Change in the Depression Level of Patients with Chronic Illness in Korea : Applying Growth Mixture Model

Eun-Mi Ham¹, Sul-Hee Lee*²

¹Department of Nursing, GLOCAL Campus, Konkuk University, 268 Chungwon-daero, Chungju-si, Chungcheongbuk-do 27478, Republic of Korea ²Department of Nursing, Kyungmin University, 545 Seobu-ro, Uijeoungbu-si, Gyunggi-do 11618, Republic of Korea

Abstract

This study aims to classify latent classes based on changes in the depression levels of patients with chronic illness and to confirm the influencing factors. The subjects of this study were 2,202 adults who had consistently shown chronic illness from the first to sixth surveys in the data of "Korean Longitudinal Study of Ageing." The growth mixture model was applied to develop latent classes as per changes in their depression levels. Based on the change patterns of chronic illness patient depression level, our studies supported a four-class model defined as "stable low," "decreasing," "increased then decreasing," and "increasing" class. Our results revealed that sex, age, income, difficulties on ADL, chronic illness severity, and duration were significant determinants of latent classes. In particular among these factors, difficulties on ADL, chronic illness severity were common factors that are likely to make those patients belong to the remaining three potential classes in reference to the stable low group. Healthcare practitioners should anticipate how the trajectories of depression in patients with chronic illness will demonstrate different changes in future and develop intervention strategies for each latent class.

Keywords: Chronic illness; Depression; Latent Class Model; Growth Mixture Model; Longitudinal; Trajectories

*Corresponding Author: Name :Sul-Hee Lee Email : shlee@kyungmin.ac.kr Contact :+82-31-828-7466 Fax :+82-31-828-7469 Date of Submission :05-10-2020

INTRODUCTION

Chronic illness itself has a negative effect on the quality of life. It differs depending on the types of diseases, but patients with chronic illness generally have difficulty in performing daily

activities because of the decline in physical function, which restricts independent living (Huang et al., 2011). Moreover, suffering from persistent pain or diseases increases their stress levels, and these factors affect their social activities and family and social relationships as well as changes the lifestyle of patients with chronic illness (Aströmet al., 1992). Such changes of life eventually increase the depression level of patients with chronic illness (Cui et la., 2008; Nitiet al., 2007). In this manner, depression in patients with chronic illness affects their health conditions (Kim et al., 2015). Given this understanding of chronic illness, multiple studies have focused on depression in patients with chronic illness. Nevertheless, previous studies have mostly focused on cross-sectional studies, thus predicting the causes and results of depression through data collection in a specific point of time. However, depression is not a transitory phenomenon at a certain time period, but has characteristics of persistence, recovery, and deterioration (Mojtabaiet al., 2004), and varies with the individual (Nagin, 1999). Given these characteristics of depression, cross-sectional studies conducted to date have a limitation that they could not dynamically identify changes in depression as per the elapsed time. To overcome this limitation, longitudinal studies on depression of patients with chronic illness are being performed (Sohnet al., 2017; Needham et al., 2010; Pruchnoet al., 2009; Bisschopet al., 2004; Aströmet al., 1992), however, they fail to provide consistent results about changes in depression of patients with chronic illness. That is, there are contradictory results of studies as follows: the depression level of patients with chronic illness increases as per the flow of time (Pruchnoet al., 2009); the depression level of patients with chronic illness decreases with time (Sohnet al., 2017; Needham et al., 2010); and the increase and decrease in the depression level are repetitive (Bisschopet al., 2004; Aströmet al., 1992). The difference in study results is attributed by certain researchers to a problem in study methods or that data might have been collected in a short time period compared to the illness duration (Henselmanset al., 2010; Huang et al., 2010). Moreover, they reported that the existing longitudinal studies considered patients with chronic illness who have different characteristics as a single population with common characteristics, thus simplifying changes in depression that can vary with characteristics of individuals into a single type or causing statistical bias such as regression toward the mean, which lead to mixed results such as increase or decrease in depression levels (Heo, 2014; Dunn et al., 2011). To overcome these limitations, certain researchers are conducting studies in which groups showing different growth curves are categorized by combining groups with similar patterns of individual changes within the same group (Dunn et al., 2011; Rose et al., 2009; Murphy et al., 2008). Identifying changes in the depression level of patients with chronic illness by applying these study methods allowed us to exactly understand conditions of high-risk groups such as maintaining high levels of depression or experiencing the increase in the depression level,

which is clinically valuable. Furthermore, identifying risk factors and protective factors by type as per changes in the depression level will make it possible to provide a theoretical framework and practical information that are essential to planning and implementing nursing interventions for high-risk groups of depression in patients with chronic illness. Therefore, this study aimed to provide more accurate information for planning and implementing nursing interventions to prevent and manage depression in patients with chronic illness by identifying patterns of changes in the depression level within the combined groups of similar patterns with patients with chronic illness, as well as by analyzing factors that differentiate each pattern.

MATERIALS AND METHODS

Subjects of study

The subjects of this study were 2,202 adults aged \geq 45 years who had consistently shown \geq 1 chronic illness diagnosed by medical doctors from the first to sixth surveys in the data called "Korean Longitudinal Study of Ageing (KLoSA)."

Measurement of study

To measure depression, CES-D 10 proposed in KLoSA was used. CES-D 10 is a reduced version of the original scale, whereas CES-D 20 (Radloff, 1977) comprises a total of ten items asking mental state and behavior for the previous week from the time of investigation, which is measured using a four-point Likert scale. Of these, to calculate the total score, two positive items were reverse coded. The scores ranged from 0 to 30 in which higher scores indicated higher levels of depression. The results of descriptive statistics and multivariate normality about depression by time point were then satisfied. Moreover, based on available variables among factors confirmed by the results of previous studies, literature, and panel data, the determinants distinguishing latent classes as per changes in the depression level of patients with chronic illness were composed of sex, age, education level, family income, marital status, disability in everyday life, severity and duration of chronic illness; moreover, the values of data from the first year (2006) were used. The education level was coded to analyze data, which were classified into above university graduation, high school graduation, middle school graduation, and below elementary school graduation. Note that income was the total family income for the previous year from the time of investigation, thus indicating the total of annual earnings, annuity income, and other income of family members. In this study, because the assumption of

normal distribution was not satisfied, data were used for analysis after natural log transformation. The marital status was remodified with its variables to dummy variables for analysis. Moreover, disability in everyday life indicates the indexed values using activities of daily living (ADL). ADL is a scale to assess the ability of performing simple activities of everyday life, based on the activities for the latest week, which comprises a total of seven items such as washing face/brushing teeth/washing hair, changing clothes, taking a bath/shower, eating meals, using a bathroom, going out of the room, and controlling the excretion of urine and feces. The score ranges from 0 to 7 in which higher scores indicates severity. The overall severity of chronic illness indicates the measurements applying the generally used Charlson's Comorbidity Index (CCI) to the modified degree of severity using comorbidity. In this study, one point of the weighted score was given to everything for 8 chronic diseases covered in this study, out of 19 diseases of CCI, except for cancer or malignant tumors equivalent to 2 points of the weighted score, and the total of the weighted scores were used for analysis where higher scores mean the high severity of chronic illness. The duration of chronic illness was measured for analysis with values of subtracting the year when the respondent was first diagnosed with chronic illness, from 2006, the year of the first investigation.

Data analysis methods

In this study, we used Cronbach's alpha for depression scales, frequency analysis and descriptive statistics analysis of each predictor, latent growth model analysis, and growth mixture model analysis. The details are listed below. First, before the analysis, the reliability of depression scales was analyzed, and the analysis of frequency and ratio of variables included in this study model, as well as descriptive statistics and correlation analysis, were conducted. SPSS Statistics Version 25.0 (IBM New York, USA) was used for Cronbach's alpha, as well as frequency and descriptive statistics analysis of variables. Second, the growth mixture model combined with a latent growth model and a latent class model was used for analysis to classify the latent classes as per changes in the depression level of subjects and to identify factors significantly affecting the classification of latent classes.

The growth mixture model is analysis according to the following procedure. First, before analyzing with the growth mixture model, the most appropriate model for the entire data is selected according to the growth mixture model analysis procedure, and then the growth mixture model is analyzed to identify the latent class based on the latent growth model. In the growth mixture model, when the independent variable is included in the model along with the latent class, it affects the classification of the latent class (Vermunt, 2010). Therefore, to control this, it was analyzed using the three-step approaches in this study.

The three-step approaches procedure is as follows. First, we estimate how many latent classes exist by estimating the unconditional model. Next, the latent class is assigned to the individual according to the calculated posterior probability. In the last, each individual's latent class is fixed by correcting the classification error that occurred in the process of assigning the latent class, and then multinomial logistic regression analysis including covariates is performed. The final study model is shown in Figure 1. Mplus Version 8.1 (Muthén&Muthén, Los Angeles, USA) was used for growth mixture model analysis.

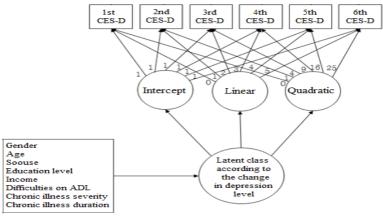


Figure 1: Study model

Ethical considerations

After getting approval for review exemption by the institutional bioethics committee, K University, the researcher conducted the study using source data from the first to sixth year of KLoSA on the website of Korea Employment Information Service.

RESULTS AND DISCUSSION

First, to explore the pattern of changes in latent classes, the goodness of fit index was compared by applying a linear model, quadratic model, and two-factor free parameters model. Both CFI and TLI are acceptable for model fit if they are more than 0.90, if RMSEA is less than 0.10, and the model fits data well; moreover, if it is <0.05, it can be considered to be an excellent model fit (Bollen*et al.*, 2006). Thus, we confirmed that a quadratic model is best for model fit when arrogating CFI, TLI, and RMSEA among three models in Table 1.

To determine the number of latent classes as per patterns of changes in the depression level referring to the equivalent results, analysis was conducted by individually increasing the number of latent classes. The results of the goodness of fit index are shown in Table 2. First, when comparing the standards of the information index AIC, BIC, and SABIC, as well as when the number of the latent classes increases, AIC, BIC, and SABIC showed a decreasing trend.

Second, A-LRT and BLRT showed significance in models that the numbers of latent classes are 2, 4, and 5. Third, the entropy value which is quality of classification showed more than 0.8 in all except for a model with 2 of the number of latent classes. Previous studies selected more than four latent classes for changes in the depression level as the final model (Lee *et* al., 2018; Hsu, 2012; Dunn*et al.*, 2011). Moreover, this study determined that the model with four latent classes was most appropriate based on the results of three standards, ratio of groups within a model, and interpretability.

Table 1: Goodness of fit index for each model

Model	χ^2	df	CFI	TLI	RMSEA
Linear model	313.18***	16	.93	.94	.09
Quadratic model	214.78***	15	.96	.96	.08
Two-factor free parameters model	303.78***	13	.94	.93	.10

CFI = comparative fit index; RMSEA = root mean square error of approximation; TLI = tucker and lewis index; p < .001

Latent class	log likelihood	free parameters	AIC	BIC	SSABIC	Entropy	A-LRT (p)	BLRT (p)	class size (n, %)
Class 2	-38897.73	16	77827.47	77918.62	77867.79	0.79	206.48 (.001)	213.19 (<.001)	1890(85.8), 312(14.2)
Class 3	-38798.12	20	77636.25	77750.19	77686.65	0.82	192.96 (.097)	199.22 (<.001)	1853(84.1), 155(7.1), 194(8.8)
Class 4	-38712.64	24	77473.27	77610.00	77533.75	0.83	165.60 (.014)	170.98 (<.001)	1724(78.3), 112(5.1) 76(3.4), 290(13.2)
Class 5	-38651.69	28	77359.38	77518.90	77429.94	0.84	118.06 (.001)	121.89 (<.001)	72(3.3), 110(5.0), 1709(77.6) 246(11.2), 65(2.9)

 Table 2: Goodness of fit according to the number of latent classes

AIC = akaike's information criterion; BIC = bayesian information criterion; SSABIC = sample size adjusted bayesian information criterion; A-LRT = adjusted likelihood ratio test; BLRT = parametric bootstrapped likelihood ratio test

To identify characteristics of four latent classes selected as the final model, changing functions of each latent class were investigated in Table 3, thus denominating those in a way of increasing legibility based on the development stages of the depression level and referring to previous studies in Figure 2. The first group comprising 78.3% of total demonstrated that the value of the depression level in the early period was close to 6, and the first and second coefficients were significant. Thus, there was a slight increase in the second and third points but no big

differences between increase and decrease. Moreover, it decreased back to the beginning level at the final stage, hence denominated as "stable low" group because it consistently maintained the low level of depression. Though the second group comprising 5.1% of total showed a high level of depression in the early period of investigation, it was denominated as a "decreasing" group because it consistently decreased afterward. The third group comprising 3.4% of total showed a value of >10 in the depression level in the early period; it increased at the second and third points. However, the depression level gradually decreased in a wide range over time and decreased to the "stable low" level at the final stage; hence, it is denominated as "increased then decreasing" group. The last group comprising 13.2% of total showed a "stable low" level of depression at an early stage, but continuously increased afterward and led to the considerably higher level than diagnostic criteria for the suspect of depression; hence, it is denominated as an "increasing" group.

Latent class	n	%	Intercept (S.E)	Linear (S.E)	Quadratic (S.E)
Stable low	1724	78.3	6.03*** (.13)	0.54*** (.11)	-0.13*** (.02)
Decreasing	112	5.1	18.11*** (.78)	-5.40*** (.88)	0.73*** (.18)
Increased thendecreasing	76	3.4	11.77*** (1.93)	5.49*** (1.00)	-1.33*** (.18)
Increasing	290	13.2	7.32*** (.45)	2.47*** (.46)	-0.16*** (.10)

Table 3: Intercept, Linear,	Quadratic coefficients and	l significance for each latent class
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S.E = Standard error

*** p<.001

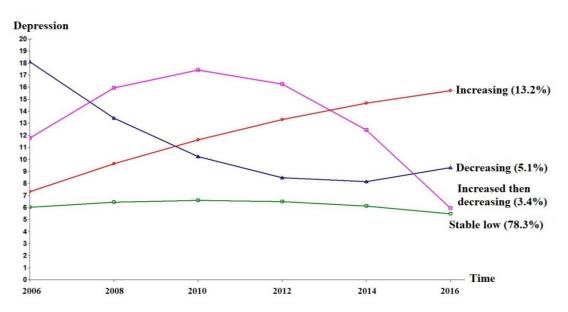


Figure 2: Type of latent classes

To confirm the determinants of classifying latent classes, conditioning models such as independent variables were analyzed using the bias adjusted three-step approaches; moreover, multinomial logit coefficients were then confirmed. By confirming the influence of variables that affect latent classes as per changes in the depression level of patients with chronic illness, all variables covered in this study were significant, as shown in Table 4. The stable low group that consistently maintained the low level of depression over time among four classes classified was set to be a reference group to examine the influence of independent variables. First, among demographic factors, females had higher possibilities of being included in the increased then decreasing group rather than the stable low group, indicating that females have higher possibilities of being included in the group with low initial value of depression, thus agreeing with the characteristics of the group in which depression in middle and old aged people is maintained at a low level or in a stable manner (Rote et al., 2015; Hsu, 2012; Liang et al., 2011; Rose et al., 2009). Next, the older the age, the more possibilities they had of being included in the increasing group. This agrees with the characteristics of incremental models in the study on the patterns of changes in depression (Rote et al., 2015) and reflects an aspect of biological ageing that when people age, the depression level increases along. Therefore, the level of depression increases due to decline in physical functions because of ageing and chronic illness. Moreover, with the higher level of education, there are additional possibilities of being included in the stable low group rather than the decreasing group. With additional income, there are additional possibilities of being included in the stable low group rather than the decreasing group or increasing group, indicating that when people are satisfied with their economic conditions, the depression level is reduced, which agrees with the previous studies that additional income lead to a lower level of depression (Hsu, 2012; Liang et al., 2011). Next, among health factors of chronically ill patients, daily life performance disorder and the severity of a chronic disease were reported to be common factors that are likely to make those patients belong to the remaining three potential classes in reference to the stable low group. That is, when the disability of doing activities of daily living and severity of chronic illness are significant, patients are more likely to belong to the decreasing group or increased then decreasing group or the increasing group rather than the stable low group, which reflects the result from the previous study that the restrictions of physical functions or activities affect depression in patients with chronic illness (Huang *et al.*, 2011). In particular, additional analysis of the degree of disability of doing activities of daily living and changes in the depression level demonstrated that they appeared to be similar. This indicates that, as per the physical health conditions and levels of functions, the depression level can appear in a similar way and such results indicate that physical health conditions of patients with chronic illness should be

recognized as the most critical factor in changes of depression level. Furthermore, the longer duration of the chronic illness increased possibilities of belonging to the decreasing group or increasing group rather than the stable low group. Thus, it is assumed that as per the disability of doing activities of daily living and the severity of chronic illness, the subjects themselves recognize their health conditions as good or bad compared to chronic illness' duration, which can then change the depression level.

Reference class	Stable low						
Comparisonclasses	Decreasing		Increased then decreasing		increasing		
Variable	B (S.E)	OR	B(S.E)	OR	B(S.E)	OR	
Gender ¹⁾	16 (.28)	.85	.87* (.37)	2.39	.06 (.18)	1.06	
Age	01 (.01)	.99	.02 (.02)	1.02	.03 ^{**} (.01)	1.03	
Spouse ²⁾	-1.21 ^{****} (.25)	.30	30 (.35)	.74	.00 (.18)	1.00	
Education level	67 ^{***} (.19)	.51	28 (.18)	.76	06 (.09)	.94	
Income	12 ^{**} (.04)	.89	06 (.05)	.94	09 ^{**} (.03)	.91	
Difficulties on ADL	.41 ^{**} (.14)	1.51	.47 ^{**} (.17)	1.60	.26 ^{**} (.11)	1.30	
Chronic illness severity	.30 [*] (.13)	1.35	.39 ^{**} (.15)	1.48	.21 ^{**} (.09)	1.23	
Chronic illness duration	.03 ^{**} (.01)	1.03	.02 (.01)	1.02	.02 ^{**} (.01)	1.02	

 Table 4: Determinants of latent class

¹⁾reference group=male; ²⁾reference group=no spouse; S.E=Standard error **p*<.05, ***p*<.01, ****p*<.001

CONCLUSION

Certain implications can be drawn in the academic and empirical aspects in this study. In terms of the academic aspect, the implications are as follows. First, using a growth mixture model, latent classes showing the trace of changes in the different level of depression within a group of patients with chronic illness were distinguished. This allowed this study to overcome the limitations of most of the existing cross-sectional studies that regarded patients with chronic illness as a single population and of the longitudinal studies using a latent growth model, and to identify multiple patterns of changes in depression. In particular, the high-risk group of depression that could not be identified with the existing longitudinal analysis, i.e., the group with the high or increasing level of depression could be identified and the effects of the relevant factors could be confirmed. Second, in the empirical aspect, this study is significant in that it identified latent classes showing various patterns of changes in depression, analyzed factors

affecting the classes, and suggested the policy grounds for mental health of chronic illness patients. To maintain the low level of depression in chronic illness patients or decrease it, it is necessary to maintain stable health conditions, and the following implications can be drawn from the results of this study. First, countermeasures to manage their health are required. In particular, the systematic management of local communities are necessary to prevent deterioration of the ability of doing daily activities and health conditions. Moreover, it is considered that if maintaining everyday life is possible without the deterioration of health conditions compared to the longer duration of illness, it will be possible to maintain the low level of depression. In this regard, a stable medical and economical supports for constant management are required in order to not worsen the severity because of chronic illness. The family income consistently leads to the low level of depression; in particular, when health conditions deteriorate and the prevalence of chronic illness becomes longer, anxiety, stress, and deterioration of the severity of diseases can affect the depression level of patients with chronic illness. Moreover, based on the results of this study, to manage and reduce depression in patients with chronic illness who can only be encountered on the medical site, preventive interventions that consider different types as per changes in the depression level are required. As a preliminary work, prior knowledge for the high-risk group with chronic illness and the accurate screening process should be prepared. For this purpose, additional studies with patients with chronic illness should be conducted to identify different characteristics of groups and predictors as per changes in the depression level. Based on the accumulated results, it is necessary to reconfirm this study's results; moreover, a follow-up study should be conducted to identify various factors affecting changes in depression level. Using such consistent follow-up studies, additional knowledge about the depression level-associated factors will be able to be accumulated.

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