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Exploratory Factor Analysis using Maximum Likelihood Estimation(MLE) and Oblique Rotation(Direct Oblimin) on Multicultural Experiences of University Students : Focusing on Principal Component Analysis(PCA) and Varimax Comparison

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Abstract[1]

Background/Objectives: This study was designed to compare the Varimax analysis of Principal Component Analysis(PCA) with the Exploratory Factor Analysis(EFA) method using Maximum Likelihood Estimation(MLE) and oblique rotation(Direct Oblimin) for the multicultural experience of university students. multicultural experience variables of college students were analyzed as two factors through Maximum Likelihood Estimation(MLE).

Methods/Statistical analysis Q1, Q2, Q3 are multicultural direct experiences, and Q4, Q5, Q6, Q7 are multicultural indirect experiences.

Findings: As a result of this study, it is suggested to use Maximum Likelihood Estimation(MLE) and oblique rotation(Direct Oblimin). As a prerequisite for applying the Maximum Likelihood Estimation(MLE), it is thought that

Improvements/Applications it is necessary to increase the accuracy of the response rate by using the face-to-face interview method when conducting a survey.

Index Terms

Maximum Likelihood Estimation(MLE), Oblique Rotation, Direct Oblimin, Principal Component Analysis(PCA), Varimax

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I. INTRODUCTION

Factor analysis is characterized by reducing the complexity of multidimensional data by reducing the dimension of factors. Factor analysis simply organizes complex and abstract concepts, and unlike other analysis techniques, the concepts of independent and dependent variables are unnecessary. In addition, factor analysis relies on quantitative methods for qualitative meaning interpretation[1]. Factor analysis(FA) analyzes an object made up of an interval scale or a ratio scale. Factor analysis(FA) analyzes the interrelationships between variables using covariance and correlation among various variables. Based on the results, it is an analysis method that identifies the correlation and structure between items and variables, and groups the information of multiple variables into a small number of factors. However, nursing and other social sciences currently use Principal Component Analysis(PCA), which is an inaccurate but commonly used method, and Varimax factor analysis, which is an orthogonal rotation method[2-5].

This method may raise some problems in the interpretation process. First, the covariance is 0 because it is a result obtained by performing orthogonal rotation, which is a rotation method, under the assumption that the factors are independent of each other. Component Score Covariance Matrix In some cases, the results are presented without checking the table properly. This is a mistake that comes from overlooking the meaning of component score covariance matrix[2-5]. According to a study comparing methods for reducing the dimension of data, both Principal Component Analysis(PCA) and factor analysis methods are used for data reduction[6].

The preceding research is a comparative study of Principal Component Analysis(PCA) and Common Factor Analysis(CFA) by Jeong and Seo (2013): a factor structure restoration perspective[7] and a dimensionality reduction method for cluster analysis of multidimensional data such as Hong, Oh and Jo (2020): comparison of Principal Component Analysis(PCA) and factor analysis[8]. Therefore, in this study, the Maximum Likelihood Estimation(MLE) method and the oblique rotation Oblimin Common Factor Analysis(CFA) was conducted using the multicultural experience variables of university students. Comparison of Principal Component Analysis(PCA) and Common Factor Analysis(CFA) of variables for the first time in nursing.

The Factor Analysis(FA) that can be done in SPSS statistics is an Exploratory Factor Analysis(EFA), and there are Principal Component Analysis(PCA) and Common Factor Analysis(CFA). The two analysis methods have the same meaning and are easy to understand in terms of data reduction, but strictly speaking, they are different concepts. Therefore, this study was attempted to change the Principal Component Analysis(PCA) to Maximum Likelihood Estimation(MLE).

The specific research objectives are as follows.

- Check the degree of variables in the multicultural experience of university students.
- Check the difference between the Maximum Likelihood Estimation(MLE) and the Common Factor Analysis(CFA) of the multicultural experience variables of university students is checked.
- Check the difference between orthogonal rotation and oblique rotation factor analysis of multicultural experience variables of university students.
- Check the difference between Varimax and Oblimin factor analysis of multicultural experience variables of university students.
- Check the reliability analysis of multicultural experience variables of university students.

II. MATERIALS AND METHOD

A. Research Design

This study was designed to compare the Varimax analysis of Principal Component Analysis(PCA) with the exploratory factor analysis method using Maximum Likelihood Estimation(MLE) and oblique rotation(Oblimin) for the multicultural experience of university students.

B. Research Data Collection

Among the primary data of the questionnaire surveyed by me, multicultural experience variables that were not used in the study were used as secondary data for analysis. The primary data questionnaire was collected from a single university student in Gwangju from March 28, 2022 to April 7, 2022. After explaining the purpose of the study to the subjects, written consent was obtained. Data were analyzed anonymously for research purposes. If you do not want the survey, you can withdraw freely.

C. Research Instrument

1) Multicultural experience questionnaire

Multicultural experience refers to direct or indirect experiences with different groups, such as various races and cultures[2]. This research tool consisted of 7 questions after revising the multicultural experience tool of Lee (2011)[9], Cho (2012)[10], Shim and Lee (2015)[11] and Munroe (2006)[12] with the advice of three professors with doctoral degrees in nursing.

a. When I was in elementary, middle, and high

school, my school had students from multicultural families.
b. During my growing up, I tend to get along well with students from multicultural families.
c. When I was young, there was a multicultural family in my neighborhood.
d. When I was young, I admired people from countries other than developed countries such as the US, UK, and France, who were not Koreans, as a model for my life.
e. In the past, I liked to watch TV shows or movies that dealt with the lives and cultures of people in countries other than developed countries in the West.
f. I tend to choose to read books about the lives and cultures of people in countries other than developed countries in the past.
g. I read articles about multiculturalism covered in newspapers and TV with interest.

2) Principal Component Analysis(PCA) and Varimax Comparison

Principal Component Analysis(PCA) is a method of reducing many variables to a smaller number of principal components. By minimizing the loss of information contained in a lot of data, data is simply reduced to two or three dimensions. Varimax is an orthogonal rotation method. Varimax rotates by maintaining independence between factors. That is, there is no correlation. In the social sciences, it is rare that the correlation between factors is 0, but correlation coefficient = 0 is assumed. The results are simple and easy to interpret[2-4]. One of the main differences between Principal Component Analysis(PCA) and Factor Analysis(FA) in mathematical terms is the values found in the diagonal of the correlation matrix, the basis of both methods. The total variance of each variable is a result of the sum of the shared variance with another variable, the common variance, and the unique variance inherent to each variable[13,14]. There are three types of orthogonal rotation methods: Varimax, Qwertimax, and Equimax.

3) Maximum Likelihood Estimation and Oblique Rotation(Direct Oblimin)

The Maximum Likelihood Estimation(MLE) method is the most used method in common factor analysis. Common Factor Analysis(CFA) is a method of finding out the properties inherent in data, including the dimension of data reduction. By extracting common factors between variables, and using them to find correlations between variables, the properties of each variable are reduced and explained. The Direct Oblimin of oblique rotation rotates by maintaining the relationship between factors. That is, it does not assume that there is no correlation at all. In the social sciences, it is assumed that the correlation coefficient is also non-zero because it is rare that the correlation between factors is zero. The results are complex and difficult to interpret[2-4]. There are Direct Oblimin and Promax for oblique rotation.

4) Contents of Exploratory Factor Analysis(EFA)

- Descriptive statistics
- KMO and Bartlette's test
- Correlation matrix
- Commonality
- Total variance explained
- Screen diagram
- Component change matrix
- Component matrix/Factor matrix
- Conformity test
- Rotated component matrix/ Pattern matrix/Structure matrix
- Component score coefficient matrix/Factor score coefficient matrix
- Component score covariance matrix/Factor score covariance matrix

III. RESULT AND DISCUSSION

A. Multicultural experience questionnaire descriptive statistics

The subjects of this study were 130 people. The following are the mean, standard deviation, minimum, and maximum values for the questionnaires on the multicultural experience of university students.
When I was in elementary, middle, and high school, my school had students from multicultural families(3.36±1.35point, 1~5point). During my growing up, I tend to get along well with students from multicultural families(3.55±1.09point, 1~5point). When I was young, there was a multicultural family in my neighborhood(2.68±1.34point, 1~5point). When I was young, I admired people from countries other than developed countries such as the US, UK, and France, who were not Koreans, as a model for my life(2.57±1.05point, 1~5point). In the past, I liked to watch TV shows or movies that dealt with the lives and cultures of people in countries other than developed countries in the West(3.21±1.13point, 1~5point). I tend to choose to read books about the lives and cultures of people in countries other than developed countries in the past(2.82±1.01point, 1~5point). I read articles about multiculturalism covered in newspapers and TV with interest(3.09±0.97point, 1~5point).

The item with the highest average among the items is that I tend to get along well with students from multicultural families while growing up. The question with the lowest average among the questions is that when I was young, I admired people from countries other than developed countries such as the US, UK, and France who were not Koreans, as a model for my life.

B. Multicultural experience Principal Component Analysis(PCA) and Verimax

1) KMO and Bartlette's test

KMO(Kaiser-Meyer-Olkin) : .774

Bartlett' Test of Sphericity [Chi-Square, df(*p*)]: 276.787, 21(<.001)

This value serves as a criterion for confirming whether it is appropriate to perform factor analysis on the 7 questionnaire items. Factor analysis satisfies KMO>.05 and Bartlett's p<.05, so it can be judged that the ongoing factor analysis is appropriate.

2) Correlation matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Q1	1.000	.626	.487	.259	.170	.242	.313
Q2	.626	1.000	.421	.271	.240	.287	.354
Q3	.487	.421	1.000	.376	.308	.245	.233
Q4	.259	.271	.376	1.000	.536	.478	.360
Q5	.170	.240	.308	.536	1.000	.450	.338
Q6	.242	.287	.245	.478	.450	1.000	.589
Q7	.313	.354	.233	.360	.338	.589	1.000

3) Commonality

	Initial	Extraction
Q1	1.000	.785
Q2	1.000	.712
Q3	1.000	.540
Q4	1.000	.602
Q5	1.000	.596
Q6	1.000	.676
Q7	1.000	.519

4) Total variance explained

Compo-nents	Initial eigenvalues			Extracted sum-of-squares loadings,			Rotating sum-of-squares loadings		
	Total	% Variance	% Cumulative	Total	% Variance	% Cumulative	total	% Variance	% Cumulative
Q1	3.170	45.281	45.281	3.170	45.281	45.281	2.363	33.751	33.751
Q2	1.261	18.020	63.301	1.261	18.020	63.301	2.069	29.550	63.301
Q3	.844	12.063	75.364						
Q4	.532	7.595	82.959						
Q5	.458	6.542	89.501						
Q6	.381	5.439	94.940						
Q7	.354	5.060	100.000						

Components	1	2
1	.760	.650
2	-.650	.760

5) Component change matrix

6) Component matrix

	Components	
	1	2
Q6	.708	-.419
Q4	.702	-.331
Q7	.683	-.232
Q2	.676	.504
Q1	.652	.601
Q5	.644	-.427
Q3	.643	.355

7) Rotated component matrix

	Components	
	1	2
Q6	,810	.142
Q5	.766	.094
Q4	.748	.205
Q7	.669	.268
Q1	.104	.880
Q2	.186	.823
Q3	.258	.688

8) Component score coefficient matrix

	Components	
	1	2
Q1	-.154	.495
Q2	-.098	.442
Q3	-.029	.346
Q4	.339	-.055
Q5	.374	-.125
Q6	.385	-.107

Q7	.283	.001

9) Component score covariance matrix

Components	1	2
1	1.000	.000
2	.000	1.000

C. Multicultural experience Maximum Likelihood Estimation(MLE) and Oblique Rotation(Direct Oblimin)

1) KMO and Bartlette's test

KMO(Kaiser-Meyer-Olkin) : .774

Bartlett' Test of Sphericity [Chi-Square, df(*p*)]: 276.787, 21(<.001)

This value serves as a criterion for confirming whether it is appropriate to perform factor analysis on the 7 questionnaire items. Factor analysis satisfies KMO>.05 and Bartlett's p<.05, so it can be judged that the ongoing factor analysis is appropriate. It was the same in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

2) Correlation matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Q1	1.000	.626	.487	.259	.170	.242	.313
Q2	.626	1.000	.421	.271	.240	.287	.354
Q3	.487	.421	1.000	.376	.308	.245	.233
Q4	.259	.271	.376	1.000	.536	.478	.360
Q5	.170	.240	.308	.536	1.000	.450	.338
Q6	.242	.287	.245	.478	.450	1.000	.589
Q7	.313	.354	.233	.360	.338	.589	1.000

It was the same in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

3) Commonality

	Initial	Extraction
Q1	.463	.796
Q2	.438	.517
Q3	.327	.344
Q4	.397	.456
Q5	.353	.419
Q6	.451	.576
Q7	.395	.423

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

4) Total variance explained

Compo-nents	Initial eigenvalues			Extracted sum-of-squares loadings,			Rotation squared
	Total	% Variance	% Cumulative	Total	% Variance	% Cumulative	Total
Q1	3.170	45.281	45.281	2.553	36.466	36.466	2.131
Q2	1.261	18.020	63.301	.981	14.009	50.475	2.309
Q3	.844	12.063	75.364				
Q4	.532	7.595	82.959				
Q5	.458	6.542	89.501				
Q6	.381	5.439	94.940				
Q7	.354	5.060	100.000				

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

5) Factor matrix

	Factor	
	1	**2**
Q1	.807	-.381
Q2	.700	-.167
Q3	.586	-.036
Q7	.548	.351
Q6	.544	.530
Q4	.524	.427
Q5	,446	.470

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

6) Conformity test

Chi-Square, df(*p*) : 20.249, 8(.009)

The conformity test tests whether it is appropriate to divide the variables into one another. The suitability test was conducted through a chi-square test, and the significance probability is presented. That is, it can be confirmed that it is appropriate to divide the variables into two by rejecting the null hypothesis with p <.05. The conformity test is not present in Principal Component Analysis(PCA), but is present in Maximum Likelihood Estimation(MLE).

7) Pattern matrix

	Factor	
	1	**2**
Q1	.951	-.132
Q2	.685	.065
Q3	.485	.168
Q6	-.032	.774
Q5	-.056	.674
Q4	.041	.654
Q7	.125	.579

The pattern matrix is not present in Principal Component Analysis(PCA), but is present in Maximum Likelihood Estimation(MLE).

8) Structure matrix

	Factor	
	1	**2**
Q1	.885	.342
Q2	.717	.406
Q3	.568	.410
Q6	.355	.759
Q4	.367	.675
Q5	.280	.646
Q7	.414	.642

The structure matrix is not present in Principal Component Analysis(PCA), but is present in Maximum Likelihood Estimation(MLE).

9) Factor correlation matrix

Factor	**1**	**2**
1	1.000	.499
2	.499	1.000

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

10) Factor score coefficient matrix

	Factor	
	1	**2**
Q1	.655	.003
Q2	.208	.069
Q3	.114	.074
Q4	.046	.248
Q5	.020	.234
Q6	.042	.372
Q7	.060	.212

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

11) Factor score covariance matrix

Factor	**1**	**2**
1	1.523	1.411
2	1.411	1.462

It was found to be different in Principal Component Analysis(PCA) and Maximum Likelihood Estimation(MLE).

D. Reliability Analysis

Reliability analysis was performed based on Maximum Likelihood Estimation(MLE). Multicultural experience variables of college students were analyzed as two factors through Maximum Likelihood Estimation(MLE). Q1, Q2, Q3 are multicultural direct experiences, and Q4, Q5, Q6, Q7 are multicultural indirect experiences.

	Factor		Chronbach Alpha
	1	**2**	
Q1	.951	-.132	.753
Q2	.685	.065	
Q3	.485	.168	
Q6	-.032	.774	.770
Q5	-.056	.674	
Q4	.041	.654	
Q7	.125	.579	
Eigenvalues	3.170	1.261	
KMO(Kaiser-Meyer-Olkin)			.774
Bartlett' Test of Sphericity		Chi-Square	276.787
		df(p)	21(<.001

IV. CONCLUSION

As a result of this study, most of the nursing research dissertations and social science research dissertations so far conducted factor analysis using Principal Component Analysis(PCA) and orthogonal rotation Varimax method when analyzing factors by subclassifying variables. In future nursing research dissertations or social science research dissertations, when performing Factor Analysis(FA) of variables, it is suggested to use Common Factor Analysis(CFA), which is the correct method, and the Direct Oblimin method, which is oblique rotation. In nursing research dissertations, when statistical analysis is performed after questionnaire survey, Factor Analysis(FA) is applied to the dissertation as it is at the time of variable development, rather than a new Factor Analysis(FA).

As a prerequisite for applying the Common Factor Analysis(CFA), it is thought that it is necessary to increase the accuracy of the response rate by using the face-to-face person interview method when conducting a survey. As a method to increase the accuracy of the questionnaire response rate, it is necessary to construct a desirable questionnaire. Use easy and precise expressions. Do not use ambiguous expressions in questionnaires and answers. Ask one question at a time. Do not ask questions that elicit responses. Do not ask questions that cannot be answered. There should be no duplicate answers. Sensitive questions are circumscribed and placed at the end of the questionnaire. The structure of the questionnaire starts with something interesting or simple. Demographic sample information should be followed whenever possible[2]. Due to the COVID-19 situation and the difficulties of face-to-face person interview methods, Google Form or NAVER Form questionnaires are preferred. However, the electronic interview questionnaire has problems with low response rate and poor understanding of questions.

Finally, based on the results of this study, I would like to make the following suggestions. If you want to make a good house, you need to organize the basic blueprint well. Also, if you want to write a good quantitative dissertations, you should consider the scale and statistical method from the time of composing the questionnaire that is the basis of the dissertations. If you put your utmost sincerity when conducting a questionnaire survey, statistically good results can be obtained. As a follow-up study, a systematic literature review of papers on which Common Factor Analysis (CFA) was performed on nursing research dissertations and social science research dissertations is suggested.

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