On the models for the distribution of examination score for projecting the demand for Korean Long-Term Care Insurance

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Abstract

The Korean Long-Term Care Insurance (K-LTCI) provides financial support for long-term care service to people who need various types of assistance with daily activities. As the number of elderly people in Korea is expected to increase in the future, the demand for long-term care insurance would also increase over time. Projection of future expenditure on K-LTCI depends on the number of beneficiaries within the grading system of K-LTCI based on the test scores of applicants. This study investigated the suitability of mixture distributions to the model K-LTCI score distribution using recent empirical data on K-LTCI, provided by the National Health Insurance Service (NHIS). Based on the developed mixture models, the number of beneficiaries in each grade and its variability under the current grading system were estimated by simulation. It was observed that a mixture model is suitable for K-LTCI score distribution and may prove useful in devising a funding plan for K-LTCI benefit payment and investigating the effects of any possible revision in the K-LTCI grading system.

Keywords: demand, grading system, long-term care insurance, mixture distributions, projection, simulation

1. Background

The Korean Long-Term Care Insurance (K-LTCI) was introduced in 2008 by the National Health Insurance Service (NHIS) for the purpose of providing financial support to people who need assistance with daily activities. With the rapid aging of the population, the K-LTCI has been playing an important role in providing a social security system for the elderly in Korea. When K-LTCI was introduced, the premium rate was 0.21% of the salary. However, the premium sharply increased to 0.68% in 2020 to reflect increased cost of operations. Population projection by Statistics Korea indicates K-LTCI beneficiaries will keep increasing, and so will the associated costs. Thus, cost projection is an important task and will help provide information to devise an appropriate financial plan aimed at maintaining the sustainability of K-LTCI.

The extent of financial support from K-LTCI depends on the grade defined by the range of examination scores of applicants indicating the degree of care level needed. Therefore, the distribution of scores assigned to K-LTCI applicants can be used to model the proportion of beneficiaries in each grade level. Accordingly, annual cost of K-LTCI in future years can be estimated by the projected number of beneficiaries by year and a comprehensive model for cost structure.

The NHIS provides monthly data on the number of beneficiaries in each grade level by sex and age group upon request; this data allows us to construct a model for the distribution of scores assigned to K-LTCI applicants. In order to secure an appropriate model for score distribution, various types of model structure should be explored. The goal of this study is to investigate a variety of mixture models for score distribution and to compare them with the models explored in Kwon *et al.* (2016). There has not been any

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discussion on demand and expenditure projections for K-LTCI services since the revision of the K-LTCI scoring system in 2018. This study expects to initiate the discussion on how the current grading system might affect such projections.

The developed model is expected to be utilized in the following analyses. The main purpose of the model for score distribution is to estimate the number of beneficiaries in each grade of K-LTCI in future years. It is desirable that the estimated number of beneficiaries is interpreted with its variability. Simulation based on the developed model allows for quantifying the variability. In addition, the grading structure has been revised four times ever since K-LTCI was introduced. When further revisions on the grading structure are considered, a model for score distribution can be used to observe the effect of revision on the number of beneficiaries in each of the revised grades.

Aging population is common to many developed countries. To improve the quality of life for elderly population, every country has developed its own long-term care system as a form of social security. As projection of the number of beneficiaries and of the associated costs of long-term care system are important to guide policymaking, there has been adequate research on estimating future demands and expenditures of long-term care.

A number of previous studies have used a cell-based approach to estimate the number of persons requiring long-term care. This approach classifies population into a set of sub-populations, termed cells, based on the factors affecting the utilization of long-term care. Then, based on the projected population and utilization rate of long-term care in each cell, the number of patients who need long-term care in each is derived. Wittenberg *et al.* (1998) applied the approach to estimate the elderly population in England. The authors defined cells in terms of age, gender, dependency, and household composition and derived future demand for long-term care. Further, Linda *et al.* (2007) used a similar method to project the total cost of long-term care in Germany, Italy, Spain, and the UK.

Several studies have employed the cell-based approach to project the number of beneficiaries and the associated expenditure under K-LTCI. Yun and Kwon (2010) used sample data and considered several scenarios to obtain the proportion of K-LTCI beneficiaries in each cell defined by age, gender, household type, and health status, which are all considered drivers of long-term care expenditure. Kim and Kwon (2012), Lee and Choi (2014), and Lee and Moon (2017) followed up the discussion suggesting modified cell-based approaches.

Another approach for projection of demand for and cost of long-term care was suggested by Rickayzen and Walsh (2002) who utilized a multi-state model to reflect possible changes in health status, categorized according to the severity of functional disability, to estimate long-term care demand in UK. They constructed a mathematical formula to obtain transition probabilities from one state to another. Based on the transition probabilities, the number of persons in each state in future years is estimated based on their current proportions in each state. Their work was followed by Karlsson *et al.* (2006) in which future cost of long-term care was projected.

Leung (2004) constructed a multi-state model to project the future demand for and cost of long-term care for the elderly population in Australia. Based on the National Long-Term Care Survey (NLTCs) in the USA, Chan *et al.* (2004) employed a multi-state model to project long-term care demand in Hong Kong. Kwon and Lee (2011) projected the number of K-LTCI beneficiaries in each grade and the associated total cost for future years using a multi-state model. Furthermore, Kwon (2013) analyzed the expected number of years during which an individual will need long-term care and estimated the actuarial present value of the future cost of long-term care, all within a multi-state model framework.

Additionally, several studies used scenario analysis for projection. Choi *et al.* (2010) estimated the number of K-LTCI beneficiaries based on various scenarios, and Choi and Lee (2011) evaluated the effect of possible scenarios of future policy expanding the eligibility of K-LTCI benefit on the increase in the number of beneficiaries. Lagergren *et al.* (2018) performed scenario analysis for projecting long-term care demand and expenditure in Japan and Sweden.

Other approaches can be found as well in recent literatures. Kwon *et al.* (2016) suggested a simulation

Table 1: Changes in the grade level system of K-LTCI

Score range	Phases				
	I (2008.7–2012.6)	II (2012.7–2013.6)	III (2013.7–2014.6)	IV (2014.7–2017.12)	V (2018.1–current)
31.3–39.9	Non-grade C	Non-grade C	Non-grade C	Non-grade C	Non-grade C or Cognitive Assistance
40.0–44.9	Non-grade B	Non-grade B	Non-grade B	Non-grade B	Non-grade B or Cognitive Assistance
45.0–50.9	Non-grade A	Non-grade A	Non-grade A	Non-grade A or Grade 5	Non-grade A or Grade 5
51.0–52.9			Grade 3	Grade 4	Grade 4
53.0–54.9					
55.0–59.9		Grade 3		Grade 3	Grade 3
60.0–74.9	Grade 2		Grade 2		
75.0–94.9	Grade 2	Grade 2	Grade 2	Grade 2	Grade 2
95.0–154.3	Grade 1	Grade 1	Grade 1	Grade 1	Grade 1

method based on K-LTCI score distribution for estimating the number of persons in each grade. Xu and Chen (2019) applied Bayesian Quantile Regression to understand the relationship between the incidence of chronic diseases and long-term care demand and derived the number of patients who would need long-term care in the future. Vanella *et al.* (2020) quantified future variability of population, which affects long-term care demand, due to uncertainty in mortality rates. The authors used the Lee-Carter model to simulate various scenarios in future mortality rates and derived a possible range of long-term care demands.

The main contribution of this study is extending suitable distribution models, by investigating mixture models, of K-LTCI scores assigned to the applicants of K-LTCI. Since the grading structure of K-LTCI has been revised recently, suitability of models for the distribution of assigned K-LTCI scores based on updated data reflecting current grading structure of K-LTCI should be evaluated. This study suggests up-to-date models which is suitable for modeling K-LTCI score distribution using data from the current grading structure of K-LTCI. Finally, a more comprehensive simulation method to estimate the number of K-LTCI beneficiaries in the future based on the developed model is discussed.

The paper is organized as follows. The process for assigning grade level in K-LTCI and the data analyzed in this study are introduced in Sections 2 and 3. The selection of best mixture models and comparison with other models are discussed in Section 4. Using simulation, projections of K-LTCI beneficiaries by grade are described in Section 5, while Section 6 provides the concluding remarks.

2. Grading Structure of K-LTCI

As the detailed information on the K-LTCI is addressed in Kwon *et al.* (2016), this study addresses updated grading structure of K-LTCI. The assigned K-LTCI examination score to applicants of K-LTCI benefit varies from 31.3 to 154.3. Higher scores indicate severe health conditions requiring higher care level. Initially K-LTCI had six grades defined according to score ranges; this grading system has been revised four times since introduction. Table 1 summarizes the historical changes in the K-LTCI grading system and the grading structure during each phase of K-LTCI.

At the beginning of 2018, the grading system was revised. The revision was to introduce a grade called Cognitive Assistance. The grade shares score range with Non-grade B and C. Similar to the difference between Grade 5 and Non-grade A, an applicant of K-LTCI with dementia whose K-LTCI score is between 31.3 and 44.9 is entitled to Cognitive Assistance and eligible for K-LTCI benefits. Historically, the K-LTCI grading system has been revised to expand the number of beneficiaries and to improve homogeneity in terms of the health condition, of persons in the same grade.

Revising the grading system affects the total cost of K-LTCI since available services such as the monthly limit of financial support and the type of service depend on the assigned grade. Therefore, the

Table 2: The number of beneficiaries of K-LTCI

	Male		Female	
	Over 65	Under 65	Over 65	Under 65
2016	119,600	12,897	347,627	9,404
2017	135,722	13,393	393,632	9,690
2018	155,832	14,180	446,170	10,322
2019	180,443	15,099	509,728	10,759
2020	204,052	15,169	572,858	10,553

distribution of assigned scores should be carefully understood and modeled to estimate the number of people in each grade and their variability. Based on the estimation, the structure of services and premium rates should be adjusted accordingly and reflected in the financial management to keep the K-LTCI system sustainable. At the same time, characteristics of benefit payment and usage of service among beneficiaries of the same grade should be analyzed periodically to consider any possible revision in the grading system and to provide more practical support to people with long-term care needs.

The main challenge in modeling K-LTCI score distribution is to fit parametric models using grouped data based on current grading structure. That is, the number of beneficiaries in each grade, separated by several breakpoints, is only available information for estimating parameters of a model. A suitable model should reflect overall shape of empirical distribution while accommodating the proportion of each grade level in experience data, which will allow us to properly estimate future demand of K-LTCI and its variability in each grade. Also, models should be updated according to the revision of K-LTCI grading system that involves a change in the set of the breakpoints.

3. Data

Data on the number of persons, separated by sex and age group, in each grade of K-LTCI at the end of calendar month can be obtained upon request from the NHIS. As population data provided by Statistics Korea is based on the mid-year population, which is used in the simulation discussed in Section 6, we obtained the number of persons in each grade at the end of June in recent five years. Because only applicants with dementia are covered by K-LTCI for ages under 65, the score distribution model should be constructed separately by age group.

Table 2 summarizes the number of beneficiaries being covered by K-LTCI at the mid-point of each calendar year; the number reflects the overall increasing trend for both age groups. The significant increase in the number of beneficiaries in the older age group is due to the increase in elderly population and the introduction of the Cognitive Assistance grade. The annual rate of increase in the number of older age beneficiaries from 2016 to 2020 is 14.29% for male and 13.30% for female. The number of female beneficiaries is roughly triple the number of male beneficiaries each year; This can be explained by the fact that there are more female survivors in elderly population, and that the incidence of Alzheimer's disease, one of the commonest diseases requiring long-term care, is higher in females.

The annual rate of increase of the number of younger age beneficiaries between 2016 and 2020 was 4.14% for male and 2.92% for females; this may be due to the decrease in fertility rate over the past decades. That is, population in younger ages exposed to deterioration of health condition requiring support for daily activities did not increase as much as population in older ages. The number of female beneficiaries less than 65 years decreased in 2020 compared to that in the previous year. Unlike in the older age group, the number of male beneficiaries in the less-than-65 group is about 1.5 times the number of female beneficiaries, mainly because the incidence of vascular dementia due to stroke is more prevalent in men. Comparing the number of beneficiaries between the two age groups, the number of beneficiaries over 65 is higher than that of the beneficiaries under 65. The proportion of beneficiaries over 65 in 2020 was 93.1% for male and 98.2% for female. Therefore, it is expected that total cost of K-LTCI mostly depends on the beneficiaries aged over 65.

Table 3: The number of beneficiaries of K-LTCI

Grade	Under 65		Over 65	
	Male	Female	Male	Female
Grade 1	1,873	1,598	10,283	28,717
Grade 2	1,747	1,404	20,134	61,683
Grade 3	5,140	3,401	60,282	159,957
Grade 4	5,385	3,343	88,057	251,812
Grade 5	801	617	20,701	59,194
Cognitive Assistance	223	190	4,595	11,495
Non-grade A	1,715	1,024	20,056	53,647
Non-grade B	712	388	18,814	41,166
Non-grade C	238	113	5,180	8,082
Total	17,834	12,078	248,102	675,753

Figure 1: Histogram of the number of beneficiaries according to K-LTCI score.

As the distribution of K-LTCI score among applicants who have a grade assigned from K-LTCI is modeled in this study, the number of persons in each grade under the current grading system is used. Table 3 presents the number of persons in each grade separated by sex and age group at the end of June 2020. Table 3 is converted to histogram in Figure 1 according to the current grading system of K-LTCI. The overall shape of the histograms is similar to the plots shown in Kwon *et al.* (2016), although the grading system has been revised since then. Distribution models should reflect the patterns observed in Figure 1 that the density is increasing from the lowest possible score (31.3) to some point near the boundary of Grades 4 and 5, and then decrease gradually to the highest score (154.3). Since the range of available examination score in the K-LTCI grading system is confined, the parametric distribution model should be adjusted for support in that range.

4. Comparison of models

4.1. Mixture models

Mixing distributions is one of the frequently used methods to construct statistical models using two or more parametric distributions to fit an empirical distribution when any single parametric distribution is not able to accommodate the characteristic of distribution of given data. Various single distributions, referring an inventory of continuous distributions in Appendix A of Klugman *et al.* (2019), did not show desirable fitting results to empirical K-LTCI score distributions in Figure 1, which is consistent with the results in Kwon *et al.* (2016). Therefore, mixture distributions were considered and compared with previously suggested spliced models. A brief description of the two-component mixture models used in this study follows.

Consider two probability density functions denoted by $f_1(x)$ and $f_2(x)$ and corresponding distribution functions denoted by $F_1(x)$ and $F_2(x)$. Then, for a value of ω ($0 < \omega < 1$), the probability density function and distribution function of two-component mixture distribution, denoted by $f(x)$ and $F(x)$, are expressed by

$$f(x) = \omega \cdot f_1(x) + (1 - \omega) \cdot f_2(x) \quad (4.1)$$

$$F(x) = \omega \cdot F_1(x) + (1 - \omega) \cdot F_2(x) \quad (4.2)$$

Although the parametric distributions used in this study have support over $[0, \infty]$ or $[-\infty, \infty]$, the range of K-LTCI score is $[31.3, 154.3]$. Therefore, the range of $f(x)$ should be adjusted by dividing by $F(154.3) - F(31.3)$ so that the adjusted probability density function has support on available K-LTCI score range. Then, since we have grouped data according to break points dividing grades of K-LTCI, the likelihood function $L_m(\theta)$ where θ indicates parameters included in the model is expressed by

$$L_m(\theta) = \prod_{i=1}^6 \left[\frac{F(x_i) - F(x_{i-1})}{F(154.3) - F(31.3)} \right]^{n_i} \quad (4.3)$$

where $x_0, x_1, \dots, x_6$ are 31.3, 40.0, $\dots$, 154.3, the current break points of K-LTCI grades corresponding to the last column of Table 1 and n_i is the number of persons having a K-LTCI grade equivalent to i^{th} lowest score interval. Parameters involved in $f_1(x)$ and $f_2(x)$ together with α are estimated using maximum likelihood estimation. Various combinations of two component distributions associated with equation (4.1) were considered and models were selected based on Akaike Information Criterion (AIC). Considering parsimony of a model based on grouped data with only six breakpoints, two-components model was preferred unless the fitting result is undesirable.

As expressed in equation (4.3), parameters are included in both numerator and denominator in each term of the product. Therefore, finding maximum likelihood estimates of parameters is non-linear optimization problem as the exponent of each term in the product is a lot greater than total number of parameters. For optimization, Microsoft Excel Solver function was used to obtain parameters maximizing log-likelihood function using various initial values of parameters as there may exist many local maxima in the target function.

For both males and females under 65 years, a combination of two Burr distributions was found to be the most appropriate model. Also, a combination of inverse paralogistic distribution and inverse Weibull distribution was selected for both sexes over age 65. Together with beta distribution used in the next section, the form of a component probability density function in the selected models in this study is expressed as follows

- Burr distribution: $\frac{\alpha \gamma (x/\theta)^\gamma}{x [1 + (x/\theta)^\gamma]^{\alpha+1}}, \quad x \in (0, \infty)$
- Inverse paralogistic distribution: $\frac{\tau^2 (x/\theta)^{\tau^2}}{x [1 + (x/\theta)^\tau]^{\tau+1}}, \quad x \in (0, \infty)$

Table 4: Selected mixture models

Group	Sex	Component	Estimated parameters	ω	AIC
Under 65	Male	$f_1(x)$: Burr	$\hat{\theta} = 43.8562$	0.6953	58,498.58
			$\hat{\gamma} = 21.4845$		
		$f_2(x)$: Burr	$\hat{\alpha} = 0.0866$		
			$\hat{\theta} = 69.1023$		
	Female	$f_1(x)$: Burr	$\hat{\gamma} = 15.1080$	0.6953	58,498.58
			$\hat{\alpha} = 7.1377$		
Over 65	Male	$f_1(x)$: Burr	$\hat{\theta} = 44.6004$	0.4915	790,395.23
			$\hat{\gamma} = 20.0319$		
		$f_2(x)$: Burr	$\hat{\alpha} = 0.0845$		
			$\hat{\theta} = 69.4587$		
	Female	$f_1(x)$: Burr	$\hat{\gamma} = 15.1050$	0.5085	2,131,460.64
			$\hat{\alpha} = 7.1442$		
		$f_2(x)$: Burr	$\hat{\theta} = 54.1579$		
			$\hat{\gamma} = 4.8193$		
	Male	$f_1(x)$: Inverse paralogistic	$\hat{\theta} = 36.3763$	0.4915	790,395.23
			$\hat{\tau} = 9.1044$		
		$f_2(x)$: Inverse Weibull	$\hat{\theta} = 54.1579$		
			$\hat{\tau} = 9.1044$		
	Female	$f_1(x)$: Inverse paralogistic	$\hat{\theta} = 39.4435$	0.5085	2,131,460.64
			$\hat{\tau} = 13.0356$		
		$f_2(x)$: Inverse Weibull	$\hat{\theta} = 53.2873$		
			$\hat{\tau} = 13.0356$		

- Inverse Weibull distribution: $\frac{\tau(x/\theta)^\tau e^{-(x/\theta)^\tau}}{x}$, $x \in (0, \infty)$
- Beta distribution: $\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \cdot \frac{(x-a)^{\alpha-1}(b-x)^{\beta-1}}{(b-a)^{\alpha+\beta-1}}$, $x \in (a, b)$

Component distributions of mixture models, their estimated parameters and AIC values of selected models are summarized in Table 4. In addition, Figure 2 presents the graphs of selected models superposed on the histograms in Figure 1.

In addition, for the best five mixture models, Bayesian information criterion (BIC), mean absolute percentage error (MAPE), and comparison of $F(x)$ with corresponding value of empirical distribution at the breakpoints were presented in Appendix. It was found that the selected models based on AIC tend to have desirable values of discrepancy measures so that mixture models can be considered suitable for K-LTCI score distribution model.

4.2. Comparison with spliced models

Splicing is another flexible method to fit an empirical distribution that was explored to model K-LTCI score distribution in Kwon *et al.* (2016). A spliced model uses two or more distribution functions that are applied to disjoint intervals. If two probability density functions, denoted by $g_1(x)$ and $g_2(x)$, are used, then spliced model $g(x)$ having support on $[c_0, c_1]$ with break point b ($c_0 < b < c_1$) is expressed as

$$g(x) = \begin{cases} u \cdot \frac{g_1(x)}{G_1(b) - G_1(c_0)}, & c_0 \leq x < b, \\ (1-u) \cdot \frac{g_2(x)}{G_2(c_1) - G_2(b)}, & b \leq x \leq c_1, \end{cases} \quad (4.4)$$

where $G_1(x)$ and $G_2(x)$ are distribution functions corresponding to $g_1(x)$ and $g_2(x)$, respectively. In order to model K-LTCI score distribution, $c_0 = 31.3$ and $c_1 = 154.3$ were used. Then, likelihood function $L_s(\theta)$ is expressed as

$$L_s(\theta) = \prod_{i=1}^6 [G(x_i) - G(x_{i-1})]^{n_i} \quad (4.5)$$

Figure 2: Graphs of selected mixture models.

Table 5: Selected spliced models

Group	Sex	Component	Estimated parameters	u	AIC
Under 65	Male	$g_1(x)$: Inverse paralogistic	$\hat{\tau} = 4.9922$ $\hat{\theta} = 42.9032$	0.5088	58,492.56
		$g_2(x)$: Beta	$\hat{\alpha} = 0.3860$ $\hat{\beta} = 1.5149$		
	Female	$g_1(x)$: Inverse Weibull	$\hat{\tau} = 5.4339$ $\hat{\theta} = 41.9637$	0.4699	40,228.92
		$g_2(x)$: Beta	$\hat{\alpha} = 0.4535$ $\hat{\beta} = 1.5114$		
Over 65	Male	$g_1(x)$: Inverse paralogistic	$\hat{\tau} = 2.3488$ $\hat{\theta} = 76.3038$	0.6344	790,393.23
		$g_2(x)$: Beta	$\hat{\alpha} = 0.5059$ $\hat{\beta} = 2.9545$		
	Female	$g_1(x)$: Inverse Weibull	$\hat{\tau} = 2.9385$ $\hat{\theta} = 68.3062$	0.6295	2,131,458.64
		$g_2(x)$: Beta	$\hat{\alpha} = 0.6005$ $\hat{\beta} = 3.3003$		

where $G(x)$ is distribution function obtained from equation (2.4) and $x_0, x_1, \dots, x_6$ and n_i are the same as in equation (2.3). As a result of mathematical formulation in equations (4.4) and (4.5), the shape of the spliced distribution model is discontinuous at the breakpoint b . Even if the estimation process is constrained so that $g_1(x)$ and $g_2(x)$ be connected at the breakpoint, flexibility of the model decreases and fitting results are likely to be unsatisfactory.

A number of two-component spliced models were investigated with $b = 60$, which divides the entire K-LTCI score range into the interval associated with Grades 1–3 and remaining interval. When b is treated as a parameter of a model, the shape of the fitted distribution was not properly matched with empirical

Figure 3: Graphs of selected spliced models.

Table 6: Assumption of the proportion of surviving K-LTCI applicants

Population assumption	Male		Female	
	Over 65	Under 65	Over 65	Under 65
Middle	0.067193	0.000780	0.137695	0.000576
High	0.067141	0.000779	0.140320	0.000570
Low	0.067249	0.000781	0.140554	0.000571

data. Therefore, the $x_1, \dots, x_5$ was explored as a value of b and the most optimal value turned out to be $b = 60$. Table 5 summarizes the results of estimation of the selected models. Figure 3 gives the graphs of fitted spliced models.

Comparing selected mixture models with the counterparts of the spliced models, the latter attain slightly better AIC values. However, the large jump at the breakpoint of spliced models is remarkable. As discussed in Kwon *et al.* (2016), this may distort simulation results of observing the effect of possible changes in the K-LTCI grading system. Also, determination of breakpoint of spliced models is another modeling issue, which is not required in mixture models. Therefore, the mixture model has lower model risk than the spliced model for the purpose of scenario analysis on the variation of the K-LTCI grading system.

5. Simulation

Since the current K-LTCI grading system was introduced in 2018, there have been no discussions on the projection of the number of beneficiaries and the associated costs. Based on the developed mixture models in Section 5 and other assumptions, the number of K-LTCI beneficiaries in each grade and their variability was projected using simulation. The followings are the descriptions of simulation algorithm and relevant assumptions,

- Step 1. Population structure: The population size of each age group is an important indicator of the degree of risk to health conditions requiring long-term care. Statistics Korea provides projected population by age at the midpoint of each future year up to 2067. There are three scenarios for population

Figure 4: Graphs of selected spliced models.

Table 7: Assumption of the proportion of Grade 5 and Cognitive Assistance

Grade	Male		Female	
	Over 65	Under 65	Over 65	Under 65
Grade 5	0.450004	0.266372	0.449838	0.328252
Cognitive assistance	0.116301	0.139797	0.135257	0.212813

projection: High, Middle, and Low. The Middle scenario is based on the prospect that past trend of demographic factors will continue in the future, while the High scenario indicates an optimistic outlook in which fertility rate is higher and mortality rate is lower than in the Middle scenario and the Low scenario represents its opposite. Future changes in population according to the three scenarios are visualized in Figure 4.

- Step 2. Number of surviving K-LTCI applicants: Out of the number of population in each age group (over/under age 65) and sex obtained in the previous step, the total number of surviving K-LTCI applicants who have K-LTCI score is derived. Based on the number of beneficiaries in Table 2 and the number of persons in Non-grades A, B, and C, the proportion of the number of surviving K-LTCI applicants in corresponding population can be obtained. Using recent three-year population data based on three scenarios, the assumptions for the proportions were set as shown in Table 6. Based on the assumptions, the number of surviving K-LTCI applicants among the projected population is simulated.
- Step 3. Distribution of surviving K-LTCI applicants in each grade: The simulated number of surviving K-LTCI applicants is distributed according to the selected mixture models derived in Section 5. For each surviving K-LTCI applicant, a score is simulated using inverse transform method and then assigned a grade under the current K-LTCI grading system.
- Step 4. Proportion of surviving applicants with dementia in Non-grades A, B, and C: there are persons

Table 8: Projected number of beneficiaries under age 65 based on the Middle scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	2,583	50.76	2,329	48.06
	Grade 2	3,346	57.29	2,731	52.05
	Grade 3	6,112	78.23	4,254	64.90
	Grade 4	5,994	77.41	3,822	60.80
	Grade 5	755	27.36	593	24.29
	Cognitive assistance	18	4.26	120	10.90
2040	Grade 1	2,235	47.01	2,008	45.34
	Grade 2	2,897	53.45	2,353	48.12
	Grade 3	5,287	72.90	3,667	60.44
	Grade 4	5,188	71.46	3,294	57.57
	Grade 5	654	25.34	510	22.64
	Cognitive assistance	16	3.99	104	10.17
2050	Grade 1	1,907	43.63	1,719	41.50
	Grade 2	2,470	49.56	2,016	45.11
	Grade 3	4,511	67.20	3,139	56.26
	Grade 4	4,425	65.61	2,821	53.37
	Grade 5	557	23.57	437	21.01
	Cognitive assistance	13	3.65	89	9.49
2060	Grade 1	1,573	40.26	1,455	37.90
	Grade 2	2,039	45.28	1,707	41.58
	Grade 3	3,722	60.58	2,660	51.32
	Grade 4	3,652	60.55	2,388	48.73
	Grade 5	460	21.69	370	19.37
	Cognitive assistance	11	3.31	75	8.66

with dementia who are eligible for K-LTCI benefit in Non-grade A, B, and C. Therefore, the simulated numbers in the score range 45.0–50.9 should be separated into Grade 5 and Non-grade A. Likewise, the simulated numbers in the score range 31.3–44.9 should be divided into the numbers in Cognitive Assistance and in Non-grades B and C. Using experience data for three years, the assumptions for the proportion of beneficiaries in Grade 5 with K-LTCI score between 45.0–50.9 and the proportion of beneficiaries in Cognitive Assistance with K-LTCI score between 31.3–44.9 were set as presented in Table 7. Based on the assumption, the number of beneficiaries in Grade 5 and in Cognitive Assistance was simulated.

- Step 5. Repeat Step 2 through Step 4 for each population projection assumption in Step 1)

Finally, the estimated number of beneficiaries in each grade in years 2030, 2040, and 2050, and its variability were obtained after 10,000 simulations. The results are summarized in Tables 8–13. As expected, the number of K-LTCI beneficiaries under age 65 is projected to decrease over time owing to the decreased in population size. However, the number of beneficiaries over age 65 will increase up to 2050 and decrease thereafter. Since K-LTCI beneficiaries are clustered toward the older ages, long-term care expenditures will be a significant burden to both individual and the government. Therefore, a model for K-LTCI expenditure, considering all elements affecting the cost, needs to be constructed to obtain a reliable estimation on the future cost of long-term care provided by K-LTCI. This will allow us to build the necessary infrastructure such as long-term care facilities and adequate caregiving resources to meet the high future demand for long-term care.

Table 9: Projected number of beneficiaries under age 65 based on the High scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	2,662	51.31	2,380	48.49
	Grade 2	3,450	58.23	2,791	52.67
	Grade 3	6,299	79.52	4,347	65.97
	Grade 4	6,179	78.30	3,904	63.53
	Grade 5	779	27.72	606	24.67
	Cognitive Assistance	19	4.36	123	11.16
2040	Grade 1	2,366	48.41	2,117	45.86
	Grade 2	3,066	55.49	2,484	49.32
	Grade 3	5,599	74.47	3,868	62.14
	Grade 4	5,492	74.67	3,475	58.90
	Grade 5	692	26.18	539	23.16
	Cognitive Assistance	17	4.03	109	10.50
2050	Grade 1	2,081	46.26	1,883	43.35
	Grade 2	2,697	52.12	2,208	47.01
	Grade 3	4,923	69.78	3,440	58.89
	Grade 4	4,829	69.39	3,090	55.79
	Grade 5	608	24.83	479	21.99
	Cognitive Assistance	15	3.85	97	9.97
2060	Grade 1	1,808	42.37	1,694	41.15
	Grade 2	2,343	48.05	1,986	44.40
	Grade 3	4,278	64.18	3,094	56.13
	Grade 4	4,195	64.62	2,779	52.14
	Grade 5	529	23.04	431	20.80
	Cognitive Assistance	13	3.59	87	9.36

Table 10: Projected number of beneficiaries under age 65 based on the Low scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	2,518	50.54	2,247	47.45
	Grade 2	3,262	57.31	2,636	51.64
	Grade 3	5,957	77.23	4,105	64.53
	Grade 4	5,842	75.53	3,686	60.97
	Grade 5	737	27.01	571	23.81
	Cognitive Assistance	18	4.23	116	10.74
2040	Grade 1	2,117	45.51	1,868	43.19
	Grade 2	2,743	52.07	2,189	46.76
	Grade 3	5,007	71.02	3,412	58.79
	Grade 4	4,912	69.80	3,065	55.66
	Grade 5	619	24.71	475	21.83
	Cognitive Assistance	15	3.84	97	9.87
2050	Grade 1	1,744	41.77	1,527	38.76
	Grade 2	2,261	47.53	1,790	42.39
	Grade 3	4,128	64.70	2,790	52.28
	Grade 4	4,049	63.45	2,506	50.43
	Grade 5	510	22.61	389	19.76
	Cognitive Assistance	12	3.50	79	8.85
2060	Grade 1	1,368	37.13	1,211	35.03
	Grade 2	1,774	42.24	1,421	37.52
	Grade 3	3,237	56.42	2,213	47.04
	Grade 4	3,175	56.26	1,988	44.32
	Grade 5	400	19.77	308	17.17
	Cognitive Assistance	10	3.10	62	7.93

Table 11: Projected number of beneficiaries over age 65 based on the Middle scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	19,078	137.67	45,843	213.54
	Grade 2	48,187	213.81	128,160	355.42
	Grade 3	126,521	350.90	314,130	549.44
	Grade 4	179,273	420.40	455,202	654.01
	Grade 5	44,434	211.16	102,406	316.33
	Cognitive Assistance	5,670	75.10	11,914	109.84
2040	Grade 1	25,731	158.44	60,007	246.18
	Grade 2	64,988	255.45	167,754	405.34
	Grade 3	170,641	407.58	411,198	631.12
	Grade 4	241,779	482.08	595,830	747.40
	Grade 5	59,924	243.68	134,043	365.85
	Cognitive Assistance	7,645	86.66	15,595	123.91
2050	Grade 1	28,641	168.68	65,733	253.41
	Grade 2	72,342	265.18	183,747	430.85
	Grade 3	189,958	433.83	450,389	652.54
	Grade 4	269,148	516.93	652,629	781.52
	Grade 5	66,705	257.08	146,830	380.83
	Cognitive Assistance	8,509	93.11	17,082	131.28
2060	Grade 1	25,731	158.44	60,007	246.18
	Grade 2	64,988	255.45	167,754	405.34
	Grade 3	170,641	407.58	411,198	631.12
	Grade 4	241,779	482.08	595,830	747.40
	Grade 5	59,924	243.68	134,043	365.85
	Cognitive Assistance	7,645	86.66	15,595	123.91

Table 12: Projected number of beneficiaries over age 65 based on the High scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	19,394	139.37	47,437	219.20
	Grade 2	48,987	221.15	132,622	358.03
	Grade 3	128,621	353.60	325,071	557.02
	Grade 4	182,247	422.24	471,031	663.71
	Grade 5	45,165	211.80	105,971	324.40
	Cognitive Assistance	5,764	74.94	12,331	110.70
2040	Grade 1	26,611	164.69	63,021	247.42
	Grade 2	67,203	257.22	176,186	418.61
	Grade 3	176,463	414.97	431,852	639.56
	Grade 4	250,027	494.69	625,748	777.23
	Grade 5	61,961	245.62	140,781	370.75
	Cognitive Assistance	7,905	88.38	16,379	128.43
2050	Grade 1	30,138	173.56	70,304	262.64
	Grade 2	76,114	276.82	196,543	441.63
	Grade 3	199,854	441.03	481,744	677.16
	Grade 4	283,174	522.51	698,064	802.74
	Grade 5	70,177	265.49	157,053	390.57
	Cognitive Assistance	8,953	94.90	18,273	134.24
2060	Grade 1	31,048	174.85	69,414	263.64
	Grade 2	78,405	277.52	194,060	434.16
	Grade 3	205,868	447.67	475,661	676.46
	Grade 4	291,707	530.67	689,242	808.10
	Grade 5	72,298	265.90	155,068	389.42
	Cognitive Assistance	9,221	95.84	18,041	135.68

Table 13: Projected number of beneficiaries over age 65 based on the Low scenario

Year	Grade	Male		Female	
		Number of beneficiaries	Standard deviation	Number of beneficiaries	Standard deviation
2030	Grade 1	18,717	136.68	45,997	215.07
	Grade 2	47,273	217.47	128,585	353.57
	Grade 3	124,134	346.60	315,177	548.02
	Grade 4	175,882	416.32	456,707	652.24
	Grade 5	43,589	207.09	102,753	317.45
	Cognitive Assistance	5,562	74.00	11,955	108.69
2040	Grade 1	24,761	155.62	59,247	241.23
	Grade 2	62,537	247.59	165,620	404.96
	Grade 3	164,211	399.31	405,954	624.04
	Grade 4	232,651	473.19	588,256	742.36
	Grade 5	57,662	238.96	132,342	362.76
	Cognitive Assistance	7,356	86.29	15,399	124.93
2050	Grade 1	27,056	163.93	63,626	250.38
	Grade 2	68,334	260.58	177,867	414.33
	Grade 3	179,422	416.09	435,971	643.09
	Grade 4	254,230	488.29	631,740	761.41
	Grade 5	63,007	249.93	142,129	375.98
	Cognitive Assistance	8,039	90.03	16,538	129.36
2060	Grade 1	27,081	164.91	60,317	245.65
	Grade 2	68,399	259.39	168,605	409.54
	Grade 3	179,602	419.84	413,290	626.24
	Grade 4	254,475	498.27	598,851	746.33
	Grade 5	63,073	247.09	134,728	361.43
	Cognitive Assistance	8,047	90.07	15,675	123.30

6. Conclusion

The demand for long-term care for an individual and its associated costs are expected to increase as citizens are living longer than before and are therefore, more likely to require assistance to do so. Furthermore, due to low fertility rates in recent years, the proportion of elderly population is set to increase resulting in higher social infrastructure and long-term care expenditure needs. K-LTCI has been playing an important role as a social security system, providing support for the elderly who need long-term care. Proper planning to finance future costs of K-LTCI is crucial to maintaining its sustainability.

Several approaches to project future demand for K-LTCI have been suggested ever since the plan was introduced. One of the approaches utilize K-LTCI score distribution to estimate the number of beneficiaries in each grade of K-LTCI as the type and amount of benefit depends on the grade determined by K-LTCI score. This study explored mixture models based on empirical K-LTCI score distribution and compared them with the spliced models suggested by previous studies. Based on simulation using the developed mixture distributions, the number of beneficiaries in each grade and its variability were estimated. However, as there has been no study on K-LTCI demand projection based on the current grading system launched in 2018, this study hopes to initiate an up-to-date discussion.

It was observed that mixture distribution can be a good model for K-LTCI score distribution. The model can be utilized to project future K-LTCI beneficiaries as illustrated in this study. Securing experience data regarding K-LTCI cost for each age group, sex, and grade provide for projection of K-LTCI costs. Also, the developed model can be utilized to evaluate the effect of any possible change in the K-LTCI grading system in case of further revision of the grading system. The appropriateness of a model should be regularly tested and developed using updated and more detailed experience data. In addition, consideration of other methods for estimating model parameters of mixture distribution such as minimizing discrepancy between model output and empirical data is a possible area of future research.

The eventual goal of the discussion is to construct a comprehensive model for funding the K-LTCI.

Since there are many elements of the K-LTCI system, factors affecting the cash flow of the program should be studied and carefully reflected in the model. Also, the role of individual health insurance and its management, which complements K-LTCI is another possible area for further research.

Appendix:

Candidate mixture models and comparison of metrics of goodness-of-fit

(1) Males under 65

Model No.	$f_1(x)$	$f_2(x)$	AIC	BIC	MAPE
1	Burr	Burr	58,498.58	58,490.02	0.0854
2	Inverse Burr	Inverse Paralogistic	58,498.72	58,491.39	0.9261
3	Burr	Inv Burr	58,499.05	58,490.50	0.5215
4	Inverse Paralogistic	Inverse Paralogistic	58,531.70	58,525.59	4.0634
5	Inverse Burr	Inverse Burr	58,571.32	58,562.77	6.0400

CDF value at x						
x	Empirical	Model 1	Model 2	Model 3	Model 4	Model 5
31.3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
45.0	0.0658	0.0658	0.0652	0.0662	0.1377	0.0754
51.0	0.2069	0.2070	0.2093	0.2065	0.2776	0.1996
60.0	0.5088	0.5089	0.5079	0.5090	0.5884	0.5160
75.0	0.7970	0.7972	0.7975	0.7968	0.8633	0.7939
95.0	0.8950	0.8949	0.8952	0.8960	0.9717	0.8975
154.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

(2) Females under 65

Model No.	$f_1(x)$	$f_2(x)$	AIC	BIC	MAPE
1	Burr	Burr	40,234.92	40,226.37	0.0009
2	Inverse Burr	Inverse Burr	40,234.92	40,226.37	0.0130
3	Inverse Paralogistic	Inverse Paralogistic	40,236.74	40,230.63	1.6614
4	Burr	Inverse Weibull	40,239.02	40,231.69	1.9729
5	Burr	Inverse Paralogistic	40,239.03	40,231.70	1.9736

CDF value at x						
x	Empirical	Model 1	Model 2	Model 3	Model 4	Model 5
31.3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
45.0	0.0572	0.0573	0.0573	0.0919	0.0390	0.0596
51.0	0.1931	0.1932	0.1932	0.2235	0.1907	0.1908
60.0	0.4699	0.4699	0.4700	0.4974	0.4746	0.4746
75.0	0.7514	0.7515	0.7516	0.7643	0.7507	0.7507
95.0	0.8677	0.8678	0.8678	0.8821	0.8686	0.8686
154.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

(3) Males over 65

Model No.	$f_1(x)$	$f_2(x)$	AIC	BIC	MAPE
1	Inverse Paralogistic	Inv Weibull	790,395.23	790,389.12	0.0022
2	Inverse Paralogistic	Inverse Gamma	790,395.23	790,389.12	0.0051
3	Inverse Weibull	Inverse Weibull	790,395.81	790,389.70	0.1716
4	Inverse Burr	Inverse Paralogistic	790,397.23	790,389.90	0.0014
5	Burr	Inverse Gamma	790,399.23	790,390.68	0.0015

x	CDF value at x					
	Empirical	Model 1	Model 2	Model 3	Model 4	Model 5
31.3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
45.0	0.1152	0.1254	0.1390	0.1160	0.1263	0.1232
51.0	0.2795	0.2896	0.3033	0.2804	0.2906	0.2874
60.0	0.6344	0.6446	0.6582	0.6355	0.6455	0.6424
75.0	0.8774	0.8875	0.9012	0.8786	0.8885	0.8853
95.0	0.9586	0.9687	0.9823	0.9596	0.9697	0.9665
154.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

(4) Females over 65

Model No.	$f_1(x)$	$f_2(x)$	AIC	BIC	MAPE
1	Inverse Paralogistic	Inv Weibull	2,131,460.64	2,131,454.53	0.0008
2	Inverse Paralogistic	Inverse Paralogistic	2,131,460.64	2,131,454.53	0.0019
3	Inverse Paralogistic	Inverse Gamma	2,131,460.64	2,131,454.53	0.0053
4	Inverse Burr	Inverse Paralogistic	2,131,462.64	2,131,455.31	0.0076
5	Burr	Inverse Weibull	2,131,462.64	2,131,455.31	0.0075

x	CDF value at x					
	Empirical	Model 1	Model 2	Model 3	Model 4	Model 5
31.3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
45.0	0.0899	0.0907	0.0907	0.0962	0.0906	0.0929
51.0	0.2569	0.2577	0.2577	0.2631	0.2576	0.2599
60.0	0.6295	0.6303	0.6303	0.6358	0.6302	0.6325
75.0	0.8662	0.8671	0.8670	0.8725	0.8670	0.8693
95.0	0.9575	0.9583	0.9583	0.9638	0.9582	0.9605
154.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

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Received January 22, 2021; Revised March 27, 2021; Accepted April 21, 2021