International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 6 (2018) pp. 4415-4422
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Exploring Fuzzy Set Qualitative Comparative Analysis to Health-Related OECD Data

Kyoungho Choi, Ph. D.[1], Jung Keun Cho, Ph. D.[2*]

[1] *Department of Basic Medical Science, Jeonju University, Republic of Korea.*
[2*]*Department of Radiological Science, Jeonju University, Jeonju, Republic of Korea.*
[1]*Orcid: 0000-0001-7892-8739,* [2*]*Orcid: 0000-0001-5336-6397*

** Corresponding author*

Abstract

The objective of this study was to determine the relationship between variables through health-related data. For this, data of an official statistic from 31 OECD Nations about life satisfaction of senescence and personal subjective health were used. In addition, a process of fuzzy-set qualitative comparative analysis (fsQCA) was described in detail. It has the property of connecting qualitative and quantitative research method. As a result, four combinations of causal variables were found, which was sufficient through fsQCA. After comparing regression analysis and fsQCA, it was discovered that fsQCA was better for discovering the causal relation. Through this research, we hope that fsQCA will be more used for studies to discover causal relations in health science field.

Keywords: fs Qualitative comparative analysis, Sufficient condition, Necessity condition, Regression analysis, Health science field.

INTRODUCTION

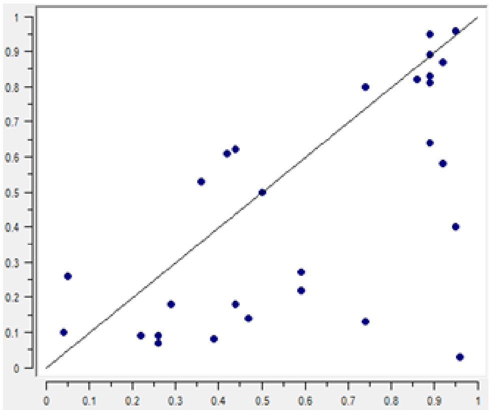
Today, life expectancy is increased thanks to improvement of medical technic. However, most aged people have more than three chronical diseases and are confronted by fundamental health problems of old age. During old age, retrogression of physical function is inevitable and it exposes aged people to various disease and risk of having illness and this makes the one need medical care and palliative care. This makes them need medical care and palliative care. In the process of solving such problem, a role of the nation is being magnified. Park (2016) has tried to prove statistically that national public support can influence life satisfaction of senescence by using a hierarchical linear model to data from 31 OECD Nations. Although net effect analysis (structural equation model, multiple regression, hierarchical linear model, analysis of variance) can verify direct and indirect effects of an independent variable toward a dependent variable, it cannot verify the relation between causal variables. Therefore, in regression analysis, it will be considered as a net effect that does not overlap in the competition between dependent variables. Therefore, Analysis can be performed, except variables which have strong correlations with each other. A case will be naturally excluded when high correlational variables make a strong synergy by coupling with each other. Moreover, when one dependent variable has a strong net effect, it does not give the answer, regardless whether the independent variable will occur by this variable (Choi, 2009). In contrast, fuzzy-set qualitative comparative analysis (fsQCA) can identify combinations of causal conditions and lead to outcome of interest in the real world. Moreover, fsQCA overcomes limitations of net effects analyses by assuming symmetrical relationships between variables (Ho et al., 2016). The fsQCA is developed as a methodology to combine a case-oriented qualitative analysis with a variable-oriented quantitative analysis. It was start from the development of qualitative comparative analysis it the end of the 1980s (Ragin, 1987). After that, qualitative comparative analysis of fuzzy set was developed, in which the logic of the fuzzy set was adapted (Ragin, 2000). Qualitative comparative analysis of the fuzzy set (fsQCA) is more interested in a joint causal system from interactions between variables which consist of the case, rather than a methode, which analyzes the influence of one cause on a dependent variable, assuming that other dependent variables are constant (Fiss, 2007). Moreover, fsQCA is not for large-N nor small-N. It is an appropriate methodology to intermediate-N case analysis. In other words, although most quantitative comparative analysis including regression analysis needs a lot of sample, fsQCA can analyze relatively small samples such as 5~50 cases (Fiss, 2012). Several examples of studies with ten or fewer cases have been conducted in which fsQCA provides valuable insights, for which statistical test would be unreliable (Stokke, 2007; Wind et al, 2016). In this point of view, fsQCA will give a more meaningful result when the relation between variables is considered through fsQCA in a study conducted by Choi (2016) to examine the influence of national public expenditure on life satisfaction (LS) of the aged. In other words, to understand LS, it is more proper to examine through fsQCA to know how causal variables of health public expenditure such as subjective health status (SHS), a long-term care expenditure (LTC), and funding of palliative cares (PC) makes combination to be a necessary condition for explaining LS. Thygeson et al. (2011) have used fsQCA in health research field. However, very limited studies have applied fsQCA within health research (Warren et al., 2013).

Therefore, the objective of this study was to explore whether fsQCA might be a more proper method to reveal the relation between variables through health-related data. Thus, fsQCA allows knowing whether a combination of any causal variables can clarify dependent variable, a clarification that multiple linear regressions does not offer. To do this, fsQCA will be introduced first. Then the method of analysis and process of applying the fsQCA will be introduced in detail. Concluding remarks are also provided. This study will contribute to the use of fsQCA in health science field in the future.

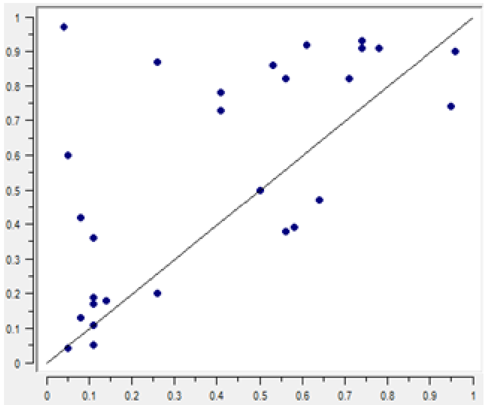
REVIEW OF fsQCA

Overview: The fsQCA was developed as a methodology to combine a case-oriented qualitative analysis with a variable-oriented quantitative analysis, starting from qualitative comparative analysis (QCA) by Ragin (1987). After that, fsQCA was modified by Ragin (2000), in which the logic of fuzzy set was adapted. A fuzzy set methodological approach is relatively in the developing process (Ragin, 2006; Smithson, 2005; Verkuilen, 2005). However, among many social scientists, it is already a subject of debate. It has attracted some negative criticisms (Lieberson, 2004; Seawright, 2004). In spite of this, the number of researchers who use fsQCA is constantly increasing. The fsQCA was developed in order to include advantages from both qualitative analysis and quantitative analysis. It is a grand methodology. If it is properly conducted, it can play a role as a bridge between these two methodologies (Lee, 2014). The fsQCA has special property that is different from variable oriented analysis or case-oriented analysis. Based on Lee et al. (2015), first, fsQCA gives more degree of freedom to a researcher in comparison with quantitative analysis to exam causal complexities included in conjunctional causation. In fsQCA, causal condition can consist of a combination. Therefore, when one needs to know the influence of a causal variable on a dependent variable in a multivariate regression analysis, the level of the rest dependent variables is fixed. However, in fsQCA, a joint causal system is focused which allows one to determine the effect of interaction between each property in sample cases. Second, in fsQCA, the method of characterizing a sample case is flexible. In the simple set theory, there are only two cases for one example: belonging to one set or not. On the other hand, the fuzzy set theory makes the level of membership possible. This kind of calibration allows one to measure qualitative concept against quantity. Third, fsQCA makes it possible to exam whether a set of combination of some causal conditions can be a necessary or sufficient as a dependent variable, which is the result.

Procedures: A fsQCA execution process is generally performed in the following procedure. First, a response variable is set which is necessary for solving the research problem while a causal variable is selected which is assumed to have influence on the response variable. Selecting variables is performed based on a theory which is discovered from preceding research. Second, raw data of response and casual variable are acquired. Third, raw data of response and casual variable are converted to fuzzy score. When a condition is dichotomous (e.g., PC), this condition defines its membership or non-membership. However, the study uses fuzzy-set calibration to set membership when conditions are continuous variables (e.g., LS, SHS, LTC, PM). The fsQCA allows partial membership of cases in a set based on three anchor values (percentiles 0.95, 0.5, and 0.05), with full membership equal to 0.95 or higher, a crossover point of maximum ambiguity equal to 0.5, and full non-membership equal to 0.05 or lower (Ragin, 2008). This study uses consistency and coverage metrics to assess the necessity and sufficiency analyses as described by Ragin (2000). Consistency measures the degree to which cases having the effect also exhibit causal or constructive characteristic. In other words, it measures the proportion of members of the subset that are members of the superset. Consistency is to set relationship as p-value for statistical inference. The higher the consistency, the stronger the set relationship. In general, we look for set-theoretical relationships with consistencies greater than 0.9. Coverage measures how much a consistent subset “covers” the superset. In the case of “necessary” causes, coverage can be interpreted as the degree to which the cause “is relevant” to the effect (Thygeson et al., 2011). With the fsQCA approach, theoretically, condition A is necessary for outcome Y if in each case the degree of membership in Y is consistently less than or equal to the degree of membership in A (Y≤A). Condition A is sufficient to Y if across all cases the degree of membership in condition A is consistently less than or equal to the degree of membership in Y (Wind et al., 2016). Graphical representation about the necessary condition and sufficient condition is shown in



Necessary condition



Sufficient condition

Figure 1: Graphical representation of fuzzy relationships.

Third, a true table analysis is performed to express all possible logical combination (2K=16) of casual conditions (e.g., k=4) to explain the response variable. Fourth, in the true table analysis, combinations are summarized based on consistency and frequency. At this time, frequency cutoff in the true table is recommended to be more than 1 and consistency cutoff is recommended to be over than 0.75 (Ragin, 2008). Fifth, a combination of casual variables which explain the response variable can be classified to explain the meaning based on included case. A mathematical principle about fsQCA and detail for procedures in <Figure 2> has been shown in Mendel ・Korjani (2012).

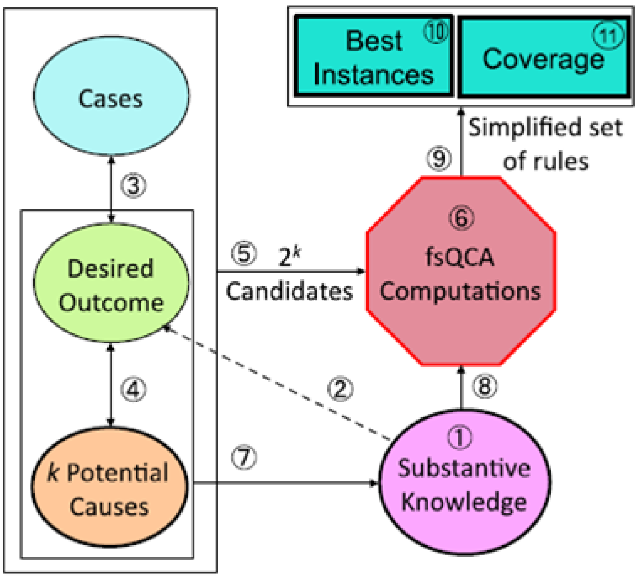


Figure 2. A summary of fsQC procedures.

MATERIALS & METHODS

Data: This study used data from 31 OECD countries regarding five variables (LS, life satisfaction; SHS, subjective health status; LTC, long-term care expenditure; PC, funding of palliative cares; PM, public medical expenditure). These data were obtained from OECD official statistic, World Value Survey, Ranking palliative care across the world (Park, 2016).

Outcome condition: In this research, outcome condition which is an independent variable is life satisfaction of the aged. Life satisfaction of the aged is a level of feeling valuable about one´s daily life and current life for those who are more than 65 years old. It means subjective satisfaction about general life. Life satisfaction is often mixed with quality of life which is a similar concept. However, different from quality of life, life satisfaction reflects the cognitive satisfaction about personal life (Netuveli・Blane, 2008). Outcome condition of this study came from World Value Survey.

Explanatory conditions: Explanatory conditions corresponding to dependent variables use PM and LTC from official OECD statistic data and SHS from World Value Survey. Since there was no unified data source of national data about palliative care, ranking palliative care across the world was used as a reference. PM has shown a high relation with subjective health condition of the aged (Garcia-Munoz et al., 2014). LTC means public support which compensates disability in daily life caused by aging. PC means institutional intervention and arbitration to eventually improve quality of life while it respects the sanctity and choice of the person who suffers from life threatening diseases.

Analysis tool: For analysis, fsQCA 2.5 Software (Ragin・Sean, 2014) was used. This analysis tool has been used by more than 80% of researchers for fuzzy-set qualitative comparative analysis. It can be freely downloaded from the following website: http://www.u.arizina.edu/~cragin/fsQCA/software.shtml. The fsQCA generates three possible solutions: complex, parsimonious, and intermediate. This study used the intermediate solution because all assumptions complied with theoretical and substantive knowledge. In addition, previous studies also support this choice (Nunez-Pomar et al. 2016).

RESULTS

One purpose of this research was to explore the usefulness of fsQCA for discovering relations between variables using health-related data. Therefore, the process used to produce the result will be introduced according to procedures shown in section 2.2 in detail.

Descriptive statistics: <Table 1> shows descriptive statistics and calibration values for outcome and explanatory variables. There are many ways to convert raw data to fuzzy score in fsQCA. Since one general method used for calibration is by using three anchor values (percentiles 0.95, 0.5, and 0.05) to convert raw data to fuzzy score, it is also used for this research.

Table 1. Descriptive statistics and calibration values

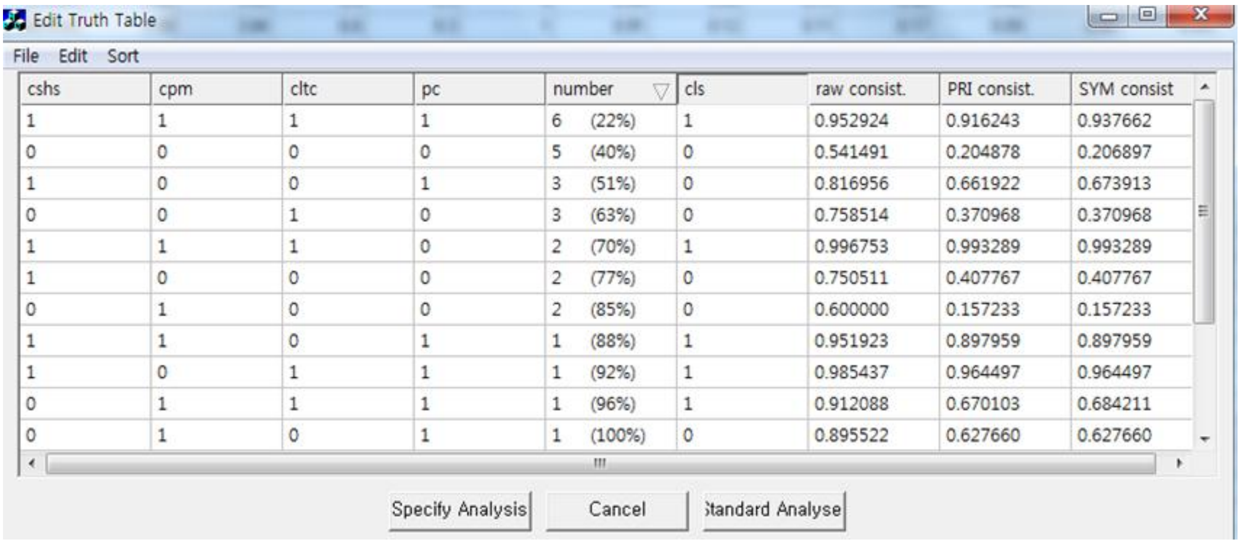
	LS	SHS	PM	LTC
Mean	7.315	3.452	9.190	1.032
SD	0.710	0.375	2.521	0.891
Minium	5.9	2.6	5.1	0.0
Maximum	8.5	4.0	17.9	3.6
calibration values				
Percentile 5	5.950	2.622	5.280	0.060
Median	7.280	3.420	9.200	0.900
Percentile 95	8.330	3.958	14.60	3.540

Necessary conditions: It was then determined whether the four explanatory variables (SHS, PM, LTC, PC) might meet necessary condition for outcome variable. According to Romero et al. (2016), the condition is necessary if one has a high score of consistency with threshold of 0.9. Although consistency for conditions was relatively high (0.422~0.869), none of them met the threshold. Therefore, these conditions were unnecessary for the occurrence of LS.

Table 2. Necessary conditions from fsQCA for SHS, PM, LTC, PC for the occurrence (and no occurrence) of LS

	Life satisfaction		~Life satisfaction	
	Consistency	Coverage	Consistency	Coverage
SHS	**0.869**	**0.824**	0.593	0.477
~SHS	0.565	0.448	**0.835**	0.781
PM	0.786	0.672	0.515	0.513
~PM	0.590	0.586	**0.785**	0.669
LTC	**0.867**	**0.678**	0.502	0.463
~LTC	0.611	0.573	**0.877**	**0.697**
PC	0.669	0.598	0.350	0.331
~PC	0.422	0.402	0.650	0.578

True table analysis and summing up: True table analysis is used to explain the result by summing up a combination of casual (explaining) condition as 0 and 1. It shows all logical combinations of casual conditions. For summarization, frequency and consistency are used. This process is used to eliminate casual combinations under cutoff. If all cases are relatively small, frequency and cutoff are fixed as 1 or 2. In addition, consistency cutoff is recommended to be 0.75 (Ragin, 2008). In this research, frequency cutoff was 1 while consistency cutoff was 0.9.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cshs	cpm	cltc	pc	number	cls	raw consist.	PRI consist.	SYM consist
1	1	1	1	6 (22%)	1	0.952924	0.916243	0.937662
0	0	0	0	5 (40%)	0	0.541491	0.204878	0.206897
1	0	0	1	3 (51%)	0	0.816956	0.661922	0.673913
0	0	1	0	3 (63%)	0	0.758514	0.370968	0.370968
1	1	1	0	2 (70%)	1	0.996753	0.993289	0.993289
1	0	0	0	2 (77%)	0	0.750511	0.407767	0.407767
0	1	0	0	2 (85%)	0	0.600000	0.157233	0.157233
1	1	0	1	1 (88%)	1	0.951923	0.897959	0.897959
1	0	1	1	1 (92%)	1	0.985437	0.964497	0.964497
0	1	1	1	1 (96%)	1	0.912088	0.670103	0.684211
0	1	0	1	1 (100%)	0	0.895522	0.627660	0.627660

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Figure 3. Example of a true table (frequency cutoff of 1, consistency cutoff of 0.9).

Intermediate solution: As shown in <Table 3>, intermediate solution indicates four combinations of causal (explanatory) conditions that can produce outcome condition (LS). The consistency of intermediate solution based on Quine-McCluskey algorithm was 0.909917. According to Eng and Woodside (2012), a fsQCA is informative when consistency is above 0.74. Also, the coverage (0.656138) of the four conditions seems adequate. The coverage is a concept similar to determination coefficient (R2) which is used as an indicator for model explanation in regression analysis. Sufficient conditions can explain 65.6% of the empirical evidence (Woodside, 2014). Overall, the consistency (0.909917) and coverage (0.656138) of the four conditions are appropriate.

Table 3. Finding fsQCA intermediate solution for SHS, PM, LTC, PC, and life satisfaction

Model: LS = f(SHS, PM, LTC, PC)			
frequency cutoff: 1 consistency cutoff: 0.9 all variables are present	raw coverage	unique coverage	consistency
PC * LTC * PM	0.411204	0.013111	0.905512
PC * LTC * SHS	0.417163	0.019070	0.954979
PC * PM * SHS	0.441001	0.042908	0.914710
LTC * PM * SHS	**0.581049**	0.182956	**0.966303**

The intermediate solution indicates that four combinations of conditions are related to each other extremely frequently as shown below.

path 1: PC * LTC * PM → LS

Case with greater than 0.5 membership in path 1: NETHERLAND (0.86, 0.74), BELGIUM (0.71, 0.82), FRANCE (0.71, 0.32), JAPAN (0.62, 0.47), NEW ZEALAND (0.61, 0.92), SWITZLAND (0.61, 0.92), AUSTRIA (0.56, 0.82), and UK (0.53, 0.86).

path 2: PC * LTC * SHS → LS

Case with greater than 0.5 membership in path 2: NETHERLAND (0.83, 0.74), NORWAY (0.78, 0.91), BELGIUM (0.65, 0.82), NEW ZEALAND (0.61, 0.92), SWITZLAND (0.61, 0.92), AUSTRIA (0.56, 0.82), and UK (0.53, 0.86).

path 3: PC * PM * SHS → LS

Case with greater than 0.5 membership in path 3: USA (0.95, 0.78), NETHERLAND (0.83, 0.74), SWITZLAND (0.76, 0.92), BELGIUM (0.65, 0.82), NEW ZEALAND (0.65, 0.92), AUSTRIA (0.60, 0.82), and UK (0.53, 0.86).

path 4: LTC * PM * SHS → LS

Case with greater than 0.5 membership in path 4: NETHERLAND (0.83, 0.74), DENMARK (0.74, 0.91), BELGIUM (0.65, 0.82), NEW ZEALAND (0.61, 0.92), SWITZLAND (0.61, 0.92), AUSTRIA (0.56, 0.82), SWEDEN (0.56, 0.90), and UK (0.53, 0.86).

Finally, a total of 12 nations have membership values larger than 0.5 in the results from path 1 to path 4. They correspond to nations inside of the circle shown in <Figure 4>.

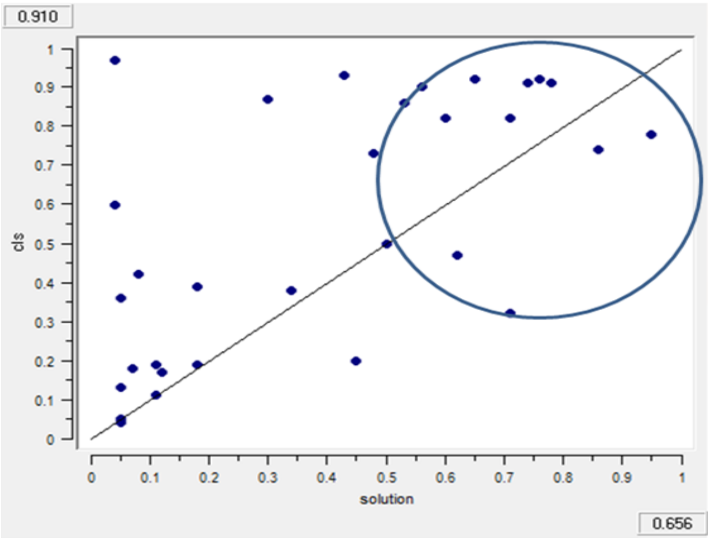

Figure 4. Path1 + path2 + path3 + path4 vs. LS.

Multiple linear regression: When a stepwise multiple linear regression is performed, result is shown in <Table 4> by using outcome variable as an independent variable and explanatory variables as dependent variables. The percent of variance explained through regression model is 44.6%, which is less than 65.6% in fsQCA. Moreover, it shows that SHS is the only statistically meaningful variable. The reason is that there are high relations between explanatory variables. In other words, when there are correlations between explanatory variables in regression analysis, specific variable is not included in the predictive model. However, fsQCA can explain the relation with dependent variable through a combination of explanatory variables. Therefore, it is a more proper analysis method than regression method. In conclusion, fsQCA opens a new research framework to explore the complexity of health-related variables. Using fsQCA, it is possible to establish different combinations of conditions and sets of countries associated with them (Coduras et al., 2016).

Table 4. Analysis of stepwise linear regression model

Dependent variable: life satisfaction		
R square: 0.446		
Independent variables	B	p-value
Constant	2.953	0.003
SHS	1.264	0.000
PM	0.400	0.792
LTC	0.249	0.100
PC	0.015	0.929

DISCUSSION

In this research, to understand life satisfaction, it is analyzed how health-related public expenditures such as subjective health status, long-term care expenditure, funding of palliative care, and public medical expenditure make combinations. Data used for this study were obtained from official statistic from 31 OECD nations and fsQCA was used as an analysis method. FsQCA has been used for summarizing data, testing existing hypotheses and theories, quickly overviewing basic assumptions of the analysis, and developing new theoretical arguments. However, it is mainly used for checking the coherence of data with claims of subset relations. The fsQCA has some advantages compared to regression analysis. First, it is possible to using insufficient but non-redundant part of an unnecessary but sufficient condition (INSU). INSU means that a variable which has no meaningful influence in the regression analysis plays a significant role in the combination with other variables in fsQCA. Second, fsQCA is applicable to necessary condition. It is very important to verify from which condition that the causal relation of causal and response condition comes from. Third, fsQCA is applicable to causal relations in a causal combination. In regression analysis, it is assumed that casual variable independently influences the response variable. However, in fsQCA, a combination of casual variable forms a causal relation that affects the response condition. In other words, fsQCA not only can eliminate the downfall of multi-collinearity, it also allows researchers to look at combinations of predictor variables in their ability to predict outcome variables (Greenbalgb, 2017). Because of these advantages, fsQCA is frequently used with regression analysis for analyzing cause and effect (Kim, 2015).

Such advantages of fsQCA were also founded in this research. In other words, subjective health status was selected as a meaningful variable for explaining the life satisfaction of the aged. It was also founded that all other casual variables were INSU in fsQCA. Namely, fsQCA confirmed that other casual variables except subjective health were meaningful variables in the combination of four final conditions: PC * LTC * PM, PC * LTC * SHS, PC * PM * SHS, and LTC * PM * SHS. Moreover, fsQCA is a more proper analysis method than regression since the percent of variance explained from fsQCA was 65.6%, which was higher than 44.6% from the regression analysis. Besides, this research has significance. By introducing the procedure of fsQCA in detail, it helps researchers who try to discover the relation between variables using health-related data. Therefore, this research might contribute to more use of fsQCA in health science field for research to discover causal relations.

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