Estimating Health-State Transition Probabilities Using Repeated Cross-sectional Data from the 2021 and 2024 Surveys of Older Persons in Thailand[1]

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Abstract

As population aging accelerates globally, understanding the dynamics of health transitions among the elderly is crucial for public health planning. In developing contexts like Thailand, where longitudinal data are limited, estimating these dynamics remains challenging. This study develops a three-state Markov model (Independent, Dependent, and Death) using repeated cross-sectional data from the National Statistical Office's Survey of the Older Persons in Thailand (2021 and 2024). We estimated age- and sex-specific 3-year transition probabilities to capture health dynamics. The results indicate that the probability of maintaining current health status decreases with age, while the probability of transitioning to dependency and death steadily increases, reflecting the natural physiological decline associated with aging. Beyond these general trends, the findings confirm the existence of a "morbidity–mortality paradox": males exhibit high mortality from an independent state but low morbidity, whereas females demonstrate greater longevity accompanied by higher rates of transition to dependency. To demonstrate the utility of these estimates, we provided a calculation method for projecting the population categorized by health status from 2024 to 2036. This study confirms the feasibility of using repeated cross-sectional data to estimate health dynamics in resource-limited settings and highlights the urgent need for age- and gender-specific long-term care policies.

Keywords: *multi-state model; Markov transitions; activities of daily living; cross-sectional data; population projection; Thailand*

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[1] The article title has been changed to reflect the current content.

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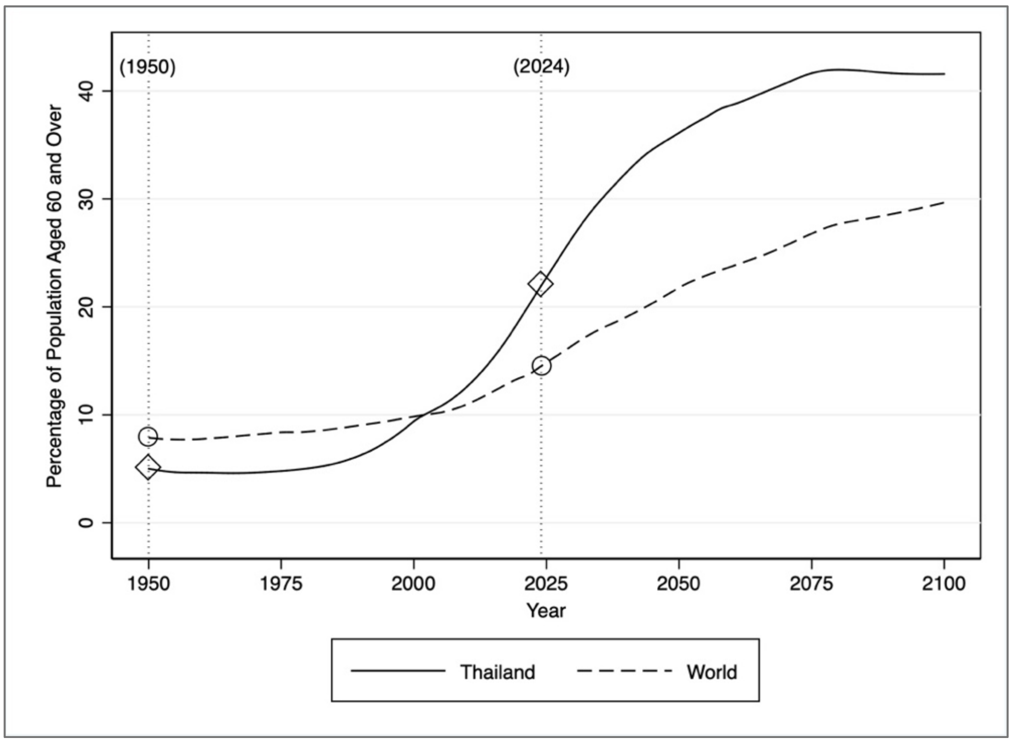
1. Introduction

The decline in birth and death rates due to demographic transitions in many countries has resulted in a rapid increase in the proportion of elderly people worldwide (United Nations, 2023, 2024a). Similarly, in Thailand, the proportion of elderly people was 5.00% in 1950 but increased to 21.19% in 2023 (United Nations, 2024b). Based on population projections, this upward trend in the proportion of elderly people in Thailand is expected to continue in the future, as shown in Figure *1*.

Figure 1 The proportion of the population aged 60 years or older in Thailand and globally, from 1950 to 2100.



Data source: Estimates and projections from the "World Population Prospects 2024". (United Nations, 2024b)

While increased life expectancy is a testament to public health success, it raises critical questions in about the quality of those additional years—specifically, whether they are lived in good health or with disability. Thailand, as an upper-middle-income country (OECD, 2025), should consider future health data for its aging population in order to prepare its public health system. This is because reports from the World Health Organization indicate that the burdens of disability and death in low- and middle-income countries are significantly higher than in high-income countries (World Health Organization, 2015).

Understanding the dynamics of health transitions—how individuals move between states of independence, dependency, and death—is essential for forecasting future care needs. Ideally, such analyses rely on longitudinal data (Courgeau, 2001; Pitacco, 1995; van den Hout, 2016). However, in many developing nations, including Thailand, high-quality longitudinal surveys on aging are scarce or suffer from high attrition rates. Conversely, nationally representative cross-sectional surveys on issues concerning the elderly are conducted at regular intervals by the National Statistical Office under the name of the Survey of Older Persons in Thailand (National Statistical Office, 2024).

Previous studies in Thailand have largely relied on transition probabilities derived from other countries (Srithamrongsawat et al., 2014; Tantirat et al., 2020) or have used static prevalence rates for projections (Chandoevwit & Vajragupta, 2017; Loichinger & Pothisiri, 2018), which have limitation to capture the dynamic nature of health deterioration and mortality. This study addresses this gap by developing a discrete-time Markov model using repeated cross-sectional data from 2021 and 2024. The objectives are to (1) estimate age- and sex-specific transition probabilities between independent, dependent, and dead states, and (2) demonstrate a calculation method for projecting the future health status of the Thai elderly population up to 2036.

2. Estimating Health Transitions from Cross-Sectional Data

To analyze the dynamics of health status changes among the elderly, this study employs a multi-state model (or multi-state survival model), a statistical approach widely applied in epidemiology, actuarial science, and demography to study processes involving transitions between states, whether in health or other demographic aspects (Dickson et al., 2019; van den Hout, 2016; Willekens, 2003).

2.1 The Markov Chain Approach

The health transition process is conceptualized as a stochastic process, specifically a Markov chain. A fundamental assumption of this model is the Markov property, which posits that the future state of an individual depends solely on their current state, independent of their history (Dickson et al., 2019; Levin & Pere, 2017; van den Hout, 2016). While real-world health trajectories may not strictly adhere to this property, Markov models are empirically proven to provide robust approximations for population-level estimation (van den Hout, 2016).

In a discrete-time framework, the model estimates transition probabilities (p_{ij}), representing the likelihood of an individual moving from state i to state j over a specific interval. These probabilities must satisfy two conditions: (1) probability of a state transition must be between 0 and 1 ($0 \leq p_{ij} \leq 1$), and (2) the sum of probabilities for all possible transitions from a starting state i must equal 1 ($\sum_j p_{ij} = 1$) (Ibe, 2013)

2.2 The Use of Cross-Sectional Data

Ideally, estimating transition probabilities requires longitudinal data that tracks individuals over time (Ibe, 2013; van den Hout, 2016). However, such data are often scarce or costly in developing nations. Consequently, researchers have developed methodologies to estimate these probabilities using repeated cross-sectional data.This estimation relies on the critical assumption of a stationary population between the two survey points. A stationary population implies constant age-specific mortality rates, a constant number of births, and, crucially, zero net migration (a closed population) (Preston et al., 2001). Under these conditions, the structure of the population remains constant over time, allowing researchers to link the observed prevalence rates with mortality rates to solve for the unknown transition probabilities via a system of equations (Albarran et al., 2005; Kessy et al., 2024; Naka et al., 2020; Nuttall et al., 1994; Rickayzen & Walsh, 2002).

Furthermore, due to the limitations of cross-sectional data, particularly the absence of observed recovery rates, it is standard practice to assume irreversible health deterioration (no recovery) (Albarran et al., 2005; Davis et al., 2002; Lim et al., 2019; Nuttall et al., 1994; Sherris & and Wei, 2021). Under this assumption, individuals can only remain in their current health state or deteriorate to a dependent state or death. This approach simplifies the model parameters, allowing them to be estimable from aggregate data, while aligning with the general biological trajectory of aging (Albarran et al., 2005).

2.3 General Trends in Health Transitions

Disspite the different defination of health states, previous studies utilizing this cross-sectional estimation method have consistently identified distinct age and sex patterns. Generally, the probability of death increases with age for all health states, with those in poorer health exhibiting higher mortality risks. A key demographic pattern typically observed is that males exhibit higher mortality rates (lower survival probabilities) than females across all health states (Albarran et al., 2005; Kessy et al., 2024; Naka et al., 2020; Park & Sherris, 2023). Conversely, females tend to have a higher probability of transitioning from a healthy to a dependent state and a higher probability of remaining in a dependent state compared to males (Park & Sherris, 2023), but these values decrease with age (Kessy et al., 2024). This divergence underscores the importance of sex-disaggregated analysis in projecting future care needs.

3. Methodology

This study employs a quantitative research design based on secondary data analysis. The methodology comprises four main stages: (1) data preparation and defining health states, (2) mortality estimation via cohort subtraction, and (3) estimation of transition probabilities using numerical optimization.

3.1 Data Sources and Study Population

The primary data were obtained from the Survey of the Older Persons in Thailand, a nationally representative cross-sectional survey conducted by the Thailand National Statistical Office (NSO). We utilized two rounds:

(1) **Baseline:** 2021 (t) covering individuals aged 57 and over.
(2) **Follow-up:** 2024 ($t + 3$) covering individuals aged 60 and over.

The age criteria were selected to facilitate cohort tracking over the 3-year interval, as shown in Table *1*,assuming that a person aged x in 2021 would be aged $x + 3$ in 2024. For instance, the cohort aged 57 – 59 in 2021 corresponds to the group aged 60 – 62 in 2024. All data were weighted to reflect the national population structure.

Table 1 Coding and interpretation of age groups from the 2021 and 2024 Survey of the Older Persons in Thailand

2021 Survey		**2024 Survey**	
code	Age Group	code	Age Group
57	57 - 59	60	60 - 62
60	60 - 62	63	63 - 65
63	63 - 65	66	66 - 68
66	66 - 68	69	69 - 71
69	69 - 71	72	72 - 74
72	72 - 74	75	75 - 77
75	75 - 77	78	78 - 80
78	78 - 80	81	81 - 83
81	81 +	84	84 +

For the projection baseline and future cohort assumptions, we integrated demographic data from the United Nations' *World Population Prospects 2024* to define the baseline population and future cohort structures.

3.2 Measures and Health States

Health status was categorized based on Activities of Daily Living (ADLs)(Katz et al., 1963). The study assessed functional ability across five basic activities: feeding, transferring, toileting, dressing, and bathing. We assessed functional ability across five basic activities: feeding, transferring, toileting, dressing, and bathing. The study defined a 3-state model space $S = \{I, D, X\}$:

(1) **Independent (I):** Ability to perform all five ADLs without assistance (ADL score = 5).
(2) **Dependent (D):** Inability to perform at least one ADL without assistance (ADL score < 5).
(3) **Death (X):** An absorbing state representing mortality.

3.3 Estimation of Mortality

Since the data are cross-sectional, direct linkage of individual mortality records was not possible. We estimated the number of deaths for each age-sex cohort using the cohort subtraction method. The validity of this approach relies on the consistency of the population weights; specifically, the NSO calibrated the design weights for both survey rounds to align with the official population projection by age, sex, and region, calculated by the Thailand Office of the National Economic and Social Development Council (NESDC) (National Statistical Office, 2022, 2024). Crucially, these NESDC projections were constructed under the assumption that international migration had a negligible impact on Thailand's population structure and was therefore excluded from the calculation (NESDC, 2019). Consequently, under this closed-population framework, any observed reduction in the size of a specific birth cohort over the time interval can be attributed solely to mortality.

First, to mitigate sampling noise and potential age-reporting errors common in survey data, we applied Poisson P-splines smoothing (Currie et al., 2004; Eilers & Marx, 2021) to the weighted population counts (${}_3N_x^y$) for both years. The number of deaths (${}_3D_x$) for a cohort aged x in 2021 was calculated as:

$${}_3D_x = {}_3N_x^{2021\,(sm)} - {}_3N_x^{2024\,(sm)}$$

where ${}_{3}N_{x}^{y\,(sm)}$ represents the smoothed population of the specific 3-year age group in year y. This derived death count was then incorporated into the 2024 prevalence vector to account for the absorbing state.

3.4 Estimation of Transition Probabilities

We modeled the health transitions using a discrete-time Markov chain with a 3-year step. Given the scarcity of longitudinal data in Thailand, individual-level status transitions could not be directly tracked. Consequently, this study inferred population-level health dynamics by analyzing changes in aggregate age-specific prevalence rates across the two survey rounds.

Therefore, after adjusting the independent and dependent population counts obtained from the survey to match the smoothed population (${}_{3}N_{x}^{y}$), we can calculate the age-specific prevalence rates for each year. The values for all three statuses will be included as members of the age-specific prevalence vector for that year. Let $P_{2021}^{[x,x+2]}$ be the observed prevalence vector of independent and dependent states (with death initialized at 0) $\begin{bmatrix} I_{2021}^{[x,x+2]} & D_{2021}^{[x,x+2]} & 0 \end{bmatrix}$ at baseline, and $P_{2024}^{[x,x+2]}$ be the observed prevalence vector $\begin{bmatrix} I_{2024}^{[x,x+2]} & D_{2024}^{[x,x+2]} & X_{2024}^{[x,x+2]} \end{bmatrix}$ at follow-up (where the numerator of $X_{2024}^{[x,x+2]}$ is derived from the estimated mortality).

To quantify the health dynamics, the health state transitions over the 3-year interval for each age cohort x were simulated using a transition probability matrix ($T_{[x,x+2]}$). This matrix encapsulates the probabilities of all possible health trajectories—specifically, remaining in the same state, deteriorating to a dependent state, or dying. The structure and permissible transitions within this matrix are governed by two fundamental assumptions:

(1) **Irreversible Health Deterioration:** The model assumes no recovery to a better state once one has entered a worse state, as shown in Table *2*. This assumption is acceptable for elderly populations where functional decline is often progressive (Albarran et al., 2005).
(2) **Closed Population**: The analysis assumes zero net migration for the elderly population, implying that attrition from a cohort is solely attributable to mortality.

Table 2 the possible transition of health status from 2021 to 2024 under the assumption of irreversible health deterioration.

Health Status		**2024**		
		Independent	Dependent	Death
2021	Independent	$I \rightarrow I$	$I \rightarrow D$	$I \rightarrow X$
	Dependent	$D \nrightarrow I$	$D \rightarrow D$	$D \rightarrow X$
	Death	$X \nrightarrow I$	$X \nrightarrow D$	$X \rightarrow X$

Under these two assumptions, for each age group x, the transition probability matrix is defined as:

$$T_{[x,x+2]} = \begin{pmatrix} {}_3p_x^{II} & {}_3p_x^{ID} & {}_3p_x^{IX} \\ {}_3p_x^{DI} & {}_3p_x^{DD} & {}_3p_x^{DX} \\ {}_3p_x^{XI} & {}_3p_x^{XD} & {}_3p_x^{XX} \end{pmatrix}$$

$$= \begin{pmatrix} {}_3p_x^{II} & {}_3p_x^{ID} & {}_3p_x^{IX} \\ 0 & {}_3p_x^{DD} & {}_3p_x^{DX} \\ 0 & 0 & 1 \end{pmatrix}$$

To estimate the unknown transition probabilities (${}_3p_x^{ij}$), we constructed a system of linear equations based on the law of total probability. The relationship between the health status distribution in 2021 and 2024 is modeled by the matrix equation:

$$\hat{P}_{2024}^{[x+3,x+5]} = P_{2021}^{[x,x+2]} \times T_{[x,x+2]}$$

where $\hat{P}_{2024}^{[x+3,x+5]} = \left[\hat{I}_{2024}^{[x+3,x+5]} \quad \hat{D}_{2024}^{[x+3,x+5]} \quad \hat{X}_{2024}^{[x+3,x+5]}\right]$ represents the predicted prevalence vector for the follow-up year. By expanding the matrix multiplication, we derived a system of three distinct equations representing the predicted prevalence for each health state in 2024:

(1) Predicted Independent State:

$$\hat{I}_{2024}^{[x+3,x+5]} = I_{2021}^{[x,x+2]} \times {}_3p_x^{II}$$

(2) Predicted Dependent State:

$$\hat{D}_{2024}^{[x+3,x+5]} = \left(I_{2021}^{[x,x+2]} \times {}_{3}p_x^{ID}\right) + \left(D_{2021}^{[x,x+2]} \times {}_{3}p_x^{DD}\right)$$

(3) Predicted Death State:

$$\hat{X}_{2024}^{[x+3,x+5]} = \left(I_{2021}^{[x,x+2]} \times {}_{3}p_x^{IX}\right) + \left(D_{2021}^{[x,x+2]} \times {}_{3}p_x^{DX}\right)$$

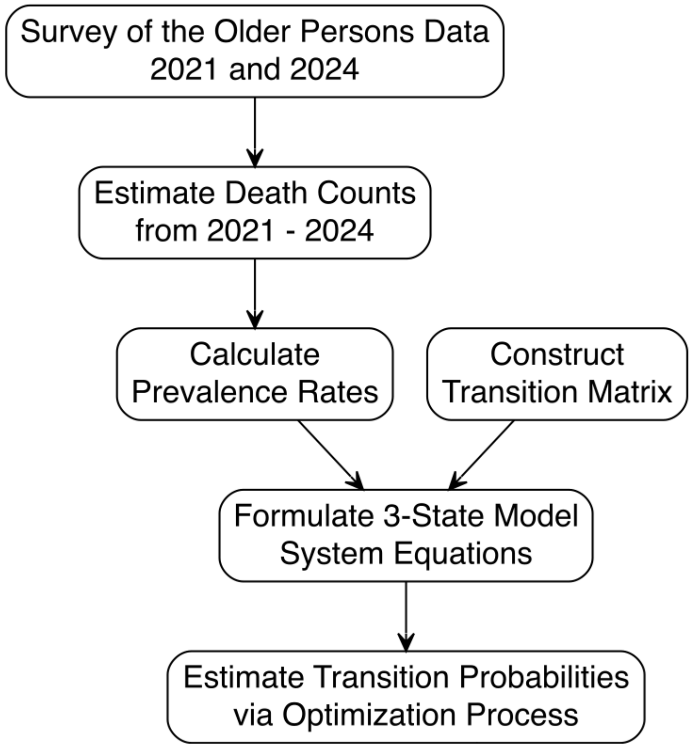
After creating the equation system, we then employed a numerical optimization technique using the Generalized Reduced Gradient (GRG) nonlinear algorithm to solve for the unknown probabilities. The objective was to minimize the sum of squared differences (SSD) between these predicted values and the actual observed values from the 2024 data:

$$Minimize\ Z = \sum_{S=\{I,D,X\}} \left(P_{2024,S}^{[x,x+2]} - \hat{P}_{2024,S}^{[x,x+2]}\right)^2$$

In order to ensure mathematical validity, the optimization process was performed subject to two fundamental constraints: (1) all transition probabilities were restricted to the closed interval [0,1] ($0 \leq p_{ij} \leq 1$). (2) the transition matrix was constrained to be row stochastic, requiring that the sum of probabilities for transitioning from any given state i to all possible future states must equal 1 ($\sum_j p_{ij} = 1$).

To ensure biological plausibility and reduce fluctuations due to small sample sizes in advanced ages, the raw transition probabilities estimated from the optimization step were smoothed using the Whittaker-Henderson method (Whittaker, 1922). We selected a smoothing parameter (lambda) of $\lambda = 10$, which offered an optimal balance between fidelity to the original data and smoothness of the age curve.

Figure 2 The analytical framework of the study.



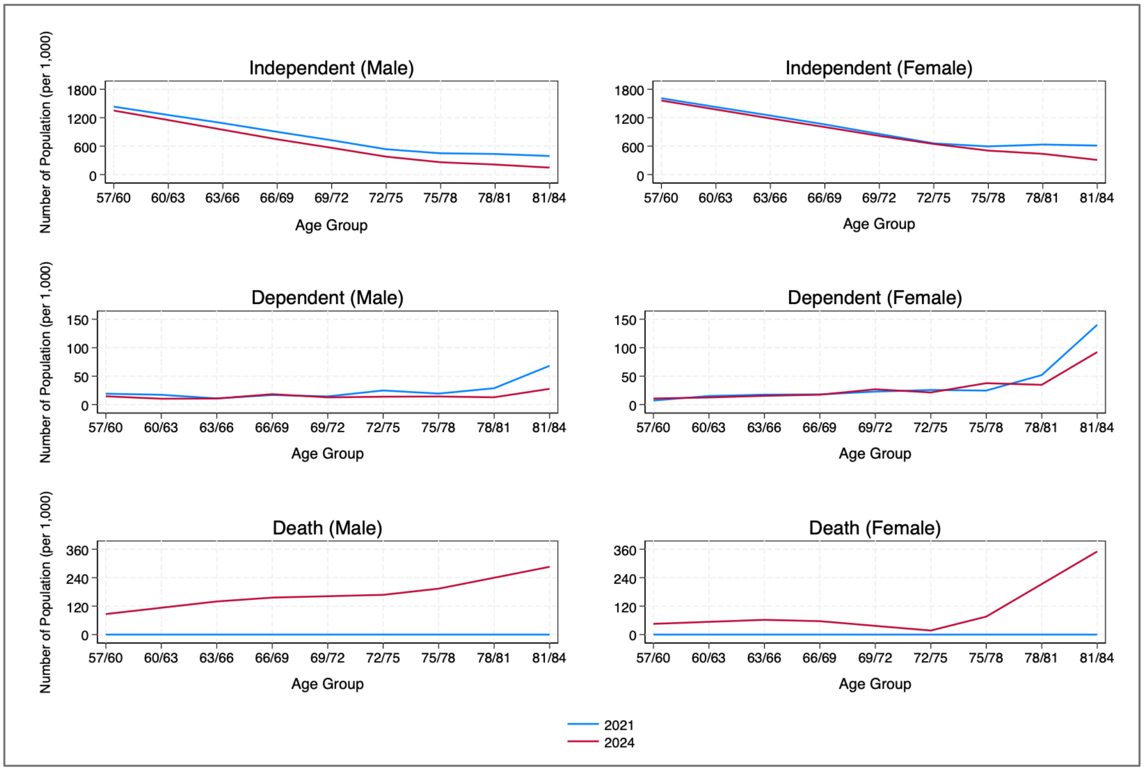
4. Results

4.1 Demographic Characteristics and Health State Dynamics

The analysis utilized data from 53,861 respondents in 2021 and 50,578 respondents in 2024. After weighting to the national population, as shown in Figure *3*, the population for both sexes in the Independent state declined significantly across all age groups as cohorts aged from 2021 to 2024. In contrast, the Dependent state revealed a distinct gender pattern: while the number of dependent males remained relatively stable, the female population exhibited a sharp increase in dependency, particularly in the oldest-old age groups.

The Death estimates confirm a striking gender disparity derived from the cohort subtraction method. The red lines in the 2024 death panels indicate the number of deaths occurring over the interval. Males exhibited a consistently high number of deaths starting from early old age, whereas females showed a lower mortality count that spiked only in the most advanced ages. In total, the model estimated approximately 1.55 million deaths among males compared to 0.91 million among females, highlighting a pattern of high attrition among men.

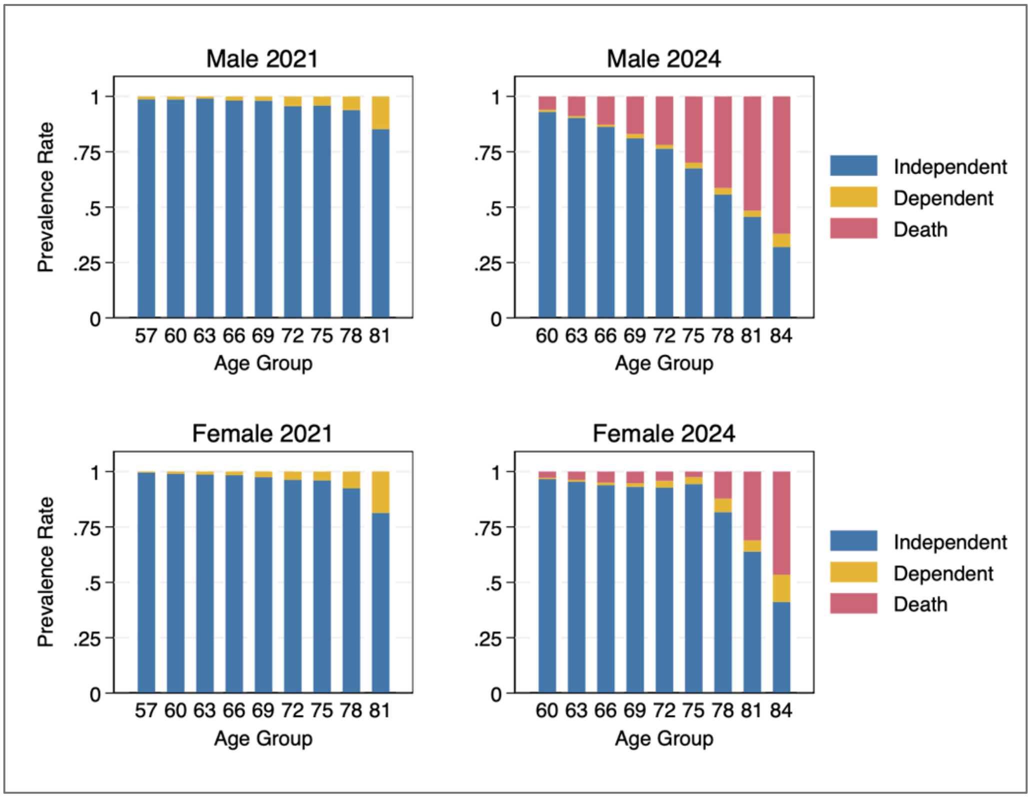
Figure 3 the changes in population counts for each health state among the same birth cohorts over the 3-year interval.



4.2 Prevalence of Health States

Figure *4* illustrates the age-specific prevalence rates for both sexes, contrasting the baseline structure (2021) with the follow-up distribution (2024) that incorporates accumulated mortality. The data reveals distinct trajectories of health decline associated with aging. At baseline, functional independence predominates across all age groups for both sexes. However, the inclusion of estimated mortality in 2024 exposes a critical divergence in health outcomes. For males, the aging process is characterized by high attrition due to mortality, while the prevalence of dependency remains compressed and relatively stable. In contrast, females exhibit a pattern of "survival with disability," where lower mortality rates compared to males are offset by a substantial expansion of the dependent population, particularly among the oldest-old cohorts.

Figure 4 Comparison of age-specific prevalence rates by health state and sex between 2021 (baseline) and 2024 (follow-up).



4.3 Transition Probabilities

The optimization process initially yielded raw age-specific transition probabilities, as illustrated in Figure 5. As expected, these raw estimates exhibit noticeable fluctuations, particularly among the oldest-old age groups, reflecting the inherent variability associated with smaller sample sizes at advanced ages. To mitigate this noise and reveal the underlying demographic patterns, Whittaker-Henderson smoothing was applied, resulting in the more coherent trends displayed in Figure 6. However, presenting all transition types on a single set of axes compresses the visualization of lower-probability transitions (such as ${}_3p_x^{ID}$), thereby obscuring subtle age-related changes. Consequently, Figure 7 separates these transitions into distinct panels with adjusted scales to facilitate a more granular examination of gender differentials and age trends.

Figure 5 Estimated 3-year transition probabilities by age and sex (unsmoothed).

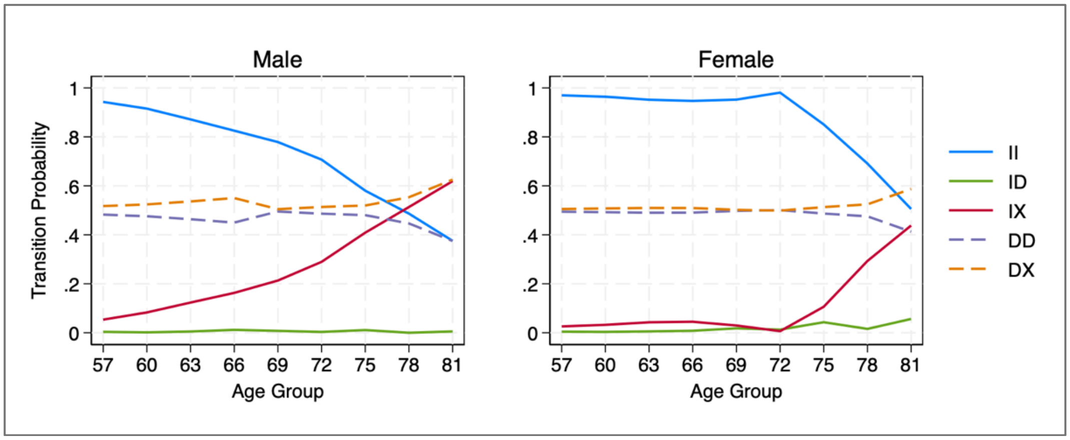


Figure 6 Smoothed 3-year transition probabilities by age and sex.

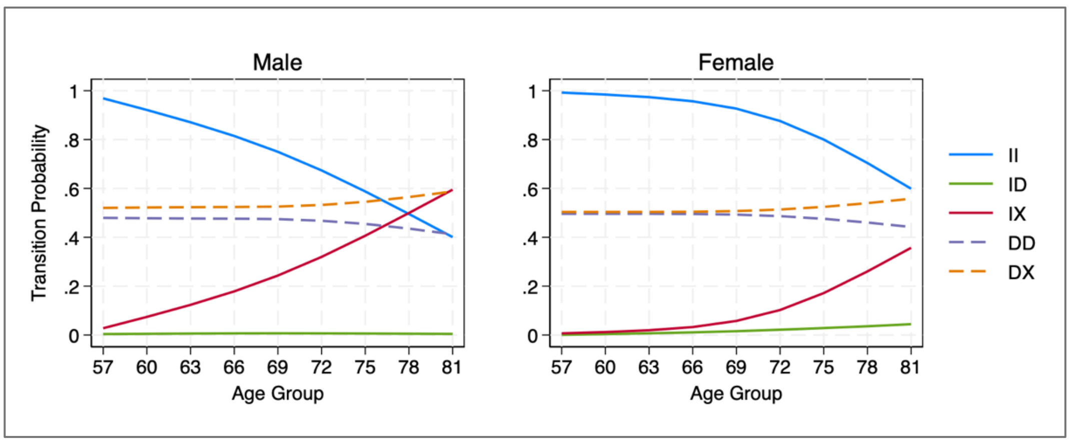
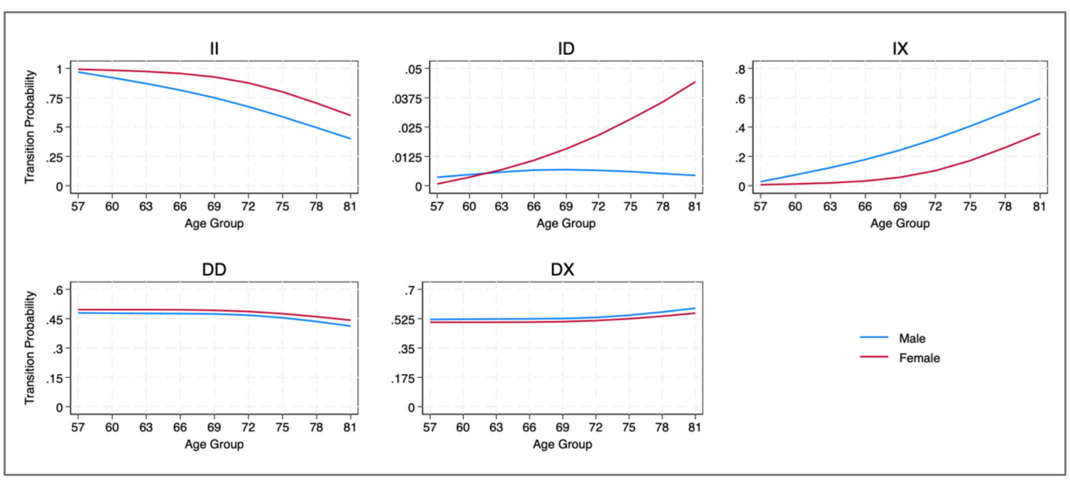


Figure 7 Comparative analysis of smoothed transition probabilities by type of transition.



From Figure *7*, The estimated 3-year transition probabilities revealed distinct age and sex patterns:

(1) **Mortality** (${}_3p_x^{IX}$ and ${}_3p_x^{DX}$): The probability of death increased with age for both sexes. However, males exhibited a significantly higher probability of dying directly from the independent state (${}_3p_x^{IX}$) compared to females. For instance, in the oldest-old age group (81+), ${}_3p_x^{IX}$ for males was approximately 0.59, compared to 0.36 for females.
(2) **Disability** (${}_3p_x^{ID}$): Females showed a markedly higher risk of transitioning from independence to dependency (${}_3p_x^{ID}$). While this probability remained low and relatively constant for males across all ages (< 0.01), it increased exponentially for females, reaching 0.04 in the 81+ age group.
(3) **Retention** (${}_3p_x^{II}$ and ${}_3p_x^{DD}$): Females had a higher probability of remaining in both independent and dependent states compared to males, reflecting their lower mortality risk but higher morbidity burden.

Theoretically, the findings confirm the existence of the "morbidity–mortality" paradox (Oksuzyan et al., 2008) or "male-female health-survival paradox" (Kulminski et al., 2008) in the Thai elderly population. Specifically, the male population exhibits a high probability of death from an independent state (${}_3p_x^{IX}$) but a low probability of entering a dependent state (${}_3p_x^{ID}$). In contrast, the female population, despite having a tendency for greater longevity, spends a longer duration living in a dependent state (${}_3p_x^{DD}$).

5. Limitation

The model assumes no recovery from disability, which may slightly overestimate dependency. Additionally, the analysis relies on the assumption of a closed population (zero migration) for the cohort subtraction method, although empirical data suggests migration among the Thai elderly is negligible (National Statistical Office, 2025; NESDC, 2019).

6. The Utility of Transition Probabilities

One of the most concrete ways to utilize probability in demography is to use it to estimate future population by health status. Although the results are not shown in this paper, the authors provide guidance for the projection using transition probabilities.

Using the smoothed age- and sex-specific transition probabilities collected in smoothed transition matrix ($T_{[x,x+2]}^{(sm)}$), we can project the number of elderly individuals in each health state (Independent, Dependent, Death) from the base year 2024 to 2036 by conducting in four consecutive 3-year cycles (i.e., 2027, 2030, 2033, and 2036), as shown in Table *3*.

Table 3 Timeline of the stepwise 3-year projection cycles (2024–2036).

Projection Cycle	**Base Year** (t)	**Result Year** ($t + 3$)
1	2024	2027
2	2027	2030
3	2030	2033
4	2033	2036

The projection model relies on the time-homogeneity assumption, implying that the transition probabilities estimated for the 2021 – 2024 interval remain constant throughout the entire projection period. For each projection cycle, the population vector at time $t + 3$ is derived from the population at time t using the matrix multiplication equation:

$$K_{t+3}^{[x+3,x+5]} = K_{t}^{[x,x+2]} \cdot T_{[x,x+2]}^{(sm)}$$

Where:

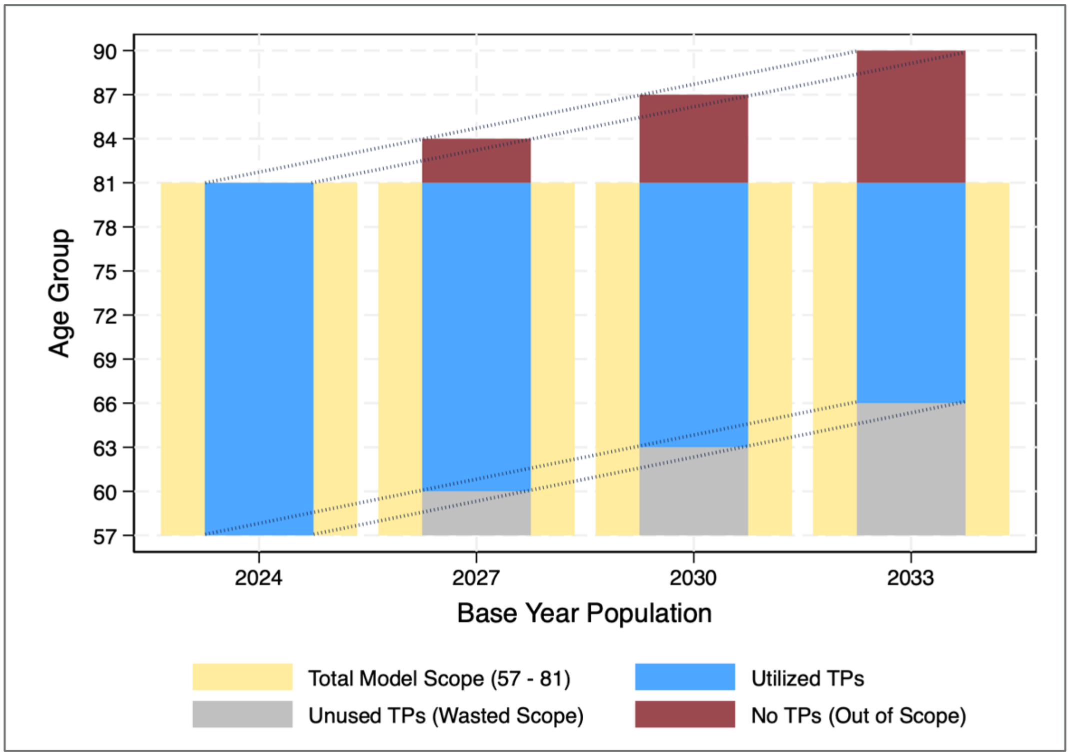
- $K_{t}^{[x,x+2]}$ is the row vector representing the number of survivors in each health state (Independent, Dependent) and the cumulative number of deaths for a specific age cohort at the beginning of the cycle (t).
- $K_{t+3}^{[x+3,x+5]}$ is the resulting vector for the same cohort as they age by 3 years.

However, to solve problem in Figure *8* and to ensure the continuity of the population structure across all age groups in every cycle, two specific adjustments have to be implemented:

(1) **New Entrants (Age 57 – 59):** Since the model focuses on the elderly (60+), each new projection cycle requires the introduction of a new pre-elderly cohort (aged 57 – 59) that will become the 60 – 62 age group in the subsequent period. The total population size for this incoming cohort can be obtained from the UN World Population Prospects 2024. To categorize them by health state, the observed prevalence rates of the 57 – 59 age group from the 2024 baseline can be used by assuming that the health profile of new entrants remains constant over time.

(2) **Open-Ended Age Group (81+):** The model defines the final age category as 81 years and over. In each projection step, survivors from the 78 – 80 cohort (who become 81 – 83) and survivors from the existing 81+ cohort (who become 84+) have to be aggregated to form the new 81+ population for the next cycle. This aggregation ensures compatibility with the dimension of the transition matrix, which is fixed for the open-ended age group.

Figure 8 Discrepancy between the fixed estimation scope and the aging cohorts during the multi-stage projection process.



Moreover, since the transition probabilities are estimated over a 3-year interval, the projection model generates population counts in 3-year cycles (e.g., 2027, 2030). For applications requiring population estimates for intermediate years (e.g., 2025, 2026), linear interpolation between the calculated projection points is a suitable approximation method to derive the annual figures.

7. Conclusion

Given the limitations of longitudinal data in Thailand, this study developed a Markov multi-state model by applying cross-sectional data from the 2021 and 2024 Survey of the

Older Persons in Thailand. The main objective was to estimate the 3-year transition probabilities between health states—independent, dependent, and death. The estimated transition probabilities indicate that stability in both independent and dependent states diminishes with age, while the risk of transitioning to dependency or death consistently rises, aligning with the natural decline of health. Most notably, the findings confirm the "morbidity–mortality paradox" or "male-female health-survival paradox" in Thailand. The male population exhibits high mortality rates directly from the independent state but a low risk of becoming dependent. Conversely, the female population demonstrates greater longevity but spends a significantly longer duration in a dependent state. Moreover, to demonstrate the application of these estimates, the study also provided a calculation method for projecting the elderly population classified by health status from 2024 to 2036.

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