심리학석사학위논문

A Comparison between Factor Structure and Semantic Representation of Personality Test Items Using Latent Semantic Analysis

잠재의미분석을 활용한 성격검사문항의 의미표상과 요인구조의 비교

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Abstract

In this thesis, semantic representation of personality test items is analyzed through LSA(Latent Semantic Analysis) and compared with factor structure to obtain implications for cognitive process of personality test item response.

Generally, a survey response process consists of four stages: comprehension, retrieval, judgement and response. Traditionally, in order to investigate construct validity of the survey the final response data have been evaluated through exploratory factor analysis. But problem may occur when analyzing factor structure using response data only because such approach can overlook inconsistency of stimulus and response. In order to solve this problem, we need to take a direct approach to semantic representation of personality test items using LSA.

In study 1, using passages generated in a limited context describing Big Five personality traits, a weighted document-term matrix is decomposed to produce semantic space. Furthermore, this thesis suggests 'semantic similarity matrix' based on semantic space to compare factor structure with semantic similarity. Using this matrix, study 2 and 3 shows resemblance between factor structure and semantic similarity of personality test items. The results shows stimulus-response consistency. Moreover, the result implies that construct validity of personality test can be evaluated with its semantic representation without analyzing response data. Also, factor

structure can be interpreted as semantic similarity of items.

Keywords : LSA, EFA, construct validity, Big Five, semantic similarity, representation

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Preface

Psychological tests are used in a variety of scenes. It can be used for a number of purposes including evaluating job candidates, diagnosing psychological problem, and exploring youth careers. Due to the popularity of psychological tests, most people would be familiar with personality tests.

When responding to psychological tests, a participant may soon recognize that meanings of some test items in the entire set is similar to each other. Sometimes the test asks exactly same questions repeatedly to screen fake responses. But more often such recognition occurs while responding to items that measure same personality trait. On the other hand, a researcher with experience of personality test development, would probably have seen same or similar terms and phrases appearing among the items measuring same trait.

Such meaning of test item that participant understood is its semantic representation constructed based on comprehending the words or sentence consists of test items. After the participant constructs the semantic representation, he then retrieves related memories and generates a response based on judgement of equivalence between the memories and its semantic representation(Tourangeau, Rips, & Rasinski, 2000). Semantic representation of personality test item is important not only because it acts as a cue for retrieving memory that is related to personality trait, but also because we can obtain implications for cognitive process of the survey respondent.

Thus, the semantic representation of a test item has a close relationship with trait itself and also with construct validity of the test. However, construct validity of personality test has traditionally been investigated through factor analysis using response data, not semantic representation. Factor analysis is used to analyze covariance of items responses in order to identify factor structure, leading to the conclusion that the test items are measuring a few latent common factors.

Meanwhile, Behaviorist approached psychology in terms of studying relationship between stimulus and response(Watson, 1913). From the behaviorist's point of view, the traditional approach using response data only in order to investigate construct validity is understood as overlooking the role of stimulus for the item. Concluding that the items are measuring some latent variable based on response data is reasoning inductively about stimulus.

Since the response-centered perspective is rather an indirect approach to investigation of construct validity, we also need a direct approach that analyzes semantic representation of test items. Because there are possibility of overlooking stimulus-response incompatibility—similar sematic representation among some items but dissimilar response to them, dissimilar semantic representation among other items but similar response to them—we have to avoid hasty generalizations and both sides of test items. Analyzing both semantic representation and response and comparing their results will provide us with richer implication about cognitive process of responding personality test item and helpful information about construct validity of the test.

Direct approach to analyze test items that commonly used in developing personality test is investigating content validity. This refers to the extent to which a measure represents all facets of a given construct(Pennington, 2003). The investigating process requires agreement of judgement among experts. Lawshe(1973) and Lynn(1986)'s methods calculate a degree of agreement arithmetically through Content Validity Ratio(CVR) Content Validity Index(CVI). Though not also these methods are rather somewhat subjective, but irrelevant to cognitive process of response.

To overcome these limitations and analyze semantic representation of personality test item directly, this thesis utilize Latent Semantic Analysis(Landauer & Dumais, 1997). LSA is an effective method for analyzing semantic representation of terms or documents using information obtained by co-occurrence of word among large amount of passages.

The purposes of the thesis are first, suggesting method that analyzes semantic representation of test items directly using LSA in order to investigate construct validity without response data; second, comparing traditional EFA result with LSA result to obtain implications for cognitive process of personality test item response.

Theoretical Background

General survey response process consists of four stages: comprehension, retrieval, judgement and response(Tourangeau, Rips, & Rasinski, 2000). Participant's response to personality test items is generated through the process. The typical method of investigating construct validity using the response data is Exploratory Factor Analysis(EFA). The most widely known personality trait structure, Big Five, is result of the method.

Meanwhile, semantic representation of personality test items is constructed based on comprehension of the item. Based on given text stimulus, text comprehension is constructing mental representation and formed mental representation is comprehended representation(이정모, 1988). In order to analyze the representation, Latent Semantic Analysis(Landauer & Dumais, 1997) that requires large amount of passages produced in context and applies dimension reduction technique is frequently used. In addition, LSA have been found capable of passage quality judgments, discourse comprehension, word/document classification. This thesis will analyze semantic representation of personality test items through LSA.

In this chapter, examination and comparison of two method are performed. First, LSA will be introduced and exemplified with exercise; second, EFA will be reviewed briefly.

Latent Semantic Analysis

LSA represents semantic representation of term or document by vector in multidimensional space through using information derived from co-occurence of word in large number of passages. The document refers to the sentence, paragraph, passages, corpus in which a word occurs. The term refers to a word.

LSA consists of three steps. the first step is constructing term-document matrix by counting all of the words occurred in each document. A word that has appearance frequency of 1 or less is removed from the matrix. Then local weight and global weight is applied to the matrix. Next step is performing Singular Value Decomposition. The weighted matrix is decomposed by SVD algorithm. During the decomposition, SVD finds new axes and selects a few that explain data pattern more appropriately. The result reveals higher-order correlation—semantic similarity—between word or documents. The constructed n-dimensional space is called *semantic space*. In the space, semantic representation of a term or a document is expressed by a vector. Cosine similarity can be calculated between two vectors measuring *semantic similarity*. Judging semantic similarity is the third step of the analysis.

To clarify each steps, small example documents of Landauer & Dumais(1997) will be used to demonstrate the technique. Example uses the titles of nine text passages, five about human computer interaction, and four about mathematical graph theory, each group's topics are rather unrelated.

c1: Human machine interface for ABC computer applications

c2: A survey of user opinion of computer system response time

c3: The EPS user interface management system

c4: System and human system engineering testing of EPS

c5: Relation of user perceived response time to error measurement

m1: The generation of random, binary, ordered trees

m2: The intersection graph of paths in trees

m3: Graph minors IV: Widths of trees and well-quasi-ordering

m4: Graph minors: A survey

To begin with, count all of the word appeared in each document and construct corresponding term-document matrix W. Row of W represents term and column of W represents documents. Cell entries W_{ij} of W is frequency of appearance of the word i in the document j.

W =

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

Next, apply appropriate weights on W. There are two kinds of weighting methods; local and global weighting. Local weighting method is applying same weighting to all entries while global weighting is applying different weighting to each rows. The weighted matrix is called X. In example, the matrix weighting is omitted for convenience.

$$X = UDV'$$

In second step, weighted matrix X is decomposed by SVD algorithm. X will be decomposed by three matrices U, D, V. If X is $m \times n$ matrix, U will be $m \times m$ orthogonal matrix, each row of U will be orthonormal eigenvectors of XX'. D is $m \times n$ diagonal matrix that its diagonal entries be eigenvalues of X. Similarly, V is $n \times n$ orthogonal matrix that its columns are orthonormal eigenvectors of $X'X$(Strang, 1976). The decomposed result is as follows.

U =

−0.22	0.11	0.29	−0.41	0.11	0.34	−0.52	0.06	−0.41
−0.2	0.07	0.14	−0.55	−0.28	−0.5	0.07	0.01	−0.11
−0.24	−0.04	−0.16	−0.59	0.11	0.25	0.3	−0.06	0.49
−0.4	−0.06	−0.34	0.1	−0.33	−0.38	0	0	0.01
−0.64	0.17	0.36	0.33	0.16	0.21	0.17	−0.03	0.27
−0.27	−0.11	−0.43	0.07	−0.08	0.17	−0.28	0.02	−0.05
−0.27	−0.11	−0.43	0.07	−0.08	0.17	−0.28	0.02	−0.05
−0.3	0.14	0.33	0.19	−0.11	−0.27	−0.03	0.02	−0.17
−0.21	−0.27	−0.18	−0.03	0.54	−0.08	0.47	0.04	−0.58
−0.01	−0.49	0.23	0.02	−0.59	0.39	0.29	−0.25	−0.23
−0.04	−0.62	0.22	0	0.07	−0.11	−0.16	0.68	0.23
−0.03	−0.45	0.14	−0.01	0.3	−0.28	−0.34	−0.68	0.18

D =

3.34	0	0	0	0	0	0	0	0
0	2.54	0	0	0	0	0	0	0
0	0	2.35	0	0	0	0	0	0
0	0	0	1.64	0	0	0	0	0
0	0	0	0	1.5	0	0	0	0
0	0	0	0	0	1.31	0	0	0
0	0	0	0	0	0	0.85	0	0
0	0	0	0	0	0	0	0.56	0
0	0	0	0	0	0	0	0	0.36

V =

−0.2	0.06	0.11	−0.95	−0.05	0.08	−0.18	0.01	−0.06
−0.61	−0.17	−0.5	−0.03	0.21	0.26	0.43	−0.05	0.24
−0.46	0.13	0.21	0.04	−0.38	−0.72	0.24	−0.01	0.02
−0.54	0.23	0.57	0.27	0.21	0.37	−0.26	0.02	−0.08
−0.28	−0.11	−0.51	0.15	−0.33	−0.03	−0.67	0.06	−0.26
0	−0.19	0.1	0.02	−0.39	0.3	0.34	−0.45	−0.62
−0.01	−0.44	0.19	0.02	−0.35	0.21	0.15	0.76	0.02
−0.02	−0.62	0.25	0.01	−0.15	0	−0.25	−0.45	0.52
−0.08	−0.53	0.08	−0.02	0.6	−0.36	−0.04	0.07	−0.45

If rank of X is r, the first r rows of U spans column space of X. Each column of X represents documents, the first r rows of U are orthonormal basis of semantic space and each column of DV' is coordinate of each document vectors. Meanwhile, the first r columns of V spans row space of X. Each row of X represents terms, the first r columns of V are orthonormal basis of semantic space and each row of UD is coordinate of each term vectors. After the weighted matrix X is decomposed, the number of dimension to reduce the original space needs to be decided. In view of matrix linear algebra, it can be inferred that the LSA model uses the projection technique on a reduced space.

The last step is comparison of semantic representations between two terms or documents in reduced semantic space. The similarity measure is cosine similarity. The comparison of semantic similarity is performed between two terms or two documents. But, comparing term with document is impossible.

In first case, Comparing semantic representation between documents through cosine similarity(hearinafter referred to as similarity) is shown. Assuming two dimensional semantic space, select first two rows of U. Coordinate of document vectors are columns of matrix C derived from DV' and their similarity is presented as C_s.

C =

c1	c2	c3	c4	c5	m1	m2	m3	m4
-0.66	-2.02	-1.55	-1.81	-0.93	-0.01	-0.05	-0.08	-0.27
0.14	-0.42	0.32	0.59	-0.27	-0.49	-1.11	-1.56	-1.35

C_s =

	c1	c2	c3	c4	c5	m1	m2	m3	m4
c1	1	0.91	1	0.99	0.88	-0.19	-0.17	-0.16	-0.01
c2	0.91	1	0.92	0.87	1	0.23	0.25	0.25	0.39
c3	1	0.92	1	0.99	0.88	-0.18	-0.16	-0.15	-0.01
c4	0.99	0.87	0.99	1	0.83	-0.28	-0.27	-0.26	-0.11
c5	0.88	1	0.88	0.83	1	0.3	0.32	0.33	0.46
m1	-0.19	0.23	-0.18	-0.28	0.3	1	1	1	0.98
m2	-0.17	0.25	-0.16	-0.27	0.32	1	1	1	0.99
m3	-0.16	0.25	-0.15	-0.26	0.33	1	1	1	0.99
m4	-0.01	0.39	-0.01	-0.11	0.46	0.98	0.99	0.99	1

Since LSA does not contain classification algorithm of document or term by similarity measure(이태헌, 2003), classifier is required. The documents are classified through k-means clustering algorithm. The number of cluster is designated as two and results are shown in Table 1. The result implies that successful classification of documents by topics.

Table 1.

Semantic representation of exemplary documents classification results

Doc.	c1	c2	c3	c4	c5	m1	m2	m3	m4
Class	1	1	1	1	1	2	2	2	2

The case shown beneath is comparing semantic representation between terms by similarity. Assuming two dimensional semantic space, select first two columns of V. Coordinate of term vectors are rows of matrix W derived from UD and their similarity is presented as W_s.

W =

human	−0.74	0.29
interface	−0.66	0.18
computer	−0.8	−0.11
user	−1.35	−0.15
system	−2.15	0.43
response	−0.89	−0.27
time	−0.89	−0.27
EPS	−1.01	0.36
survey	−0.69	−0.7
trees	−0.04	−1.25
graph	−0.12	−1.58
minors	−0.11	−1.15

$W_s =$

	human	*interface*	*computer*	*user*	*system*	*response*	*time*	*EPS*	*survey*	*trees*	*graph*	*minors*
human	1	0.99	0.87	0.89	0.98	0.78	0.78	1	0.4	-0.33	-0.29	-0.28
interface	0.99	1	0.92	0.93	1	0.84	0.84	1	0.49	-0.23	-0.19	-0.18
computer	0.87	0.92	1	1	0.95	0.99	0.99	0.89	0.79	0.17	0.21	0.23
user	0.89	0.93	1	1	0.95	0.98	0.98	0.9	0.78	0.14	0.18	0.2
system	0.98	1	0.95	0.95	1	0.88	0.88	0.99	0.55	-0.16	-0.12	-0.1
response	0.78	0.84	0.99	0.98	0.88	1	1	0.8	0.88	0.33	0.37	0.38
time	0.78	0.84	0.99	0.98	0.88	1	1	0.8	0.88	0.33	0.37	0.38
EPS	1	1	0.89	0.9	0.99	0.8	0.8	1	0.42	-0.3	-0.26	-0.25
survey	0.4	0.49	0.79	0.78	0.55	0.88	0.88	0.42	1	0.73	0.76	0.77
trees	-0.33	-0.23	0.17	0.14	-0.16	0.33	0.33	-0.3	0.73	1	1	1
graph	-0.29	-0.19	0.21	0.18	-0.12	0.37	0.37	-0.26	0.76	1	1	1
minors	-0.28	-0.18	0.23	0.2	-0.1	0.38	0.38	-0.25	0.77	1	1	1

Also, similarity among semantic representations vectors can be derived by adopting same method. Using k-meams clustering algorithm, the number of cluster is designated as two and results are shown in Table 2. The result implies that successful classification of terms by topics.

Table 2.

Semantic representation of exemplary terms classification results

term	*human*	*interface*	*computer*	*user*	*system*	*response*	*time*	*EPS*	*survey*	*trees*	*graph*	*minors*
class	1	1	1	1	1	1	1	1	1	2	2	2

LSA provided a framework to compare semantic representation of terms or documents through representing them by vector expression in the semantic space. To examine its performance, Landauer & Dumais(1997) analyzed 30,473 encyclopedia articles containing 4.6 million words. Using semantic space based on these articles, the model tried to solve synonym portion of TOEFL provided by ETS. Each synonym item consists of a stem word and four alternative words. Test takers were asked to choose the one with the most similar meaning to the stem. The model chose the alternative word that has the largest cosine value with the stem. The model's output, percentage of correct answers, was similar to that of applicants. This implies LSA can construct semantic space similar to that of human when appropriate number of dimension is determined.

In addition, LSA demonstrated high performance in judging document similarity and selecting appropriate synonym task. Correlation between two readers who grades passages of TOFEL applicants was .77 and correlations between LSA model and each readers were .68, .77. Moreover, correlation between LSA model and average applicant's ETS score was .77. the result was evidence that LSA performance is similar to or better than that of ETS readers(Landauer et al., 1996).

In conclusion, LSA is capable of semantic space organization and its efficiency is similar to that of human. Also, LSA can calculate similarity between any two documents or two term that exists in the space.

Exploratory Factor Analysis

The typical method of analyzing participant response for the personality test items in order to investigate construct validity is exploratory factor analysis(EFA). In this thesis, EFA is considered to be equivalent to common factor analysis(Tucker & MacCallum, 1997). The common factor model is shown as follows:

$$\Sigma_{zz} = B\Phi B' + U^2$$

The equation shows fundamental expression of the common factor analysis model. The variance and covariance of the item responses are given in Σ_{zz}, critical parameters of the model contained in factor loading matrix B, the matrix of common factor correlations Φ, the diagonal matrix of unique variance U^2. In other words, Σ_{zz} can be viewed as arising from two sources: the common factors, and the unique factors. Especially, common variance is main concern of EFA and factor loading matrix B plays main role that investigating factor structure and interpreting common factors.

EFA is traditionally used to measure latent variables. It has solid philosophical foundations. EFA model has developed based on the idea of the Greek atomists that appearance is to be explained by something unobserved, and Descartes‘s idea of the analysis and synthesis, idea of correlational exploratory statistics developed by empiricist and Karl Pearson(Mulaik, 1987).

This technique has been used most frequently to measure personality traits. Thurstone undertook pioneering role in the development of methods. He gave 1,300 raters sixty adjectives that are in common use for describing a person and found that five factors are sufficient to abstract data by means of multiple factor methods(Thurston, 1934).

Even before Thurston, Galton(1884) was interested in personality trait measurement. He wrote: 'one thousand words expressing personality shares a large part of theirs meaning with some of the rest'. Catell(1943) developed a set of 35 bipolar clusters of related terms and repeatedly claimed to have found dozen oblique factors, but only orthogonal five factors proved to be replicable(e.g., Digman & Takemoto-Chock, 1981; Fiske, 1949; Norman, 1963; Tupes & Christal, 1961, Goldberg, 1990). Finally, Goldberg(1990) covered previous studies and demonstrated 1,710 adjectives which describe a person are classified into five factors using EFA. He then named the factors Big Five. These factors showed cross-cultural coherence(Min, 2002). Also, widely used personality test NEO-PI-R, NEO-FFI is based on the Big Five.

In short, based on response for test items EFA was used to explore personality traits and develop personality test. In addition, traditionally, those response was the key for the analysis.

Comparison between two Analysis Method

Both methods effectively summarize the data through dimension reduction. LSA reveals the semantic similarity between words or documents through decomposing weighted term-document matrix, EFA reveals factor structure of the test through decomposing covariance matrix of the item responses.

LSA reduces a high-dimensional dataset into lower dimensions while retaining important information. It is akin to that of Principal Component Analysis. Both methods are closely related to SVD. Similar to PCA, LSA handles raw data while PCA uses covariance matrix.

Meanwhile, EFA analyzes covariance matrix. The covariance matrix is divided into common variance and unique variance which is absent from PCA. In EFA, Common variance is decomposed into factor loading matrix and factor correlation matrix. Then axis rotation process is applied to factor loading matrix in order to enhance interpretability of factors. EFA focuses on interpreting common factors, the axes of space, through rotated factor loading matrix. The matrix clearly shows the relationship between common factors and test items. Unlike EFA, LSA is concerned with judging semantic similarity among terms or document, not axes of semantic space. The axes is orthogonal, selected in order of accountability.

Focal point of the two methods may be different, but two analysis method can be related through cognitive process of test items. There is no studies of comparing semantic representation and factor structure of personality test items. Therefore, this thesis explores the way how to take advantage of LSA to investigate construct validity and attempts to obtain implications about the cognitive process.

Research Questions

To compare similarity of semantic representation among test items, semantic space must be constructed beforehand. There are related two issues: first, to creat appropriate space, what passages are needed? second, what is the appropriate number of dimensions for the space? The space will be created after discussing these issues.

Based on the space created, we need the way to compare the traditional EFA methods with semantic similarity among the items. For this, this thesis suggests *semantic similarity matrix* which can be compared to factor loading matrix representing factor structure. The result will give us some implication for the cognitive process.

Furthermore, we need to test two hypothesis: first, it is hypothesized that the semantic representations between test items measuring the same construct will be similar to each other than those of the rest; second, it is predicted that items of which semantic representations similar to each other will measure same construct. Considering responses to some of items measuring same common factor will correlated to each other, we can examine consistency of stimulus and response for personality test through these hypothesis testing.

The issues related to construct semantic space will be discussed in the next chapter in detail and the space will be created in Study 1. Study 2 and 3 will test two hypothesis based on the space.

A Framework for Comparison between Factor Structure and Semantic Representation

In this chapter, the passages required to creat semantic space and the number of dimensions for the space will be discussed. Moreover, the constructed space will be discussed in relation to existing methods.

What passages are needed to creat semantic space? To answer this question, the assumption of LSA needs to be considered. That is, a term is represented as a single vector in semantic space that documents are the axes. But, commonly used vocabularies are polysemy. The meaning of polysemy depends on the context and extended by contexts, but an LSA algorithm is not able to distinguish its meanings. Not only is the polysemy represented as a vector but even a homograph is expressed as a vector. Since the meanings of a homograph are completely different by context(Lim, 1992), the vector representing those terms must vary according to meaning. For example, The Oxford English Dictionary Online categorized the meaning of the homograph 'fine' into 6 quite disjoint meanings. If the meaning of 'fine' remains undistinguished, the vector representing 'fine' will reflect all of its meanings so that it is uninterpretable. If the dictionary is used as passages this problem will occur.

Actually, ill-fitted semantic space had been constructed when dictionary documents were used as passages. The National Institute of the Korean Language announced the 'List of Korean vocabulary for learning' consists of 5,780 words, the words are used to extract documents from The Standard Korean Dictionary in order to creat semantic space. However, the semantic similarity between vectors in the created space was rather unacceptable. For instance, similarity between '예민' and '과민' was 0.516. Nevertheless, similarity calculated between '예민하다' and '과민', 0.047, meant the two terms were completely irrelevant.

To tackle the problem, Lee(2003) generated a distinctive vector forr each meaning of an homograph which was impossible to disambiguate in an LSA model. The model succeeded in disambiguating contextual meaning of a homograph. But generating a vector per each meaning was not applicable to this study because of the difficulty in finding all of the homographs that occurred and identifying each meaning of them in the whole passages collected.

The alternative way to solve the problem is by restricting the context of the passage produced by participant. Since the meaning of homographs depends on the context, limiting it to a particular topic would make homographs used only with a specific single meaning. Then, what topic should be presented to the subjects in order to restrict the context? Prior to answering the question, we need to consider the particular context in which respondents comprehends personality test items.

Most of personality test item look as follows:

I am ________ person.

Usually, an adjective describing a person is inserted to the blank. In some cases, only an adjective is given to the respondent. This common type of personality test item asks respondents to judge their degree of agreement with those statements, and someone, usually himself/herself. In short, the context that respondents comprehends personality test items is judging someone's particular personality trait. Therefore, we should limit the topics that should be presented to the subjects the respondent is judging within specific personality trait.

Meanwhile, another issue related to creating semantic space is determining the right number of dimensions for the space. A criterion is needed to determine the number of dimensions. One of the decision criterion is classification accuracy of the passages by topics. Desirable semantic space is classifying passages by intended topics. That is, it captures similarity among the semantic representation of documents accurately. If the topics are rather disjoint, the difference among semantic representations of passages will be clear so that a few dimensions are sufficient to achieve high accuracy, and it is possible to construct a reliable semantic space.

It is possible to creat the semantic space if the passages are collected in limited a context and its number of dimension is appropriate. After that, how can a semantic representation of test items be compared with their factor structure? The factor loading is of great importance in EFA to investigate the factor structure.

Table 3.

Example of factor loading matrix(PANAS(David & Lee, 1988))

	Factor 1 (Positive Affect)	Factor 2 (Negative Affect)
Enthusiastic	**0.750**	−0.120
Interested	**0.730**	−0.070
Determined	**0.700**	−0.010
Excited	**0.680**	0.000
Inspired	**0.670**	−0.020
Alert	**0.630**	−0.100
Active	**0.610**	−0.070
Strong	**0.600**	−0.150
Proud	**0.570**	−0.100
Attentive	**0.520**	−0.050
Scared	0.010	**0.740**
Afraid	0.010	**0.700**
Upset	−0.120	**0.670**
Distressed	−0.160	**0.670**
Jittery	0.000	**0.600**
Nervous	−0.040	**0.600**
Ashamed	−0.120	**0.590**
Guilty	−0.060	**0.550**
Irritable	−0.140	**0.550**
Hostile	−0.070	**0.520**

The element of the matrix is interpreted as a correlation between factor and test item. In other words it is similarity between factor and item vector. Identifying that items are measuring a few latent factors through factor structure which is analyzed by EFA using response data means the responses also may be explained in the same manner.

For example, Table 3 is a factor loading matrix of PANAS(David & Lee, 1988). The first 10 items are highly correlated with the Factor 1 which may be interpreted as positive affect and show low correlation with Factor 2 which may be interpreted as negative affect. The results of the remaining 10 items showed the opposite. That is, responses for items measuring the positive affect factor are correlated with each other, and responses for the rest of 10 items are correlated with each other. In this way, this thesis will analyze the response data through factor structure deduced from EFA factor loading matrix.

On the other hand, LSA is able to construct a matrix which is similar to the factor loading matrix. This thesis named the matrix a *semantic similarity matrix*.

Table 4.

Example of sematic similarity matrix

	Positive Affect	Negative Affect
Enthusiastic	0.566	0.564
Interested	0.565	0.563
Determined	0.910	0.905
Excited	0.345	0.357
Inspired	0.570	0.574
Alert	0.763	0.760
Active	0.378	0.379
Strong	0.566	0.570
Proud	0.910	0.916
Attentive	0.440	0.433
Scared	0.982	0.978
Afraid	0.787	0.788
Upset	0.849	0.845
Distressed	0.524	0.521
Jittery	0.826	0.823
Nervous	0.873	0.870
Ashamed	0.422	0.420
Guilty	0.984	0.986
Irritable	0.075	0.076
Hostile	0.012	0.014

Taking advantage of created semantic space, a matrix that has an identical size to the factor loading matrix can be composed. The rows and columns of semantic similarity matrix are a semantic representation of test items and factors, respectively. The cell entries of the matrix are (cosine) similarity between items and factors. An example is presented in Table 4. The matrix can be conveniently compared with a factor loading matrix. The semantic relation between items and factors is interpreted, along the same lines as factor loading matrix.

Although the factor structure is viewed as a hierarchical relationship between factors and items, each of the cell entries of a factor loading matrix is a correlation coefficient. Also, the elements of semantic similarity matrix is cosine between factors and items. That is, the element of both matrices are similarity measures between factor and item.

Based on the discussion in this chapter, the semantic space will be created and the factor structure and semantic representation of the personality test will be compared in the next chapter.

Study 1

In this study, the sematic space was created through passages produced in limited context. Also, the appropriate number of dimension of the space was investigated.

The context of passages was limited to judging someone's personality trait, and the Big Five trait was presented to subjects. Not only has the Big Five trait structure been demonstrated many times through EFA, but it covers most of the terms describing characteristics of a person. Because of this reason, it is reasonable to exploit the Big Five personality traits for comparison.

Method

Particiapant

154 undergraduates at Seoul National University voluntarily participated in exchange for 1 course credit. The participants who were capable of passage writing in Korean were recruited from psychology classes through SNU R-point system. Informed consent was obtained from all participants. All were assigned to the same experimental tasks.

Materials

Given Big Five trait names and their description are as follows:

성실하다 맡은 일을 책임감 있게 완수하고, 계획을 철저히 세운다.
개방적이다 다양한 경험을 하는 것을 좋아하고, 변화와 도전을 즐긴다.
친화적이다 다른 사람의 입장을 존중하고 공감하며 배려한다.
정서적으로 안정적이다 걱정이 없고 태평하며 낙천적이다.
활동적이다 매사에 열정적이고 최선을 다하며, 적극적이다.

Among the five trait names, '외향성' and '신경증' were replaced by commonly used terms, '활동적이다' and '정서적으로 안정적이다', respectively. Participants may produce passages based on psychological knowledge taught in the classes, if not replaced. In order to describe each trait briefly, those of BFI-K, NEO-PI-R, NEO-FFI were used for reference.

Procedures

Given descriptions of traits, participants were asked to write short passages according to the instruction: 'if someone has the trait, describe the characteristic of him/her in detail'. They were required to write more than 500 characters for each trait. It took on average 20 minutes to complete the passages. Since the experiment was carried out online, the passages were recorded at Qualtrics.com.

Analysis

For the data analysis, the data of 9 participants with unreliable passages(repetition of same sentence, insufficiency of quantity, usage of excessive whitespaces) and that of 1 participant who did not follow instructions were excluded. Finally, excluding 1 passage because of error occurred while recording, 144 participant produced 719 passages that were included in the analysis.

The preprocessing was carried out. The process consisted of performing morphological analysis and correcting misspelling of words. It was necessary that the LSA model recognized the semantically same word differently because of morphologic transformation and typos. All of the words appeared in passages were transformed to its origin form through morphological analysis.

Morphological analysis used Korean morphological analyzer(Kang, 2002). 5,780 of fundamental Korean vocabulary were added to user-defined dictionary before the analysis began. Through the analysis, the origin forms of noun, complex noun, adjective and adverb were extracted. In the rest of the process, modules of Python 3.3 were used including regular expression(re). Then, the preprocessed passages were mainly analyzed through R 3.0.2 with lsa package(Fridolin, 2014). The package constructed document-term matrix and applied appropriate weights to the matrix. The local weight w_l applied is shown as follows:

$$w_l = \log(x_{ij} + 1)$$

x_{ij} stands for the appearance frequency of term i in document j. After adding the frequency to 1, log was taken to the sum. This approximates the standard empirical growth functions of simple learning(Laudauer & Dumais, 1997). Also, the global weight w_g applied was shown below:

$$w_g = -\sum_j p_{ij} \log p_{ij} / \log c, \;\; p_{ij} = x_{ij} / \sum_j x_{ij}$$

c stands for the number of documents, $\log c$ means normalizing constant. Global weighting that applied to the matrix was a reciprocal of entropy divided by log of number of documents. The inverse entropy measure estimated the degree to which observing the occurrence of a component specifies what context it is in. In other words, the higher weight was given to words that appeared only in a particular context, and the lower weight was applied to words that appeared evenly in contexts. Since the weighting was performed as such, for instance, importance of pronouns that appeared in most of the context were decreased. These weighting methods showed better performance than other weighting methods(Nakov et al., 2001).

The weighted term-document matrix was decomposed by SVD in order to creat semantic space. Then, the classification accuracy of passages were calculated by dimensions. K-means clustering algorithm was used to classify the passages by similarity.

Result and Discussion

The size of term-document matrix constructed was 2678 × 718. The classification accuracy of passages were calculated through 1~718 dimensional semantic space in order to find the appropriate number of dimension of the space. The results were shown by Figure 1.

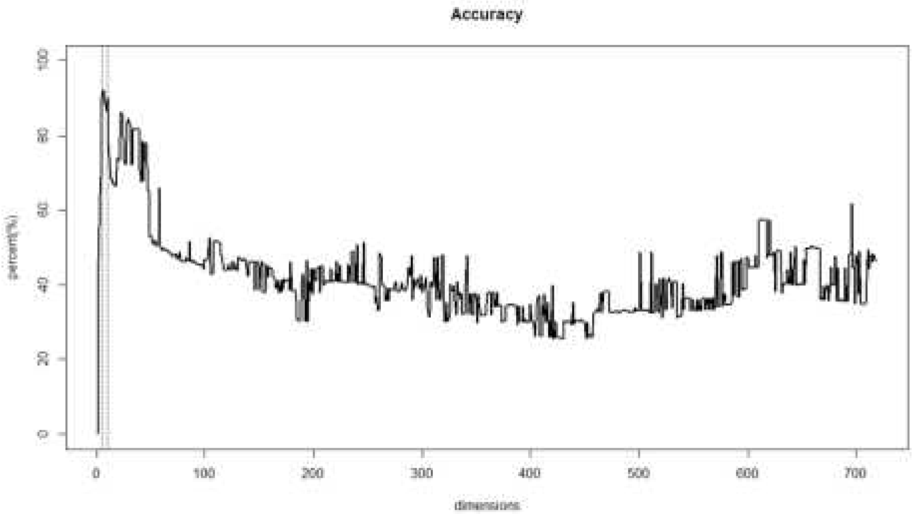

Figure 1. Passage classification accuracy by 1~719 dimensions.

The highest accuracy were shown when the dimension of the space were rather low. The accuracy were on average 90% in 5~10 dimensions. It is sufficient to conclude that the space was reliable. Since there was no big difference of performance in 5~10 dimensions, the number of dimension of the space were determined to 5. The

Figure 3 shows the classification result of passages in 5-dimensional semantic space.

Through these result, It was concluded that the difference in content between each Big Five trait descriptions were captured very well in 5-dimensional semantic space. However, the orthogonal axes of the space were uninterpretable as the Big Five traits because they were merely derived in order of variance of data explained.

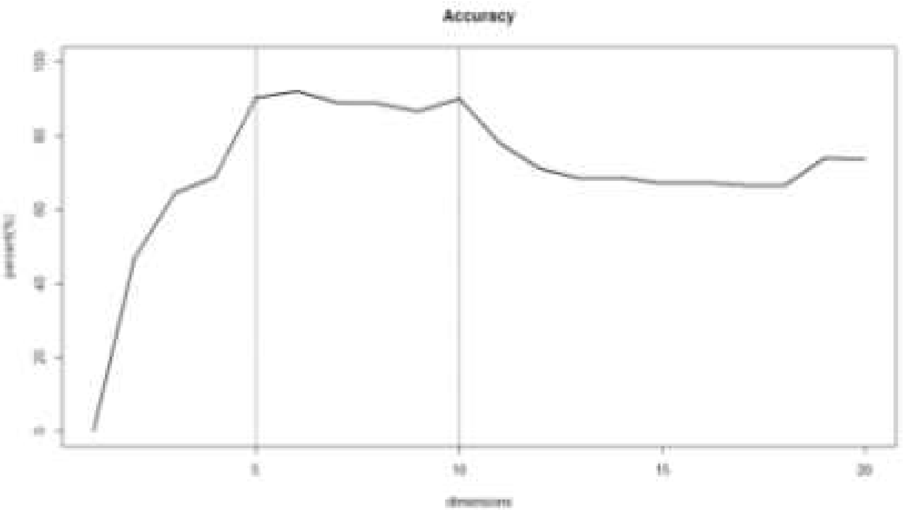

Figure 2. Passage classification accuracy by 1~20 dimensions.

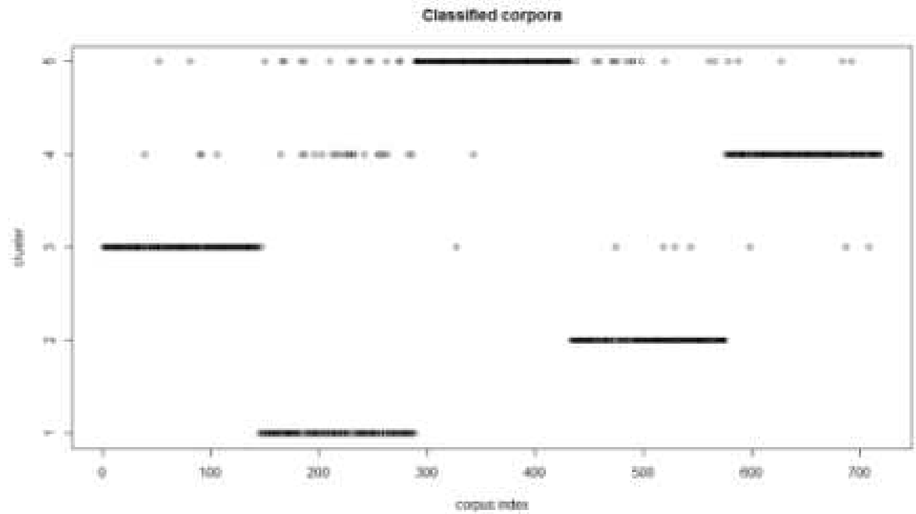

Figure 3. k-means clustering result of passages by 5 dimensions.

Study 2

Based on the 5-dimensional semantic space constructed in Study 1, the sematic similarity between items which are measuring the same trait are shown in Study 2. Through drawing comparison between factor loading matrix and semantic similarity matrix, the first hypothesis was tested: the semantic representations between test items measuring the same construct will be more similar to each other than those of the rest.

Method

Materials

The factor loading matrix and items of brief Korean Big Five Inventory(김지현 외, 2011) were used for comparison. The inventory was composed of 15 items, three items per Big Five traits.
The EFA result of inventory showed that the five factor model is appropriate since reported model fit indices of the model were GFI=.946, CFI=.916, RMSEA=.064. The dataset included 750 participants. The first column of Table 5 shows the items of inventory.

Table 5.

Brief Korean Big Five Inventory(BFI) items and extracted terms from items

Test Items	Extracted Term
1. *창의*적인	창의
2. *독창적*이며 새로운 생각을 잘 떠올리는	독창적
3. 활발한 *상상력*을 가진	상상력
4. 일을 *완벽*하게 하는	완벽히
5. 일을 능률적으로 하는	효율적
6. *믿을만*하게 일을 하는	믿음직
7. 쉽게 *침울*해 지는	침울
8. *우울*한	우울하다
9. *걱정*을 많이 하는	걱정
10. *조용한*	조용하다
11. *수다*스러운	수다
12. *외향적*이며 사교적인	외향적
13. 사려깊고 거의 모든 사람에게 *친절*한	친절하다
14. 다른 사람을 잘 *도와주며* 이타적인	도와주다
15. *용서*를 잘 하는	용서하다

In the semantic space, comparison between words or that of documents is possible while word-document comparison is not possible. For this reason, since the Big Five trait names were words, extracting key words from each items was required. As a result, The extracted term is presented in the second column of Table 5. In the case of item 5, the term ‘능률적’ did not exist in the space, so the term was substituted with the term ‘효율적’ that had similar meanings and existed in the space. By using extracted terms, comparison of semantic similarity between traits and items was performed through the space.

Also, The factor names used to the comparison were ‘성실성’, ‘개방성’, ‘외향성’, ‘친화성’, and ‘정서적 안정성’. For the comparison, the vector names were selected in the space using those words, showed in Table 6.

Table 6.
Personality traits names of brief Korean Big Five Inventory(BFI) and names of corresponding term vector in semantic space.

Names of Personality Traits	Names of Term vectors
성실성	‘성실하다’, ‘성실’
개방성	‘개방, ’개방적‘, ’개방적이다‘
외향성	‘외향적’
친화성	‘친화’, ‘친화력’
정서적 안정성	‘정서’+‘안정’

Each of the vector representing factor names was composed of sum of 1~3 term vectors. The cosine similarity between those vectors were approximately 1. However, the vector of ‘정서적 안정성’ was constructed by different method. The frequency that successive appearance of ‘정서’ and ‘안정’ was counted in each document and weighted in the same manner. Subsequently, The coordinate of weighted vector was calculated using five axes.

Analysis

The semantic similarity matrix of brief Korean BFI was constructed. And then, correlation between the matrix and the factor loading matrix was calculated. Composing matrix and calculating correlation coefficients performed through R. 3.0.2.

Result and Discussion

Table 7 is a factor loading matrix of brief Korean BFI. The matrix was derived by common factor analysis, using MLE. Table 8 is a semantic similarity matrix of the inventory and Table 9 shows correlation between factor loadings and semantic similarity.

Table 7.

Factor loading matrix of brief Korean Big Five Inventory(BFI)

	Traits				
BFI Items	개방성	성실성	외향성	친화성	정서적 안정성
1. 창의	**0.87**	0.29	0.25	0.31	−0.16
2. 독창적	**0.79**	0.23	0.27	0.26	−0.10
3. 상상력	**0.68**	0.15	0.35	0.27	−0.02
4. 완벽히	0.14	**0.71**	−0.10	0.18	−0.10
5. 효율적	0.31	**0.70**	−0.05	0.35	−0.19
6. 믿음직	0.24	**0.66**	−0.07	0.25	−0.13
7. 침울	−0.08	−0.12	−0.16	−0.10	**0.79**
8. 우울하다	−0.15	−0.15	−0.21	−0.16	**0.74**
9. 걱정	−0.04	−0.08	−0.02	0.04	**0.53**
10. 조용하다	0.20	−0.19	**0.73**	0.04	−0.20
11. 수다	0.26	−0.17	**0.71**	0.09	0.03
12. 외향적	0.34	0.21	**0.55**	0.29	−0.24
13. 친절하다	0.16	0.34	0.03	**0.68**	−0.04
14. 도와주다	0.27	0.34	0.08	**0.55**	−0.05
15. 용서하다	0.21	0.02	0.16	**0.48**	−0.06

Table 8.

Semantic Similarity matrix of brief Korean Big Five Inventory(BFI)

Extracted terms from items	Traits				
	개방성	성실성	외향성	친화성	정서적 안정성
1. 창의	**0.995**	−0.014	0.357	0.096	0.014
2. 독창적	**0.974**	0.014	0.404	0.035	0.120
3. 상상력	**0.796**	−0.033	0.690	−0.002	0.101
4. 완벽히	0.081	**0.965**	−0.119	−0.189	0.099
5. 효율적	−0.093	**0.897**	0.297	0.114	0.264
6. 믿음직	−0.040	**0.981**	−0.155	−0.117	0.042
7. 침울	−0.041	0.067	0.376	0.449	**0.876**
8. 우울하다	−0.067	0.027	0.372	0.094	**0.924**
9. 걱정	0.042	0.081	0.148	0.035	**0.987**
10. 조용하다	0.146	0.299	**0.915**	0.541	0.269
11. 수다	0.067	−0.026	**0.875**	0.032	0.068
12. 외향적	0.272	0.016	**1.000**	0.475	0.045
13. 친절하다	0.102	0.127	0.352	**0.976**	0.108
14. 도와주다	0.099	0.466	0.468	**0.865**	0.168
15. 용서하다	−0.030	0.154	0.126	**0.776**	0.540

Table 9.

Correlation between sematic similarity and factor loadings of brief Korean Big Five Inventory(BFI)

	Semantic Similarity				
Factor Loadings	개방성	성실성	외향성	친화성	정서적안정성
개방성	**0.90**	−0.18	0.21	−0.19	−0.70
성실성	0.03	**0.78**	−0.54	−0.21	−0.55
외향성	0.35	−0.40	**0.81**	0.10	−0.48
친화성	0.15	0.16	−0.11	**0.54**	−0.57
정서적안정성	−0.33	−0.33	−0.15	−0.08	**0.89**

The pattern of coefficient in Table 8 was similar to that of factor loading matrix, Table 7. Correlation between sematic similarity and factor loadings of brief Korean Big Five Inventory(BFI), Table 9, showed consistency of them.

‘상상력’ and ‘조용하다’ showed similarity with two factor names. In addition, the items related to ‘친화성’ factors showed similarity with relevant factors lower than other items. One of the reasons for lower similarity was that a lot of the passages contained the content that a person who is agreeable will also be extroverted and emotionally stable. However, The extracted 15 key words were highly similar to relevant factor names generally.

In addition, sematic similarity of the inventory were in accord with their factor structure since the diagonal entries of Table 9 showed high correlation of 0.784 on average. Table 9 brought to a conclusion that the semantic representations between test items measuring the same trait is more similar to each other than those of the rest.

Study 3

The study 3 investigates the hypothesis: it is predicted that items of which semantic representations similar to each other will measure same construct, which is the converse of the hypothesis tested in Study 2. After choosing the terms which semantic representations are similar to the Big Five trait names, the response for the terms was collected. Using the response data, Exploratory Factor Analysis was performed and the results of that were compared with the semantic similarity matrix.

Method

Participant

154 undergraduates at Seoul National University voluntarily participated in exchange for 1 course credit. They were the same participants involved in the previous study. Informed consent was obtained from all participants. All were assigned to the same experimental tasks.

Materials

3 terms for each trait were selected by similarity. The terms were highly similar with relevant trait names that were selected in Study 2 and rather dissimilar with irrelevant traits. 5 terms were

additionally included for extra analysis. All of the 20 terms existed in semantic space created in Study 1. The terms are presented below in Table 10.

Table 10.

Selected terms by personality traits

Traits	Terms
정서적 안정성	예민
	긴장, 긴장하다
	스트레스
성실성	부지런하다, 부지런
	책임감
	약속
외향성	활력
	나서다
	적극적
친화성	배려, 배려하다
	공감, 공감하다
	도와주다, 돕다
개방성	관대
	진취적
	배우다, 배우기
기타	어울리다
	신중, 신중하다
	내성적
	솔선수범
	즐거운

Since some of the terms were not adjectives describing personality, test items were developed based on the terms. The items were shown in Table 11.

Table 11.

Developed items using selected terms by traits

Terms	Developed Items
예민	예민한
긴장, 긴장하다	긴장을 잘 하는
스트레스	스트레스를 잘 이겨내는
부지런하다, 부지런	부지런한
책임감	책임감 있는
약속	약속을 꼭 지키는
활력	활력있는
나서다	나서는 것을 좋아하는
적극적	적극적인
배려, 배려하다	배려하는
공감, 공감하다	공감능력이 뛰어난
도와주다, 돕다	남을 돕는 것을 즐기는
관대	관대한
진취적	진취적인
배우다, 배우기	배우는 것을 좋아하는
어울리다	친구와 어울리는 것을 좋아하는
신중, 신중하다	신중한
내성적	내성적인
솔선수범	솔선수범하는
즐거운	즐거운

Procedures

Given test items, participants responded to the following instruction: 'For each item 1-20, mark how much you agree with the statement "I am _____" on the scale 1-7, where 1=totally disagree, 2=disgree, 3=slightly disagree, 4=neutral, 5=slightly agree, 6=agree and 7=totally agree'. It took on average 5 minutes to complete the test. Since the experiment were carried out online, the passages were recorded at Qualtrics.com. Informed consent was obtained from all participants. All were assigned to the same experimental tasks.

Analysis

For the analysis, The data of the 10 participants excluded in Study 1 were removed. As a result, response dataset of 144 participant was included in the analysis. The dataset was analyzed through EFA in order to investigate factor structure and obtain the factor loading matrix. For the analysis, CEFA 3.04(Browne et al., 2009) was used. Since the conflicting research results of the presence of correlation between Big Five traits, factor loading matrix with orthogonal rotation and that with oblique rotation were obtained. The rotation method applied to the matrix were varimax and direct obilimin, respectively. Then, comparison between semantic similarity matrix based on Table 10 and factor loading matrices were performed. The comparison used R. 3.0.2.

Result And Discussion

Table 12 shows the semantic similarity matrix of 15 items as follows:

Table 12.

Sematic similarity matrix of selected terms by personality traits

	정서적으로 안정적이다	성실하다	친화적이다	개방적이다	외향적
예민	**0.905**	0.243	0.315	0.044	0.094
긴장, 긴장하다	**0.934**	0.311	−0.058	0.018	0.015
스트레스	**0.942**	0.254	−0.010	0.068	0.178
부지런하다, 부지런	−0.054	**0.999**	−0.052	0.003	0.004
책임감	0.020	**0.993**	−0.027	0.055	0.095
약속	−0.034	**0.994**	−0.024	−0.010	−0.086
활력	0.118	0.034	0.019	−0.030	**0.847**
나서다	−0.013	0.379	0.336	0.121	**0.913**
적극적	−0.023	0.186	0.202	0.120	**0.932**
배려, 배려하다	0.072	0.089	**0.993**	0.046	0.469
공감, 공감하다	0.075	0.059	**0.987**	0.205	0.454
도와주다, 돕다	0.103	0.409	**0.892**	0.089	0.566
관대	0.147	0.054	0.122	**0.984**	0.337
진취적	0.059	0.015	0.083	**0.931**	0.564
배우다, 배우기	−0.017	0.070	−0.041	**0.860**	0.602

Next, the EFA results of five factor model are presented. According to criterion of Kaiser(1960), the number of factor that eigenvalue wes greater than 1 was five. Through maximum likelihood estimation of parameters, the measure of fit information is shown in Table 13. Also, scree plot is presented in Figure 4. The five factor model explained 63.5% of total variance.

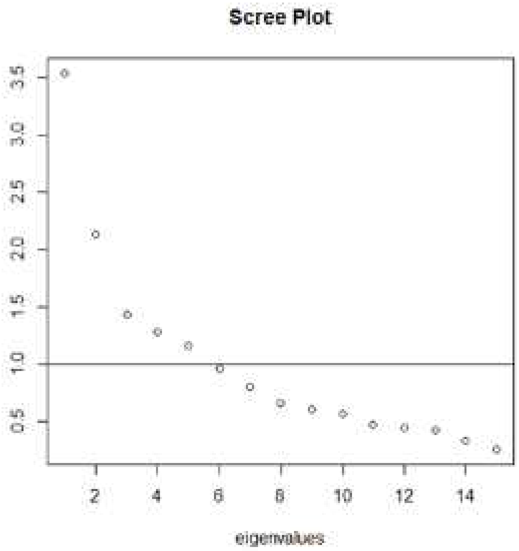

Figure 4. Scree Plot of the developed items using selected terms by traits.

Table 13.

Measure of fit information of Five Factor Model

Mesure of Fit	χ^2	df	RMSEA	RMSEA clost fit (H_0 : RMSEA $\leq$ .05)	RMSEA perfect fit (H_0 : RMSEA = .00)
	54.13	40	0.050	0.478	0.067

Model fit indices in Table 13 indicated the five factor model is acceptable since the perfect fit was not rejected. After accepting the model, the rotation was performed in order to interpret the factors. Factor loading matrix and factor correlations following oblique rotation are produced in Table 14 and 15. Also, factor loading matrix applied by orthogonal rotation is presented in Table 16.

Table 14.

Factor loading matrix following oblique rotation of five factor solutions

	성실성	개방성	개방성	정서적 안정성	외향성
예민한	0.06	-0.01	-0.12	**0.67**	-0.03
긴장을 잘 하는	-0.23	0.35	-0.06	**0.35**	-0.16
스트레스를 잘 이겨내는	0.32	-0.16	0.15	**-0.14**	0.11
부지런한	**0.42**	0.06	0.26	0.24	-0.02
책임감 있는	**0.56**	0.2	0.05	0.05	0.07
약속을 꼭 지키는	**0.58**	0.03	-0.01	-0.04	0.02
활력있는	0.12	0.18	0.06	-0.16	**0.65**
나서는 것을 좋아하는	-0.26	-0.15	0.45	0.15	**0.56**
적극적인	0.02	0.03	-0.1	0.01	**0.91**
배려하는	0.30	**0.57**	0.06	0.02	0.05
공감능력이 뛰어난	-0.04	**0.84**	0.03	-0.01	0.06
남을 돕는 것을 즐기는	0.11	**0.12**	0.64	-0.19	-0.14
관대한	0.02	0.25	**0.42**	-0.07	-0.09
진취적인	0.28	-0.05	**0.22**	0.18	0.46
배우는 것을 좋아하는	0.36	0.03	**0.34**	0.23	-0.06

Table 15.

Factor correlation matrix following oblique rotation of five factor solutions

	성실성	개방성	친화성	정서적 안정성	외향성
성실성	1				
개방성	0.35	1			
친화성	0.24	0.14	1		
정서적 안정성	0.02	-0.03	0.05	1	
외향성	0.07	0	0.24	0.09	1

Big Five traits were mainly proven as orthogonal factors(Digman & Takemoto-Chock, 1981; Fiske, 1949; Norman, 1963; Tupes & Christal, 1961), while a critique of that also exists(Saucier, 2002). Since the presence of correlation between five factors was not the focal point of the study, factor loading matrix of two solutions were presented and compared with semantic similarity matrix.

Table 16.

Factor loading matrix following orthogonal rotation of five factor solutions

	성실성	개방성	친화성	정서적 안정성	외향성
예민한	0.09	-0.03	-0.11	**0.66**	0.02
긴장을 잘 하는	-0.17	0.27	-0.05	**0.37**	-0.14
스트레스를 잘 이겨내는	0.30	-0.06	0.15	**-0.16**	0.14
부지런한	**0.47**	0.17	0.29	0.21	0.09
책임감 있는	**0.57**	0.34	0.11	0.02	0.09
약속을 꼭 지키는	**0.56**	0.18	0.04	-0.07	0.02
활력있는	0.16	0.24	0.03	-0.19	**0.64**
나서는 것을 좋아하는	-0.16	-0.17	0.35	0.13	**0.71**
적극적인	0.05	0.06	-0.16	-0.03	**0.87**
배려하는	0.36	**0.65**	0.11	0.01	0.05
공감능력이 뛰어난	0.05	**0.83**	0.08	0.00	0.04
남을 돕는 것을 즐기는	0.19	**0.20**	0.63	-0.19	0.02
관대한	0.10	0.29	**0.42**	-0.06	0.01
진취적인	0.33	0.05	**0.20**	0.14	0.55
배우는 것을 좋아하는	0.41	0.14	**0.36**	0.21	0.07

The resemblance between two matrices was mainly because of too low of correlation between factors in oblique solution. This implies that the existence of correlation between factors would not influence on the comparison.

Table 14 and 16 shows that the five factors to be interpreted as Conscientiousness, Openness to experience, Agreeableness, Neuroticism, Extraversion, respectively. In addition, 11 of 15 items showed highest factor loading on semantically related traits. Although, there were few cross-loaded items, it can be concluded that semantic representation and factor structure were similar generally based on

Table 17, 18.

Table 17.

Correlation between sematic similarity and factor loadings following oblique rotation

	Semantic Similarity				
Factor Loadings	개방성	성실성	외향성	친화성	정서적안정성
개방성	**0.397**	−0.295	−0.110	−0.348	−0.312
성실성	0.035	**0.536**	−0.223	−0.043	−0.254
외향성	−0.208	−0.278	**0.606**	0.166	−0.114
친화성	0.027	0.005	−0.084	**0.410**	−0.063
정서적안정성	−0.313	−0.434	−0.068	0.291	**0.735**

Table 18.

Correlation between sematic similarity and factor loadings following orthogonal rotation

	Semantic Similarity				
Factor Loadings	개방성	성실성	외향성	친화성	정서적안정성
개방성	**0.428**	−0.365	−0.237	−0.356	−0.357
성실성	0.011	**0.524**	−0.118	0.028	−0.254
외향성	−0.172	−0.224	**0.571**	0.194	−0.124
친화성	0.030	0.050	−0.055	**0.410**	0.022
정서적안정성	−0.329	−0.404	−0.116	0.154	**0.786**

The correlation between factor loading and semantic similarity were somewhat lower than those of Study 2, however, it is highly correlated with relevant factors. In other words, factor structure of the test were in accord with its semantic representation because the diagonal entries of Table 17 and 18 show high correlation. It could be concluded that items that semantic representations are similar to each other measure same construct. In addition, the combined result of study 2 and 3 bring to a conclusion that semantic representation and factor structure of personality test items are consistent.

General Discussion

This thesis suggested the method that analyzes semantic representation of test items directly using LSA in order to investigate construct validity without response data and obtained implications for cognitive process of personality test item response.

In order to analyze semantic representation of the item, the passages that participants produced in the limited context of judging personality traits were used to creat a semantic space. The number of dimension was determined by classification accuracy of the passages. The space had been created in Study 1. Then, the semantic similarity matrix based on the space was constructed in order to compare with the factor loading matrix that reflected factor structure of the test. In study 2, test items measuring the same construct had similar semantic representation with each other and in study 3, items that had similar semantic representation measured the same traits.

In conclusion, semantic representation and factor structure of personality test items were consistent. In other words, it showed stimulus-response consistency of test items. That is, the analyzed factor structure of the test using EFA can be interpreted as semantic relations among test items. Moreover, this implies the possibility of prediciting factor structure based on semantic similarity matrix.

Then, can the consistency be generalized to other tests that measure various constructs? To answer the question, further discussion about semantic similarity among factor names and ambiguous items are needed. These play the important role in replicating the consistency and comprehending the results of the studies.

Semantic Similarity between Factor Names

To establish stimulus-response consistency of test items, semantic representations among factor names should be separated. The semantic similarity among factor names corresponds to factor corelation matrix Φ in EFA. The Table 18 represented semantic similarity among the Big Five factor names used in the studies.

Table 19.

Semantic Similarity among the Big Five factor names

	정서적으로 안정적이다	성실하다	친화적이다	개방적이다	외향적
정서적으로 안정적이다	1				
성실하다	-0.039	1			
친화적이다	0.020	-0.005	1		
개방적이다	-0.010	0.012	0.080	1	
외향적	0.045	0.016	0.475	0.272	1

Correlation coefficient among the names should not be too high. Otherwise, the interpretation of semantic similarity matrix would be hard because factor names serve as axes in semantic similarity matrix. The constructs measured by PANAS(Positive Affect and Negative Affect Schedule; Watson & Clark, 1988) are typical examples.

The items was translated into Korean PANAS(Lee et al., 2003). The schedule is composed of 20 items measuring positive affect and negative affect. The result of semantic similarity between two constructs shown in Table 20 was obtained by the semantic space concretely created by Brown Corpus(1961). The vectors of factor names were obtained by adding 'positive' and 'negative' to 'affect' respectively. Although the corpus were not collected in limited context, the sematic similarity between '긍정(positive)' and '부정(negetive)' in the semantic space constructed in study 1 was approximately 1.

Table 20.

Sematic Similarity among the PANAS factor names

	Positive Affect	Negative Affect
Positive Affect	1	
Negative Affect	0.999734	1

Table 20 showed that semantic similarity between two factor names were almost the same because they were in antonymous relation. The antonymous relation is established in the base of homogeneity and heterogeneity of the semantic features(Kim, 1993). In other words, two words in antonymous relation have only one different semantic features while the rest of features are the same(Lim, 1992). That is, two constructs presented in Table 20 have common features in 'affect' except only one difference in the dimension of 'positive' and 'negative'. If the semantic similarity among constructs is highly correlated because they are in antonymous relations or synonymous relations, semantic similarity matrix will be hard to interpret as it was hard when interpreting the Table 21.

Table 21.

Sematic Similarity Matrix of the PANAS

	Positive Affect	Negative Affect
Nervous	0.566	0.564
Irritable	0.565	0.563
Distressed	0.910	0.905
Upset	0.345	0.357
Afraid	0.570	0.574
Hostile	0.763	0.760
Scared	0.378	0.379
Alert	0.566	0.570
Guilty	0.910	0.916
Ashamed	0.440	0.433
Active	0.982	0.978
Enthusiastic	0.787	0.788
Inspired	0.849	0.845
Proud	0.524	0.521
Strong	0.826	0.823
Interested	0.873	0.870
Excited	0.422	0.420
Determined	0.984	0.986
Attentive	0.075	0.076

Since a semantic similarity matrix calculate the similarity between factor names and items, highly similar factor names may cause the problem of composing uninterpretable matrix as it was shown in Table 20. Nevertheless, the responses of participants for the PANAS were proved that the structure of two factor, 10 items for each, is appropriate(Watson & Clark, 1988; Crawford & Henry, 2004).

The results imply that semantic similarity between factor names must be sufficiently low for stimulus-response consistency of test items. Also, the items measuring antonymous factors may make respondents only focus on one different semantic feature of the factors.

Ambiguous Items

If a semantic representation of test item is similar to that of two or more factors, the item may be called ambiguous items. In Study 3, that of 15 selected items were similar to that of only one factor. If ambiguous items are added, what will happen to the corresponding factor structure? To answer the question, five ambiguous items are added to 15 items used in Study 3. The developed 5 items using 5 terms extracted from the semantic space of Study I is in Table 22.

Table 22.

Sematic Similarity Matrix of the 5 ambiguous items added to the 15 items in study 3

		Big Five trait names				
어휘	문항	성실성	개방성	개방성	정서적 안정성	외향성
어울리다	친구와 어울리는 것을 좋아하는	0.073	0.194	**0.829**	0.393	**0.819**
신중, 신중하다	신중한	0.342	0.136	**0.846**	0.354	**0.711**
내성적	내성적인	0.120	-0.009	**0.666**	0.219	**0.969**
솔선수범	솔선수범하는	0.033	**0.706**	0.302	-0.043	**0.676**
즐거운	즐거운	0.292	0.141	0.152	**0.748**	**0.740**

The five ambiguous items that show the similarity more than 0.6 to two of the Big Five factors were chosen. The response data of respondents from Study 3 was collected. Based on the data, EFA was performed. The measure of fit information for the five factor model is presented below:

Table 23.

Measure of fit information of five factor model (20 items, 5 ambiguous items included)

Measures of fit	χ^2	df	RMSEA	RMSEA clost fit (H_0 : RMSEA $\leq$ .05)	RMSEA perfect fit (H_0 : RMSEA = .00)
	147.527	100	0.058	0.254	0.001

Although the perfect fit was rejected, the five factor model was accepted because close fit was not rejected. The factor loading matrix of the model was shown in Table 24. The factor structure of the model was hard to interpret. Only factor 5 was possible to interpret in ‘Extraversion’, the meanings of the other factors measured by items were not clear. In conclusion, the ambiguous items influenced the whole factor structure of the responses of items.

Besides, the factor loadings of ambiguous items were completely different from the semantic similarity. All of the items had similar semantic representations to Extraversion but there was only one item correlated with the factor in the factor loading matrix. These results imply that it is hard to predict the factor structure with the semantic similarity matrix when semantically ambiguous items are included in the personality test.

Table 24.

Factor loading matrix following orthogonal rotation of five factor solutions (20 items, 5 ambiguous items included)

Test Items	Factors				
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1. 예민한	0.33	-0.34	0.06	-0.24	0.15
2. 긴장을 잘 하는	0.05	-0.1	0.28	-0.22	-0.15
3. 스트레스를 잘 이겨내는	0.28	**0.47**	-0.25	0.03	-0.08
4. 부지런한	**0.58**	0.04	0.03	0.19	0.02
5. 책임감 있는	**0.46**	0.11	0.28	0.07	0.02
6. 약속을 꼭 지키는	0.30	**0.42**	0.07	0.05	-0.16
7. 활력있는	-0.03	**0.49**	0.14	0.04	**0.48**
8. 나서는 것을 좋아하는	0.04	-0.07	-0.18	0.2	**0.70**
9. 적극적인	0.05	0.09	0.05	-0.13	**0.82**
10 .배려하는	0.13	0.05	**0.67**	0.11	-0.01
11. 공감능력이 뛰어난	-0.01	0.01	**0.76**	0.06	-0.03
12 .남을 돕는 것을 즐기는	-0.02	-0.02	0.07	**0.89**	-0.03
13. 관대한	0.11	0.08	0.19	0.31	-0.08
14. 진취적인	**0.38**	0.04	0.02	0.06	**0.50**
15. 배우는 것을 좋아하는	**0.55**	-0.07	0.07	0.14	0.05
16. 친구와 어울리는 것을 좋아하는	-0.09	0.16	0.39	0.07	0.33
17. 신중한	**0.51**	0.04	0.25	-0.12	-0.18
18. 내성적인	0.15	-0.14	-0.03	0.00	**-0.72**
19. 솔선수범하는	0.37	0.05	-0.03	**0.40**	0.07
20. 즐거운	-0.07	**0.70**	0.09	-0.03	0.06

As discussed above, semantic similarity among factor names and ambiguous items provided clues for the generalization of results. To replicate consistency of stimulus-response for test items, the similarity between factor names must sufficiently low and ambiguous items should not be included. These tentative results await further refinement and correction in the light of further research.

Despite these findings, there remain three inherent limitations in this thesis. They are as followings; (1) usage of term as test items, (2) size of the semantic space, and (3) inconsistency of stimulus-response for reverse items.

The typical test items are composed of sentences. However, the studies in this thesis used single terms to represent the semantic representation of test items since the comparison with factor names required a word. For this reason, the items were needed to be compressed to key words. Moreover, in the early stage of personality testing, the adjectives describing a person were frequently used. According to Fundamental Lexical hypothesis, the most important individual differences in human transactions will come to be encoded as single terms in some or all of the world's languages(Goldberg, 1990). Assuming the hypothesis is correct, compressing the semantic representations of test item into a word is resonable.[1]

Nevertheless, extracting a term from test item composed of sentence may cause a problem of unintended transformation of meaning. In order to represent the semantic representation of sentence, Laundaur & Dumais(1997) summed up the vectors of terms which compose the sentence. However, this method may also cause a problem because semantic representation of the sentence is not the sum of that of words. For instance, the order of words appeared in sentence has great influence on forming the representation of sentence. In conclusion, the representing method that considers various aspects of sentence representation is needed.

Another limitation of the studies is related to the quantity of

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1) An insignificant difference exists between English and Korean. The expressions describing a person in Korean include adjective phrase and clause that combination of various parts of speech(Jung, 2008).

the passages collected. Is it possible to conclude that the space created in the study 1 is fully representing human's knowledge representation related to judging personality? The semantic space created through sufficient amount of the passages may cover more words than that of Study 1 and may closer to that of human.

However, there are a few problem with creating semantic space using an amount of passages. They are related to the computational load that increases proportionally to quantity of passages. To tackle the problems, further research are needed to improve the computational speed of SVD algorithm in order to decrease the required computation time. Also, the lack of memory problem is needed to be solved to construct bigger sparse term-document matrix.

The other limitation is inconsistency of stimulus-response for reverse items. In the case of reverse item, the factor loadings of the item have the same absolute value but different signs with non-reverse item while semantic representation between reverse item and non-reverse item is highly correlated[2]. This is because those items are in antonymous relation. This reverse items were handled by reverse-coding in the studies.

Nevertheless, the reverse-coding is not a answer to inconsistency of stimulus-response for reverse items. It does not explain why the inconsistency occurred. One possibility of the inconsistency is the reverse item that makes respondent focus on the

2) The factor loading of item 10 '조용한' in Korean BFI(Kim et al., 2011) to Extraversion, 0.73, was the result of reverse-coding.

different semantic feature of the items, but further research is needed to investigate the issue in detail.

In spite of those limitation inherent in the studies, this thesis suggested the analyzing method of sematic representation for test items. The semantic similarity matrix can be used as supplementary instrument in the process of developing personality test. Not only the matrix can be applied to any psychological construct and test items, but also the matrix is capable to predict factor structure if a few discussed assumptions satisfied.

In addition, the matrix has another practical advantage if it is used to the process of developing personality test. In the process, several times of pilot test are implemented in order to determine the final set of items, in general. The cost required to the pilot tests may reduced because the space can predict the factor loadings of newly developed items if the semantic space is created once. Also, The analyzing method of sematic representation through the semantic similarity matrix can contribute to interpreting the factors of factor loading matrix in EFA results. Since the each column of the matrix represents the factor names, the names can be compared with the columns of factor loading matrix. If two matrices are sufficiently similar to each other, the factors of the factor loading matrix may be named by the column vector names of the semantic similarity matrix.

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Appendix

Example R code of passage classification using LSA

```
library('rJava')
library('RWeka')
library('lsa')
library('utils')
library('stats')
setwd('file directory')

td = tempfile()
dir.create(td)
ab=1:719
conn <- file("file directory", "r")
for (i in 1:719) {
  line <- readLines(conn, 1)
  if (i < 10){ab[i]=paste('a','b','0','0',i,sep="")}
  else if (i >= 10 & i < 100){ab[i]=paste('a','b','0',i,sep="")}
  else {ab[i]=paste('a','b',i,sep="")}
  write( line, file=paste(td, ab[i], sep="/") )}

text_mat=textmatrix(td)
dim(text_mat)
colnames(text_mat)

nn=nrow(text_mat);x=0;y=1;
for (z in 1:nn){
  if(length(which(text_mat[z,]!=0))==1)
  { x[y]=z;
    y=y+1;  }}
text_mat=text_mat[-x,]
```

```
dim(text_mat)

weight_tm=lw_logtf(text_mat)*1/entropy(text_mat)

doc_vector=0;accuracy=0;
for (i in 2:719){
  doc_matrix=matrix(ncol=719,nrow=i)
  doc_matrix=diag(LSAspace$s[1:i])%*%t(LSAspace$d[,1:i])
  cos_docvec=cosine(doc_matrix)
  set.seed(1)
  clustered=kmeans(cos_docvec,5)$cluster

  a=table(factor(clustered[1:144],levels=1:5))
  b=table(factor(clustered[145:288],levels=1:5))
  c=table(factor(clustered[289:433],levels=1:5))
  d=table(factor(clustered[434:577],levels=1:5))
  e=table(factor(clustered[578:722],levels=1:5))
  f.mat=cbind(a,b,c,d,e)

  correct=0;j=c();m=c()
  j=which(f.mat==max(f.mat),arr.ind=T)[1]
  m=which(f.mat==max(f.mat),arr.ind=T)[2]
  correct[1]=max(f.mat)
  for (k in 2:5){
    correct[k]=max(f.mat[-j,-m])
    j[k]=which(f.mat==max(f.mat[-j[1:k-1],-m[1:k-1]]),arr.ind=T)[1]
    m[k]=which(f.mat==max(f.mat[-j[1:k-1],-m[1:k-1]]),arr.ind=T)[2]    }
  accuracy[i]=sum(correct)/719 }
write.csv(accuracy,'file directory')

plot(accuracy[1:719],lwd='2',type='l',main='Accuracy',xlab='dimensions',ylab='percent(%)',ylim=c(0,1
))
plot(accuracy[1:10],lwd='2',type='l',main='Accuracy',xlab='dimensions',ylab='percent(%)',ylim=c(0,1)
)
abline(v=5,lty='dotted');abline(v=10,lty='dotted')
```

Abstract in Korean

수검자의 인지과정은 ‘이해’, ‘인출’, ‘판단’, ‘응답’의 4단계를 거친다. 성격검사의 구성타당도를 검증하기 위해 주로 사용되는 수검자의 응답 자료는 이러한 인지과정을 거친 뒤 생성된 것이며, 이는 전통적으로 탐색적 요인분석을 통해 분석되었다. 그러나 반응 자료만을 이용하여 검사문항의 구성타당도를 추론하는 것은 자극-반응 불일치를 간과한 것이기 때문에, 검사문항이 지닌 의미표상을 직접적으로 분석하는 법이 필요하다. 본 연구는 잠재의미분석을 활용하여 검사문항의 의미표상에 직접적으로 접근하는 법을 제안하고, 이를 기존의 분석 결과와 비교하여 수검자의 인지과정에 대한 함의를 얻는다. 잠재의미분석을 수행하기 위해 연구 1에서는 제한된 맥락에서 피험자에게 수집된 성격요인을 묘사하는 지문을 바탕으로 구성한 가중 어휘-문서 행렬을 5차원으로 축소하여 의미공간을 구성하였다. 더 나아가, 본 연구는 성격검사의 요인구조와 의미표상을 비교하기 위해 의미유사도행렬을 제안하였다. 연구 2와 3에서는 이를 요인부하량 행렬과 비교하여 일치도가 높음을 보임으로서 성격검사의 의미표상구조과 요인구조가 유사함을 보였다. 이는 요인명 간 의미유사도가 높지 않고, 애매한 검사문항이 없을 때 가능하다. 이러한 제약조건 하에서 본 연구는 잠재의미분석을 활용하여 반응자료 없이 검사문항의 의미표상을 분석하여 구성타당도를 확인할 수 있는 방법을 보였을 뿐만 아니라, 수검자의 반응자료를 통해 분석한 요인구조를 의미표상 간 유사도로 해석할 수 있는 가능성을 보였다.

주제어 : 잠재의미분석, 탐색적요인분석, 구성타당도, Big Five, 의미유사도, 의미표상

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