Using Fuzzy Automata to Develop An Integrated Model for Personal Involvement in Advertising

Ting-Yu Chen and Hsiao-Pin Wang

Abstract

Because of the reason that the individuals' thoughts have the complicated and uncertain characteristics in the field of social science, this study makes the most of the fuzzy sets, which solve uncertain and imprecise conditions, to transform the opinions belonging to human beings into the quantitative numbers. Advertising involvement is regarded as the object for this empirical study which comprehensively collects plenty of antecedents and consequences for advertising involvement. We take advantage of the fuzzy automata to develop an integrated model of advertising involvement. The results indicate that in addition to the selection of implications, a fitting model relies on the selection of compositions in the fuzzy automata. On the average, the standard composition, which is one of compositions in this study, is the most appropriate method for developing a model of advertising involvement.

Keywords: Fuzzy set, Advertising involvement, Fuzzy automata, Implication, Composition.

1. Introduction

Traditionally, scientists consider that "uncertainty" is undesirable in science and should be avoided by all possible means. Zadeh [43] proposed fuzzy set theory which differed from crisp sets to calculate the "uncertainty". In the fuzzy sets (FSs), uncertainty is regarded crucial to science. FSs are not only an ineluctable plague, but also have a great utility and solve imprecise conditions. There are plenty of applications in the FSs, such as decision-making [31], quality control [38], medical diagnosis [3]. However, few studies take advantage of FSs in the marketing field for the time being. Consumers' involvement is one of the most important topics in the marketing research. Owing to manifestation of salient effects on previous studies in other filed, we anticipate making the most of FSs to apply to involvement.

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Involvement plays a crucial role in the field of consumer behavior and is often regarded as an important variable in marketing strategy [5]. In the past decades, involvement has been developed in a great number of types. Due to the diverse name and definition of involvement, some scholars classified it. Houston and Rothschild [14] categorized the concept of involvement to be three types: situational involvement, enduring involvement, and response involvement. Zaichkowsky [45] divided involvement into three different types: product involvement, advertising involvement, and purchasing involvement. As far as marketing is concerned, advertising involvement is widely used. It is because all products are in need of being advertised when going on sale. Businesses care about the consumer's reaction after a consumer watches the advertisement. Generally speaking, a consumer who will accept the advertising message actively or passively depends on the degree to which he or she is involved in the advertisement [18]. Andrews et al. [2] proposed that consumers with high advertising involvement have more search and shopping behavior, more complexity of decision process, greater time spent examining alternatives, and greater perceived product attribute differences. Hence, we can realize how vital the advertising involvement is. In addition, the factors which result in different degree of involvement are also essential. If the marketers have a comprehensive acquaintance of causal relationship of advertising involvement, they can plan an appropriate marketing strategy according to the different conditions. However, few studies develop a complete relationship among advertising involvement and its antecedents and consequences.

In the social science, a great amount of studies use statistical method which is in need of discerning the functional relationship among variables. If there are too many variables in a study, the experimental and computing process get more complicated and even are hard to be executed. Nevertheless, the automata have the merits of dealing with a great number of variables and solving the difficult calculation at the same time. Furthermore, the automata transform sequences of input state into sequences of output state. The transformation is accomplished by a dynamically changing internal state. The internal states, which are a dynamic situation, not only determine the output states at the current time, but also have the ability of storage to be used at the next time.

The entire process of this machine is similar to an individual's involvement development because involvement is a concept of continuity that the current involvement state would affect the next involvement state. In this machine, the antecedents of advertising involvement can be regarded as input states; the subconstruct of advertising involvement as internal states; the consequences of advertising involvement as output states. A state- transition fuzzy relation connects advertising involvement and its antecedents; a response fuzzy relation connects advertising involvement and its consequences. Therefore, it is suitable for us to use automata to develop an integrated advertising involvement model.

In this study, we try to develop a model in the fuzzy automata and generate some operations which can be used in the machines. We anticipate the new method can deal with consumers' advertising involvement state and obtain a model inclusive of antecedents and consequences. With this integrated model, marketing researchers would gain an overall understanding of advertising involvement.

2. Advertising Involvement

A. *Basic Concept*

Advertising involvement has been a central construct in advertising research seeking to explain consumer responses toward advertisements. For instance, Petty and Cacioppo's [29] Elaboration Likelihood Model highlights the influence of elaboration toward the ad message on brand attitude formation. Advertising involvement also has been shown to affect the structural relationships among consumer response (e.g., ad and brand cognitions, ad and brand attitudes) for advertisements (e.g., [25]).

Advertising involvement is an individual level, internal state variable whose motivational properties are evoked by a particular advertising message. That is, advertising involvement can indicate the amount of arousal, interest or drive evoked by an ad message. In general, consumers with high advertising involvement will take initiative in searching and paying attention to advertising messages; consumers with low advertising involvement will passively deal with the advertising messages he receives. Numerous researchers have recently conceptualized involvement with advertising as an internal state of arousal based on intensity, persistence, and direction [2], [23], [26]. The construct of involvement has emerged as an important factor in studying the effectiveness of advertising. In numerous studies such as Krugman [18], Wright [41], Rothschild and Ray [33], Petty and Cacioppo [29], Petty et al. [30], involvement generally refers to a mediating variable in determining if the advertisement is effectively relevant to the receiver.

Involvement is difficult to be observed or measured directly. As a consequence, we need other variables to conjecture the degree of involvement. There are two ways to measure involvement. One is unidimensional construct, and the other is multidimensional construct. However, Rothschild [32] considered that unidimensional construct would not account for the level of involvement comprehensively. Thus, multidimensional construct is recommended. Zaichkowsky [44] constructed a context-free 20 item scale named the Personal Involvement Inventory (PII). Later, Zaichkowsky [46] revised the PII and demonstrated that one could use the scale to measure involvement with advertising. The revised PII consisting of affective and cognitive subscales is called RPII and reliably reduced to 10 scale items. Other scales like Wells' Reaction Profile [39] and Schlinger's View Response Profile [35] have been commonly used to measure consumer response to advertising. Wells' Reaction Profile is measured on 8-point, bipolar scales with 26 items and breaks into three major factors named attractiveness, meaningfulness, and vitality. Schlinger's View Response Profile is measured on Likert 7-point with 18 items and breaks into four major factors named entertainment, confusion, relevant news, and brand reinforcement.

We reviewed a great amount of studies and collected the antecedents affecting advertising involvement and consequences affected by advertising involvement in order to develop a complete model for advertising involvement. As to advertising involvement, we tried using different advertising involvement scales for understanding which one of them was the most appropriate in the fuzzy automata. Three advertising involvement scales were presented. Zaichkowsky's RPII [46], Wells' Reaction Profile [39], and Schlinger's View Response Profile [34] will be used to measure consumers' responses to the ads.

B. *Antecedents for Advertising Involvement*

Zaichkowsky [45] based on prior studies pertaining to advertising involvement to propose a conceptualizing framework for the antecedents of advertising involvement. According to this framework, the antecedents of advertising involvement can be generalized three factors which are personal factor, stimulus factor, and situational factor. Hence, we categorize the antecedents collected from the literature into these three types.

The first type is personal factor. Laurent and Kapferer [22] used five antecedents of involvement to construct the Consumer Involvement Profiles (CIP). The five antecedents were interest, pleasure, sign, risk probability, and risk Importance. They considered the nature of involvement was affected by the five antecedents. Andrews et al. [2] pointed out that Need for cognition would affect advertising involvement because individuals with a high need for cognition tended to perceive more messages and had a high intrinsic motivation to process messages in the ads. Gotlieb and Sarel [12] proposed that when the communicator in the advertisement had higher credibility, a higher level of advertising involvement would be activated than when the message was communicated by a source of lower credibility. Laczniak et al. [20] manifested that individuals' product knowledge and product involvement would contribute significantly to receivers' ultimate levels of advertising involvement. Lee [23] proposed that if individuals had expectancy for the ads, they would elicit more advertising involvement.

The second type is stimulus factor. Krugman [18] hypothesized that media may differ in the inherent levels of advertising involvement they create, with print media stimulating relatively greater involvement than television. Wright [42] considered that regarding mass media communication, audio transmissions typically differ from print transmissions in the information load forced on the receiver. Audio transmission is temporal in nature, and the rate of transmission is usually beyond the receiver's control. Print is spatial, and exposure rate is usually controlled by the receiver. However, some investigators have argued that television is a more involving medium than is print [40]. Tyebjee [37] suggested that advertisers may consider a number of operational variables such as the type of media, the degree of repetition, the length of the message, the tone of the message, and quantities of information. Muehling et al. [28] manifested that individuals watching comparative ads would elicit high levels of advertising involvement than watching noncomparative ads.

The third type is situational factor. Zaichkowsky [46] proposed a conceptualization that the purchase importance and occasion were considered as the antecedent for the advertising involvement. Howard and Kerin [15] based on Zaichkowsky's study [44] and suggested that people who were shopping for a product were highly involved with information in an advertisement for that product.

C. *Consequences for Advertising Involvement*

Wright [42] hypothesized that advertising involvement would affect attitudinal acceptance while the results didn't support his hypothesis. Laczniak et al. [21], and Andrews and Durvasula [1] manifested that individuals under high advertising involvement would generate more message-related cognitive response. Petty et al. [30], Gardner et al. [11], Andrews and Durvasula [1], and Laczniak et al. [20] proposed that individuals under high advertising involvement would elicit more recall for the ads they read. Laczniak et al. [21] proposed that individuals under high advertising involvement would generate more message attention and execute a brand evaluation; on the contrary, individuals under low advertising involvement would generate less message attention and execute a non-brand evaluation. Laczniak and Muehling [19] proposed that individuals under high advertising involvement would elicit more belief strength and attitude toward the ads.

Figure 1 illustrates the model of advertising involvement we want to develop.

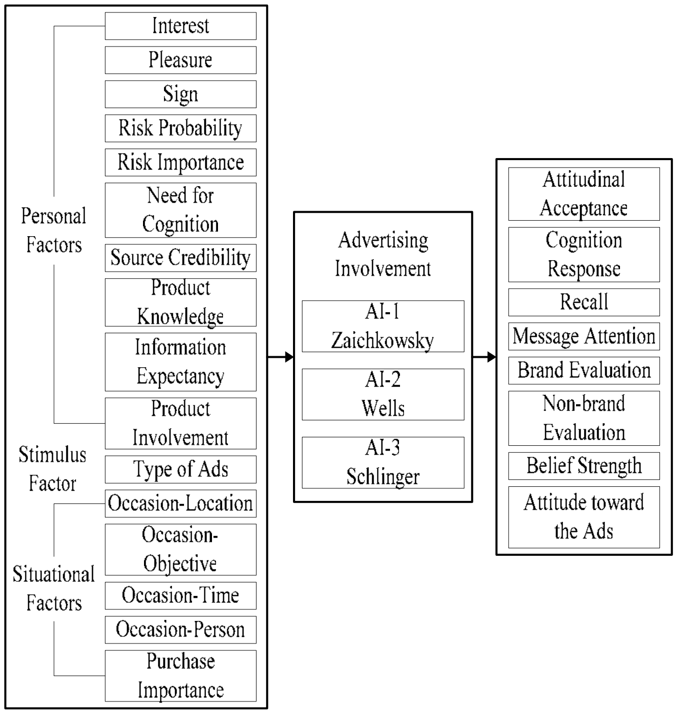

Figure 1. The configuration of antecedents and consequences for the model of advertising involvement.

For some reason, not all of the antecedents for advertising involvement will be processed in our study. It is because we restrict our type of advertisement to a print advertisement. The antecedents used in TV advertisement will be eliminated, including ads repetition, message length, message tone, and information quantity, which are proposed by Tyebjee [37]. Besides the elimination of the inappropriate antecedents, we alter antecedent-occasion because it consists of diverse situation. Schiffman and Kanuk [34] proposed segmentation for occasion, such as occasion-location, occasion-objective, occasion-time and occasion-person. Based on above consideration, we decide that the antecedents for advertising involvement are: Interest, Pleasure, Sign, Risk Probability, Risk Importance, Need for Cognition, Source Credibility, Product Knowledge, Information Expectancy, Type of Ads, Occasion-Location, Occasion-Objective, Occasion-Time, Occasion-Person, Purchase Importance, and Product Involvement. The consequences for advertising involvement are: Attitudinal Acceptance, Cognitive Response, Recall, Message Attention, Brand Evaluation, Non-brand Evaluation Strategy, Belief Strength, and Attitude toward the Ads.

3. Research Methods

A. *Operations for FSs*

Zadeh [43] based on classical sets to proposed fuzzy set (FS) theory. FSs characterized by the degree of membership and non-membership in which the values befall between 0 and 1 process in fuzzy logic. Let *X* denotes the scope of elements. A fuzzy set *A* of a universe *E* of discourse is characterized by a membership function $\mu_A(x)$ associating a real number in the interval $[0,1]$ with each element *x* in *X*, to present the degree of membership of *x* in *A*. If $\mu_A(x)=1$ then *x* belongs to the set *A* completely while if $\mu_A(x)=0$ then *x* does not belongs to set A. We use 4 basic *t*-conorms (fuzzy union) and *t*-norms (fuzzy intersection). 4 *t*-conorms are as follows.

Standard union: $u(a,b)=\max\{a,b\}$, (1)

Algebraic sum: $u(a,b)=a+b-ab$, (2)

Bounded sum: $u(a,b)=\min\{1,a+b\}$, (3)

Drastic union: $u(a,b)=\begin{cases} a & \text{when } b=0, \\ b & \text{when } a=0, \\ 1 & \text{otherwise.} \end{cases}$ (4)

Four *t*-norms are as follows.

Standard intersection: $i(a,b)=\min\{a,b\}$, (5)

Algebraic product: $i(a,b)=ab$, (6)

Bounded difference: $i(a,b)=\max\{0,a+b-1\}$, (7)

Drastic intersection: $i(a,b)=\begin{cases} a & \text{when } b=1, \\ b & \text{when } a=1, \\ 0 & \text{otherwise.} \end{cases}$ (8)

The Hamming Distance between two FSs is defined as follows:

$$d(A,B)=\sum_{i=1}^{n}\left|\mu_A(x_i)-\mu_B(x_i)\right|. \quad (9)$$

B. *Correlation between FSs*

In the FSs, every set can be regarded as a variable and then computed the intensity of the relationship. Chiang and Lin [8] proposed correlation of FSs which based on the concept of mathematical statistics. The correlation coefficient can not only explain the strength of the relationship between two FSs, but tell us the positive or negative direction as well. The equation of correlation coefficient is as follows.

$$r_{A,B}=\frac{\sum_{i=1}^{n}(\mu_A(x_i)-\bar{\mu}_A)(\mu_B(x_i)-\bar{\mu}_B)/(n-1)}{S_A\cdot S_B},$$

where

$$\bar{\mu}_A=\frac{\sum_{i=1}^{n}\mu_A(x_i)}{n} \text{ and } S_A^2=\frac{\sum_{i=1}^{n}(\mu_A(x_i)-\bar{\mu}_A)^2}{n-1}.$$

C. *Implication for FSs*

In the fuzzy automata, the selections of implications and compositions are quite important. It may influence the accountability of the model. The implications and compositions are constructed by fuzzy logic deriving from classical logic of set theory. When two sets are associated with each other and then form a fuzzy relation, we call implication. In classical logic, an implication, $\mathcal{J}$, can be defined in several distinct forms. These forms are equivalent in classical logic, but not equivalent in fuzzy logic. Hence, we have to discuss separately. Here we introduce four kinds of implications as follows.

S-implication: $\mathcal{J}(a,b)=u(c(a),b)$. (10)

R-implication: $\mathcal{J}(a,b)=\sup\{x\in[0,1] \,|\, i(a,x)\le b\}$. (11)

QL1-implication: $\mathcal{J}(a,b)=u[c(a),i(a,b)]$. (12)

QL2-implication: $\mathcal{J}(a,b)=u[i(c(a),c(b)),b]$. (13)

In (10)-(13), we know implication is formed by employing *t*-conorm and *t*-norm. In the last section, we introduced four different *t*-conorms and *t*-norm. As a result, using (1)-(4), S-implication can generate four implicators. Other three implications also can obtain themselves four implicators. That is, sixteen implicators can be used in this study and are presented in Table 1.

Table 1. Fuzzy implicators.

S and R Implication		
Implicator	Equation	
S 1-1	$\max\{1-a,b\}$	(14)
S 1-2	$1-a+ab$	(15)
S 1-3	$\min\{1,1-a+b\}$	(16)
S 1-4	$\begin{cases} b & \text{when } a=1 \\ 1-a & \text{when } b=0 \\ 1 & \text{otherwise} \end{cases}$	(17)
R 1-1	$\begin{cases} 1 & \text{when } a\le b \\ b & \text{when } a>b \end{cases}$	(18)
R 1-2	$\begin{cases} 1 & \text{when } a\le b \\ \frac{b}{a} & \text{when } a>b \end{cases}$	(19)
R 1-3	$\min\{1,1-a+b\}$	(20)

R 1-4	$\begin{cases} b & \text{when } a=1 \\ 1 & \text{otherwise} \end{cases}$	(21)

Table 1. Fuzzy implicators. (Cont.)

Implicator	QL1 and QL2 Implication Equation	
QL 1-1	$\max\{1-a, \min\{a,b\}\}$	(22)
QL 1-2	$1-a+a^2b$	(23)
QL 1-3	$\max\{1-a,b\}$	(24)
QL 1-4	$\begin{cases} b & \text{when } a=1 \\ 1-a & \text{when } a\neq 1, b\neq 1 \\ 1 & \text{when } a\neq 1, b=1 \end{cases}$	(25)
QL 2-1	$\begin{cases} \max(1-b,b) & \text{when } a\leq b \\ \min(1-a,b) & \text{when } a>b \end{cases}$	(26)
QL 2-2	$1-b-a+2ab+b^2-ab^2$	(27)
QL 2-3	$\begin{cases} 1-a & \text{when } a+b\leq 1 \\ b & \text{when } a+b>1 \end{cases}$	(28)
QL 2-4	$\begin{cases} 1 & \text{when } a=0 \\ 1 & \text{when } a\neq 1, b=0 \\ 0 & \text{when } a=0, b=0 \\ b & \text{otherwise} \end{cases}$	(29)

D. *Composition for FSs*

By means of fuzzy implication, two sets associate and become a fuzzy relation. The composition is a combination of a fuzzy set and a fuzzy relation or a combination of two fuzzy relations. We employ sup-*t* composition, where t refers to a *t*-norm, generalized the standard max-min composition and max-$*$ composition [4]. The "$*$" stands for *t*-norm that there are 4 basic types used in this study, such as standard, algebraic, bounded, and drastic intersection which are (5)-(8), respectively. The sup-*t* composition of a fuzzy set $A\in[0,1]$ and a fuzzy relation $K\in[0,1]$, is the fuzzy set given by

$$(K\circ A)(y)=\bigvee_{x\in X} t(A(x),K(x,y))\ \forall y\in Y, \tag{30}$$

where "$\circ$" means composition, "$\vee$" means maximum, and "*t*" means *t*-norm.

E. *Fuzzy Automata*

Fuzzy automata are one of the fuzzy systems in the FSs. The sequences of input states can be transformed into the sequences of output states in terms of this machine in the discrete time [17]. The transformation from input states to output states is supported by a changing internal state in this machine.

Doostfatemeh and Kremer [10] indicated that automata provide a systematic approach and are able to incorporate approximate reasoning into systems which imprecision is one of the intrinsic property, just like the way human brains do. Involvement can be regarded as the internal state in the automata; the antecedent for the involvement can be regarded as the input state; the consequence for the involvement can be regarded as the output state. Thus, it is suitable for us to use automata to develop an integrated advertising involvement model. A finite fuzzy automaton, *A*, is a fuzzy relational system defined by the quintuple

$A=[X,Y,Z,R,S]$,

where *X* is a nonempty finite set of the antecedents for advertising involvement; *Y* is a nonempty finite set of the consequences for advertising involvement; *Z* is a nonempty finite set of subconstruct of advertising involvement; *R* is a fuzzy relation on *Z*×*Y*; *S* is a fuzzy relation on *X*×*Z*×*Z*.

Let $X=\{x_1,x_2,\cdots,x_n\}$, $Y=\{y_1,y_2,\cdots,y_m\}$, $Z=\{z_1,z_2,\cdots,z_q\}$ be initial parameters in the beginning machine, and A^t, B^t, C^t denote the antecedents, consequences, advertising involvement at time *t*, respectively. The scheme of fuzzy automata is illustrated in Figure 2. Given A^t at some time *t*, the C^t can be generated by state-transition fuzzy relation *S*; B^t can be generated by response fuzzy relation *R*.

Given a sequence $A^1, A^2, \cdots$, and initial parameters *Z* of the initial internal state, initial parameters *X* and *Z* constructing fuzzy relations *S* by implicator (14)-(29), and initial parameters *Z* and *Y* constructing fuzzy relation *R* by implicator. (14)-(29) allow us to generate the corresponding sequences $C^1, C^2, \cdots$, and $B^1, B^2, \cdots$.

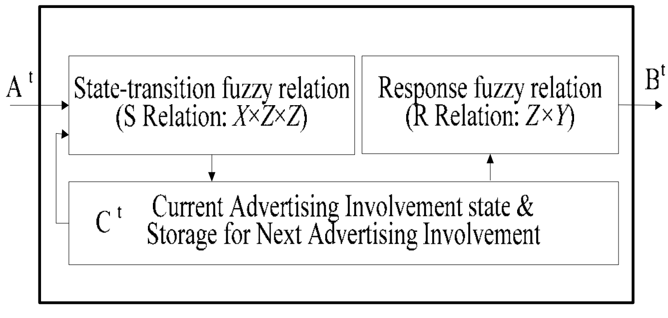

Figure 2. Basic scheme of fuzzy automata.

For any given antecedent A^t, the ternary state-transition relation *S* is converted into a binary relation, S_{A^t}, on *Z*×*Z* by the equation

$$S_{A^t}(z_i,z_j)=\max\{\min\{A^t(x_k),S(x_k,z_i,z_j)\}\}, \tag{31}$$

where degree of membership takes max-min takes max-min and for all pairs $(z_i,z_j)\in Z\times Z$. Then, assuming the present advertising involvement Z is given, the advertising involvement C^t and the consequence

B^t are determined by the compositions (32) and (33), respectively. The way of composition has 4 types, standard, algebraic, bounded, and drastic, in (30).

$$C^t = Z \circ S_{A^1} \circ S_{A^2} \circ \ldots \circ S_{A^t}, \tag{32}$$

$$B^t = C^t \circ R. \tag{33}$$

We state the algorithm for using the fuzzy automata to develop an appropriate integrated model of advertising involvement. The most important parts in the fuzzy automata are the setting of initial data which are regarded as the parameters and form fuzzy relations *S* and *R* inside the initial machine, the selection of implicators, and the selection of compositions. This study tries to look for which one of the initial parameters, implicators, and compositions has the best effects for developing a model of advertising involvement. Note that the iteration number is designated as 3000 times because of trial and error results from preliminary simulation data. The proposed algorithm is as follows.

Step 1. Randomly divide samples into 10 groups which have equal number of subjects.

Step 2. Use random numbers to generate the initial parameters inside the initial fuzzy automata.

The initial antecedents:

$X = \{x_1, x_2, \ldots, x_i \mid x_i \in [0,1]\}$.

The initial consequences:

$Y = \{y_1, y_2, \ldots, y_j \mid y_j \in [0,1]\}$.

The initial advertising involvement:

$Z = \{z_1, z_2, \ldots, z_k \mid z_k \in [0,1]\}$.

Step 3. Use initial parameters *X* and *Z* to generate fuzzy relation *S* and use initial parameters *Y* and *Z* to generate fuzzy relation *R* by (14)-(29).

Step 4. Put in the subjects' antecedent state, A^t, and use (31) to obtain S_{A^t}.

Step 5. Use (30) and (32) to generate subjects' advertising involvement state, E^t.

Step 6. Use (30) and (33) to generate subjects' consequent state, B^t.

Step 7. Use (9) to compute each subject's deviation between real values investigated from subjects and predicted values generated from this machine for the advertising involvement state and the consequent state.

Step 8. Compute an average of deviations, which have the number of *j* + *k*, for each subject.

Step 9. Execute from Step 2 to Step 8 for 3000 times.

Step 10. Choose the initial parameters which can generate the smallest deviations for each 10 groups out of 3000 times.

Step 11. Use one-way ANOVA to have a mean test on the average deviations for each 10 groups. If there is a significant difference in the average deviations for each 10 groups, execute from Step 2 to Step 11 until what there is no significant difference.

Step 12. Take the minimum average of deviations among 10 groups to be the best result under specific initial parameters, implicator, and composition.

F. *Numerical Illustration*

This numerical example wants to demonstrate a process of developing a model of advertising involvement by means of the fuzzy automata.

Assume that in the beginning, there are 4 antecedents of advertising involvement, 3 subconstructs of Wells' advertising involvement, and 2 consequences of advertising involvement with initial parameters in $[0,1]$ from random numbers:

$X = \{(x_1 : \text{Interest}, 0.2), (x_2 : \text{Pleasure}, 0.5),$
$(x_3 : \text{Sign}, 0.4), (x_4 : \text{Product Knowledge}, 0.3)\},$
$Y = \{(y_1 : \text{Message Attention}, 0.4), (y_2 : \text{Recall}, 0.3)\},$
$Z = \{(z_1 : \text{Meaningfulness}, 0.5),$
$(z_2 : \text{Attractiveness}, 0.6), (z_3 : \text{Vitality}, 0.2)\},$

where (x_1: Interest, 0.2) represents the degree to which an individual is interested in the specific object is 0.2. Now, use the initial parameters generated with random numbers to construct the state-transition fuzzy relation and response fuzzy relation by implicator. Assume the following implicator is used in (16) which is one of 16 implicators.

$\mathcal{J} = (a,b) = \min\{1, 1 - a + b\}$.

Then, we obtain a matrix for *R* relation

$$R = \begin{array}{c} \\ z_1 \\ z_2 \\ z_3 \end{array} \begin{array}{c} \begin{array}{cc} y_1 & y_2 \end{array} \\ \begin{bmatrix} 0.9 & 0.8 \\ 0.8 & 0.7 \\ 1.0 & 1.0 \end{bmatrix} \end{array},$$

where

$z_1 \times y_1 = \min\{1, 1 - 0.5 + 0.4\} = 0.9$,

and the three-dimensional array

$$S=\left[\begin{array}{cc} \begin{array}{c} x_1 \\ \begin{array}{c|ccc} & z_1 & z_2 & z_3 \\ z_1 & 0.5 & 0.6 & 0.2 \\ z_2 & 0.5 & 0.6 & 0.2 \\ z_3 & 0.5 & 0.6 & 0.2 \end{array} \end{array} & \begin{array}{c} x_2 \\ \begin{array}{c|ccc} & z_1 & z_2 & z_3 \\ z_1 & 0.5 & 0.6 & 0.2 \\ z_2 & 0.5 & 0.6 & 0.2 \\ z_3 & (0.8 & 0.9 & 0.5 \end{array} \end{array} \\ \begin{array}{c} x_3 \\ \begin{array}{c|ccc} & z_1 & z_2 & z_3 \\ z_1 & 0.5 & 0.6 & 0.2 \\ z_2 & 0.5 & 0.6 & 0.2 \\ z_3 & 0.7 & 0.8 & 0.4 \end{array} \end{array} & \begin{array}{c} x_4 \\ \begin{array}{c|ccc} & z_1 & z_2 & z_3 \\ z_1 & 0.5 & 0.6 & 0.2 \\ z_2 & 0.5 & 0.6 & 0.2 \\ z_3 & 0.6 & 0.7 & 0.3 \end{array} \end{array} \end{array}\right]$$

where

$x_1 \times z_1 \times z_1 = \min\{1, 1-0.2+0.5\} \times z_1$

$= 1 \times z_1 = \min\{1, 1-1+0.5\} = 0.5.$

Assume that an individual's antecedent states of advertising involvement are as follows.

$A^1 = \{(x_1, 0.3), (x_2, 0.4), (x_3, 0.6), (x_4, 0.5)\}.$

And the ternary state-transition fuzzy relation S is converted into a binary relation, S_{A^1} by (31), where

$S_{A^1} = (z_1, z_2) = \max\{\min\{0.3, 0.5\}, \min\{0.4, 0.5\},$

$\min\{0.6, 0.5\}, \min\{0.6, 0.5\}\} = 0.5.$

Use (30) and (32) to compute C^1 and use (30) and (33) to compute B^1. Assume that we select the algebraic composition.

$$C^1 = \begin{bmatrix} 0.5 & 0.6 & 0.2 \end{bmatrix} \circ \begin{bmatrix} 0.5 & 0.6 & 0.2 \\ 0.5 & 0.6 & 0.2 \\ 0.6 & 0.6 & 0.4 \end{bmatrix} = \begin{bmatrix} 0.30 & 0.36 & 0.12 \end{bmatrix},$$

where the degree of the first subconstruct of advertising involvement is 0.30 calculated as follows.

$\max\{0.5 * 0.5, 0.6 * 0.5, 0.2 * 0.6\}$

$= \max\{0.25, 0.30, 0.12\} = 0.30.$

$$B^1 = \begin{bmatrix} 0.30 & 0.36 & 0.12 \end{bmatrix} \circ \begin{bmatrix} 0.9 & 0.8 \\ 0.8 & 0.7 \\ 1.0 & 1.0 \end{bmatrix}$$

$= \begin{bmatrix} 0.288 & 0.252 \end{bmatrix}.$

The results represent that when an individual's the membership degree that Interest is 0.3; Pleasure is 0.4; Sign is 0.6; Product Knowledge is 0.5, the fuzzy automata can calculate the individual's degree for subconstruct of advertising involvement that the membership degree for Meaningfulness is 0.30; for Attractiveness is 0.36; for Vitality is 0.12. Furthermore, consequences are also calculated. The membership degree for Message Attention is 0.288; for Recall is 0.252.

4. Research Design

A. *Measurement*

In the social science, lots of studies explore human beings' cognition and attitude which are difficult to obtain a quite certain answer from subjects because the individuals' thinking logic is complicated and uncertain. Nevertheless, fuzzy logic more corresponds to the way human beings are thinking and solves the vagueness of questions. Moreover, Likert Scale and Semantic Differential Scale are widely used in the investigation for convenience, but the two scales are a kind of interval scale that the length of interval is always not equivalent and generates error of estimation [9]. Therefore, this study adopted Graphic Rating Scale (GRS) which has an advantage of allowing subjects to mark on the line at will and reflecting subjects' inner thoughts more factually. GRS not only improves the weakness of interval scale which is not equivalent length for every subject, but depicts the degree to which subjects give as well.

The measurement of variables is from the literature and modified into the form of Graphic Rating Scales. Table 2 shows the resource of variables and reliability analysis Some antecedents, Information Expectancy [23], Occasion-Location, Occasion-Objective, Occasion-Time, Occasion-Person [34], are not in the Table 2 because they are measured with only one item. Type of Ads can not measured directly and needs to be manipulated. The Cronbach α for every variable reaches at least 0.7. It represents the entire questionnaire has acceptable reliability.

Table 2. Measurement of variables.

Variable	Source	Item N0.	Cronbachα
Antecedent of AI			
Interest	Kapferer and Laurent [16]	3	0.7012
Pleasure	Kapferer and Laurent [16]	3	0.7869
Sign	Kapferer and Laurent [16]	3	0.7960
Risk Probability	Kapferer and Laurent [16]	4	0.9085
Risk Importance	Kapferer and Laurent [16]	3	0.8665
Need for Cognition	Cacioppo et al. [6]	18	0.9099
Source Credibility	Gotlieb and Sarel [12]	6	0.8948
Product Knowledge	Smith and Park [36]	4	0.9346
Purchase Importance	Mittal [27]	3	0.8326
Product Involvement	Zaichkowsky [44]	20	0.9608
Advertising Involvement			
AI-1 (Zaichkowsky)	Zaichkowsky [46]	10	0.9683
AI-2 (Wells)	Wells [39]	26	0.9667
AI-3 (Schlinger)	Schlinger [35]	17	0.8306
Consequence of AI			
Attitudinal Acceptance	Wright [41]	3	0.9161
Cognitive Response	Lord and Burnkrant [24]	6	0.7880
Recall	Ho [13]	4	0.8729
Message Attention	Laczniak et al. [21]	5	0.9361
Brand Strategy	Laczniak et al. [21]	6	0.9539
Non-brand Strategy	Laczniak et al. [21]	6	0.9294
Belief	Laczniak and Muehling [19]	5	0.7791
Attitude toward the Ad	Laczniak and Muehling [19]	5	0.9213

B. *Manipulation and Design*

There are two antecedent variables, Type of Ads and Source Credibility, in need of manipulating. We use two-factorial experimental design with two levels for each factor. The design obtains four scenarios by 2 (Types of Ads: comparative ad vs. non-comparative ad) × 2 (Source Credibility: expert endorser vs. citizen endorser). We adopted the cell phone to be stimulus product in the study because almost every college student had the experience of using cell phone. Subjects would have different opinions and attitudes toward a well-known stimulus product. As we know, ads have a couple of categories, such as print ads, TV commercials, online ads, etc, but we focus on the print ads in this study.

The experimental ads imitate the real form of cell phones in the market. To avoid extra-experimental artifacts due to the use of an existing cell phone brand, a fictitious brand called Bason is featured in the experimental ads. The content of ad is composed of five main parts, including the advertising theme, claims, endorser, comparativeness, and basic specification for the cell phone. The detailed content of experimental ads is as follows.

- Theme: The ads are featured the new cell phone with technological 4G.
- Claims: Belief strength, one of the consequent variables, needs to measure with five attributes of experimental product; therefore, a pretest is executed. In this pretest, subjects were 46 undergraduate students in one of College of Management in north Taiwan with convenience sampling after we eliminated the 4 invalid samples. The valid rate is 92%. Originally, we chose the five prior attributes while the attribute, Brand, is not appropriate because we use a virtual brand in this study. Hence, the final five attributes are Price, Figure, Color, Operational Convenience, and Size.
- Endorsers: We set up that the title of the expert endorser is the chief of telecom research institute and let the expert endorser wear the suit to show his profession. We set up that citizen endorser is a salaryman who wears the shirt without a suit.
- Comparativeness: The speed and the electromagnetic wave for 4G cell phone are the main idea which we focus on. In the comparative ad, we compare 4G with 3G for its high speed and low electromagnetic wave. In the noncomparative ad, we describe the merit of 4G cell phone instead of comparing.
- Basic specification: The introduction of specifications for a cell phone in the ads is necessary. There are several descriptions for the experimental cell phone, including screen display, cameras, video, audio, messaging features, connectivity, memory, dimensions, weight, bands, color, battery, talk time, standby time.

C. *Subjects*

In this study, we adopted college students to be our subjects. Calder et al. [7] suggested that research sample had better possess the characteristic of high homogeneity, because high homogeneity could not only obtain more correct inference, but also reduce the problem of covariance yielded from heterogeneous samples. 169 undergraduate students, enrolled in one of College of Management in north Taiwan, served as subjects for the study. After removing incomplete questionnaires, final samples were 161. The valid return rate was 95.27%. Since the main purpose of the study is to test the theoretical model, the use of a convenience sampling is considered to be appropriate.

5. Empirical Studies

The results of the manipulation check indicate that subjects seeing the expert endorser in the ads elicited more source credibility than subjects seeing the citizen endorser in the ads (M=0.49 vs. 0.38, p<0.001). The manipulation is successful in source credibility with the expert and citizen endorsers.

A. *Measurement*

Whether the fuzzy automata generate good models or not, it depends on the selection of initial parameters which construct the fuzzy relation S and R inside the initial machine, the selection of implicators, and the selection of compositions. Hence, we tried the different combination of initial parameters, implicators, and compositions to find the best models. The real values of antecedents investigated from subjects were put into the automata and then generated predicted values for advertising involvement and consequences. If the deviations between the real values and predicted values for advertising involvement and consequences were smallest, we would consider the model was accepted.

Table 3 shows ANOVA results for all implicators and the algebraic composition employed in the fuzzy automata for AI-1. The numbers in the table are the minimum deviations after the machine executes 3000 times initial parameters for each group. The results show that separated 10 groups for cross-validation are successful. There is no significant difference among 10 groups. Since the deviations for 10 groups have no statistical difference, the minimum deviation of 10 groups becomes the best result for the specific implicator and composition used in the fuzzy automata. The minimum deviations are showed in bold words. For example, if the fuzzy automata employ S 1-1 implicator and the algebraic composition to develop model, 17.7% is the minimum deviation which can be generated. Table 3 is one of ANONVA tables we illustrate. Actually, according to different advertising involvement scales and compositions, this study can obtain 16 ANOVA tables.

Table 3. ANOVA for AI-1 and algebraic composition.

Implicator	Group(%)										Mean (%)	p-value
	1	2	3	4	5	6	7	8	9	10		
S 1-1	18.0	**17.7**	18.0	18.7	17.9	17.8	**17.7**	18.0	18.5	18.3	18.1	0.991
S 1-2	16.4	16.3	16.5	17.2	16.5	16.4	**15.8**	16.5	17.2	16.8	16.6	0.985
S 1-3	15.7	15.3	15.6	16.3	15.5	15.6	**14.8**	15.7	16.3	15.9	15.7	0.979
S 1-4	15.2	15.2	15.4	16.1	15.0	15.2	**14.7**	15.4	16.0	15.4	15.4	0.990
R 1-1	16.2	16.4	16.0	16.8	**15.9**	16.1	**15.9**	16.2	16.7	16.3	16.3	0.998
R 1-2	15.5	15.6	15.4	16.2	15.2	15.4	**15.1**	15.6	16.0	15.6	15.6	0.994
R 1-3	15.7	15.3	15.6	16.3	15.5	15.6	**14.8**	15.7	16.3	15.9	15.7	0.979
R 1-4	15.2	15.2	15.4	16.1	15.0	15.2	**14.7**	15.4	16.0	15.4	15.4	0.990
QL 1-1	18.5	18.3	18.6	19.2	18.3	18.2	**18.1**	18.6	18.9	18.8	18.6	0.996
QL 1-2	18.7	18.5	18.7	19.2	18.6	18.5	**18.1**	18.8	19.3	18.9	18.7	0.993
QL 1-3	18.0	**17.7**	18.0	18.7	17.9	17.8	**17.7**	18.0	18.5	18.3	18.1	0.991
QL 1-4	16.0	16.5	16.2	16.9	16.7	16.6	**15.3**	16.5	17.0	16.8	16.5	0.967
QL 2-1	16.9	16.7	16.7	17.5	16.5	16.6	**16.4**	16.9	17.2	17.0	16.8	0.997
QL 2-2	17.1	16.9	17.1	17.9	17.1	17.0	**16.6**	17.1	17.8	17.5	17.2	0.988
QL 2-3	18.0	**17.7**	18.0	18.7	17.9	17.8	**17.7**	18.0	18.5	18.3	18.1	0.991
QL 2-4	18.0	**17.7**	18.0	18.8	17.9	17.8	**17.7**	18.0	18.5	18.3	18.1	0.991

Tables 4-6 present the results collected from 16 ANOVA tables. In Table 4, the numbers in the third column for the algebraic composition are captured from the bold words in Table 3.

Table 4. The best results for AI-1 (Zaichkowsky).

Implicator	Composition(%)			
	Standard	Algebraic	Bounded	Drastic
S 1-1	14.7	17.7	21.5	44.7
S 1-2	14.7	15.8	18.8	44.7
S 1-3	14.7	14.8	15.9	35.8
S 1-4	14.6	14.7	14.8	44.7
R 1-1	15.2	15.9	16.8	26.0
R 1-2	14.6	15.1	17.1	33.9
R 1-3	14.7	14.8	15.9	35.8
R 1-4	14.6	14.7	14.8	44.7
QL 1-1	14.7	18.1	20.2	44.7
QL 1-2	15.0	18.1	22.2	44.7
QL 1-3	14.7	17.7	21.5	44.7
QL 1-4	15.0	15.3	16.0	44.7
QL 2-1	14.9	16.4	20.6	44.7
QL 2-2	14.8	16.6	20.3	44.7
QL 2-3	14.7	17.7	21.5	44.7
QL 2-4	15.2	17.7	21.5	44.7

We find that on the average, it seems that the selection of composition is more important than the selection of implicators. The use of standard composition can obtain smaller deviations than other compositions. When standard, algebraic and bounded compositions combine with any 16 implicators, the deviations between real values and predicted values are similar. However, the drastic composition which combines with different implicators can generate unequal results. Specifically, the drastic composition combining with S 1-3, R 1-1, R 1-2, and R 1-3 can generate smaller deviations than combining the other 12 implicators. It is because the fuzzy relations constructed by these 4 specific implicators often generate 0 or 1 degree. At the same time, the drastic composition is characterized by dealing with only 0 or 1 degree in the FSs. As a consequence, the drastic composition theoretically has effects when combining with these 4 implicators while no reaction to other 12 implicators.

Table 5. The best results for AI-2 (Wells).

Implicator	Composition(%)			
	Standard	Algebraic	Bounded	Drastic
S 1-1	12.4	15.4	19.4	45.9
S 1-2	12.8	13.5	17.4	45.9
S 1-3	12.6	13.2	14.7	31.5
S 1-4	12.6	12.6	12.5	45.9
R 1-1	14.3	14.1	14.9	23.9
R 1-2	12.9	13.7	15.0	30.0
R 1-3	12.6	13.2	14.7	31.5
R 1-4	12.6	12.6	12.5	45.9
QL 1-1	12.4	14.4	15.8	45.9
QL 1-2	12.9	15.5	18.5	45.9
QL 1-3	12.4	15.4	19.4	45.9
QL 1-4	12.8	13.3	14.4	45.9
QL 2-1	12.7	14.5	18.9	45.9
QL 2-2	12.8	14.1	18.4	45.9
QL 2-3	12.4	15.4	19.4	45.9
QL 2-4	14.3	15.4	19.4	45.9

Table 6. The best results for AI-3 (Schlinger).

Implicator	Composition(%)			
	Standard	Algebraic	Bounded	Drastic
S 1-1	13.2	15.0	16.3	44.6
S 1-2	14.1	14.2	15.6	44.6
S 1-3	13.7	13.9	15.9	29.6
S 1-4	13.3	12.9	13.5	44.6
R 1-1	16.3	15.4	16.0	24.4
R 1-2	13.6	15.0	15.9	27.7
R 1-3	13.7	13.9	15.9	29.6
R 1-4	13.3	12.9	13.5	44.6
QL 1-1	13.5	13.6	15.9	44.6
QL 1-2	14.0	15.1	18.5	44.6
QL 1-3	13.2	15.0	16.3	44.6
QL 1-4	14.6	15.0	15.1	44.6
QL 2-1	14.6	16.1	19.5	44.6
QL 2-2	13.7	14.4	15.9	44.6
QL 2-3	13.2	15.0	16.3	44.6
QL 2-4	16.2	15.6	16.3	44.6

In the following, we discuss in two parts: the viewpoints of implications and compositions. Table 7 presents the results in the viewpoint of implications. If using R implication, the fuzzy automata generate the smallest deviations between real values and predicted values. S implication generates second smallest deviations. QL1 and QL2 generate larger deviations relatively. Table 8 shows the results in the viewpoint of compositions. The results indicate if using standard composition, the fuzzy automata generate smallest deviations. If using drastic composition, the automata generate the largest errors. It is because the equation of drastic composition makes the predicted values computed in 0 or 1 degree for advertising involvement states and consequence states. In the real situation, the degree of advertising involvement states and consequence states investigated from the subjects has low possibility to be 0 or 1. Therefore, we consider the drastic composition is not appropriate for computing in the fuzzy automata.

Table 7. The selection of implications for the best results.

	Advertising Involvement Scales		
Implication	AI-1	AI-2	AI-3
S implication	22.7%	21.1%	20.9%
R implication	20.3%	18.4%	18.9%
QL1 implication	24.2%	22.6%	22.4%
QL2 implication	24.4%	23.2%	22.8%
Average error	22.9%	21.3%	21.3%

Table 8. The selection of compositions for the best results.

	Advertising Involvement Scales		
Composition	AI-1	AI-2	AI-3
Standard	14.8%	12.8%	14.0%
Algebraic	16.3%	14.1%	14.6%
Bounded	18.7%	16.6%	16.0%
Drastic	41.7%	41.7%	40.4%
Average error	22.9%	21.3%	21.3%

Furthermore, this study used three different advertising involvement scales as the internal states in the fuzzy automata because we want to know which one of the scales was the most appropriate for operating in the machine. Both Table 7 and Table 8 indicates whatever it is in viewpoint of implication or composition, relatively, AI-2 and AI-3 have better performance to serve as internal state in the machine although there is no significant difference among the three scales in statistics.

Next, correlation for FSs will be introduced. In this study, we not only develop a model which is inclusive of all variables collected from the literature in the fuzzy automata, but also develop another model which merely is composed of correlated relationship that the antecedents significantly correlate with subconstructs of advertising involvement and the subconstructs of advertising involvement have a significant correlation with the consequences. As long as the variables correlate with one of subconstructs of advertising involvement, we consider that there are relationships between the variables and advertising involvement.

According to correlation analysis in Table 9, three kinds of advertising involvement correlate with all consequences while not all antecedents correlate with advertising involvement. For AI-1, 10 antecedents correlate with Zaichkowsky's advertising involvement, including Interest, Pleasure, Sign, Risk Probability, Risk Importance, Source Credibility, Product Knowledge, Product Involvement, Occasion-Time, and Purchase Importance. For AI-2, 7 antecedents correlate with Wells' advertising involvement, including Interest, Pleasure, Sign, Source Credibility, Product Knowledge, Product Involvement, and Purchase Importance. For AI-3, 8 antecedents correlate with Schlinger's advertising involvement, including Interest, Pleasure, Source Credibility, Product Knowledge, Product Involvement, Type of Ads, Occasion-Location, and Purchase Importance. We employ these correlated variables to develop another model and contrast between the model which is composed of all variables and the model which is composed of correlated variables.

Table 9. Correlation analysis.

	AI-1	
Variable	Cognition	Affection
Antecedent of AI		
Interest	0.364***	0.276***
Pleasure	0.369***	0.296***
Sign	0.200*	0.140
Risk Probability	-0.185*	-0.135
Risk Importance	0.216**	0.115
Need for Cognition	0.039	-0.025
Source Credibility	0.311***	0.332***
Product Knowledge	0.334***	0.246**
Information Expectancy	0.119	0.022
Product Involvement	0.390***	0.322***
Type of Ads	0.070	0.043
Occasion- Location	0.012	0.054
Occasion- Objective	0.030	0.044
Occasion- Time	0.174*	0.151
Occasion- Person	0.102	0.083
Purchase Importance	0.278***	0.230**
Consequence of AI		
Attitudinal Acceptance	0.607***	0.636***
Cognitive Response	0.584***	0.583***
Recall	0.446***	0.460***
Message Attention	0.548***	0.518***
Brand Strategy	0.503***	0.476***
Non-brand Strategy	0.421***	0.433***
Belief Strength	0.321***	0.342***
Attitude toward the Ad	0.761***	0.843***

Table 9. Correlation analysis. (Cont.)

	AI-2		
Variable	Meaningfulness	Attractiveness	Vitality
Antecedent of AI			
Interest	0.318***	0.245**	0.270**
Pleasure	0.348***	0.275***	0.288***
Sign	0.166*	0.118	0.094
Risk Probability	-0.154	-0.078	-0.090
Risk Importance	0.090	0.063	0.070
Need for Cognition	-0.055	-0.054	0.006
Source Credibility	0.434***	0.355***	0.345***
Product Knowledge	0.286***	0.229**	0.278***
Information Expectancy	0.073	0.037	0.096
Product Involvement	0.365***	0.299***	0.309***
Type of Ads	0.084	0.056	0.098
Occasion- Location	0.107	0.038	0.097
Occasion- Objective	0.092	0.042	0.041
Occasion- Time	0.115	0.128	0.123
Occasion- Person	0.099	0.098	0.141
Purchase Importance	0.259**	0.222**	0.256**
Consequence of AI			
Attitudinal Acceptance	0.718***	0.686***	0.679***
Cognitive Response	0.606***	0.567***	0.562***
Recall	0.513***	0.438***	0.443***
Message Attention	0.540***	0.501***	0.470***
Brand Strategy	0.482***	0.468***	0.440***
Non-brand Strategy	0.465***	0.442***	0.418***
Belief Strength	0.414***	0.367***	0.353***
Attitude toward the Ad	0.843***	0.907***	0.833***

Table 9. Correlation analysis. (Cont.)

Variable	AI-3 Entertainment	Confusion	Relevant News	Brand Reinforcement
Antecedent of AI				
Interest	0.167*	-0.263**	0.169*	0.105
Pleasure	0.223**	-0.227**	0.278***	0.171*
Sign	0.101	0.024	0.064	0.081
Risk Probability	-0.083	0.086	-0.047	0.040
Risk Importance	0.066	0.066	0.150	0.013
Need for Cognition	0.022	0.023	0.038	-0.038
Source Credibility	0.434***	-0.072	0.265**	0.433***
Product Knowledge	0.160**	-0.149	0.244**	0.183**
Information Expectancy	-0.091	-0.005	0.071	-0.032
Product Involvement	0.204**	-0.260**	0.243**	0.176**
Type of Ads	0.106	-0.226**	0.118	0.009
Occasion- Location	0.052	-0.216**	0.047	-0.027
Occasion- Objective	0.044	-0.150	0.059	0.020
Occasion- Time	0.038	-0.072	0.098	0.105
Occasion- Person	0.038	-0.067	0.129	0.077
Purchase Importance	0.136	-0.255**	0.148	0.082
Consequence of AI				
Attitudinal Acceptance	0.658***	-0.249**	0.574***	0.706***
Cognitive Response	0.494***	-0.336***	0.625***	0.456***
Recall	0.474***	-0.301***	0.467***	0.346***
Message Attention	0.480***	-0.152	0.439***	0.373***
Brand Strategy	0.401***	-0.142	0.430***	0.336***
Non-brand Strategy	0.464***	-0.141	0.445***	0.356***
Belief Strength	0.352***	-0.195*	0.342***	0.350***
Attitude toward the Ad	0.810***	-0.257**	0.593***	0.695***

Tables 10 and 11 present the contrast between two different models. The results show that there is no significant different performance under viewpoint of implications and compositions. Two models which are composed of all variables and the machine processing correlated variables have similar deviations. We consider that the fuzzy automata should possess the merit of dealing with variables which have no relationship or have interaction effects. It deserves to be mentioned that when the fuzzy automata employ AI-3 as the internal state, the deviations which two models have are the same. Nevertheless, the deviations are a little difference between two models when the machine employs AI-1 and AI-2 as the internal states. It is because that according to correlation analysis, the antecedent-Type of Ads, which is coded in the form of 0 or 1, does not correlate with AI-1 and AI-2. Without this kind of variable, when using the drastic composition, the machine obtains larger deviations. This is why AI-1 and AI-2 have higher deviations in the model consisting correlated variables only.

Table 10. Contrast between two fuzzy conditions for implication.

Implication	AI-1(%) a	AI-1(%) b	AI-2(%) a	AI-2(%) b	AI-3(%) a	AI-3(%) b
S-implication	22.7	23.2	21.1	21.8	20.9	20.9
R-implication	20.3	22.4	18.4	21.4	18.9	18.6
QL1-implication	24.2	23.9	22.6	22.2	22.4	22.5
QL2-implication	24.4	24.5	23.2	23.0	22.8	23.3
Average deviation	22.9	23.5	21.3	22.1	21.3	21.3

Note: "a" represents all variables in the fuzzy automaton; "b" represents only correlated variables in the fuzzy automaton.

Table 11. Contrast between two conditions for composition.

Composition	AI-1(%) a	AI-1(%) b	AI-2(%) a	AI-2(%) b	AI-3(%) a	AI-3(%) b
Standard	14.8	14.8	12.8	12.6	14.0	13.8
Algebraic	16.3	16.4	14.1	14.0	14.6	14.9
Bounded	18.7	18.8	16.6	16.3	16.0	16.2
Drastic	41.7	44.1	41.7	45.4	40.4	40.5
Average deviation	22.9	23.5	21.3	22.1	21.3	21.3

Note: "a" represents all variables in the fuzzy automaton; "b" represents only correlated variables in the fuzzy automaton.

B. *Discussion*

Sixteen implicators are used to construct the relation. We find that no matter what the implicators are adopted, they can generate similar percentage of errors. It seems that the selection of implicators is not significant. However, not every implicator going with the algebraic composition can generate the reasonable results. In the fuzzy automaton, except S1-3, R1-2, R1-3, and QL2-1, the rest of implicators go with the algebraic composition will generate the same predicted values even if subjects have different degree of antecedent for advertising involvement.

There are four compositions used in the automaton, such as standard composition, algebraic composition, bounded composition, and drastic composition. Specifically, if using the drastic composition, the automaton will generate large errors because of the formula. Except S1-3, R1-1, R1-2, and R1-3, the rest of the sixteen implicators going with the drastic composition will generate the degree of membership which always maintains zero in the fuzzy automaton; whereas, the degree of membership always maintains zero and the degree of the non-membership always maintains one in the fuzzy automaton. The drastic composition is merely suitable for the variables which have the degree of zero or one. However, out of all experimental variables, only type of ads corresponds with the characteristic of zero or one. Therefore, we consider the drastic composition is not appropriate for the fuzzy automaton to deal with advertising involvement. Besides the drastic composition, bounded composition also has the problem in the formula. Although the bounded composition will not generate lots of the degree of zero or one for predicted values, it is still unreasonable. Based on the formula, the zero value generated by the automaton usually occurs in the degree of membership while one value occurs in the degree of non-membership. In fact, the degree of membership is often higher than the degree of non-membership for the real values which derive from the subjects responding to the questionnaire. It is an opposite condition between predicted values and real values. As a consequence, we consider the bounded composition is also not appropriate for the automaton. Although standard composition does not generate zero value or one value for the predicted values, it is still not appropriate used in the automaton. It is because the standard composition adopts max-min for calculating while the method of max-min, which both takes the upper bound and lower bound in the sets, would lose a lot of information. At the same time, when constructing state-transition relation, the automaton also adopts max-min to reduce the dimension. Executing max-min twice would result in the loss of information more seriously. It turns out that the subject's predicted values are the same even if they have different degree of antecedent for advertising involvement. Due to above reasons, we consider the algebraic composition has the best effects among these four compositions.

6. Conclusions

As far as the marketing researchers are concerned, advertising involvement is an important segmentation variable. The advertisers view advertising involvement as a vital factor for advertising effects. Advertising involvement has been discussed for several decades while little literature proposes a complete integrated model. In this study, we comprehensively collect the antecedents and consequences for advertising involvement. Because the model that we attempt to develop includes too many variables, it is difficult to judge the functional relations among these variables and not appropriate to use a traditional statistical method. We take advantage of the automata, which is capable of dealing with lots of variables, to develop an integrated model of advertising involvement.

The concept of advertising involvement is successfully led in the fuzzy automata to be the internal state in this study. On the average, we do well to develop a model of advertising involvement in terms of some implicators, compositions, and initial parameters which construct the fuzzy relations S and R in the fuzzy automata. With the model, we can simply compute an individual's degree of advertising involvement and the degree of consequence for advertising involvement as long as obtaining his/ her degree of antecedent for advertising involvement.

According to the analyses, we realize that in the operation of the fuzzy automata, the prerequisite of the accurate predicted values is the selection of compositions. Because using the drastic composition, the machine generates larger deviations than other compositions due to the characteristic of its equation. The drastic composition would be regarded as the inappropriate method in this study. In general, the standard composition has the better effects used in the machine whether it combines with any kind of implicators.

For the time being, Zaichkowsky's RPII is the most popular scales to measure the advertising involvement in the marketing field. In this study, we try to use three different kinds of scales as the internal state in the fuzzy automata. However, the results show that Wells' and Schlinger's advertising involvement scales have better performance relatively. On the contrary, Zaichkowsky's RPII does not perform very well as we expect. We suggest that when studying the topic of involvement in the FSs, the researchers can choose Wells' or Schlinger's advertising involvement scales instead of Zaichkowsky's scale.

Based on the correlation analysis, we take the significantly correlated variables in the machine to acquire another model. The finding is that the two models which consist of all variables and only correlated variables obtain similar deviations and effects. In other words, although there is not equivalent number of variables in the machine, the machine generates similar deviations. We consider that the fuzzy automata are capable of dealing with any kind of functional relation, such as interaction or non-correlated relation.

Consumers under high advertising involvement indeed elicit more attitudinal acceptance (attitude toward the ads, product attitude, and purchase intention), recall, message attention, etc. Those behavioral responses are very vital to the marketing researchers and advertisers who want to know when consumers are seeing the advertisement for 4G cell phones, what kind of responses they have. With the model, marketing researchers and advertisers can affect antecedents of advertising involvement to indirectly enhance consumers' behavioral responses for 4G cell phones.

Finally, three suggestions are proposed. First, in this study, only four implications and compositions were used. We suggest trying different t-conorms and t-norms to generate new implications and compositions which may obtain smaller deviations and better models. Second, this study only focused on the print ads. The TV commercials and online ads are also recommended. Third, due to the constraint of the resource and time, only 169 samples were collected in this study. We consider the future research would investigate more samples. Moreover, before developing the model, we should eliminate the heterogeneous subjects in order to obtain a better model.

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