[Research Paper]

ISSN 1225-1151 (Print)
ISSN 2234-0793 (Online)
Journal of the Korean Society of Clothing and Textiles
Vol. 44, No. 3 (2020) p.556~571
https://doi.org/10.5850/JKSCT.2020.44.3.556

A Recommender System Model Using a Neural Network Based on the Self-Product Image Congruence

Joo Hee Kang · Yoon-Jung Lee*†

Research Institute of Human Ecology, Korea University
*Dept. of Home Economics Education, Korea University
Received April 24, 2020; Revised May 27, 2020; Accepted June 5, 2020

Abstract

This study predicts consumer preference for social clothing at work, excluding uniforms using the self-product congruence theory that also establishes a model to predict the preference for recommended products that match the consumer's own image. A total of 490 Korean male office workers participated in this study. Participants' self-image and the product images of 20 apparel items were measured using nine adjective semantic scales (namely elegant, stable, sincere, refined, intense, luxury, bold, conspicuous, and polite). A model was then constructed to predict the consumer preferences using a neural network with Python and TensorFlow. The resulting Predict Preference Model using Product Image (PPMPI) was trained using product image and the preference of each product. Current research confirms that product preference can be predicted by the self-image instead of by entering the product image. The prediction accuracy rate of the PPMPI was over 80%. We used 490 items of test data consisting of self-images to predict the consumer preferences for using the PPMPI. The test of the PPMPI showed that the prediction rate differed depending on product attributes. The prediction rate of work apparel with normative images was over 70% and higher than for other forms of apparel.

***Key words*:** Feed Forward Neural Network (FFNN), Product image, Self-image, Self-product congruity, Work apparel preference

I. Introduction

Recommender systems are used in online shopping malls to reduce the fatigue resulting from consumers' decision-making process and to assist in purchasing decisions. Most apparel shopping malls have adopted a recommender system due to the sociality of clothing. Furthermore, as clothing represents the wearer's image, it contains important information that influences the perception of others. For example, clothing that is appropriate to the situation creates a favorable impression in others (Adam & Galinsky, 2012), and an appearance considered positive by others is beneficial to daily life (Benson et al., 1976; West & Brown, 1975). In particular, office workers tend to purchase clothing that can present a professional image (Kang et al., 2011), and a previous study has indicated that such workers can enhance their salary or position by wearing such apparel (Peluchette et al., 2006). In addition, office workers can generate a professional image through proactive appearance management, thereby obtaining an advantageous position by forming a competent and successful image in their interactions with others (Yoo, 2010). In recent years, there has been a decrease in clothing-related guidelines, or dress codes, in organizations, accompanied by an emphasis on maintaining a young and creative image. Nevertheless, workers should choose

†Corresponding author
E-mail: yleehe@korea.ac.kr
This article is based on a Doctoral Thesis.

clothes that represent a compromise between their personality and organizational norms, which continue to exist to some extent. Hence, the demand for recommender services is expected to increase.

In general, a recommender system suggests products that elicit similar preferences among users or that have a similar preference to other products because this perceived similarity affects users' product purchase decision-making (Lee & Kim, 2016). However, it is difficult to estimate the underlying reason for the preference for the selected product since the system only recognizes similarities among individuals. In addition, it is difficult to recommend unique or new products using similarity-based system, because the system will repeatedly display conventionally designed products (Katsov, 2017/2019). Another problem with similarity-based system is the cold-start problem that prediction is impossible unless the similarity data is previously collected. For these reasons, recent research on recommender systems has considered consumer characteristics such as physical, social, and psychological factors for improved prediction. For example, a previous study used eight adjectives to build a system that measured style, brand, and event words (church, wedding, etc.) to recommend appropriate clothes for specific situations (Shen et al., 2007). Another study proposed a recommender system that used semantic differential scales considering the consumer's perception of their body shape (Zeng et al., 2013). However, the semantic scales used in previous studies were arbitrarily selected by the researchers rather than grounded on a theoretical basis, and they focused mainly on the external factors of the product or the physical appearance of the individuals, meaning they were inadequate at representing the psychological factors, such as consumers' affect.

It is well-documented in the literature that clothing is considered an extension of self and consumers express their self-image through dress (Rhee, 2007). In this regard, a system should recommend products that can match the image desired by the wearer, thereby expressing the consumer's emotion or sociality as a fashion product (Zeng et al., 2013). The current study intends to suggest a model for developing a more predictable clothing recommender system based on the theoretical findings of fashion consumer studies on self-product image congruence, whereby consumers prefer a product that matches their image of themselves.

II. Literature Review

1. Self-Product Image Congruence

Sirgy (1982) defined *self-congruity* as the congruence between the self-image and the product-user image, arguing that consumers prefer products and brands that are consistent with themselves. Applying the theory of Sirgy and Danes (1982), Govers and Schoormans (2005) proved that consumers prefer products that show consistency between the product-user image and their own image. In the case of products that place a high value on design, each product has a different personality, depending on the cognitive style (Meneely & Portillo, 2005), and the congruity between the product personality and the self-image has a positive effect on the attachment to products with high perceived design values (Choi et al., 2007).

Since self-image is related to personality, role expectations, clothing values and benefits, and lifestyle, the primary aspects of the self-concept align closely with a person's values and their ideological pursuit (Chung, 2016). As clothing is a product in which design value is important, people can maintain, protect, and improve their image as they feel an association between their own self and the product, thereby arousing their self-esteem and sense of superiority. Therefore, the congruity between the self-image and the clothing image can affect the preference for apparel from a symbolic consumption perspective.

In most previous studies, products were considered to have a personality similar to that of a person, thus semantic differential scales were used to measure the product image as well as the personal image. In order to measure the self-product congruence, researchers used either the discrepancies between the self-image and the product image or a perceived degree scale of the congruity of the product with the self. In this study,

consumers' self-image was used to predict consumers' preference for apparel products on the premise that consumers prefer products with images congruent with their self-image. In the previous study that dealt with the effect of self-product image congruence on clothing preference, regression analysis was used to examine the relationship between the variables (Bae & Chung, 2006; Chung, 2016; Hong & Kim, 2015; Malhotra, 1981; Son, 2009). In the prediction research, however, neural networks model is known to general better prediction than regression model (Kim, 2012). In this research, the measurement of images was adopted to the semantic scale composed of adjectives, and the prediction of self-product image congruence on clothing preference was investigated using neural networks.

2. Clothing Recommender System

People with a low level of fashion involvement or who are less knowledgeable in fashion may require a recommender system to reduce the fatigue inherent in decision-making. Shen et al. (2007) suggested a system that can recommend clothing based on the situation in which the clothing is to be worn. This system displayed a product which was appropriate to the consumer's goal rather than to the consumer's attitude toward a specific product. This scenario-based recommender system offers practical benefits because it can provide recommendations even when no prior information is available, e.g. when a consumer is new to a shopping mall. The system can suggest categories beyond the existing ones in congruence with consumers' diversifying thoughts and lifestyles. Shen et al. (2007) used words to describe the products as well as the situation. They encoded the clothing products, brands, clothing types, and situations using six tuples, i.e., luxurious, formal, funky, elegant, trendy, and sporty. For example, the researchers inputted the values for the words related to the occasion 'wedding' as [5, 9, 5, 9, 6, 1], for the brand 'Levi's' as [4, 2, 7, 3, 6, 6], and for the clothing type 'shirt' as [7, 8, 4, 6, 5, 1], in which each number represents the degree to which the product/situation corresponds to each of the six tuples. If the direction 'boss' birthday party' was entered into the system, the appropriate clothes were browsed according to the similarity analysis. As a result, the user's occasion and taste could be considered based on a consumer- and product-oriented method rather than a seller-oriented method. However, the scoring (such as brand, clothing type and occasion words) used in this study was pre-determined by the researcher rather than according to the data; thus, if the opinions differ between the consumer and the researcher, the consumer may not be satisfied with the recommended results.

Zhang et al. (2019) proposed an intelligent recommender system to satisfy the emotional needs of consumers based on the use of affective words representing the consumer's body shape and a specific clothing style. Because the established system based on the consumer's shopping history has low accuracy, their system considered the consumer's knowledge and experience of accepting products. The purpose of their study was to profile clothing to construct a system that could suggest clothing that was suited to consumers based on their physical size and preferences or needs (using semantic factors such as style keywords and visual factors such as images). The measurements and weight were used for the consumer's physical information in addition to the style keywords, 'elegant, feminine, young, sexy, classic, romantic, folk, and sport' as well as verbal descriptions of the preferred product style. In this study, the semantic scale was used to measure the affective factors of consumers, but only the style keywords that represent appearance factors were considered in the analysis. Moreover, as for the stimulus selection method, only the stimuli that most consumers would prefer were selected, which limited the accurate profiling of consumers seeking unique products.

As mentioned above, clothing recommender systems in the previous studies were established with a focus on information about the consumer's body shape and the appearance factors of the product. However, according to the research on recommend system development, the emotional or psychological factors have more positive influence on consumer satisfaction than the technical and physical factors such as color and sha-

pe (Kim & Park, 2018). Therefore, it is advisable to consider the psychological factors of consumers in a recommender system.

3. A Recommender System Using Self-Product Congruence

This research intends to propose a model for recommending work clothes suitable for consumers using their self-image and product image information based on the self-product congruence theory. Previous research has underlined that the consumer derives affective value from a product in addition to functional value and that the congruence between the product image and the self-image affects their preference (Choi et al., 2007; Govers & Schoormans, 2005; Johar & Sirgy, 1991; Jordan, 2003; Sirgy, 2015). However, previous studies related to clothing recommender systems focused only on the appearance factors of consumers and products.

The current research suggests a model, called the PPMPI (Preference Prediction Model using Product Image) for the recommender system based on psychological factors, i.e. self-image, rather than physical or functional factors, and devises the model presented in <Fig. 1>.

This model assumes that the consumer prefers a product that is similar to their own image. For example, as a product having an elegant image matches user's self-image, the response will be positive. The current research seeks to confirm the possibility of predicting preference with the self-image, estimated on the same scale as the product image, is fed into the PPMPI. That is, the PPMPI assumes that 'preferred product image equals the self-image'. In real shopping situation, consumers cannot check all products' images. In this case, if the system has consumers' self-image data, and with the product image evaluated by the sellers, the preferences can be inferred by searching for the product image which matches the consumers' self-image. Through this process, even a newly opened shopping mall can avoid the cold-start problem, using PPMPI system for prediction.

III. Research Methods

1. Study 1: Creation of a Short-Form Semantic Scale to Measure Self-Product Congruence

In order to consider the congruity between the self-image and the product image, the measurement scales for the two concepts should be equal. In order to efficiently and conveniently measure the two concepts in an analogous manner, the scale has to be simplified. Therefore, prior to the main study of model verification, a preliminary study was conducted aimed at developing a short version of the scale. In a practical approach, the short-form scale is effective in measuring the psycholo-

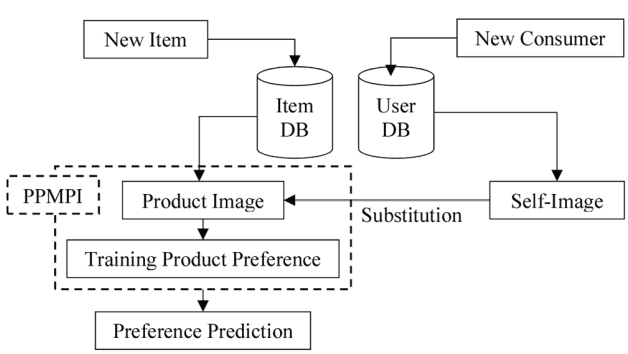

Fig. 1. PPMPI flow chart.

gical aspects of consumers because it reduces the time and cost associated with measuring (Kemper et al., 2019).

1) Sampling and Data Collection

The data were collected through an online survey service provider, Macromill Embrain. The survey procedure was approved by the Institutional Review Board (IRB) prior to the data collection. The survey was conducted between April 10 and 16, 2018, involving office workers over the age of 26 who were living in the following metropolitan areas: Seoul (42.9%), Gyeonggi-do (31.9%), Incheon (8.4%), Daegu (6.8%), Busan (4.7%), and Gwangju (2.6%). The demographic characteristics of the participants are presented in <Table 1>.

2) Measures

According to the literature on semantic differential scales (Malhotra, 1981), using adjectives with opposite meanings does not adequately reflect the actual self-image due to negative meanings, thereby limiting the scope of the research (Hong et al., 2008); hence, the unidirectional semantic scale was adopted for the current study. Based on the semantic scales used in previous studies (Bae & Chung, 2006; Hong & Kim, 2015; Son, 2009), only those adjectives considered appropriate for expressing both the self-image and the clothing product image were selected in this study. A total of 63 adjectives were selected. In the literature, the following five factors are commonly identified for the semantic scales for self-image evaluation: activity, mildness, attractiveness, conspicuousness, and ability. Therefore, we classified the adjectives from previous research in to the five factors as shown in <Table 2> below.

The questionnaire consisted of three parts: Part 1 comprised questions measuring the self-image; Part 2 contained questions measuring the product images; and Part 3 included questions about the demographic characteristics of the respondents. According to the literature, the self is multi-faceted and thus has to be measured considering the situation. In this study, the self-images were measured as a product-expressive and situational self-image because the materialized self-image expressed by a clothing product is the most effective means of reflecting the clothing preference in the workplace (Bae & Chung, 2006; Rhee, 2007). Therefore, in Part 1 the question "What is your preferred clothing image when you go to work?" was posed to measure the self-image of the respondents, and the respon-

Table 1. Demographic characteristics of the sample in study 1

Variable	Category	Frequency (Persons)	Percentage (%)
Gender	Male	99	51.8
	Female	92	48.2
Marriage	Unmarried	99	51.8
	Married	92	48.2
Age	Above 26 below 30	63	33.0
	Above 31 below 35	31	16.2
	Above 36 below 40	34	17.8
	Above 41 below 45	42	22.0
	Above 46	21	11.0
Current working period	Under 1 year	16	8.4
	1 years - under 3 years	47	24.6
	3 years - under 5 years	32	16.8
	5 years - under 7 years	35	18.3
	7 years - under 9 years	20	10.5
	Above 9 years	41	21.5

Table 2. Semantic scales

Factor	Semantic adjectives
Activity	active, aggressive, energetic, young, open, mannish, pleasant, intellectual*, sociable, bold*, progressive, casual, sporty, conspicuous*, individual*
Mildness	conservative, easy, decent*, ordinary, comfortable*, warm, soft, gentle
Attractiveness	luxury, sensible, romantic, refined, good-looking, delicate, elegant, attractive, fashionable, fancy*, stylish, sensual, classic, modern, mature, reassure, basic, neat, individual*, bold*
Conspicuousness	conspicuous, intense, fashioned, sexual, strong, match (-), natural (-), simple (-), fancy*
Ability	responsible, sincere, polite, modest, stable, noble, formal, rational, authoritative, reliable, professional, logical, reasonable, quiet, conservative, slight (-), intellectual*, descent*, comfortable*

*: Adjectives included in two or more factors
(-): Reverse coded scales

dents were asked to indicate how much each of the 63 adjectives represented their self-image. In Part 2, an image of a typical piece of work apparel was presented as a stimulus, and the respondents were asked to mark how much each of the 63 adjectives described the product image. Both the self-image and the product image were measured on 5-point Likert scales (1 = strongly disagree to 5 = strongly agree).

The data were analyzed using the R program. First, in order to reduce the self-image scale, common factor analysis was performed with the function 'factanal()' in psych packages on the collected 63 adjectives.

2. Study 2: The PPMPI Model Verification

1) Sampling and Data Collection

The data were collected by the same online survey company after the data collection procedure had been approved by the Institutional Review Board (IRB). The data collection started on November 11, 2019, and lasted for seven days. Unlike in the preliminary study, the main study included images of apparel products as stimuli. Therefore, the survey was distributed only to those participants who were likely to wear the apparel items shown in the stimuli at work: Working men aged between 25 and 50 who were living in metropolitan areas and did not wear uniforms at their workplaces. The participants resided in different metropolitan areas across the country (Seoul 38.6%, Gyeonggi-do 28.6%, Incheon 5.5%, Busan 4.1%, Daegu 2.7%, Daejeon 2.9%, Gwangju 1.4%, and elsewhere 16.3%). A total of 490 working men participated in this study. The participants' demographic characteristics are shown in <Table 3>.

2) Measures

The short form of the semantic scale, consisting of three factors (ability, classic, and novelty) and nine adjectives (elegant, stable, sincere, refined, intense, luxury, bold, conspicuous, and polite), drawn from study 1, was used to measure the self-images of participants and the product images. Both the self-image and the product image were measured on 5-point Likert scales (1 = strongly disagree to 5 = strongly agree).

3) Stimulus Development

The stimulus images of clothing that are likely to be worn at workplace were collected from a global shopping website (www.gilt.com) in May 2019. Traditional suit styles, as well as casual styles or business casual styles were included because consumers are expected to have difficulty making a decision regarding these outfits due to the variety of designs. Accordingly, selected stimuli were composed of three types of style: casual, business casual, suit. In addition, stimuli were selected to include even number of items across item types (top/bottom) and colors (neutral/warm or cool). The compositions of stimuli are presented in <Fig. 2>.

The 20 images of the apparel items used as stimuli were as shown in <Fig. 3> which was selected the criteria on styles, types, and colors. The stimuli were con-

Table 3. Demographic characteristics of the sample in study 2

Variable	Category	Frequency (Persons)	Percentage (%)
Marriage	Married	180	36.7
	Unmarried	300	61.2
	The others	4	0.8
Age	20s	100	20.4
	30s	130	26.5
	40s	130	26.5
	50s	130	26.5
Occupation	Office worker	308	62.9
	Labor position	34	6.9
	Service/salesperson	34	6.9
	Executive position	22	4.5
	Professional position	43	8.8
	Government	29	5.9
	Teacher	20	4.1

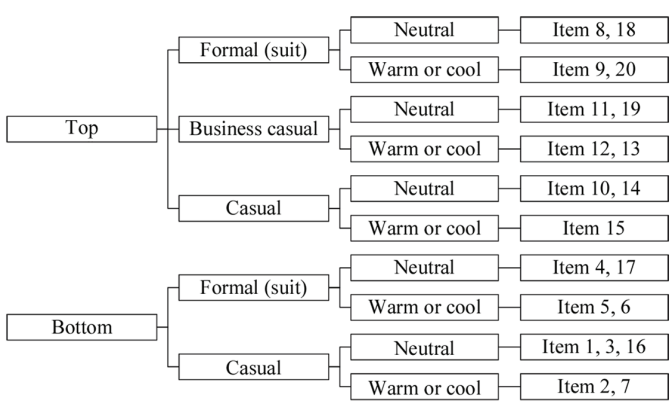

Fig. 2. Sort of stimuli.

sisted of eleven tops and nine bottoms. Also, eight suit styles, four business casual styles, and eight casual styles were selected. For bottom items, only formal suits and casual categories were included because business casual pants were almost identical with formal pants in pictures. The stimuli were comprised of eleven neutral color items including different shades of grey, and nine warm- or cool-colored items.

4) Analysis Method

The goal of using machine learning is to improve performance by statistical and mathematical algorithms (Zaccone & Karim, 2018). That is, the computer program or machine can extract a model by figuring out rules or patterns from training data. Machine learning is a method to find models which can solve problems without clear standards or rules. Almost machine learning algorithm aims to optimize the model and to minimize the loss of the training error and the model's complexity using a regularization. The entire learning process requires a training dataset, a validation dataset, and a test dataset.

Fig. 3. Stimuli

Neural networks are the core of the supervised machine learning, the multilayer perceptron is organized (Zaccone & Karim, 2018). In the case of Feed Forward Neural Network (FFNN), the first layer receives the input data and the last layer produces the output data such as a classification. Also, two or more hidden layers are composed in the architecture, to calculate the outcome.

The R program was used for the statistical analysis, and Python was used to build the model using neural network analysis. To perform the neural network analysis, the TensorFlow 2.0 package was used. The researchers judged that the FFNN is the most frequently used method in machine learning (Saito, 2016/2017; Zaccone & Karim, 2018) because it has a high accuracy for classification when the predictor is a nominal variable (Kim, 2012; Saito, 2016/2017).

IV. Results

1. Study 1

The average KMO value was over .90, and Bartlett's sphericity test was significant (χ^2=213.1, *df*=41, *p*<.001), confirming the suitability of the construct for factor analysis. The number of factors with eigenvalue over 1.0 was seven. However, when the results with more than 4 factors were examined, the relative contributions of the factors were low with less than 10% of explanatory variance and no adjectives showing high load on the factors. Therefore, the two factors (activity and mildness) were excluded for the subsequent analysis. As a result of repeating the common factor analysis with a Varimax rotation, a three-factor solution was considered the most appropriate, resulting in factors with even explanatory variances of above .20. Based on the three-factor solution, nine adjectives, or three highly loaded adjectives from each of the factors, were selected, as shown in <Table 4>. The total explanatory variance in the factor analysis was 70.3%, and the reliability was higher than 0.80 for all factors. The factors were named in reference to previous research. As 'polite', 'sincere', and 'stable' were extracted from 'ability' factor in previous studies, factor 1 was named 'ability'. Although adjectives in factor 2, composed of 'elegant', 'luxury', and 'refined', were include in the attractiveness factor in previous studies, selected adjectives closed the calm image not the bouncing image. Consequently, factor 2 was named as 'classic'. Factor 3 was consisted of 'conspicuous', 'intense', and 'bold'. As these adjectives belonged to conspicuousness and activity or attractiveness in the previous study, the name of factor 3 was determined to 'novelty'.

Also, reliability analysis was performed for each fac-

Table 4. Results of the common factor analysis

Variable	Factor			Cronbach's α
	Ability	Classic	Novelty	
Polite	0.86			.89
Sincere	0.84			
Stable	0.82			
Elegant		0.81		.88
Luxury		0.78		
Refined		0.75		
Conspicuous			0.81	.85
Intense			0.80	
Bold			0.73	
Explained variance (%)	24.8	22.9	22.6	
Accumulate explained variance (%)	24.8	47.7	70.3	

tor to calculate Cronbach's alpha coefficient. The internal consistency of the factors was confirmed by analyzing the correlation between the questions, as shown in <Table 5>. Each item belonging to the same factor had a higher correlation than .60. Although, the correlations between the 'ability' items and the 'classic' items, and between the 'ability' items and the 'novelty' items were significant, the correlation scores were generally not higher than .40.

The purpose of factor analysis was to reduce the number of measurement items to manageable numbers, while maintaining the conceptual structure of the construct. Therefore, even though three factors were identified through factor analysis, the nine measurement items were used for subsequent analysis, not the factors.

2. Study 2

In this study, the researchers constructed a model to predict consumer preference (dichotomous scale, prefer (1)/not prefer (0)) using FFNN. The scores measured on the self-image and product image scales for each adjective were normalized. As neural networks can enter more variables than other statistical analyses, all adjectives which were selected in the study 1 were fed into neural networks, not the factors. Also, the nominal variables were changed to one-hot encoding. In order to improve the performance, the PPMPI was used for the active function, Relu, at the input layer and hidden layers because the PPMPI had many nodes in each layer. Also, the Softmax function that was appropriate for the classification was used at the output layer. A total of three hidden layers were formed and five nodes were created for all hidden layers. The batch size was 100, the learning rate was 0.01, and the training epoch was 50. To minimize the loss, the Adam Optimizer function in TensorFlow 2.0 was used. For training and validating, this study used the k-fold function in the Scikit-learn package. In this study, 4-fold cross-validation was performed in order to train and validate the data, as shown in <Table 6>.

The PPMPI was trained and validated with 9,800 data items, which consisted of the input variables (the product image using nine semantic scales) and the output variables (the preferences for 20 apparel items). To verify the model based on the premise that consumers prefer clothing similar to themselves, the self-images of the 490 respondents were used as test data in the trained model, PPMPI. The test data involving the self-image and the number of items comprised ID 1 to 25 allocated to item 1 and its preferences, ID 26 to 50 allocated to item 2 and its preferences, and ID 51 to 75 allocated to items 3 and items in order. Twenty-five subjects were assigned to items 1 to 10 and 24 subjects were assigned to items 11 to 20, as shown in <Table 7>. The prediction accuracy rate of PPMPI was calculated

Table 5. Results of the intercorrelation analysis

	1. Polite	2. Sincere	3. Stable	4. Elegant	5. Luxury	6. Refined	7. Conspicuous	8. Intense	9. Bold
1. Polite	1.00								
2. Sincere	.74***	1.00							
3. Stable	.72***	.70***	1.00						
4. Elegant	.30***	.37***	.25***	1.00					
5. Luxury	.14	.22**	.15*	.72***	1.00				
6. Refined	.31***	.36***	.29***	.73***	.67***	1.00			
7. Conspicuous	−.07	.05	−.04	.42***	.42***	.37***	1.00		
8. Intense	−.08	.07	−.02	.35***	.33***	.33***	.69***	1.00	
9. Bold	−.06	.07	−.04	.39***	.38***	.33***	.66***	.62***	1.00

*p<.05, **p<.01, ***p<.001
1, 2, 3 included in the factor 'ability', 4, 5, 6 included in the factor 'classic', and 7, 8, 9 included in the factor 'novelty'

Table 6. Example of training and validation data set

Structure	ID	Item no.	Normalized product image value									
			A	B	C	D	E	F	G	H	I	Y
Training (75%) & validation (25%) data (*N*=9,800)	1	1	0.25	0	0.25	0.25	0	0.25	0.25	0.25	0	0
	2	1	0.25	0.25	0.25	0.50	0.25	0	0.50	0.75	0	0
	3	1	0.25	0.25	0.25	0.50	0	0	0.25	0.50	0.50	0
	…	…	…	…	…	…	…	…	…	…	…	…
	490	1	0.25	0.25	0.25	0.75	0.75	0.5	0.75	0.75	0.50	0
	1	2	0	0	0	0	0	0	0	0	0	0
	2	2	0.50	0.50	0.50	0.75	0.50	0.50	0.50	0.25	0.50	1
	3	2	0.25	0.75	0.75	0.50	0	0.25	0	0.25	0.50	1
	…	…	…	…	…	…	…	…	…	…	…	…
	490	2	0.25	0.50	0.50	0.25	0.50	0.25	0.25	0.25	0.50	1
	…	…	…	…	…	…	…	…	…	…	…	…
	1	20	0.75	0.50	0.50	0.75	0.25	0.75	0.50	0.25	0.75	1
	2	20	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	1
	3	20	0.75	0.75	0.75	0.50	0.50	0.50	0.25	0.25	0.75	1
	…	…	…	…	…	…	…	…	…	…	…	…
	490	20	0.50	0.75	0.75	0.50	0.25	0.50	0.50	0.50	0.75	1

A is elegant, B is stable, C is sincere, D is refined, E is intense, F is luxury, G is bold, H is conspicuous, and I is polite.
Y is a dependent variable, preference; preference '0' means 'not prefer' and '1' means 'prefer'.

Table 7. Example of test data set

Structure	ID	Item no.	Normalized self-image value								
			A	B	C	D	E	F	G	H	I
Test data (*N*=490)	1	1	0.50	0.50	0.75	0.50	0.25	0.50	0.25	0.25	0.75
	2	1	0.50	0.50	0.50	0.50	0.25	0.25	0.25	0.50	1.00
	...	...	...	...	...	...	...	...	...	...	...
	25	1	0.50	0.75	0.75	0.75	0.50	0.50	0.50	0.50	0.50
	26	2	1.00	0.50	0.75	0.75	0.75	1.00	1.00	0.00	1.00
	27	2	1.00	0.75	0.50	0.75	0.50	1.00	0.75	0.50	1.00
	...	...	...	...	...	...	...	...	...	...	...
	50	2	0.50	0.75	0.50	0.50	0.25	0.25	0.00	0.25	0.75
	...	...	...	...	...	...	...	...	...	...	...
	466	20	0.50	0.50	0.75	0.75	0.50	0.25	0.25	0.50	0.50
	467	20	0.75	0.75	0.75	1.00	0.50	0.50	0.25	0.50	0.25
	...	...	...	...	...	...	...	...	...	...	...
	490	20	0.50	0.75	0.75	0.50	0.50	0.50	0.50	0.25	0.50

A is elegant, B is stable, C is sincere, D is refined, E is intense, F is luxury, G is bold, H is conspicuous, and I is polite.

by applying the activation function, i.e., the Relu function to the input layer and hidden layers and Softmax function to the output layer. The calculated accuracy rate for PPMPI model was 83.7% (cost = 0.38). This result means that PPMPI could predict product's preference with a high accuracy when the product image was fed as input data. Also, the cost value, which is obtainable through Adam Optimizer function in TensorFlow is important in interpreting the model. The low value of cost means that the correct answer is less likely to be wrong (Saito, 2016/2017). Consequently, the probability of the false output of the PPMPI is low (Saito, 2016/2017), as the cost value was 0.38.

In the field of science and technology, it is common to examine the satisfaction of the recommend system built by machine learning with new subjects after establishing a system. In this case, the recommend system is considered satisfactory. However, the purpose of this study was to confirm the viability of recommendation system of PPMPI model, which was developed based on the self-product congruence theory rather than to evaluate the recommendation system. Therefore, to validate the power of the PPMPI, a product's preference calculated through the PPMPI was compared with the actual preference, as shown in <Table 8>. The actual preference was measured by asking participants to evaluate each product (from item 1 to item 20) on dichotomous scales (‘prefer’ coded as ‘1’, and ‘not prefer’ coded as ‘0’). The predicted preference was computed on the FFNN using the test data. The matched ratio is the proportion of how the actual preference is coincidence to the predicted preference. As a result of the ana-

Table 8. Matched ratio between actual preference and predicted preference

Item no.	Actual preference	Predicted preference	Matched ratio	Item no.	Actual preference	Predicted preference	Matched ratio
1	0	0	72.0%	2	0	1	36.0%
	0	0			0	1	
	0	0			0	1	
	…	…			…	…	
3	0	1	32.0%	4	1	1	76.0%
	0	1			1	0	
	1	1			1	1	
	…	…			…	…	
5	0	1	44.0%	6	1	1	52.0%
	0	1			1	1	
	0	0			0	0	
	…	…			…	…	
7	0	1	36.0%	8	0	1	56.0%
	0	0			1	1	
	0	1			1	1	
	…	…			…	…	
9	1	0	36.0%	10	0	0	52.0%
	0	1			1	1	
	0	1			1	1	
	…	…			…	…	

‘Not prefer’ coded as ‘0’, and ‘prefer’ coded as ‘1’

Table 8. Continued

Item no.	Actual preference	Predicted preference	Matched ratio	Item no.	Actual preference	Predicted preference	Matched ratio
11	0	1	54.2%	12	1	1	54.2%
	0	1			0	0	
	1	0			1	0	
	…	…			…	…	
13	0	1	33.3%	14	0	1	33.3%
	0	1			0	1	
	1	1			0	1	
	…	…			…	…	
15	0	1	29.2%	16	1	1	33.3%
	0	1			0	1	
	0	0			0	0	
	…	…			…	…	
17	1	0	75.0%	18	1	1	79.2%
	0	0			0	0	
	1	1			0	0	
	…	…			…	…	
19	0	1	62.5%	20	0	1	66.7%
	1	1			1	1	
	0	1			0	1	
	…	…			…	…	
Total matched ratio				50.6%			

'Not prefer' coded as '0', and 'prefer' coded as '1'

lysis, the total matched ratio between the predicted and measured preferences was 50.6%. As a result of confirming the preferred prediction accuracy for each item, the accuracies of items #1, #4, #17, #18, #19, and #20 were higher than 60%. Also, the accuracies of items #5, #6, #8, #10, #11 and #12 were over 40%. On the other hand, the accuracies of items #2, #3, #7, #9, #13, #14, #15, and #16 were found to be less than 40%. The PPMPI test showed that the prediction rate differed depending on the product attributes. In the case of work apparel with normative images, the prediction rate was over 70% and higher than for other apparel.

V. Conclusion

This study attempted to predict the consumer preference for clothing products based on the congruence between the self-image and the clothing product image. To this end, the self-image was explained as a situational product-expressive self-image that is expressed by clothing in a work situation. Hence, the PPMPI presented in the study is a model in which the product image is used for training and the self-image is used for testing; that is, the recommended product image was tested against the self-image in a model that was trained by the product images of 20 outfits and their measured preferences.

For this purpose, the research was conducted in two steps. In the first study, a short version of the scale for the measurement of both the self-image and the product image was developed. The preferred self-image in the workplace was composed of three dimensions with high

-loaded variance: ability, classic, and novelty. Three adjective scales, 'polite', 'sincere', and 'stable', were considered in the factor 'ability', another three adjective scales, 'elegant', 'refined', and 'luxury', were considered in the factor 'classic', and another three adjective scales, 'intense', 'bold', and 'conspicuous', were considered in the factor 'novelty'. Therefore, in study 1, through common factor analysis, a short semantic scale with nine adjective items was extracted.

Study 2 involved the verification of the model. In this study, the short scale developed from study 1 was used to collect a new set of data for training and testing the model. The data were used to predict consumer preferences using FFNN, which was one of the artificial intelligence analyses. Initially, the preference was measured on a 5-Likert scale. However, the prediction accuracy rate was higher when the scale was switched to 'prefer (coded as 1)' or 'not prefer (coded as 0)' compared to the original measured scale. The training data set was constructed with the product image and its preference on 20 stimuli, and the test data set was constructed with the self-image and each allocated product stimuli. Subsequently, the PPMPI printed out the predicted preference for each allocated product as a result of FFNN. The prediction accuracy rate of the PPMPI was over 80%. The test of the PPMPI showed that the prediction rate differed depending on the product attributes. In the case of work apparel with normative images, the prediction rate was over 70% and was higher than for other apparel.

The model for predicting consumer preference, PPMPI, proposed in this study is based on theories of social science. Future technological studies related to clothing recommender systems could provide theoretical implications using the model and measurement variables of this study.

This study has several implications, both academic and practical. In terms of the academic implication, first, this study presents a model of a recommender system based on social science (psychological) variables. In the prior research based on technology, the values of some variables, such as words expressing the situation, were manipulated to ease the calculation by the recommender system (Shen et al., 2007), but the choice of such words was rather arbitrary and was not justified on a theoretical basis. In other studies, the clothing recommendation system used the physical factors of consumers and products, not their psychological factors (Kim, 2009; Zhang et al., 2019). Hence, the current study makes a contribution in that it enhances the interest in psychological factors in the field of artificial intelligence. In other words, this study suggests that using consumers' psychological or motivational factors, and not only the similarity data alone, for preference prediction may help improve the performance of artificial intelligence.

Second, the model has a high predictive ratio and can predict the preferences for various products. Most recommender systems provide recommendations that are similar to a product that was positively evaluated by a consumer in the past or recommend commonly preferred products that were selected by other consumers who show a similar tendency (Deshpande & Karypis, 2004; Ekstrand et al., 2011). Therefore, the recommended product may not go beyond what the system considers to be commonly preferred. However, the PPMPI can recommend various products that have product images that are similar to the consumer's self-image, even for the consumers with a very unique self-image and a preference for unique items.

Third, the PPMPI shows that the substitute method can explain the self-product congruence. In previous studies, the difference value between the self-image and the product image was used, or the consumer measured how much they matched the product. This direct replacement method can offer the possibility to attempt new methods of analysis. In addition, the analysis method using Python and TensorFlow can be directly applied in business practices because the result can be outputted and applied immediately.

The limitations of this study and the suggestions for future studies are as follows. First, this study was performed with Korean male office workers, with a focus on outfits to be worn in the workplace. The self-congruity model may need to be tested assuming different situations. Hence, future research may extend the scope

to varied situations, such as 'when going on a picnic', 'when meeting a significant other', and so on. Furthermore, female consumers or other subculture groups may be investigated using various types of clothing. This will allow for an understanding of the reasons for the preferences and enable further generalizations of the model. More factors related to the clothing preference at the workplace, such as the type of occupation, the level of salary or personal values, would also foster more diverse recommendations for consumers. Second, for the analysis, the current research implements the neural network method, which is the most commonly used form of artificial intelligence. More complicated and elaborate functions may be considered to improve the accuracy between the predicted preference and the estimated preference. Considering multiple variables as input variables would enable a more precise prediction. Consumers' self-image or clothing preferences may differ according to their situation. Accordingly, the short version of the semantic scale extracted in study 1 would need to be tested for its robustness for different samples and in different wearing situations. Finally, the matched ratio between predicted preference and actual preference was relatively low. This study focused on self-product image congruence in order to explore the viability of this psychological model, in the future research, it is recommended to increase the matching ratio by combining other factors such as color or shape, along with the psychological factors.

References

Adam, H., & Galinsky, A. D. (2012). Enclothed cognition. *Journal of Experimental Social Psychology*, *48*(4), 918-925. doi:10.1016/j.jesp.2012.02.008

Bae, H. J., & Chung, I. H. (2006). The desired self-images and the fashion product unities of male college students according to situation. *Journal of the Korean Society of Clothing and Textiles*, *30*(7), 1135-1145.

Benson, P. L., Karabenick, S. A., & Lerner, R. M. (1976). Pretty pleases: The effects of physical attractiveness, race, and sex on receiving help. *Journal of Experimental Social Psychology*, *12*(5), 409-415. doi:10.1016/0022-1031(76)90073-1

Choi, H.-M., Kim, N.-M., Lee, M.-K., & Kim, H.-R. (2007). Effects of the congruity between product personality and consumer self-image on the perceived design value and product attachment. *Korea Journal of Business Administration*, *20*(1), 265-288.

Chung, I. H. (2016). Effect of self-image congruence, clothing preference and reference price on payment intention price. *Journal of the Korean Society of Clothing and Textiles*, *40*(1), 148-157. doi:10.5850/JKSCT.2016.40.1.148

Deshpande, M., & Karypis, G. (2004). Item-based top-*N* recommendation algorithms. *ACM Transactions on Information Systems*, *22*(1), 143-177. doi:10.1145/963770.963776

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends® in Human-Computer Interaction*, *4*(2), 81-173. doi:10.1561/1100000009

Govers, P. C. M., & Schoormans, J. P. L. (2005). Product personality and its influence on consumer preference. *Journal of Consumer Marketing*, *22*(4), 189-197. doi:10.1108/07363760510605308

Hong, W.-E., Hong, J.-W., & Kwak, Y.-S. (2008). The development for internet ad copy image adjective for computer and IT industries by network analysis. *Korean Corporation Management Review*, *15*(2), 127-141.

Hong, Y. J., & Kim, Y. I. (2015). Preferred fashion style based on the men's self-image including fashion involved circumstances. *Journal of the Korean Society of Costume*, *65*(8), 1-21. doi:10.7233/jksc.2015.65.8.001

Johar, J. S., & Sirgy, M. J. (1991). Value-expressive versus utilitarian advertising appeals: When and why to use which appeal. *Journal of Advertising*, *20*(3), 23-33. doi:10.1080/00913367.1991.10673345

Jordan, P. W. (2003). *Designing pleasurable products: An introduction to the new human factors*. London: CRC Press.

Kang, M., Sklar, M., & Johnson, K. K. P. (2011). Men at work: using dress to communicate identities. *Journal of Fashion Marketing and Management*, *15*(4), 412-427. doi:10.1108/13612021111169924

Katsov, I. (2019). *Introduction to algorithmic marketing* (J. H. Cho, Trans.). Seoul: acorn publishing Co. (Original work published 2017)

Kemper, C. J., Trapp, S., Kathmann, N., Samuel, D. B., & Ziegler, M. (2019). Short versus long scales in clinical assessment: Exploring the trade-off between resources saved and psychometric quality lost using two measures of obsessive-compulsive symptoms. *Assessment*, *26*(5), 767-782. doi:10.1177/1073191118810057

Kim, J.-I. (2009). A recommendation method of similar clothes on intelligent fashion coordination system. *Journal of Korea Multimedia Society*, *12*(5), 688-698.

Kim, K.-W., & Park, D.-H. (2018). Emoticon by emotions: The

development of an emoticon recommendation system based on consumer emotions. *Journal of Intelligence and Information Systems*, *24*(1), 227-252. doi:10.13088/jiis.2018.24.1.227

Kim, M. J. (2012). Performance comparison of internal accounting control assessment models applying logistic regression and neural networks. *Korea International Accounting Review*, *46*, 1-30. doi:10.21073/kiar.2012..46.001

Lee, I., & Kim, S.-H. (2016). The effect of popularity cue on purchase intention: The moderating role of product types and self-brand connection with perceived similarity as a mediating role. *Journal of Consumer Studies*, *27*(1), 1-25.

Malhotra, N. K. (1981). A scale to measure self-concepts, person concepts, and product concepts. *Journal of Marketing Research*, *18*(4), 456-464. doi:10.1177/002224378101800407

Meneely, J., & Portillo, M. (2005). The adaptable mind in design: Relating personality, cognitive style, and creative performance. *Creativity Research Journal*, *17*(2-3), 155-166. doi:10.1080/10400419.2005.9651476

Peluchette, J. V., Karl, K., & Rust, K. (2006). Dressing to impress: Beliefs and attitudes regarding workplace attire. *Journal of Business and Psychology*, *21*(1), 45-63. doi:10.1007/s10869-005-9022-1

Rhee, E.-Y. (2007). *Fashion marketing* (2nd ed.). Paju: Gyomoon Publishers.

Saito, G. (2017). *Deep learning from scratch* (Gaeapmaebsi, Trans.). Seoul: Hanbit Media. (Original work published 2016)

Shen, E., Lieberman, H., & Lam, F. (2007). What am I gonna wear?: Scenario-oriented recommendation. *Proceedings of the 12th International Conference on Intelligent User Interfaces*, *USA*, 365-368. doi:10.1145/1216295.1216368

Sirgy, M. J. (1982). Self-concept in consumer behavior: A critical review. *Journal of Consumer Research*, *9*(3), 287-300. doi:10.1086/208924

Sirgy, M. J. (2015). Self-image/product-image congruity and advertising strategy. In V. Kothari, D. R. Arnold, T. Cavusgil, J. D. Lindquist, J. Nathan, & S. Reid (Eds.), *Proceedings of the 1982 Academy of Marketing Science (AMS) Annual Conferenc* (pp. 129-133). Cham: Springer.

Sirgy, M. J., & Danes, J. E. (1982). Self-image/product-image congruence models: Testing selected models. In A. Mitchell (Ed.), *NA - Advances in Consumer Research*, *Vol. 9* (pp. 556-561). Ann Arbor, MI: Association for Consumer Research.

Son, E.-Y. (2009). *A study on clothing preference images and factors affecting the decision-making processes of casual wear by lifestyle types of the middle-aged male* (Unpublished master's thesis). Yonsei University, Seoul.

West, S. G., & Brown, T. J. (1975). Physical attractiveness, the severity of the emergency and helping: A field experiment and interpersonal simulation. *Journal of Experimental Social Psychology*, *11*(6), 531-538. doi:10.1016/0022-1031(75)90004-9

Yoo, H. (2010). *The professional image and strategic appearance management in workplace* (Unpublished doctoral dissertation). The Catholic University of Korea, Bucheon.

Zaccone, G., & Karim, M. R. (2018). *Deep learning with TensorFlow: Explore neural networks and build intelligent systems with Python* (2nd ed.). Birmingham: Packt Publishing.

Zeng, X., Koehl, L., Wang, L., & Chen, Y. (2013). An intelligent recommender system for personalized fashion design. *Proceedings of 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS)*, *Canada*, 760-765. doi:10.1109/IFSA-NAFIPS.2013.6608496

Zhang, J., Liu, K., Dong, M., Yuan, H., Zhu, C., & Zeng, X. (2019). An intelligent garment recommendation system based on fuzzy techniques. *The Journal of The Textile Institute*. doi:10.1080/00405000.2019.1694351

Joo Hee Kang

Research Professor, Research Institute of Human Ecology, Korea University

Yoon-Jung Lee

Professor, Dept. of Home Economics Education, Korea University