sensitivity analysis: in each of the 27 subdistricts concerned, the number of participants exceeding the target was set aside, choosing either those with the most favourable profile (fewest conditions, then lowest posterior probability of complex multidomain membership), those with the least favourable profile, or participants at random. In each scenario, prevalences were recomputed, and the three-class model was re-estimated (300 random starts; 20 random replicates); class shares were also computed with class membership held at the main-model posterior probabilities (500 random replicates). Sensitivity analyses are labelled SA1–SA10 to distinguish them from the Supplementary Tables.

2.8.6. Software

Analyses were performed in Python (versions 3.10–3.11) using NumPy, SciPy, pandas and statsmodels (version 0.15.0). LCA, multilevel LCA, the BLRT, BVRs and the three-step estimators were implemented in purpose-written code. To verify this code, the primary single-level solution was cross-checked against StepMix (version 3.0.0) [44], which yielded identical modal class assignments for all participants, and the bias-adjusted three-step coefficients of Model 4 were compared with those of StepMix's ML-corrected three-step estimator (Table S7D). All steps from data cleaning and variable derivation to class enumeration, three-step estimation and sensitivity analyses were scripted with fixed random seeds. The seeds were 100 + K for the K-class models during enumeration and K for the corresponding BLRT, 1000K + M for the multilevel models with M latent clusters, 2026 for re-estimation of the selected model and for the StepMix cross-check, 77 for the sensitivity solutions, 20260928 for the descriptive cluster bootstrap, 11 for the log-linear cluster bootstrap and 5 for the distal-outcome bootstrap; they are listed with the computational environment in Table S11. During revision, the selected model was re-estimated in a separate environment (Python 3.13.18, NumPy 2.5.3, SciPy 1.18.1, pandas 3.0.5), which reproduced its log-likelihood (−25,646.7), class sizes and the modal class assignment of all 12,115 participants. The analysis scripts are not deposited in a public repository; they are available from the corresponding author on request, together with a data dictionary and a synthetic dataset that has the same structure as the analytic dataset but contains no real records, so that the code can be inspected and run without access to participant-level data.

2.9. Ethical Considerations

The study, including data collection and the present analysis, was approved by the Human Research Ethics Committee of the Maha Sarakham Provincial Public Health Office (certificate no. 17/2568, 30 September 2025), before interviewer training and data collection began. Before the interview, participants were informed of the purpose of the survey, that their information would be kept confidential and used only for research and academic purposes, that participation would not affect them, and that they could decline to answer or stop at any time without giving a reason. Verbal informed consent was obtained by the interviewer before the interview began and was confirmed by the interviewer on the first page of the online data-collection form; the remaining questions could not be accessed until consent had been confirmed. The analytic dataset contained no names, addresses or telephone numbers. The 9Q, MNA and fall-risk items were administered as part of a popu-

lation health survey. Interviewers recorded item responses on the electronic form without calculating scores, and scores were derived by the research team after data collection had been completed; individual screening results were therefore not available at the time of the interview. Individual feedback, referral and follow-up of participants with positive screening results were outside the scope of the approved protocol, and because identifying information was removed before the dataset was released for analysis, the research team could not re-contact participants. The ethics committee approved this procedure, in which the 9Q, including the self-harm item, was administered without real-time scoring or a study-specific referral procedure. After data collection, the aggregated results were returned to every participating subdistrict at community feedback forums, and a subdistrict-level dashboard was provided so that subdistrict health-promoting hospitals and local administrative organisations could use the findings in their own follow-up activities; because the data were de-identified, this follow-up could not be directed at individual participants. In the analysed data, 1017 participants (8.4%) had a 9Q score ≥ 7 and 571 (4.7%) reported thoughts of self-harm (9Q item $9 > 0$); only aggregated results are reported. The absence of real-time scoring and of a referral pathway is acknowledged as a limitation. The consent information stated that the project data would be destroyed after the project had been completed. The de-identified data are therefore retained securely by the research team until two years after the close of the funded project and then destroyed, and the Data Availability Statement has been aligned with this period.

3. Results

3.1. Participant Characteristics

A total of 12,115 older adults from 527 villages in 39 subdistricts were included (median 311 participants per subdistrict; range 240–424). The mean age was 69.6 years (SD 7.1); 56.3% were aged 60–69, 33.7% 70–79 and 10.0% ≥ 80 years, and 58.8% were women (Table 1). Most participants had primary education or less (87.7%) and were engaged in agriculture (78.7%); 63.8% were married and 28.8% widowed. Personal monthly income was $\leq$1000 baht for 30.1%, 41.9% reported insufficient income and 76.6% had household debt. Overall, 15.7% had two or more chronic conditions and 30.8% reported study-defined polypharmacy (>3 medications/day).

Table 1. Characteristics of participants, overall and by number of co-occurring conditions (depressive symptoms, malnutrition risk, fall-related mobility risk), $N = 12{,}115$.

Characteristic	Overall (n = 12,115)	0 Conditions (n = 7631)	1 Condition (n = 3183)	2 Conditions (n = 1039)	3 Conditions (n = 262)	p	Cramér's V
Demographic							
Age, years, mean (SD)	69.6 (7.1)	68.3 (6.3)	70.8 (7.4)	74.1 (8.4)	74.0 (8.4)	<0.001	$\varepsilon^2 = 0.059$
Age group, n (%)						<0.001	0.187
60–69	6822 (56.3)	4853 (63.6)	1537 (48.3)	345 (33.2)	87 (33.2)		
70–79	4081 (33.7)	2354 (30.8)	1208 (38.0)	412 (39.7)	107 (40.8)		
≥80	1212 (10.0)	424 (5.6)	438 (13.8)	282 (27.1)	68 (26.0)		
Female, n (%)	7123 (58.8)	4324 (56.7)	1954 (61.4)	672 (64.7)	173 (66.0)	<0.001	0.060
Marital status, n (%)						<0.001	0.076
Married	7734 (63.8)	5189 (68.0)	1896 (59.6)	537 (51.7)	112 (42.7)		
Widowed	3488 (28.8)	1928 (25.3)	1033 (32.5)	402 (38.7)	125 (47.7)		
Divorced/separated	273 (2.3)	169 (2.2)	72 (2.3)	28 (2.7)	4 (1.5)		
Single	620 (5.1)	345 (4.5)	182 (5.7)	72 (6.9)	21 (8.0)		
Education, n (%)						<0.001	0.087
No schooling	231 (1.9)	86 (1.1)	72 (2.3)	52 (5.0)	21 (8.0)		
Primary	10,395 (85.8)	6481 (84.9)	2784 (87.5)	910 (87.6)	220 (84.0)		
Secondary or higher	1489 (12.3)	1064 (13.9)	327 (10.3)	77 (7.4)	21 (8.0)		
Main occupation, n (%)						<0.001	0.186
Agriculture	9531 (78.7)	6396 (83.8)	2385 (74.9)	632 (60.8)	118 (45.0)		
Not working	1840 (15.2)	714 (9.4)	627 (19.7)	364 (35.0)	135 (51.5)		
Other	744 (6.1)	521 (6.8)	171 (5.4)	43 (4.1)	9 (3.4)		

Table 1. *Cont.*

Characteristic	Overall (n = 12,115)	0 Conditions (n = 7631)	1 Condition (n = 3183)	2 Conditions (n = 1039)	3 Conditions (n = 262)	p	Cramér's V
Economic							
Personal income, THB/month, *n* (%)						<0.001	0.087
≤1000	3649 (30.1)	2015 (26.4)	1073 (33.7)	436 (42.0)	125 (47.7)		
1001–3000	4113 (33.9)	2532 (33.2)	1122 (35.2)	366 (35.2)	93 (35.5)		
3001–5000	2288 (18.9)	1577 (20.7)	563 (17.7)	125 (12.0)	23 (8.8)		
>5000	2065 (17.0)	1507 (19.7)	425 (13.4)	112 (10.8)	21 (8.0)		
Insufficient income, *n* (%)	5077 (41.9)	2934 (38.4)	1420 (44.6)	545 (52.5)	178 (67.9)	<0.001	0.118
Household debt, *n* (%)						<0.001	0.038
No debt	2835 (23.4)	1688 (22.1)	794 (24.9)	286 (27.5)	67 (25.6)		
Low	4273 (35.3)	2781 (36.4)	1068 (33.6)	347 (33.4)	77 (29.4)		
Moderate	4255 (35.1)	2738 (35.9)	1099 (34.5)	330 (31.8)	88 (33.6)		
High	752 (6.2)	424 (5.6)	222 (7.0)	76 (7.3)	30 (11.5)		
Main income source, *n* (%)						<0.001	0.102
Own work	3906 (32.2)	2851 (37.4)	847 (26.6)	178 (17.1)	30 (11.5)		
Children	435 (3.6)	283 (3.7)	112 (3.5)	30 (2.9)	10 (3.8)		
State welfare	5043 (41.6)	3031 (39.7)	1422 (44.7)	480 (46.2)	110 (42.0)		
Other	2731 (22.5)	1466 (19.2)	802 (25.2)	351 (33.8)	112 (42.7)		
Social							
Living arrangement, *n* (%)						<0.001	0.081
Alone	643 (5.3)	387 (5.1)	163 (5.1)	71 (6.8)	22 (8.4)		
Spouse	6446 (53.2)	4421 (57.9)	1536 (48.3)	396 (38.1)	93 (35.5)		
Children/grandchildren	4789 (39.5)	2696 (35.3)	1407 (44.2)	544 (52.4)	142 (54.2)		
Relatives	237 (2.0)	127 (1.7)	77 (2.4)	28 (2.7)	5 (1.9)		
Main family caregiver, *n* (%)						<0.001	0.093
Spouse	5351 (44.2)	3705 (48.6)	1255 (39.4)	316 (30.4)	75 (28.6)		
Child/grandchild	6270 (51.8)	3648 (47.8)	1804 (56.7)	651 (62.7)	167 (63.7)		
No caregiver	494 (4.1)	278 (3.6)	124 (3.9)	72 (6.9)	20 (7.6)		
Holds a community role, *n* (%)	3316 (27.4)	2279 (29.9)	786 (24.7)	201 (19.3)	50 (19.1)	<0.001	0.080
Participates in elderly school/club/religious group, *n* (%)	5821 (48.0)	3894 (51.0)	1433 (45.0)	405 (39.0)	89 (34.0)	<0.001	0.088
Health							
Number of chronic conditions, *n* (%)						<0.001	0.103
0	6756 (55.8)	4555 (59.7)	1667 (52.4)	451 (43.4)	83 (31.7)		
1	3458 (28.5)	2089 (27.4)	943 (29.6)	341 (32.8)	85 (32.4)		
≥2	1901 (15.7)	987 (12.9)	573 (18.0)	247 (23.8)	94 (35.9)		
Hypertension	3434 (28.3)	1992 (26.1)	959 (30.1)	368 (35.4)	115 (43.9)	<0.001	0.082
Diabetes	2536 (20.9)	1458 (19.1)	727 (22.8)	272 (26.2)	79 (30.2)	<0.001	0.066
Dyslipidaemia	720 (5.9)	404 (5.3)	219 (6.9)	70 (6.7)	27 (10.3)	<0.001	0.041
Stroke	191 (1.6)	60 (0.8)	54 (1.7)	47 (4.5)	30 (11.5)	<0.001	0.145
Study-defined polypharmacy (>3 medications/day), *n* (%)	3734 (30.8)	2023 (26.5)	1101 (34.6)	468 (45.0)	142 (54.2)	<0.001	0.145
BMI, kg/m^2 (Asian cut-offs), *n* (%)						<0.001	0.227
<18.5	842 (7.0)	0 (0.0)	585 (18.4)	206 (19.8)	51 (19.5)		
18.5–22.9	5195 (42.9)	3067 (40.2)	1477 (46.4)	532 (51.2)	119 (45.4)		
23.0–24.9	2959 (24.4)	2272 (29.8)	508 (16.0)	142 (13.7)	37 (14.1)		
≥25.0	3119 (25.7)	2292 (30.0)	613 (19.3)	159 (15.3)	55 (21.0)		
Ever attended community health screening, *n* (%)	11,708 (96.6)	7404 (97.0)	3066 (96.3)	988 (95.1)	250 (95.4)	0.004	0.033
Health behaviours (past week)							
Vigorous activity ≥ 3 days, *n* (%)	3702 (30.6)	2476 (32.4)	935 (29.4)	228 (21.9)	63 (24.0)	<0.001	0.068
Muscle-strengthening ≥ 3 days, *n* (%)	3904 (32.2)	2576 (33.8)	985 (30.9)	269 (25.9)	74 (28.2)	<0.001	0.051
≥5 portions fruit/vegetables on ≥5 days, *n* (%)	7249 (59.8)	4846 (63.5)	1745 (54.8)	543 (52.3)	115 (43.9)	<0.001	0.103
Any smoking, *n* (%)	1286 (10.6)	746 (9.8)	388 (12.2)	112 (10.8)	40 (15.3)	<0.001	0.041
Any alcohol, *n* (%)	1906 (15.7)	1219 (16.0)	502 (15.8)	144 (13.9)	41 (15.6)	0.378	0.016
Tooth-brushing ≥ 2 times daily every day, *n* (%)	10,867 (89.7)	7093 (92.9)	2770 (87.0)	827 (79.6)	177 (67.6)	<0.001	0.174
Home environment							
House structurally unsound, *n* (%)	1300 (10.7)	586 (7.7)	422 (13.3)	200 (19.2)	92 (35.1)	<0.001	0.167
Door thresholds, *n* (%)	8102 (66.9)	5073 (66.5)	2136 (67.1)	703 (67.7)	190 (72.5)	0.197	0.020
Uneven floor levels, *n* (%)	6236 (51.5)	3725 (48.8)	1707 (53.6)	621 (59.8)	183 (69.8)	<0.001	0.087
Sleeps on the floor, *n* (%)	5625 (46.4)	3454 (45.3)	1540 (48.4)	503 (48.4)	128 (48.9)	0.010	0.031
Toilet outside the house, *n* (%)	3221 (26.6)	1927 (25.3)	915 (28.7)	304 (29.3)	75 (28.6)	<0.001	0.040
Squat toilet, *n* (%)	5528 (45.6)	3345 (43.8)	1569 (49.3)	494 (47.5)	120 (45.8)	<0.001	0.049
No bathroom grab bar, *n* (%)	10,144 (83.7)	6416 (84.1)	2665 (83.7)	862 (83.0)	201 (76.7)	0.014	0.030
Built-in cement water tank in bathroom, *n* (%)	5471 (45.2)	3410 (44.7)	1450 (45.6)	483 (46.5)	128 (48.9)	0.380	0.016
Clutter of unused items, *n* (%)	3575 (29.5)	1967 (25.8)	1045 (32.8)	418 (40.2)	145 (55.3)	<0.001	0.131

Table 1. *Cont.*

Characteristic	Overall (n = 12,115)	0 Conditions (n = 7631)	1 Condition (n = 3183)	2 Conditions (n = 1039)	3 Conditions (n = 262)	p	Cramér's V
Hazardous walkway around house, n (%)	1891 (15.6)	935 (12.3)	598 (18.8)	252 (24.3)	106 (40.5)	<0.001	0.150
Hazardous materials, n (%)	2789 (23.0)	1520 (19.9)	808 (25.4)	318 (30.6)	143 (54.6)	<0.001	0.139
Home hazard score (0–11), mean (SD)	4.4 (2.0)	4.2 (1.9)	4.7 (2.0)	5.0 (2.1)	5.8 (2.2)	<0.001	ε^2 = 0.022
Cooks with charcoal, n (%)	7726 (63.8)	4872 (63.8)	2093 (65.8)	620 (59.7)	141 (53.8)	<0.001	0.045
Area							
Urban municipality (Talat, Mueang), n (%)	357 (2.9)	292 (3.8)	48 (1.5)	12 (1.2)	5 (1.9)	<0.001	0.068

Note: Values are n (%) unless stated otherwise; percentages are column percentages. Columns group participants by the number of the three conditions present (0–3): depressive symptoms (9Q ≥ 7), malnutrition risk (MNA-SF ≤ 11) and fall-related mobility risk (fall in the past 3 months or gait impairment/walking aid; Morse items 1, 3 and 5). "1 condition" includes participants with any one of the three conditions, "2 conditions" those with any two, and "3 conditions" those with all three; the columns are mutually exclusive. The frequency of each specific combination is shown in Figure 2B. p values: Pearson χ^2 (categorical) or Kruskal–Wallis (continuous), not adjusted for clustering within subdistricts (design effects 2–14; Table S2) and shown for descriptive purposes only; effect sizes: Cramér's V or ε^2. Health-behaviour items (3A–2S–1F, Department of Health Service Support) were coded 1–5, 5 = most favourable. Home hazard score = count of the 11 home hazards shown. BMI is a component of the MNA-SF (item F) and was therefore not used as a predictor of latent class membership. Bold and italic formatting indicates category headings used to group related characteristics.

3.2. Prevalence and Co-Occurrence of the Three Conditions

The prevalence of depressive symptoms (9Q ≥ 7) was 8.4% (95% CI 6.8–10.3), including 1.4% (0.9–2.2) with moderate-to-severe symptoms; 4.7% (3.5–6.3) reported thoughts of self-harm. Malnutrition risk (MNA-SF ≤ 11) was present in 24.5% (22.5–26.7), of whom most were at risk rather than malnourished (malnourished 1.5% [1.2–1.8]), and 41.9% (38.6–45.3) had a calf circumference < 31 cm. A fall in the previous 3 months was reported by 3.7% (2.9–4.7), gait impairment or walking-aid use by 14.9% (13.1–17.0), and either (fall-related mobility risk) by 17.0% (15.0–19.3) (Figure 2A); the composite therefore reflects mainly gait impairment or walking-aid use and does not represent the prevalence of falls. Clustering within subdistricts was modest in terms of ICCs (0.002–0.044) but, given the large cluster sizes, yielded design effects of up to 14.5. Weighted estimates were similar to unweighted estimates (Table S2).

Two or more conditions co-occurred in 10.7% (9.3–12.4) and all three in 2.2% (1.7–2.8) of participants. The conditions were mutually associated: after adjustment for age, sex and the third condition, the aOR was 2.64 (2.19–3.18) for depressive symptoms and malnutrition risk, 2.74 (2.13–3.53) for depressive symptoms and fall-related mobility risk, and 2.58 (2.23–2.98) for malnutrition risk and fall-related mobility risk. The combination of all three conditions was observed in 262 participants, compared with 42 expected under independence (O/E 6.18, 95% CI 5.17–7.47), whereas single conditions occurred less often than expected (O/E 0.66–0.79) (Figure 2B). The excess of the triple combination relative to independence persisted when the MNA-SF items overlapping with mobility and mood were removed (O/E 5.85). However, most of this excess was attributable to the pairwise associations: under a log-linear model including all pairwise associations but no three-way term, 246.9 triads were expected (O/E 1.06, 95% CI 1.01–1.12). The three-way interaction was small (ratio of odds ratios 1.39, 95% CI 1.04–1.89; cluster-bootstrap Wald $p = 0.030$; Rao–Scott-corrected likelihood-ratio $\chi^2 = 4.77$, df = 1, $p = 0.029$) and similar after adjustment for age group and sex (O/E 1.07; ratio of odds ratios 1.43, 95% CI 1.06–1.98; bootstrap Wald $p = 0.024$; Rao–Scott $p = 0.022$) (Table S7A). The design effect of the three-way coefficient was close to 1 (1.05 unadjusted, 1.12 adjusted), much smaller than the design effects of the prevalence estimates, so correcting for clustering changed these p values little.

3.3. Latent Class Enumeration

Fit statistics for models with one to six classes are shown in Table 2. The BIC was lowest for the three-class model (51,509.7), which also had the highest relative entropy (0.818). AIC continued to decrease slightly beyond three classes, whereas SABIC was virtually identical for three and four classes (51,436.6 and 51,436.5) and increased thereafter, and the BLRT was significant up to six classes ($p < 0.01$ to $p = 0.03$), but models with four or more classes had lower entropy (0.69–0.74), lower minimum AvePP (0.45–0.67), smaller classes (1.0–3.3%) and poorer replication of the best log-likelihood. The three-class model was therefore selected; its best log-likelihood was replicated in all 10 final-stage solutions during enumeration (Table 2) and in all 20 final-stage solutions when the selected model was re-estimated with 1000 random starting values. The three-class model did not reproduce all observed response patterns (L2 = 139.6, df = 48); BVRs indicated residual association of calf circumference with the 9Q (BVR 6.23) and MNA-SF (BVR 6.49) categories, whereas all other BVRs were <3.1 (Table S3).

Table 2. Fit statistics for latent class models with 1–6 classes (N = 12,115).

Classes	LL	Parameters	AIC	BIC	SABIC	Entropy	Min AvePP	Smallest Class, %	L^2 (df)	LL Replicated	BLRT *p*
1	−26,655.0	7	53,324.1	53,375.9	53,353.6	—	—	100.0	2156.2 (64)	1/1	—
2	−25,772.4	15	51,574.7	51,685.7	51,638.1	0.710	0.840	14.6	390.9 (56)	10/10	<0.01
3	**−25,646.7**	**23**	**51,339.4**	**51,509.7**	**51,436.6**	**0.818**	**0.740**	**6.5**	**139.6 (48)**	**10/10**	**<0.01**
4	−25,621.8	31	51,305.6	51,535.1	51,436.5	0.738	0.627	3.3	89.8 (40)	9/10	<0.01
5	−25,604.5	39	51,287.1	51,575.8	51,451.8	0.690	0.668	2.4	55.3 (32)	6/10	<0.01
6	−25,593.4	47	51,280.7	51,628.6	51,479.3	0.721	0.454	1.0	32.9 (24)	1/10	0.03

Note: LL = log-likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-size-adjusted BIC; AvePP = average posterior probability of the assigned class; L^2 = likelihood-ratio chi-square against the saturated model; BLRT = parametric bootstrap likelihood ratio test of K − 1 vs. K classes (100 bootstrap samples). LL replicated = the number of the best final-stage solutions (from 500 random starts) reaching the maximum log-likelihood. Indicators: 9Q (3 levels), MNA-SF (3 levels), calf circumference < 31 cm, fall in past 3 months, gait impairment/walking aid. Bold row = selected model.

3.4. Latent Class Profiles

The three classes were labelled according to their item-response probabilities (Figure 3A; Table S4). The low-burden class (77.3%) had low probabilities of all indicators (depressive symptoms 5.1%, malnutrition risk 4.9%, recent fall 1.9%, gait impairment 8.5%), although 35.7% had a calf circumference < 31 cm. The nutritional-risk class (16.2%) was defined by malnutrition risk (100%, almost entirely in the at-risk range) and low calf circumference (63.4%), with modestly elevated depressive symptoms (11.2%) and gait impairment (20.5%) and few falls (3.3%). The complex multidomain class (6.5% model-estimated; 565 participants, 4.7%, by modal assignment) was characterised mainly by gait impairment (78.2%) and malnutrition risk (70.2%, including 21.2% malnourished), with elevated probabilities of depressive symptoms (40.9%, including 9.7% moderate-to-severe) and a recent fall (26.8%). Because these probabilities are well below 1, only about one-quarter of the class was expected to have all three conditions (24.1% model-implied; 26.0% posterior-weighted), although 46.4% of participants modally assigned to the class did (Table S7B). What distinguished the class from the nutritional-risk class was therefore mainly the high probability of gait impairment or walking-aid use (78.2% vs. 20.5%), together with more frequent malnourishment (21.2% vs. 0.8%), depressive symptoms (40.9% vs. 11.2%) and recent falls (26.8% vs. 3.3%), rather than the simultaneous presence of all three conditions in every member. Average posterior probabilities were high for the low-burden class (0.984) and moderate for the nutritional-risk (0.740) and complex multidomain (0.775) classes. The classification-error matrix indicated that only 55.8% of complex-multidomain members would be assigned modally to that class, 25.9%

to the nutritional-risk class and 18.3% to the low-burden class (Table S3). Modal assignment is therefore unsuitable for identifying individual members of this class; all class-specific estimates used bias-adjusted three-step estimators that take classification error into account.

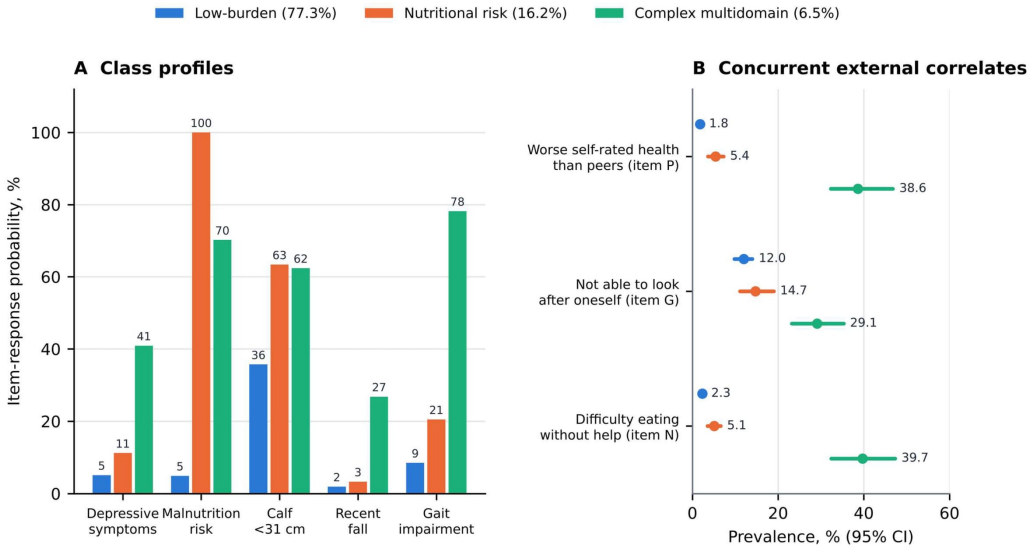

Figure 3. Latent class profiles and external correlates. (**A**) Probability of each indicator in the three latent classes (class sizes in legend; malnutrition risk = MNA-SF ≤ 11, depressive symptoms = 9Q ≥ 7). (**B**) Prevalence of concurrently measured external correlates not used to define the classes (MNA items P, G and N), estimated with the bias-adjusted maximum-likelihood three-step approach; 95% CIs from 1000 cluster-bootstrap replicates.

3.5. Factors Associated with Class Membership

In the fully adjusted model (Figure 4), with small-sample-corrected 95% CIs (jackknife standard errors, t(38) critical values), membership of the complex multidomain class relative to the low-burden class was associated with older age (70–79 years: aOR 1.70, 95% CI 1.19–2.42; ≥80 years: 4.39, 2.57–7.48), not working (4.23, 2.45–7.29), insufficient income (1.97, 1.25–3.12), high household debt (2.45, 1.22–4.91), one chronic condition (2.25, 1.58–3.22) and two or more chronic conditions (3.54, 2.17–5.78), study-defined polypharmacy (2.45, 1.69–3.55), smoking (1.91, 1.005–3.647) and a higher home hazard score (1.44 per additional hazard, 1.28–1.62). Twice-daily tooth-brushing (0.21, 0.13–0.34), adequate fruit and vegetable intake (0.68, 0.48–0.97) and cooking with charcoal (0.55, 0.37–0.81) were inversely associated. Estimates for having no family caregiver (2.00, 0.94–4.26) and alcohol use (1.54, 0.92–2.59) were imprecise. Before adjustment for health and behavioural factors (Model 2), the aORs for insufficient income (2.70) and high household debt (3.20) were larger (Table S5).

Membership of the nutritional-risk class was associated with older age (70–79 years: 1.90, 1.64–2.19; ≥80 years: 4.22, 3.27–5.45), female sex (1.29, 1.08–1.55), being single, divorced or separated (1.56, 1.19–2.04), not working (1.42, 1.07–1.88), study-defined polypharmacy (1.43, 1.17–1.75), smoking (1.74, 1.37–2.21) and the home hazard score (1.09, 1.02–1.17), and inversely with fruit and vegetable intake (0.74, 0.57–0.96), tooth-brushing (0.63, 0.46–0.85) and two or more chronic conditions (0.70, 0.53–0.93). Associations were consistent in direction across the sequential models (Table S5), and no VIF exceeded 2.4. Estimates for personal income ≤ 1000 baht (1.38, 0.999–1.902) and social participation (0.78, 0.611–1.006) were imprecise. With conventional cluster-robust (sandwich) standard errors, CIs were slightly narrower and those for these two factors excluded 1 (1.03–1.85 and 0.62–0.99); conclusions for the complex multidomain class did not depend on the variance estimator, although the lower limit for smoking was close to 1 with the jackknife (Table S9).

Results were similar with the nine-item home hazard score (cluster-robust CIs) (complex multidomain 1.51, 1.33–1.72; nutritional risk 1.11, 1.04–1.19), and omitting tooth-brushing changed the other complex-class aORs by no more than 21% (largest changes: age ≥ 80 years, 4.39 to 5.29; fruit and vegetable intake, 0.68 to 0.55) and the nutritional-risk aORs by no more than 4% (Table S10). The bias-adjusted three-step coefficients agreed with those from StepMix (maximum absolute difference < 0.01 on the log-odds scale; Table S7D).

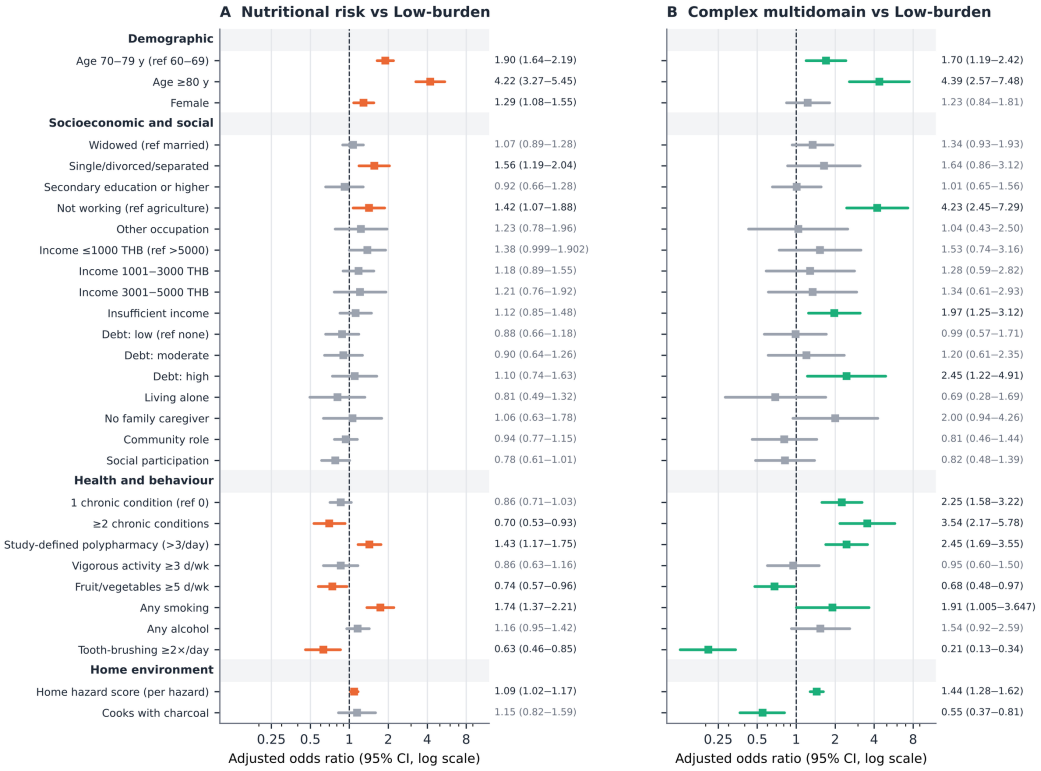

Figure 4. Factors associated with membership of the nutritional-risk (**A**) and complex multidomain (**B**) classes relative to the low-burden class. Adjusted odds ratios from the bias-adjusted three-step multinomial model with all covariates entered simultaneously; 95% CIs from leave-one-subdistrict-out jackknife (CR3-type) standard errors with t(38) critical values (39 subdistricts); conventional cluster-robust CIs are given in Table S9. Polypharmacy = study-defined polypharmacy (>3 medications/day). Coloured estimates have CIs excluding 1.

3.6. Concurrent External Correlates

The classes differed in concurrently measured characteristics not used to define them (Figure 3B; Table S4). Self-rated health worse than peers was reported by 1.8% (1.3–2.4) of the low-burden class, 5.4% (3.6–7.3) of the nutritional-risk class and 38.6% (32.3–46.8) of the complex multidomain class; the corresponding figures were 12.0%, 14.7% and 29.1% for not being able to look after oneself (MNA item G) and 2.3%, 5.1% and 39.7% for difficulty eating without help. Relative to the low-burden class, the complex multidomain class had 36.8 (30.6–45.0), 17.2 (10.9–23.8) and 37.5 (30.3–45.0) percentage-point higher prevalences of these outcomes, respectively.

3.7. Between-Subdistrict Heterogeneity and Sensitivity Analyses

Class prevalence varied considerably across subdistricts: the BCH-corrected proportion of the complex multidomain class ranged from 0% to 24.0% (interquartile range 2.8–8.8%) and that of the nutritional-risk class from 0.3% to 34.0%. Nonparametric multilevel models fitted the data better than single-level models (BIC based on 39 subdistricts favoured

M = 5 latent subdistrict clusters for K = 3), but their best solutions replicated poorly (2–12 of 60 starts) and shifted the class structure (low-burden 53.2%, nutritional risk 33.3%, complex multidomain 13.5%; κ = 0.24 versus the main model) (SA9; Table S6).

Modal class assignment was essentially unchanged by design weighting (SA4; one of 12,115 participants reassigned, κ = 0.9998) and unchanged by exclusion of the urban municipality (SA5; κ = 1.000), and was highly consistent when Morse Fall Scale categories replaced the fall indicators (SA6; κ = 0.946) (Table S6). The different class sizes under design weighting reflect the reweighting of subdistricts with different class compositions rather than reclassification of individuals. Agreement was moderate when the MNA-SF items overlapping with mobility and mood were removed (SA7; κ = 0.655) and fair when calf circumference was removed (SA1; κ = 0.441), when the MNA-SF and calf circumference were combined into a joint item (SA10; κ = 0.403) or when multimorbidity and polypharmacy were added as indicators (SA3; κ = 0.227). Across three-class single-level specifications, a large low-burden class (73–84%) was consistently identified, and one class had higher probabilities of depressive symptoms, malnutrition risk, recent falls and gait impairment than the low-burden class in every specification (Table S8). Its size and composition, however, depended on the indicators used. In specifications with at least moderate agreement with the main model (SA4–SA7; κ = 0.655–1.000), it comprised 5.0–8.5% and had a profile similar to that of the main complex multidomain class. When calf circumference was removed (SA1) or combined with the MNA-SF (SA10), it became a smaller and more severe class (1.9% and 0.9%; depressive symptoms 56.3% and 81.6%, malnutrition risk 100%, gait impairment 88.7% and 86.6%) whose expected membership consisted mainly of main-model complex multidomain members (77% and 87%) but which contained only 23% and 12% of that class's expected members; most of the others moved to a broader intermediate class, and many main-model nutritional-risk members moved to the low-burden class (Table S8). When multimorbidity and polypharmacy were added (SA3), a multimorbidity–polypharmacy class (15.1%) with low probabilities of the three conditions emerged, and the class most similar to the complex multidomain class (11.7%) combined main-model complex and nutritional-risk members and had lower probabilities of depressive symptoms (31.0%) and gait impairment (58.5%). In the four-class solutions (SA2, SA8), the class with the highest probabilities of depressive symptoms and gait impairment and with malnutrition risk in all members comprised 1.0% and 3.3%. The size of this class is therefore uncertain: the main estimate of 6.5% is conditional on the indicator set, closely agreeing specifications gave 5.0–8.5%, and the range across all three-class specifications was 0.9–11.7%. The size and definition of the intermediate nutritional-risk class likewise depended on how nutrition and muscle mass were operationalised. In the bounding analysis of the 478 interviews beyond the minimum sample, setting aside the participants with the most favourable profiles—the scenario consistent with the additional residents being more accessible and healthier—gave a complex multidomain class of 6.3% when the model was re-estimated (6.7% with membership held fixed), whereas the opposite extreme gave 4.0% (4.8%); random removal gave 5.9–6.9% across 20 re-estimated replicates. Across the two extreme scenarios, the prevalence of depressive symptoms, malnutrition risk and fall-related mobility risk ranged from 7.0% to 8.7%, 22.6% to 25.5% and 14.1% to 17.7%, respectively, and random removal changed each prevalence by less than 0.2 percentage points.

Of the 1301 participants with two or more conditions, 470 (36.1%) were modally assigned to the complex multidomain class, 780 (60.0%) to the nutritional-risk class and 51 (3.9%) to the low-burden class. Using posterior probabilities as fractional membership, the two-or-more-conditions rule flagged 10.7% of participants; its agreement with complex multidomain membership corresponded to a sensitivity of 72.2%, specificity of 93.5%, positive predictive value of 43.5% and negative predictive value of 98.0%. Requiring all

three conditions increased the positive predictive value to 78.0% but reduced sensitivity to 26.0% (Table S7C). Because the classes were derived from the same indicators, and every member of the nutritional-risk class has at least one condition by construction, these figures describe agreement with the latent classification rather than diagnostic accuracy.

4. Discussion

4.1. Principal Findings

This community-based study of 12,115 older adults across 39 subdistricts of Maha Sarakham Province, Thailand, identified substantial overlap among depressive symptoms, malnutrition risk, and fall-related mobility risk, highlighting the multidimensional nature of health vulnerability in later life. The simultaneous presence of all three conditions was observed 6.2 times more frequently than expected under statistical independence. However, this excess co-occurrence was largely explained by pairwise associations, with only a small additional three-way interaction. These findings suggest that the three conditions are interconnected, although the observed clustering does not necessarily indicate a distinct underlying syndrome or a common causal mechanism. Latent class analysis identified three population-level profiles: a low-burden class (77.3%), a nutritional-risk class (16.2%), and a complex multidomain class (6.5%). The complex multidomain class was characterised predominantly by gait impairment and malnutrition risk, accompanied by elevated probabilities of depressive symptoms and recent falls. Nevertheless, the estimated prevalence and composition of this class were sensitive to the selection and specification of indicators, with its proportion ranging from 0.9% to 11.7% across sensitivity analyses. This variation indicates that the latent classes should be interpreted as exploratory, model-dependent representations of co-occurring health vulnerabilities rather than stable clinical categories or validated tools for individual risk classification. The complex multidomain profile was also associated with socioeconomic disadvantage, including not working, insufficient income, and high household debt, as well as multimorbidity, study-defined polypharmacy, smoking, and household environmental hazards. Participants in this class were more likely to report poorer health than their peers, reduced perceived ability to look after themselves, and difficulty eating without assistance. These concurrent characteristics suggest that nutritional, psychological, functional, and socioeconomic vulnerabilities frequently coexist among older adults. However, because the external correlates were measured during the same survey and some originated from the same nutritional assessment instrument, these associations should be interpreted descriptively rather than as independent validation of the latent class structure. The findings partially supported the study hypothesis. Although a subgroup with elevated probabilities of all three conditions was identified, only approximately one-quarter of its members were estimated to experience the complete triad (24.1% based on model-implied probabilities and 26.0% based on posterior-weighted estimates). Therefore, the complex multidomain class is more appropriately interpreted as a profile dominated by mobility impairment and nutritional vulnerability, with additional psychological and fall-related risks, rather than a distinct group uniformly experiencing all three conditions. From a public health perspective, these findings support consideration of integrated, multidomain assessment within community-based older adult healthcare, particularly where nutritional vulnerability coexists with mobility limitations and depressive symptoms. Nevertheless, the cross-sectional design precludes conclusions regarding temporal sequence or causality, and the sensitivity of class membership to model specification limits the use of these profiles for individual screening or service allocation. Further longitudinal research and external validation are needed to determine whether similar vulnerability patterns persist over time and whether integrated assessment and targeted interventions improve health outcomes.

4.2. Comparison with Previous Studies

The prevalence estimates were lower than most previous Thai and regional reports. Depressive symptoms (8.4%) were less common than the 18.5% reported in a rural Thai community study [5] and the subgroup estimate of 17.7% (five studies) for rural Southeast Asia in a meta-analysis of rural older adults in Asia [6]; malnutrition risk on the MNA-SF (24.5%) was lower than the pooled Thai estimate of 37.8% [4]; and only 3.7% reported a fall in the previous three months, compared with 34.5% over six months in another rural Maha Sarakham sample [7]. Differences in cut-offs and settings explain part of this gap, but the difference in fall history is not explained by the recall period alone: a three-month prevalence of 3.7% corresponds to roughly 7% over six months if falls occur evenly over time, still less than one-quarter of the earlier estimate. Falls without injury are often forgotten [45], and interviews were conducted face to face by interviewers nominated by subdistrict health-promoting hospitals, often local health personnel, which may have encouraged socially desirable responses about mood and falls; interviewer effects on sensitive items are well documented [46]. Interviewer identifiers were not available in the released dataset, so interviewer effects could not be separated from subdistrict effects, and the between-subdistrict variation in prevalence (ICCs up to 0.044; complex-class prevalence 0–24%) may partly reflect them. For these reasons, fall history was combined with observed gait impairment or walking-aid use (14.9%), and the resulting indicator should be interpreted as fall-related mobility risk rather than fall occurrence.

The co-occurrence pattern is consistent with the view of depression, malnutrition and falls as geriatric syndromes that share risk factors and pathways [8]. The mutual associations we observed (adjusted odds ratios 2.6–2.7 for each pair) are of similar magnitude to those reported for malnutrition and depression [9] and for depression, malnutrition and falls [10], although evidence on depression and falls has been inconsistent across reviews [11]. The class structure resembled that reported in a latent class analysis of intrinsic capacity among community-dwelling older adults in China, in which 79.4% were relatively healthy and 7.8% had concurrent declines in locomotion, psychological function, cognition and vitality [14]. This convergence across different instruments is consistent with the existence of a small multidomain subgroup, but in our data the size of this class ranged from 0.9% to 11.7% across specifications, and the intermediate nutritional-risk class also depended on how nutrition and muscle mass were measured (Tables S6 and S8); the similarity in size should therefore not be over-interpreted.

Two further points bear on the interpretation of the classes. First, the indicators were categorised from continuous scores, and the low-burden and nutritional-risk classes differed mainly in the level of the MNA-SF; these classes may represent different severities along a single nutritional dimension (quantitative classes) rather than qualitatively distinct subgroups, a distinction that LCA of categorised indicators cannot resolve [47]. Factor mixture or continuous latent-variable models of the item-level scores would help to establish whether the complex multidomain class is a qualitatively distinct configuration or the upper tail of a continuum. Second, calf circumference behaved differently from the other indicators. With the 31 cm cut-off, it clearly separated the low-burden class (35.7% below the cut-off) from both at-risk classes (63.4% and 62.4%) but did not distinguish the nutritional-risk from the complex multidomain class. The substantial change in the solution when it was removed (SA1; $\kappa = 0.441$) is therefore more plausibly explained by its residual local dependence with the MNA-SF and 9Q categories (BVRs 6.49 and 6.23; Table S3) than by a lack of discriminating information. Calf circumference shares the anthropometric content of the MNA-SF, in which it substitutes for body mass index, and was associated with depressive symptoms beyond what the classes explained; when it was removed or merged with the MNA-SF (SA10), participants were re-partitioned: many main-model nutritional-

risk members were assigned to the low-burden class, and the complex multidomain class was divided between a broader intermediate class and a smaller, more severe multidomain class (Table S8). Because calf circumference was recorded only as the MNA item score, we could not examine whether the higher Asian cut-offs [29], which would classify more older adults as having low muscle mass, alter the class structure. Together with the structural overlap between MNA-SF items and the gait and depression indicators, these findings indicate that the class boundaries, and particularly class sizes, are partly determined by measurement choices. This residual dependence is not multicollinearity in the regression sense, but it has an analogous consequence: when two indicators share content, part of their association is absorbed by the class structure, so the boundary between the nutritional-risk and complex multidomain classes partly reflects the overlap between instruments rather than a distinct subgroup.

4.3. Robustness of the Class Structure and Implications for Its Use

Three features of the class solution were stable across specifications: a large low-burden class (73–84% in every three-class single-level specification); a class with higher probabilities of depressive symptoms, malnutrition risk, recent falls and gait impairment than the low-burden class; and the predominance of gait impairment and malnutrition risk in that class. Its size, composition and boundary with the nutritional-risk class were not stable. In specifications that agreed at least moderately with the main model (SA4–SA7), the complex multidomain class comprised 5.0–8.5%; when calf circumference was removed or combined with the MNA-SF, it became a smaller and more severe class (1.9% and 0.9%); when multimorbidity and polypharmacy were added, it became larger and less specific (11.7%); and the multilevel model, which replicated poorly, gave 13.5% (Tables S6 and S8). We therefore regard the complex multidomain class as an exploratory, model-dependent profile and the estimate of 6.5% as a modelling estimate conditional on the indicator set, not as a stable population prevalence. Among the alternative specifications, SA7 provides the most direct check on indicator overlap because it removes the MNA-SF items on mobility and neuropsychological problems; the fact that it reproduced a class of similar size and profile ($\kappa = 0.655$) supports, but does not establish, the main interpretation. Whether the profile can be reproduced in other samples, with continuous indicators and against independent outcomes, remains to be shown.

Uncertainty in individual assignment has a separate implication. Only 55.8% of the expected members of the complex multidomain class would be assigned to it modally (Table S3), and only 44% of the older adults flagged by a two-or-more-conditions rule were expected members (Table S7C). The classes therefore describe how risks are distributed and combined in the older population of the study subdistricts, which is relevant to planning, but they are not suitable for labelling individual older adults or for individual clinical decisions. For individuals, the relevant information remains each person's screening results, which already indicate the need for further assessment; whether combining them identifies people who benefit more from integrated care is a separate question that requires prospective validation against outcomes such as falls, dependency and hospitalisation.

4.4. Factors Associated with the Complex Multidomain Class

Socioeconomic disadvantage was a prominent correlate of the complex multidomain class. Not working, insufficient income and high household debt were each associated with roughly two- to four-fold odds of membership after adjustment for age, health and behaviours (Figure 4). Because this model also adjusted for chronic conditions, polypharmacy and behaviours, which may lie on pathways from socioeconomic disadvantage to these syndromes, the aORs describe conditional associations rather than total effects [41];

estimates before adjustment for health and behavioural factors were somewhat larger (Model 2, Table S5). In an agrarian population in which most older adults continue to farm, withdrawal from work may be both a consequence of declining capacity and a pathway to financial strain; the cross-sectional design does not allow these directions to be separated. Multimorbidity and study-defined polypharmacy were also strongly associated with the complex class, underlining the overlap between geriatric syndromes and chronic disease management [8].

Several behavioural and environmental associations merit cautious interpretation. Twice-daily tooth-brushing was strongly and inversely associated with both at-risk classes. Because 89.7% of participants reported this behaviour, the minority who did not are likely to be distinguished by limited capacity for self-care, and the association probably reflects reverse causation, reduced functional capacity or socially desirable reporting rather than a protective effect of brushing itself. Oral health remains relevant to nutrition, as tooth loss is associated with malnutrition risk in older adults [48], but these data do not support oral health promotion as a specific lever for preventing membership of the at-risk classes. Each additional home hazard was associated with 44% higher odds of complex multidomain membership, consistent with evidence linking the home environment to falls in rural Thailand [7,26]. The inverse associations of cooking with charcoal and, for the nutritional-risk class, of having two or more chronic conditions are unlikely to be protective: continuing to cook probably marks preserved functional capacity, and people with cardiometabolic conditions may have higher body weight and more regular contact with health services. These associations should be regarded as hypotheses.

4.5. Policy Implications for Community-Based Care of Older People

The findings suggest four potential implications for the organisation of community-based care in Maha Sarakham and similar provinces; because the classes are model-dependent and do not classify individuals reliably (see Robustness of the class structure and implications for its use), each should be regarded as a hypothesis to be tested rather than an established recommendation. First, screening results could be interpreted together rather than condition by condition. Depressive symptoms, nutritional status and fall risk are already assessed in routine screening of older people, but the results are recorded and followed up separately. A simple rule that flags older adults with two or more of these conditions would flag 10.7% of this sample, including everyone with the full triad. In our data, the rule agreed only partly with latent class membership: it flagged an estimated 72% of complex multidomain members and left 94% of non-members unflagged, but only 44% of those flagged were expected members, whereas nearly half (47.5%) were expected members of the nutritional-risk class (Table S7C). Because the latent classes were derived from the same screening indicators, these figures reflect agreement with the latent classification rather than diagnostic accuracy. Such a rule may therefore be useful for prompting a fuller integrated assessment rather than as a case-finding tool, and its validity against clinical outcomes such as incident dependency, falls and hospitalisation should be evaluated prospectively before adoption. This approach is consistent with the WHO ICOPE framework, which calls for integrated, person-centred assessment and care plans covering mobility, vitality and psychological capacity [12].

Second, older adults with this profile may represent a preventive target that falls between existing programmes. Thailand's community-based long-term care programme focuses on older people who are already dependent [18,20], yet most members of the complex multidomain class did not report being unable to look after themselves (29.1% did, compared with 12.0% of the low-burden class; MNA item G). Because this item is crude, depends on self-perception and was also endorsed by 12% of the low-burden class, it cannot

establish functional independence, and activities of daily living were not assessed; the finding suggests, but does not demonstrate, that many members of this class are not yet dependent. Extending care-manager review to older adults with co-occurring positive screening results, with medication review for polypharmacy, nutritional support, follow-up of depressive symptoms and fall-prevention exercise, could delay their transition to dependency; this requires evaluation in intervention studies.

Third, local administrative organisations have levers that match the correlates identified. Under the Older Persons Act, they are responsible for social welfare and elderly quality-of-life activities [19]. The associations with insufficient income, household debt and home hazards suggest that welfare assessment, financial counselling and home-modification budgets could be directed preferentially to older adults with co-occurring conditions, rather than distributed uniformly. The gap between observed hazards and older adults' own risk perception reported in Maha Sarakham [7] indicates that home assessments should be conducted by trained staff rather than relying on self-report.

Fourth, resource allocation could be informed by local data. The prevalence of the complex multidomain class ranged from 0% to 24% across subdistricts, suggesting that uniform per capita allocation may underserve some communities. Part of this variation may reflect differences in interviewers and measurement, so linking routine screening data from primary care and local government databases and standardising assessment procedures are prerequisites for using such data to target resources.

4.6. Strengths and Limitations

The strengths of this study include a large sample drawn from 39 subdistricts, standardised instruments, anthropometric measurements taken by trained interviewers, a complete dataset, and a latent class approach that followed current recommendations, including bias-adjusted three-step estimation, small-sample-corrected cluster-robust inference and ten sensitivity analyses.

Several limitations should be considered; for each, we note its likely effect on the findings. First, the cross-sectional design precludes causal inference and temporal ordering. Associations such as those with not working, tooth-brushing and cooking with charcoal may reflect reverse causation or reduced functional capacity, so the correlates of class membership should be read as markers for further study rather than as causes or intervention targets.

Second, subdistricts were selected purposively for data-system readiness, sampling fractions varied widely, and the order in which the 478 residents interviewed beyond the minimum sample (3.9% of participants) were approached was not documented, so their selection may not have been random. Better-organised subdistricts and more accessible residents are likely to be healthier, which would bias prevalence estimates downwards; the additional interviews were nevertheless retained because they were collected with the same procedures, and excluding them would discard valid data and reduce precision. In a bounding analysis, setting these interviews aside changed the estimated share of the complex multidomain class to 6.3% under the more plausible scenario that they were healthier residents and to 4.0% under the most unfavourable assumption (see Between-subdistrict heterogeneity and sensitivity analyses in the Results), and the near-identical classification with design weighting (SA4; $\kappa = 0.9998$) indicates that unequal sampling fractions did not drive the class solution. The numbers of older adults who could not be contacted, were ineligible at the visit or were replaced were not recorded systematically (Figure 1), so the participation rate is an upper bound. Inference is restricted to the older population of the 39 study subdistricts and should not be generalised to the province or to Northeast Thailand.

Third, the fall-related indicator combined a self-reported fall in the previous three months with gait impairment or walking-aid use taken from an instrument designed for inpatients [30]. Falls are multifactorial, and the indicator does not capture muscle strength, balance, cognition, medication use or exposure to hazardous activities; limited mobility may also reduce exposure to falls. Short recall and the forgetting of non-injurious falls [45] probably led to under-reporting of fall history (3.7%), which would attenuate associations involving falls. The composite should therefore not be interpreted as fall incidence, and without prospective follow-up we cannot show that the profiles predict future falls. Because gait impairment was assessed in broad categories, it may reflect reduced muscle strength, balance deficits or difficulty with functional tasks. Objective measures of physical performance, such as gait speed, the five-time chair stand test and the Short Physical Performance Battery [49], which the Asian Working Group for Sarcopenia recommends for assessing physical performance [29], and the Timed Up and Go test [50], would allow future studies to establish which impairments underlie this component and to test the profiles against incident falls.

Fourth, calf circumference was recorded only against the MNA cut-off of 31 cm, which is lower than the sex-specific cut-offs recommended for Asian populations (34 cm for men and 33 cm for women) [29], so low muscle mass is likely to have been under-ascertained. Because a single threshold was applied to both sexes and calf circumference varies with age, sex and body size, this misclassification may not be independent of the other indicators or of class membership, and its direction and effect on the class solution cannot be established with certainty. It may have blurred the distinction between the low-burden and at-risk classes, but it may also have shifted class boundaries and sizes and affected the associations of class membership with characteristics such as sex and age. The indicator also showed residual local dependence with the MNA-SF and depression categories, and its removal changed the class solution substantially (SA1). Its contribution to the class structure should therefore be confirmed with continuous measurements and population-specific cut-offs.

Fifth, the MNA-SF overlaps by construction with the gait and depression indicators; the sizes of the nutritional-risk and complex multidomain classes depended on indicator specification (complex multidomain class 0.9–11.7%); and the assignment of individuals to the complex class was uncertain (55.8% correctly assigned by modal assignment). These features do not invalidate the finding that a minority of older adults combine mobility impairment, malnutrition risk and depressive symptoms, which was present in every specification, but they mean that the estimated size of this minority should not be used as a planning target and that the classes should not be used to identify individuals (see Robustness of the class structure and implications for its use).

Sixth, multilevel models could not be estimated stably, and interviewer identifiers were not available, so between-subdistrict variation may partly reflect interviewer effects. Face-to-face interviews by local health personnel may have encouraged socially desirable reporting, which would lower the reported prevalence of depressive symptoms and falls. Responses given with the help of an authorised assistant, whose number was not recorded, may not reflect the participant's own experience on the 9Q and the self-harm item.

Seventh, the external correlates came from the same MNA instrument and interview as the indicators and are subject to shared-method variance; they aid the description of the classes but are not independent criterion measures, and item G reflects self-reported ability to look after oneself rather than assessed functional dependence. The home-environment checklist was developed for this study, included very common items and was assessed for content relevance only as part of the whole instrument.

Eighth, screening scores were derived only after data collection, so participants who screened positive for depressive symptoms ($n = 1017$) or reported thoughts of self-harm

($n = 571$) were not referred through the study. Future community surveys that include mental-health screening should score the 9Q and the self-harm item automatically on the electronic form, alert the interviewer to a positive result, follow a predefined referral pathway to the subdistrict health-promoting hospital or community mental-health services in line with national protocols, train interviewers to respond to distress, and keep a secure linkage key within the health service so that participants who screen positive can be followed up, with these procedures approved in advance by the ethics committee.

Finally, people with severe dementia were excluded, and cognition and activities of daily living were not assessed, so the burden of co-occurring conditions is likely to be underestimated. Taken together, several of these limitations would be expected to bias prevalence estimates downwards, whereas their effects on the class structure are less certain; they bear more on the size and boundaries of the classes and on their use for individuals than on the existence of the co-occurrence pattern itself.

5. Conclusions

Depressive symptoms, malnutrition risk and fall-related mobility risk were mutually associated among older adults in the study subdistricts, and a small, model-dependent subgroup—6.5% in the main model, 5.0–8.5% in closely agreeing specifications and 0.9–11.7% across all indicator specifications—was characterised by mobility impairment and malnutrition risk with elevated depressive symptoms and falls, together with socioeconomic disadvantage, multimorbidity, study-defined polypharmacy and home hazards, and already reported poorer health and more difficulty with self-care and eating. Because class size and individual assignment were uncertain, these findings describe population-level patterns rather than a tool for identifying individuals. Considering existing screening results together, and linking older adults with multiple risks to coordinated health, social welfare and home-modification support delivered by primary care and local government, is a hypothesis worth testing as a route to preventing dependency. Longitudinal and intervention studies are needed to confirm these associations, to evaluate the validity of count-based screening rules against clinical outcomes and to test such integrated approaches.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/healthcare14234090/s1: Table S1: Study subdistricts, registered older population, planned and achieved sample; Table S2: Prevalence of the three conditions and their indicators: unweighted and weighted estimates, design effects and intraclass correlations; Table S3: Diagnostics of the selected three-class model: (A) bivariate residuals; (B) classification-error matrix; Table S4: Item-response probabilities and concurrent external correlates by latent class; Table S5: Sequential three-step models (Models 1–3): adjusted odds ratios (95% CI) for class membership relative to the low-burden class; Table S6: Sensitivity analyses SA1–SA10: model fit, class sizes and agreement with the main model; Table S7: Additional analyses: (A) log-linear models of the three-way interaction; (B) number of conditions by modal class assignment; (C) agreement of count-based rules with complex multidomain class membership; (D) cross-check of the bias-adjusted three-step estimates against StepMix; Table S8: Item-response probabilities of the sensitivity solutions (SA1–SA10); Table S9: Leave-one-subdistrict-out jackknife (CR3-type) standard errors and t(38)-based 95% confidence intervals for the fully adjusted model (Model 4); Table S10: Fully adjusted model re-estimated with the nine-item home hazard score and after omitting tooth-brushing; Table S11: Random seeds and computational environment; File S1: Verbal informed consent script (original Thai and English translation); File S2: STROBE checklist for cross-sectional studies.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and was approved by the Human Research Ethics Committee of the Maha Sarakham Provincial Public Health Office (certificate no. 17/2568; date of approval: 30 September 2025).

Informed Consent Statement: Verbal informed consent was obtained from all participants before the interview. Verbal rather than written consent was used because the study was a minimal-risk, interviewer-administered household survey and most participants had limited formal education (87.7% had primary education or less); this procedure was approved by the Human Research Ethics Committee of the Maha Sarakham Provincial Public Health Office (certificate no. 17/2568). The interviewer presented a standard information statement on the first page of the electronic data-collection form and recorded each participant's decision in a required consent item that preceded all interview questions. The consent script, in the original Thai with an English translation, is provided as Supplementary File S1.

Data Availability Statement: The de-identified data supporting the findings of this study are not publicly available because they were collected under a community health programme and contain information that could compromise participant privacy. They are available from the corresponding author upon reasonable request, subject to permission from the project Network Collaboration to Drive Maha Sarakham toward a Healthy Province and approval from the Human Research Ethics Committee of the Maha Sarakham Provincial Public Health Office. Requests can be considered only until two years after the close of the funded project, after which the data will be destroyed, as stated in the consent information. The analysis scripts are likewise not deposited in a public repository; they are available from the corresponding author on request, together with a data dictionary and a synthetic dataset that allow the code to be run without access to participant-level data.

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Abbreviations

The following abbreviations are used in this manuscript:

2Q	2-question depression screening
9Q	9-question depression rating scale (Thai)
AIC	Akaike information criterion
ANOVA	analysis of variance
aOR	adjusted odds ratio
AvePP	average posterior probability
BCH	Bolck–Croon–Hagenaars method
BIC	Bayesian information criterion

BLRT	bootstrap likelihood ratio test
BMI	body mass index
BVR	bivariate residual
CI	confidence interval
CR3	jackknife cluster-robust variance estimator
CVI	content validity index
ICC	intraclass correlation coefficient
ICOPE	Integrated Care for Older People
IOC	index of item–objective congruence
L^2	likelihood-ratio chi-square statistic
LAO	local administrative organisation
LCA	latent class analysis
LL	log-likelihood
ML	maximum likelihood
MNA	Mini Nutritional Assessment
MNA-SF	Mini Nutritional Assessment Short-Form
O/E	observed-to-expected ratio
SA	sensitivity analysis
SABIC	sample-size-adjusted Bayesian information criterion
SD	Standard deviation
STROBE	Strengthening the Reporting of Observational Studies in Epidemiology
THB	Thai baht
VIF	Variance inflation factor
WHO	World Health Organization

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