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CAUSAL MODELING OF WEB-ADVERTISING EFFECTS BY IMPROVING SEM BASED ON DEMATEL TECHNIQUE

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Causal analysis greatly affects the efficiency of decision-making. Scholars usually adopt structural equation modeling (SEM) to establish a causal model recently. However, statistical data allow researchers to modify the model frequently to arrive at good model fitness, and SEM is often misapplied when the data are merely fitted to an SEM and the theory is then extended from the analytical result based on presumed hypotheses. This paper proposed SEM modified by DEMATEL technique, taking causal model of Web-advertising effects for example. Having revealed that the new model is the one that conforms to actual data and is better than initial model, the results confirm that the DEMATEL technique can be an efficient, complementary, and confident approach for reprioritization of the amended modes in a SEM model. In addition, the most important factor affecting the Web-advertising effects may be found via the modified model, which benefits the manager for making strategic marketing plans.

Keywords: Web-advertising effects; structural equation modeling (SEM); DEMATEL; multiple criteria decision making (MCDM); network relation map (NRM).

1. Introduction

Structural equation modeling (SEM), the analysis of causal links between a set of latent constructs measured by observed variables, is widely used in various disciplines, including marketing,[1,2] human resources management,[3] psychology,[4,5] sociology,[6] environmental studies,[7] healthcare,[8,9] migration research,[10] cross-national,[11,12] computer science,[13] and many others.

One of the biggest problems concerning SEM is the problem of model modification. Most SEM models have been modified to provide a better fitness or be more succinct. As often happens in SEM, the data may be inconsistent with the initially hypothesized model of the researcher, which implies that the researcher must either modify or abandon the model. In practice, researchers frequently choose the former.[14] Researchers usually engage in model trimming using Critical ratios (CRs) or modification indices (MIs) to improve the models.

Just as Chin[15] (the chief editor of *MIS Quarterly*) argued that "The models that are initially tested are typically rejected. With modification indices and other such information, the researcher may follow a process of changing and re-estimating the model until if fits the data. The final model is mistakenly believed to be correct". Arbuckle and Wothke[16] disputed that in trying to improve upon a model, "a modification must only be considered if it is makes theoretical or common sense", critical ratios (CRs) or modification indices (MIs) alone should not be used utterly as a guide.[17] This purely data-driven model for the amendment without theoretical foundation will cause the following fallacies:

(1) Increasing the probability for the unique characteristic contained by the special samples in foundation of covariance matrix is prone to cause the error of capitalization on chance. The new amended model may only match with the researchers' usage of special sample characteristics; however, it may appear any case for lack of goodness-of-fit when it is applied to the other samples in the population.[18]
(2) SEM cannot detect and improve the problem of model specification errors by modification indices.[19,20]
(3) "When should the modification procedure end?" To seek for fit may include too much parameter estimation (fit for fitting?). In the pursuit of a continuous fit would result in a model of overfitting.[21]
(4) The nature of data analysis is changed from confirmatory to exploratory.[22,23]

In recent years, a number of scholars have proposed Multiple Criteria Decision-Making (MCDM) theory to strengthen the comprehensiveness and reasonableness of the decision-making process.[24–27] To improve the above-mentioned drawbacks, this article uses two methods to establish the evaluation model for the effectiveness of Web advertising, which is based on an MCDM model to address on dependent relationships among criteria, decision-making trial and evaluation laboratory (DEMATEL), and structural equation modeling (SEM). The paper found out the main factors having impact on Web-advertising effects via literatures, built an initial causal model by SEM and modified the model through DEMATEL technique. The DEMATEL technique may illustrate the interrelations and feedback among criteria.[28] Because DEMATEL may build the complex relationship between each dimension/criterion the network relation map (NRM), it can provide a reasonable basis to modify model for SEM, which prevents from using statistical data to drive model modification. The researchers would not simply pursue a well-fitting model and avoid causing overfitting. A researcher probably re-inspects the causality among the various dimensions, refraining from being limited in the initial hypotheses and path relations, and thus reduces the risk of faulty results in model specification. Consequently, the model fit and causal analysis may be meaningful, thus influential to the efficiency of decision-making.

The rest of this paper is organized as follows. In Sec. 2 the basic concepts of proposed novel causal modeling by improving SEM based on DEMATEL technique are introduced. In Sec. 3, an empirical study of Web-advertising effects is illustrated to demonstrate the proposed novel causal modeling. The results in Sec. 4, and discussions and implications are presented in Sec. 5. And then, in Sec. 6, conclusions and contributions are appeared. Finally, remarks are proposed in Sec. 7.

2. Novel Causal Modeling by Improving SEM Based on DEMATEL Technique

2.1. *Structural equation modeling (SEM)*

In angle of development thread of statistics and methodology, SEM is not a new technique. Because the computer got popularized and improved with the function, some scholars[29–31] integrated factor analysis with path analysis, joined the analytical technology of the computer, and proposed the preliminary concept of SEM. Jöreskog and Sörbom[32] further developed the analysis skill of the matrix so as to deal the analyzing problems of covariance structure. Because LISREL is very similar with covariance structure models, early scholar named covariance structure models as LISREL model. Henceforth, scholars proposed some software one after another, which can be divided as two main types. One is based on components such as PLSPATH while another is based on covariance such as LISREL, EQS,[33,34] AMOS,[35] MPLUS,[36] CALLS,[37] and RAMONA.[38] Partial least square (PLS) is an analyzing technique to probe or construct foreseeing models, especially the analysis of casual model between latent variables.[39] It's better than common linear construction relation model and won't be restricted by rigorous distributional assumptions and sample size.[40] Sellin[41] declared that PLS is "a flexible and extremely powerful technique for the examination of path models with latent constructs measured by multiple indicators." In addition, PLSPATH can handle two types of relationships between latent variables and the associated observed variables, inward mode and outward mode.[40] The SEM software packages such as LISREL and EQS cannot dispose the inward mode.[40] The absence of standard errors is one of the limitations of the use of the PLSPATH program, which should be paid attention to.[40] Among the SEM software which are based on covariance, LISREL, EQS, and Amos are the most widely used. These three methods are very close to each other in terms of efficiency, functionality, parameter estimation, and fitting criteria and have a very slight difference.[42] Albright and Park[43] had used AMOS, LISREL, MPLUS, and CALIS to conduct a confirmatory factor analysis and showed that the analytical results for these four types of software were substantially identical. Early on, scholars often used LISREL as a tool for SEM methodology analysis. However, AMOS is far more user-friendly, so nowadays journal submissions using it are rising quickly and fast approaching equality in numbers with LISREL applications recent years.[44] There are two major advantages for AMOS. First, AMOS combines SPSS software which is the most familiar for researchers. Second, AMOS is very user-friendly with icons as the operation interface making it even easy for user without the ability of writing programs to use.[44] Therefore, the paper adopts AMOS as the analysis tool.

SEM technique deals with relations of multiple criteria constructs simultaneously and fits in proving positive research. The primary aim of SEM technique is to analyze latent variables and causal relations between latent constructs to verify the advanced hypothesis, consequently being called as causal model technique.

The SEM methodology is a confirmatory modeling for data analysis; therefore, researchers must have a theoretical foundation for their proposed research models which are guided by theories. No matter it is to prove any causal relationships or confirm internal structure, both depend on clarifying the contents and the properties of prior research variables, and a clear description of hypothetical relations. Moreover, researchers advance the concrete structural hypothetical relations and seek for statistical confirmation. The investigation of the variable structural relations in the areas of sociological and behavioral science mainly consists of a group of indirectly observed, measured abstractly latent constructs. Precise statistical data is required to prove the existence of the construct, which is one of the major advantages of SEM methodology.[19]

In addition, SEM technique includes one or more linear regression equations that express how the endogenous variables depend upon the exogenous variables. SEM technique is akin to combine multiple regression and factor analysis. As such SEM expresses the linear causal relationship between two separate sets of latent constructs (which may have been derived by two separate factor analyses). A multiple regression is required to test for several dependent variables from the same set of independent variables simultaneously, particularly if it is possible for one dependent variable to simultaneously cause another with multivariate analysis. SEM technique is a powerful method for effectively dealing with multicollinearity (when two or more variables are highly correlated) which is another benefit of SEM over multiple regression and factor analysis.[42]

2.2. *Decision-making trial and evaluation laboratory (DEMATEL)*

The DEMATEL technique, which originates from the Geneva Research Centre of the Battelle Memorial Institute,[28,45] was used to investigate and solve the complicated problem group. DEMATEL technique was developed in the belief that the proper use of scientific research methods could facilitate comprehension of the specific problematique, the cluster of intertwined problems, and contribute to recognition of practical solutions by a hierarchical structure. The methodology, according to the characteristics of objective affairs, can verify the interdependence among the variables/attributes/criteria and confine the relation that reflects the characteristics with an essential system and evolution trend.[46,47] The method is a practical and useful tool, especially for visualizing the structure of complex causal relationships with matrices or digraphs. The matrices or digraphs show a contextual relation between the elements of the system, in which a numeral represents the strength of influence of each element. Thus, the DEMATEL technique is able to convert the relationship between the causes and effects of criteria into an intelligible structural model of systems.

DEMATEL technique, a very popular method used in Japan and Taiwan, has been widely applied in a number of disciplines, including airline safety,[48,49] e-learning,[50,51] decision-making,[52–54] knowledge management,[55,56] Operations Research,[57,58] business policy,[59] selecting systems,[60] agriculture,[61] innovation,[62,63] consumer behavior,[64] and others. The method can be summarized as follows:

Step 1: Calculate the direct-influence matrix by scores (depending on the views of the experts) and evaluate the relationship among elements (or called variables/attributes/criteria) of mutual influence, using the scale ranging from 0 to 4 (indicating "No influence (0)," to "Very high influence (4)"); the digraph portrays a contextual relationship between the elements of the system as shown in Fig. 1. For example, an arrow from "b" to "a" represents that "b affects a", and its influence score is 2. Subjects are asked to indicate the direct effect they believe each element exerts on every other element j, as indicated by d_{ij}. The matrix $\boldsymbol{D}$ of direct relations is thus obtained.

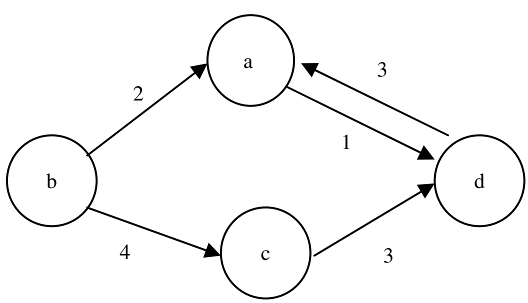


Fig. 1. The directed graph.

Step 2: Normalizing the direct-influence matrix: on the basis of the direct-influence matrix $\boldsymbol{D}$, the normalized direct-relation matrix $\boldsymbol{X}$ is acquired by using Eqs. (1) and (2).

$$\boldsymbol{X} = k\boldsymbol{D}. \tag{1}$$

$$k = \max_{i,j}\left\{\frac{1}{\max_i \sum_{j=1}^{n} d_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} d_{ij}}\right\}, \quad i, j \in \{1, 2, \ldots, n\}. \tag{2}$$

Step 3: Attaining the total-influence matrix: once the normalized direct-influence matrix $\boldsymbol{X}$ by summation for i or j is obtained, the total-influence matrix $\boldsymbol{T}$ is arrived at through Eq. (3), in which the $\boldsymbol{I}$ is denoted as the identity matrix.

$$\begin{aligned}\boldsymbol{T} &= \boldsymbol{X} + \boldsymbol{X}^2 + \boldsymbol{X}^3 + \cdots + \boldsymbol{X}^k \\ &= \boldsymbol{X}(\boldsymbol{I} + \boldsymbol{X} + \boldsymbol{X}^2 + \cdots + \boldsymbol{X}^{k-1})[(\boldsymbol{I} - \boldsymbol{X})(\boldsymbol{I} - \boldsymbol{X})^{-1}] \\ &= \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{X}^k)(\boldsymbol{I} - \boldsymbol{X})^{-1},\end{aligned} \tag{3}$$

then $\boldsymbol{T} = \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{X})^{-1}$, when $k \to \infty$, $\boldsymbol{X}^k = [0]_{n\times n}$, where $\boldsymbol{X} = [x_{ij}]_{n\times n}$, $0 \leq x_{ij} < 1$, $0 < (\sum_{j=1}^{n} x_{ij}, \sum_{i=1}^{n} x_{ij}) \leq 1$ and at least one summation $\sum_{j=1}^{n} x_{ij}$ or $\sum_{i=1}^{n} x_{ij}$ Eq. (1), but not all, then $\lim_{k\to\infty} \boldsymbol{X}^k = [0]_{n\times n}$.

Step 4: Analyzing the results: in the stage, the sum of rows (given influence) and the sum of columns (received influence) are separately expressed as influential vector $\boldsymbol{d} = (d_1, \ldots, d_i, \ldots, d_n)'$ by factor j ($j = 1, 2, \ldots, n$) and influential vector $\boldsymbol{r} = (r_1, \ldots, r_j, \ldots, r_n)'$ by factor i ($i = 1, 2, \ldots, n$) using Eqs. (4)–(6). Then, when $i, j \in \{1, 2, \ldots, n\}$ and $i = j$ the horizontal axis vector $(\boldsymbol{d} + \boldsymbol{r})$ is made by adding vector $\boldsymbol{d}$ to vector $\boldsymbol{r}$, which exhibits total important influence of each criterion. Similarly, the vertical axis vector $(\boldsymbol{d} - \boldsymbol{r})$ is made by deducting vector $\boldsymbol{d}$ from vector $\boldsymbol{r}$, which may separate criteria into a cause group and an affected group. In general, when $\boldsymbol{d}_i - \boldsymbol{r}_i$ is positive, the criterion is to belong to the cause group. On the contrary, if the $\boldsymbol{d}_i - \boldsymbol{r}_i$ is negative, the criterion is to belong to the affected group. Therefore, the causal-and-effect graph can be achieved by plotting the data set of $\{(d_i + r_i, d_i - r_i) | i = 1, 2, \ldots, n\}$, providing valuable approaching for making decisions.

$$\boldsymbol{T} = [t_{ij}]_{n\times n}, \quad i, j \in \{1, 2, \ldots, n\}, \tag{4}$$

$$\boldsymbol{d} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = [t_i]_{n\times 1} = [d_i]_{n\times 1}, \tag{5}$$

$$\boldsymbol{r} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} = [t_j]_{n\times 1} = [r_j]_{n\times 1}, \tag{6}$$

where vector $\boldsymbol{d} = (d_1, \ldots, d_i, \ldots, d_n)$ and vector $\boldsymbol{r} = (r_1, \ldots, r_j, \ldots, r_n)$ express the sum of rows and the sum of columns based on total-influence matrix $\boldsymbol{T} = [t_{ij}]_{n \times n}$, separately.

2.3. *The procedures of combined with SEM and DEMATEL*

The procedures of this proposed model combined with SEM and DEMATEL are displayed as follows (Fig. 2).

3. An Empirical Study of Web-Advertising Effects

The paper provides an empirical example for Web-advertising effects (WAE) to make obviously the proposed method.

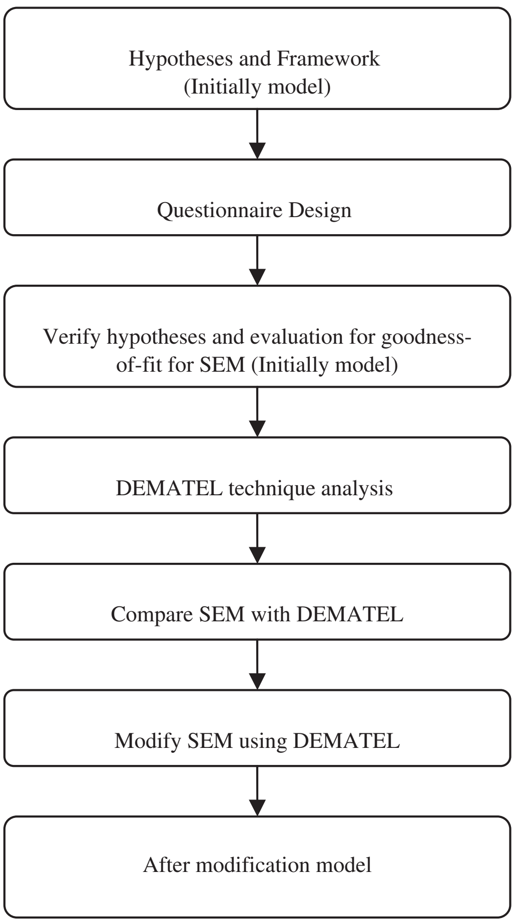


Fig. 2. The proposed model procedures.

3.1. *Hypotheses and framework*

This article establishes a causal relationship model for WAE. Through the use of a literature review, this research examines Web advertisements for computer products to determine which factors significantly influence the effectiveness of Web advertising (Appendix A). Additionally, based on the scholars' previous researches,[65,66] the paper adopts: (1) advertising click-through (ACT), (2) recall effect (RE), (3) attitude toward brand (ATB), and (4) purchasing intention (PI) so as to measure Web advertising effects. The study established some hypotheses via literature review (Appendix A) as follows:

- H1: Web-use extent of consumers has a direct negative influence on the attitudes toward Web advertising;
- H2: Attention of consumers to Web advertising has a direct positive influence on attitudes toward Web advertising;
- H3: Web-advertising design has a direct positive influence on the product-involvement level of consumers;
- H4: Attitude of consumers toward Web advertising has a direct positive influence on Web-advertising effects;
- H4a: Attitude of consumers toward Web advertising has a direct positive influence on advertising click-through;
- H4b: Attitude of consumers toward Web advertising has a direct positive influence on advertising recall effect;
- H4c: Attitude of consumers toward Web advertising has a direct positive influence on Attitude toward brand;
- H4d: Attitude of consumers toward Web advertising has a direct positive influence on purchase intention;
- H5: Level of product involvement of consumers has a direct positive influence on Web-advertising effects;
- H5a: Level of product involvement of consumers has a direct positive influence on advertising click-through;
- H5b: Level of product involvement of consumers has a direct positive influence on ad-recall effect;
- H5c: Level of product involvement of consumers has a direct positive influence on their attitudes toward brand; and
- H5d: Level of product involvement of the consumers has a direct positive influence on purchase intention.

3.2. *Questionnaire design*

3.2.1. *Questionnaire 1 for SEM*

Groups with Internet experiences were the survey subjects for the questionnaire in this study; that is, discussions were conducted with those groups that had global information-browsing experiences. Ten college students, who were regular Internet users, were selected for conducting focused group discussions. The literature reviews and participants of the focus group were gathered to design a preliminary questionnaire draft. To obtain effective measurement tools, this study amended the questionnaire using the pretest and pilottest. The Cronbach's α value and the factor analysis methods were used to verify the reliability and validity of scales.

The sample subjects in this study with Internet-use experience underwent convenience sampling. Questionnaires were distributed at the International Computer Show in Taiwan. 598 questionnaires were returned. Invalid questionnaires (with incomplete answers) were eliminated, yielding 555 valid questionnaires. The valid-questionnaire return rate was 92.81%.

The overall Cronbach's α reliability value was 0.86, showing the consistency of the questionnaire. From factor loading attained from factor analysis, all question items had a factor loading greater than 0.50 (between 0.59 and 0.91) and the respective cumulative percent of variance for each factor was greater than 50% (between 51.55% and 83.16%), showing that the questionnaire of this study possessed convergent validity. In addition, the development of this questionnaire was for study purposes, attained in accordance with literature review, and was the result of repeated discussions and corrections; thus, this questionnaire possessed content validity.

3.2.2. *Questionnaire 2 for DEMATEL*

To discuss interdependence among the dimensions, the dimensions of SEM were regarded as dimensions and variables, similar to those in DEMATEL.

The Questionnaire was finalized through an interview approach and delivered to four types of experts who had extensive previous experience of surfing the Internet: (1) computer salesmen; (2) Web-ad entrepreneurs; (3) marketing professors; and (4) consumers who had surfed the Internet over ten years and had several online trading experiences regarding as experts. To find the correlation among dimensions, 12 respondents were requested to provide pair-wise comparison in terms of influences and directions between each factor.

3.3. *Verification of hypotheses and evaluation for goodness-of-fit for SEM*

In terms of "model fit test," as a reference based on previous studies,[67–71] a good model should conform to the following: goodness-of-fit index (GFI), increased Fit index (IFI), and the comparative fit index (CFI) should be greater than 0.9; adjust goodness-of-fit index (AGFI) should be less than 0.8; root mean square error of approximation (RMSEA) should be less than 0.05, and χ^2 relative value to degree of freedom (χ^2/df) should be not exceed 3. This paper is based on the above principles in verifying model fitness.

Table 1. Initial model-fitness analysis.

Fit Index	Proposed Criteria	Results
The ratio of Chi-square and degrees of freedom (χ^2/df)	<3	2.561
Goodness-of-fit index (GFI)	>0.9	0.898
Increased fit index (IFI)	>0.9	0.919
Comparative fit index (CFI)	>0.9	0.919
Adjusted goodness-of-fit index (AGFI)	>0.8	0.877
Root-mean square error of approximation (RMSEA)	<0.05	0.053

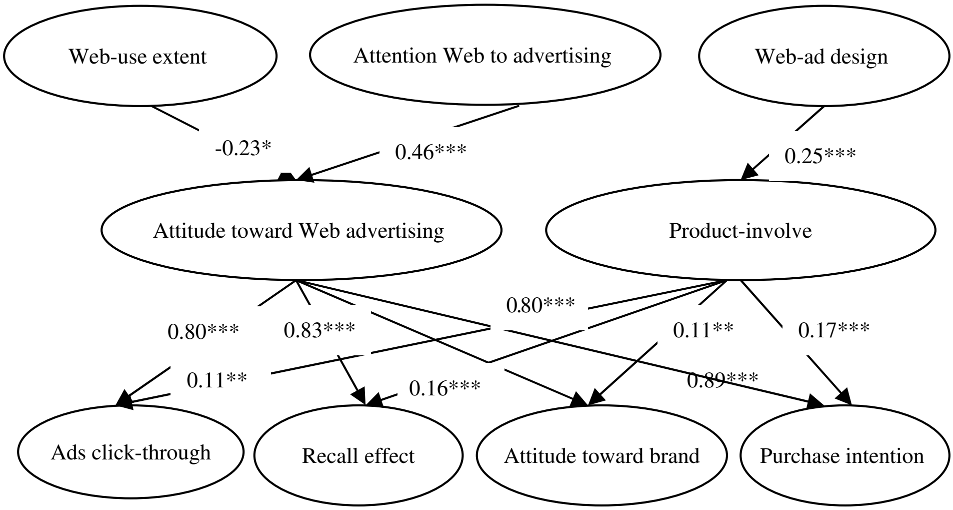
Results of model fitness for initial model (Table 1) addressed that the ratio of Chi-square and degrees of freedom (χ^2/df) was 2.561 (<3), in general, the primary model and observation data possessed a good fitness. In addition, the GFI value was 0.898 (very close to 0.9), CFI value was 0.919, IFI value was 0.919, AGFI value was 0.877, and the RMSEA value was 0.053. In the above-mentioned analysis, RMSEA indices do not conform to the approved standard values. However, Jarvenpaa *et al.*[72] suggested that the RMSEA value less than 0.08 would be acceptable. In summary, the initial model was not very well-fitting but acceptable.

The relationship between the respective factors and the effects of Web advertising in the initially structural model of this study were shown in Fig. 3. The results exhibited that all p-values did not exceed the critical values at the 0.05 (or 0.01, or 0.001) significance level and verified the posited relationships among the latent constructs (Table 2). The following conclusions could be drawn from the SEM analysis:

(1) according to H1 and H2, Web-use extent (WUE) and Attention to Web advertising (AWA) both significantly and directly affected Attitudes toward Web advertising (ATWA), but in opposing directions; the former had a negative impact and the latter caused a positive influence;
(2) according to H3, Web-ad design (WAD) had a significant and direct effect on Product-involvement level (PIL) of consumers, which in turn had a significant and direct influence on WAE (drawing from H4a to H4d); that is, as WAD improves, ATWA level would be enhanced, causing WAE to grow;
(3) drawing from H4 and H5, both ATWA and PIL significantly and directly affected the four dimensions (ACT, RE, ATB, and PI) of WAE; and
(4) according to H2 and H5, AWA impacted on WAE through influencing the ATWA; that is, as AWA increased, ATWA level would be enhanced, causing WAE to grow.

3.4. *The analysis and results of the DEMATEL technique*

As stated above, the dimensions of SEM were used as the factors and variables under one dimension, similar to the criteria used for DEMATEL by experts. The first, the normalized direct-influence matrix is shown in Table 3. Subsequently, the



Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Fig. 3. Initial model structural graph.

Table 2. Hypothesis verification.

Hypothesis	Assumed Relationship	Estimated Value	p-Value	Result
H1: WUE → ATWA	−	−0.232	0.018*	Supported
H2: AWA → ATWA	+	0.459	0.000***	Supported
H3: WAD → PIL	+	0.253	0.000***	Supported
H4a: ATWA → ACT	+	0.796	0.000***	Supported
H4b: ATWA → RE	+	0.827	0.000***	Supported
H4c: ATWA → ATB	+	0.799	0.000***	Supported
H4d: ATWA → PI	+	0.886	0.000***	Supported
H5a: PIL → ACT	+	0.113	0.008**	Supported
H5b: PIL → RE	+	0.160	0.000***	Supported
H5c: PIL → ATB	+	0.108	0.008**	Supported
H5d: PIL → PI	+	0.171	0.000***	Supported

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

total-influence matrix was calculated; it is displayed in Table 4; the degrees of influence are presented in Table 5. It was necessary to set a threshold value "p" for explaining the structural relation among factors while simultaneously keeping the complexity of the whole system to a manageable level. Here the threshold value "p" was set as 0.7. Only those factors whose effect in the total-influence matrix was greater than 0.7 were exhibited in the causal diagrams; thus, the network relation map (NRM) was illustrated in Fig. 4. Finally, the cause-and-effect relations among the criteria and dimensions were grouped together in Table 6. Several results were

Table 3. The direct-influence matrix of criteria.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}
f_1	0.0000	3.0000	1.8333	1.7500	1.9167	1.9167	2.0000	3.1667	2.8333	2.6667	3.0833	2.4167	1.5833	1.9167	1.5000	1.3333
f_2	2.7500	0.0000	1.8333	1.9167	1.4167	2.0000	1.5000	2.8333	2.5000	2.5833	2.9167	2.0000	1.6667	1.6667	1.8333	1.7500
f_3	2.0833	2.0833	0.0000	2.3333	2.2500	1.9167	2.0833	1.5833	1.3333	1.7500	1.0000	1.5000	3.0000	3.3333	3.1667	3.2500
f_4	2.0000	1.9167	2.2500	0.0000	1.7500	1.8333	2.0000	1.5833	1.4167	1.5000	1.2500	2.0000	3.1667	3.2500	3.0833	3.1667
f_5	1.8333	1.5833	2.6667	3.4167	0.0000	2.6667	2.6667	1.7500	2.2500	2.1667	2.5000	1.9167	1.6667	1.6667	2.0833	2.0000
f_6	2.0833	1.7500	2.5000	3.3333	3.1667	0.0000	3.0000	2.1667	2.1667	1.6667	2.4167	1.4167	1.5000	1.5000	1.5833	1.8333
f_7	1.9167	1.5000	2.6667	3.4167	3.0833	2.7500	0.0000	2.0000	2.4167	2.0000	2.2500	2.0833	1.8333	1.5833	1.7500	1.9167
f_8	2.8333	2.3333	1.6667	1.7500	1.8333	1.9167	1.7500	0.0000	3.0000	2.6667	2.9167	2.6667	1.5000	1.7500	1.7500	1.5833
f_9	2.0833	2.3333	1.8333	1.7500	1.7500	1.6667	1.8333	2.7500	0.0000	2.6667	3.0833	3.0000	2.0000	1.9167	1.7500	1.8333
f_{10}	2.1667	2.3333	2.0833	1.5833	1.8333	1.6667	1.5833	2.8333	2.8333	0.0000	2.9167	3.0000	2.1667	1.8333	1.9167	2.2500
f_{11}	2.2500	2.5833	1.9167	1.8333	1.8333	2.0000	1.9167	2.9167	2.9167	2.9167	0.0000	3.0833	1.9167	1.8333	2.0000	1.7500
f_{12}	1.7500	2.1667	1.6667	1.2500	1.7500	1.5000	1.7500	3.0000	3.0833	3.0833	3.1667	0.0000	2.0000	1.6667	1.8333	1.7500
f_{13}	1.5833	1.6667	2.3333	1.9167	1.6667	1.4167	1.8333	1.5000	1.5000	1.9167	1.9167	1.8333	0.0000	2.5000	2.3333	2.2500
f_{14}	2.0000	1.8333	2.4167	2.0000	1.4167	1.5000	1.6667	1.8333	1.8333	1.8333	1.7500	2.0000	2.6667	0.0000	2.5000	2.3333
f_{15}	1.4167	1.8333	2.6667	1.9167	2.2500	1.8333	2.3333	1.7500	1.5833	1.5833	1.8333	1.5000	2.7500	2.4167	0.0000	2.4167
f_{16}	1.3333	1.5833	2.3333	2.0833	2.0000	2.0833	2.5000	1.6667	1.8333	1.6667	1.6667	1.5833	2.3333	2.3333	2.5833	0.0000

Table 4. The total-influence matrix of criteria.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}
f_1	0.6068	0.6957	0.6984	0.6855	0.6488	0.6270	0.6600	0.7539	0.7482	0.7294	0.7754	0.7124	0.6788	0.6762	0.6746	0.6651
f_2	0.6485	0.5840	0.6652	0.6565	0.6054	0.5992	0.6165	0.7103	0.7042	0.6924	0.7344	0.6678	0.6488	0.6386	0.6509	0.6438
f_3	0.6448	0.6536	0.6364	0.6878	0.6441	0.6133	0.6501	0.6908	0.6871	0.6841	0.6989	0.6672	0.7039	0.7015	0.7060	0.7029
f_4	0.6336	0.6406	0.6872	0.6144	0.6222	0.6022	0.6386	0.6813	0.6797	0.6686	0.6953	0.6707	0.6987	0.6901	0.6943	0.6913
f_5	0.6519	0.6544	0.7195	0.7288	0.5962	0.6447	0.6770	0.7106	0.7260	0.7095	0.7523	0.6932	0.6813	0.6704	0.6898	0.6831
f_6	0.6475	0.6471	0.7031	0.7159	0.6694	0.5633	0.6743	0.7085	0.7118	0.6849	0.7377	0.6686	0.6642	0.6538	0.6648	0.6663
f_7	0.6601	0.6583	0.7258	0.7354	0.6841	0.6526	0.6116	0.7233	0.7370	0.7120	0.7532	0.7038	0.6913	0.6742	0.6874	0.6869
f_8	0.6642	0.6612	0.6757	0.6668	0.6296	0.6102	0.6366	0.6506	0.7328	0.7102	0.7511	0.6999	0.6587	0.6542	0.6627	0.6534
f_9	0.6488	0.6645	0.6843	0.6707	0.6311	0.6074	0.6425	0.7276	0.6568	0.7142	0.7589	0.7121	0.6761	0.6629	0.6676	0.6645
f_{10}	0.6625	0.6765	0.7033	0.6789	0.6449	0.6186	0.6483	0.7425	0.7452	0.6554	0.7681	0.7244	0.6929	0.6734	0.6845	0.6875
f_{11}	0.6775	0.6955	0.7125	0.6988	0.6576	0.6390	0.6691	0.7588	0.7616	0.7467	0.7052	0.7400	0.6994	0.6859	0.6991	0.6877
f_{12}	0.6268	0.6465	0.6652	0.6433	0.6175	0.5901	0.6264	0.7191	0.7241	0.7102	0.7461	0.6185	0.6612	0.6419	0.6548	0.6477
f_{13}	0.5597	0.5699	0.6193	0.5984	0.5563	0.5305	0.5690	0.6099	0.6122	0.6110	0.6401	0.5998	0.5459	0.6035	0.6070	0.6004
f_{14}	0.5941	0.5985	0.6464	0.6247	0.5730	0.5547	0.5883	0.6448	0.6470	0.6347	0.6633	0.6293	0.6421	0.5608	0.6358	0.6268
f_{15}	0.5880	0.6065	0.6635	0.6346	0.6043	0.5730	0.6153	0.6511	0.6497	0.6372	0.6745	0.6253	0.6537	0.6353	0.5784	0.6389
f_{16}	0.5778	0.5920	0.6465	0.6305	0.5905	0.5718	0.6118	0.6404	0.6474	0.6305	0.6615	0.6190	0.6347	0.6246	0.6391	0.5653

Table 5. The influence of concern criteria.

Dimensions	Symbols	Criteria	$d_i + r_i$	$d_i - r_i$
WUE	f_1	One's surfing the Internet period (SIP)	21.1285	0.9437
	f_2	Average time spent surfing the Internet per day (ATS)	20.7111	0.2220
AWA	f_3	The frequency of exposed to Web advertising (FEWA)	21.6245	−0.0796
	f_4	The response of seeing Web advertising (RSWA)	21.2795	−0.0624
WAD	f_5	Flash design is an important factor in attracting consumers' attention (FDAA)	20.9638	1.0137
	f_6	Pay attention to picture and text web interface allotment (APT)	20.3784	1.1836
	f_7	Pay attention to the display of highlighted color (ADHC)	21.2321	0.9613
PIL	f_8	Level of importance of the product (LIP)	21.8416	−0.4055
	f_9	The product brings a consumer excitement (PBE)	21.9606	−0.3810
	f_{10}	The product means a lot to a consumer (PMC)	21.9376	0.0757
	f_{11}	Level of the product appealing (LPA)	22.7501	−0.2814
	f_{12}	Level of concerning the product (LCP)	21.2912	−0.2124
ATWA	f_{13}	Faith content in Web advertising (FCWA)	20.0644	−1.1991
	f_{14}	Advertising information serve as a good reference (AISR)	20.3116	−0.5829
	f_{15}	Most Web advertising are pleasant (WAP)	20.6262	−0.5675
	f_{16}	In favor of Web advertising in general (FWA)	20.3947	−0.6281

Table 6. Cause and effect criterion/dimension.

Cause Dimension	Cause Criterion	Effect Criterion	Effect Dimension
WUE	f_1	$f_8, f_9, f_{10}, f_{11}, f_{12}$	PIL
	f_2	f_8, f_9, f_{11}	
AWA	f_3	$f_{13}, f_{14}, f_{15}, f_{16}$	ATWA
WAD	f_5	$f_3, f_4,$ f_8, f_9, f_{10}, f_{11}	AWA, PIL
	f_6	$f_3, f_4,$ f_8, f_9, f_{11}	
	f_7	$f_3, f_4,$ $f_8, f_9, f_{10}, f_{11}, f_{12}$	
PIL	f_{10}, f_{11}	f_3	AWA

obtained from Tables 6 and Fig. 4, which were summarized as follows:

(1) The key causal factors whose values of $(d_i - r_i)$ were positive, including SIP (f_1), ATS (f_2), FDAA (f_5), APT (f_6), and ADHC (f_7); these criteria were classified under two dimensions: WUE and WAD. Both acted as independent variables. The result was the same as the SEM analysis.

(2) The main effect factors whose values of $(d_i - r_i)$ were negative, such as LIP (f_8), PBE (f_9), PMC (f_{10}), LPA (f_{11}), and LCP (f_{12}), FCWA (f_{13}), AISR (f_{14}),

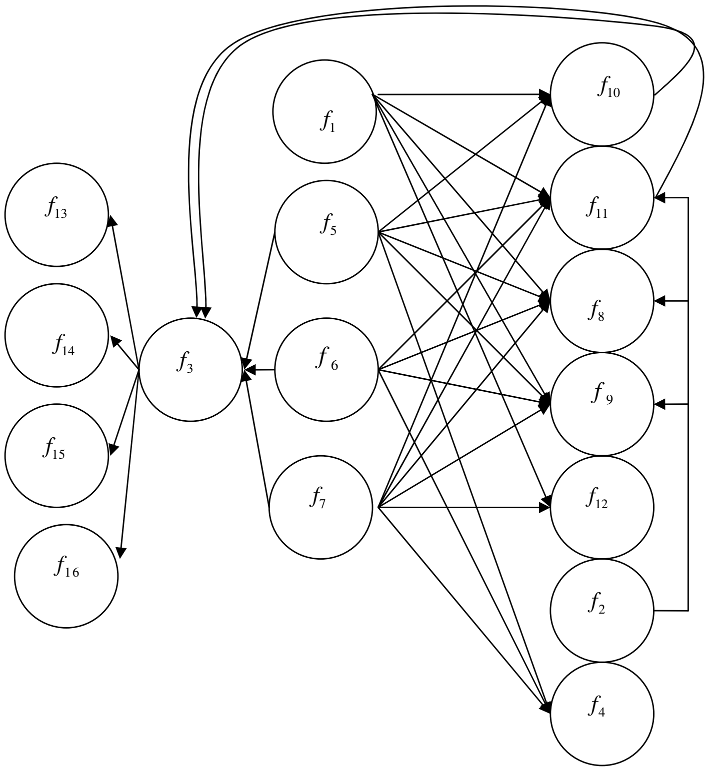


Fig. 4. The network relation map.

WAP (f_{15}), and FWA (f_{16}), were intensely affected by the others. These criteria were classified into two dimensions: PIL and ATWA. Both played the part of intermediary variables; therefore, this result was in close accord with the prediction. (Although the value of $(d_i - r_i)$ for PMC (f_{10}) was positive, judging from the concept of viewing the situation as a whole, the value of $(d_i - r_i)$ for PIL was negative.) The result was the same as that of the SEM analysis.

(3) It is worth noting that criteria such as FEWA (f_3) and RSWA (f_4), classified into the dimension of AWA, had negative values of $(d_i - r_i)$. Drawing from Table 4 and Fig. 5, FEWA (f_3) and RSWA (f_4) may be affected by FDAA (f_5), APT (f_6), and ADHC (f_7), which belong to the dimension of WAD. FEWA (f_3) and RSWA (f_4) may affect FCWA (f_{13}), AISR (f_{14}), WAP (f_{15}), and FWA (f_{16}), which belong to the dimension of ATWA. That is, AWA not only has an impact on ATWA but is also affected by WAD.

(4) In view of the casual diagram of total relation, SIP (f_1) directly affected LIP (f_8), PBE (f_9), PMC (f_{10}), LPA (f_{11}), and LCP (f_{12}); moreover, ATS (f_2) directly affected LIP (f_8), PBE (f_9) and LPA (f_{11}). These criteria ($f_8 - f_{12}$) were classified under PIL; their relationship implied that WUE had a direct positive influence on the PIL.

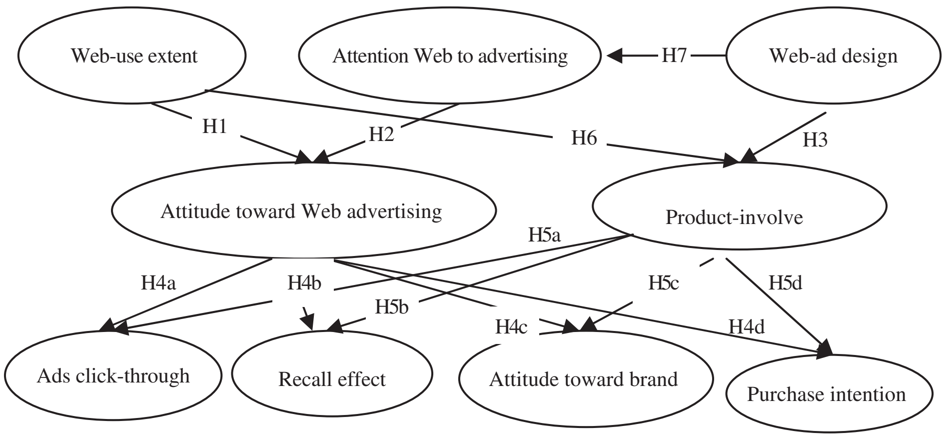


Fig. 5. Study framework after modification.

(5) FEWA (f_3) impacted on FCWA (f_{13}), AISR (f_{14}), WAP (f_{15}), and FWA (f_{16}); these criteria (f_{13}–f_{16}) are classified under the dimension of ATWA and showed that AWA had an influence on ATWA; this result closely resembled the findings for SEM.
(6) PMC (f_{10}) and LPA (f_{11}) impacted on FEWA (f_3); that is, PIL affected AWA.

3.5. *Using DEMATEL to modify SEM model*

Because of the requirement of *a priori* specifications for SEM, the relationships among dimensions were determined in advance by the researchers on the basis of available literature. In fact, it is possible that several relationships among dimensions might have been neglected by the researchers. Hence, this study used the DEMATEL technique for further analysis.

On the basis of the results of DEMATEL analysis, there are some possible relationships among the dimensions, which can be listed as follows:

(1) People usually collect information through surfing the Internet nowadays, which has become the main approach of acquiring knowledge. WUE had a direct positive influence on PIL. Heavy users of the Internet can often acquire and accumulate information of related products through various communities or search engines. In this situation, consumers form individual opinions and develop involvement in a certain product following the pattern shown by their linked communities, thus increasing the PIL. Singh and Rothschild[73] further stressed that the repetition effects of commercial advertising contribute to learning by consumers for acquiring more information. As WUE increases, PIL may be extended.
(2) WAD had a direct significant impact on AWA. A vivid and interesting advertisement is able to catch the eyes of people and draw their attention to it.

Weilbacher[74] believed that a successful advertisement lures customers to buy or view the product or a company in a more favorable light.

(3) PIL affected AWA. It may result from the research object being goods shown over a computer. In the absence of related research, it is necessary to deeply probe whether the relationship does really exist.

According to the above analysis, the study further proposed two hypotheses H6 and H7 as follows:

H6: Web-use extent of the consumers has a direct positive influence on product-involvement level.

H7: Web-ad design has a direct positive influence on attention to Web advertising.

The new research framework was displayed in Fig. 5.

4. Results

The DEMATEL analysis revealed a new relationship between the variables, led to Hypotheses H6 and H7, and was instrumental in constructing a new research model. Study results demonstrated that the relative value of degree of freedom (χ^2/df) is 2.401, which is less than the cut-off value of 3.0; in general, the new study model and observation data possessed a good fit. In addition, the GFI value is 0.905, CFI value is 0.927, and the IFI value is 0.928, meaning that all are greater than the required 0.90. The AGFI value is 0.884 greater than 0.8. The RMSEA value is less than 0.05, indicating that the new model may be established. Generally speaking, the indicators conform to basic requirement values, so the study possesses a good model fit, that is, the new model conforms well to actual data.

After modification, the new model was analyzed by SEM. The results of the comparison between the modified and unmodified models are presented in Table 7. An examination of the fitness index shows that the goodness-of-fit of the modified model is better than that for the unmodified model: The GFI value rose to 0.905 (more than the cut-off value of 0.9) from 0.898 (less than 0.9), and the RMSEA value declined to 0.05 from 0.053, exceeding the threshold value 0.05. Overall, the indicators all conform to the basic requirement of values, showing that the modified

Table 7. Comparing of model fitness.

Fit Index	Model after Modification	Model before Modification
The ratio of Chi-square and degrees of freedom (χ^2/df)	2.410	2.561
Goodness-of-fit index (GFI)	0.905	0.898
Increased fit index (IFI)	0.928	0.919
Comparative fit index (CFI)	0.927	0.919
Adjusted goodness-of-fit index (AGFI)	0.884	0.877
Root mean square error of approximation (RMSEA)	0.050	0.053

Table 8. Verification of model hypotheses after modification.

Hypothesis	Assumed Relationship	Estimated Value	p-Value	Result
H1: WUE → ATWA	−	−0.197	0.007**	Supported
H2: AWA → ATWA	+	0.474	0.000***	Supported
H3: WAD → PIL	+	0.240	0.000***	Supported
H4a: ATWA → ACT	+	0.796	0.000***	Supported
H4b: ATWA → RE	+	0.830	0.000***	Supported
H4c: ATWA → ATB	+	0.802	0.000***	Supported
H4d: ATWA → PI	+	0.889	0.000***	Supported
H5a: PIL → ACT	+	0.123	0.005**	Supported
H5b: PIL → RE	+	0.171	0.000***	Supported
H5c: PIL → ATB	+	0.118	0.006**	Supported
H5d: PIL → PI	+	0.183	0.000***	Supported
H6: WUE → PIL	+	0.341	0.000***	Supported
H7: WAD → AWA	+	0.277	0.000***	Supported

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

model possesses a good model fit. Thus, the new model conforms to actual data better than the initial model.

The test results for hypothesis verification are shown in Table 8. The results show that, in addition to Hypotheses H1–H5, the two newly proposed Hypotheses H6 and H7, are supported as well. Hence, the proposed model differs from the initial one based on SEM with respect to certain results. Through the revised SEM by DEMATEL techniques, the results of this study suggest several important relationships:

(1) Judging from Hypotheses H1 and H4, WUE influences WAE through ATWA. Judging from hypotheses H6 and H5, WUE influences WAE through PIL. That is, WUE influences WAE through ATWA as well as PIL; however, they work in opposite directions, so the manner in which WUE influence WAE depends on the ebb and flow of these two effects. As WUE increases, customer's PIL may increase, causing WAE to rise. On the other hand, the higher the WUE is, the more interference net users receive, which may then cause a negative attitude toward Web advertising and influence WAE. Consequently, how the increase of the WUE influences the WAE depends on the ebb and flow of these two effects. Because of the rapid development of networks, the WUE grows with each passing day, and investigation of how the extent of Web use influences the effect of Web advertising becomes even more important and is worthy of scholars' further analysis.
(2) In the initial SEM model, AWA is an independent variable; however, because H7 is supported, based on H7, H2, and H4, WAD affected WAE through AWA and ATWA (i.e., WAD → AWA → ATWA → WAE). Accordingly, hierarchy effects exist among WAD, AWA, ATWA, and WAE. AWA transforms from an independent variable to an intermediary variable in the new modified model. In

Table 9. Total impact effect.

Variables		WAD	WUE	AWA	PIE	ATWA
AWA	After modification	0.277	—	—	—	—
	Before modification	—	—	—	—	—
PIL	After modification	0.24	0.341	—	—	—
	Before modification	0.253	—	—	—	—
ATWA	After modification	0.131	−0.197	0.474	—	—
	Before modification	—	−0.232	0.459	—	—
ACT	After modification	0.134	−0.115	0.377	0.123	0.796
	Before modification	0.028	−0.185	0.366	0.113	0.796
RE	After modification	0.15	−0.105	0.393	0.171	0.83
	Before modification	0.04	−0.192	0.38	0.16	0.827
ATB	After modification	0.134	−0.118	0.38	0.118	0.802
	Before modification	0.027	−0.186	0.367	0.108	0.799
PI	After modification	0.161	−0.113	0.422	0.183	0.889
	Before modification	0.043	−0.206	0.407	0.171	0.886

Note: Total impact effect is the summary of direct effect and indirect effect.

addition to ATWA and PIL, AWA is also a significant intermediary variable impinging on WAE. In the past, scholars tended to regard AWA as an independent variable and discussed only the intermediary characteristics of PIL and ATWA, but they neglected the intermediary effect of AWA.

Finally, the study used total impact analysis to compare the two models, and the results are presented in Table 9. Before modification, the total impact effects of AWA on ACT, RE, ATB, and PI are 0.366, 0.393, 0.380, and 0.367, respectively; the total impact effects of WAD are 0.028, 0.040, 0.027, and 0.043, respectively, and the total impact effects of WUE are 0.185, 0.192, 0.186, and 0.206, respectively; therefore, among all the independent variables, AWA had the largest impact on WAE. After modification, AWA is no longer an independent variable but an intermediary variable. The total impact effects of WAD on ACT, RE, ATB, and PI are 0.134, 0.150, 0.134, and 0.161, respectively, and the total impact effects of WUE are 0.115, 0.105, 0.118, and 0.113, respectively. Thus, the total impact effects of WAD on ACT, RE, ATB, and PI are greater than WUEs, meaning that WAD is the most important factor affecting WAE.

5. Discussions and Implications

When the initial model is a poor fit, the researcher should identify the possible reasons for this poor fit, such as violation of the assumption that the data distribution, non-linear relationship between variables, too many missing values, mistaken model specification, etc.[75,76] However, many researchers do not understand the reasons in practice and amend the model in according to modification indices (MIs) or Critical ratios (CRs). A clear abuse of SEM may happen when data are simply consistent with the model and the theory is then extended from the analytical result based on presumed hypotheses.[14,15,42,77,78] The essence of SEM is verifying the rationality of the presumed hypothetical model provided by the researcher. Though modification of the model efficaciously assists researchers in attaining the best goodness-of-fit index, the principle of theoretical derivation is violated. Therefore, there is some controversy among researchers about model-modification procedures.[14,15,18,19,21,42,77–82]

The researchers originally intended to release certain parameters when the model-fit evaluation was not good. However, solely considering technical adjustability without any theoretical basis results in SEM losing its confirmatory essence and still retains the value of exploration. Hence the validity of adopting SEM to deal with the problems portrayed by the researcher has been queried.[81] The modified model is reanalyzed using the same data set, not necessarily because it is a truly "better" model, but simply because the model has been fitted to a particular sample data set. Although the researcher acquired an acceptable model, other samples or population cannot be inferred from the theorized model because of the above-mentioned modifying process. This result usually implies that the theoretical basis of the expost modified model of the researcher is not sufficiently efficient.[80–82]

It is extremely necessary to construct the causal hypothesis of SEM according to basic theory. All post hoc modifications to a model must make substantive sense and be theoretically justifiable. Not numerical data set but the substantive theory drives force behind model conceptualization and evaluation. A very serious problem arises if researchers reckon on giving the statistical data their priority and reverse the basic concept by modifying the model. Without a strong theoretical basis for the relationships, letting the data determine the theory and drive model modification creates the probability for a special sample based on covariance matrix to include unique characteristics broader. Finally, the model is likely to be accepted.[18]

Maintaining in pursuit of good-fit may result in too many parameters being evaluated (fit for fitting). The continual modification often results in an over-fitted model. The problem of an over-fitted model is the addition of several improper parameters or erroneous elimination of evaluated parameters. Owing to an acceptable model-fit index, which corresponds to actually observed data, the over-fitted model will consequently not be rejected in SEM analysis and cause incorrect models to be regarded as an ideal model. This is the key reason why model modification is questioned.

Constructing causal model is consistent with sound theoretical basis. It requires knowledge and understanding of the theoretical, substantive, and philosophical foundations of the specific research questionnaires. If not, the researcher may mistake the model specifications by omitting important variables/paths or by including insignificant relations when establishing the path diagrams. A misfit observed data-model usually arises from model specification errors. Model specification errors mean the omission of important exogenous variables in the model and the important link path between the variables in the model, the containment of unimportant parameters, and inappropriate relation in the model or researchers having problems with theories or methods. Furthermore, SEM is a statistical technique without directionality (independent variables and dependent variables are set up by the researcher), so opposite directions may lead to identical results. Unfortunately, SEM cannot perceive the faults in model specification by the modification index.[19]

A number of studies[83–85] have indicated that it is more likely to be successful for the amendment by the limited theory-driven model than the data-driven model. Compared to the data-driven model which amendment model is in accordance with revision of criteria, DEMATEL method provided by this study uses theory-driven model as the method of amendment. To re-examine the causal relationships among all dimensions on the basis of the experts' opinions from industrious, governmental, and academic aspects, and then to test the initial model constructed by the researchers in order to find out the amendment direction for SEM methodology under the reasonably foundation. Respondents judge the relationship between two variables according to their specialty, resulting in three relationships: A affects B ($A \rightarrow B$), B affects A ($B \rightarrow A$), or A and B mutually affect each other ($A \leftrightarrow B$). Thus, DEMETAL provides another tool for examining the accuracy of researchers' initial hypotheses. It will not be confined in the researchers initially hypotheses and path relation, reduce the model specifications errors, minimize the occurrence of capitalization on chance error, maintain the nature of confirmatory and over-fitting model will not be occurred.

6. Conclusions and Contributions

This study established a causal modeling of WAE, which is verified through the SEM statistical technique to confirm its efficiency. The proposed model used SEM to find the causal factors and applied DEMATEL to determine which dimension/criterion was more important and greatly influenced the WAE, carried out comparisons of pairs of mutual relationships in the survey materials and clarified the problem. The combining of SEM and DEMATEL techniques may increase the faith that the results are valid when two different methods engender comparable conclusion.[86] The study revealed the new relationship between variables in accordance with the result of the DEMATEL analysis, advanced H6 and H7, and then recognized WAD as the most significant factor influencing WAE. Revising the conclusion of the original model — the original SEM model analysis found that AWA was the most significant factor influencing WAE — the empirical research revealed that AWA was an important intermediary variable as, after modification, AWA transformed from an independent variable to an intermediary variable. Thus, the crux of the problems could be deduced based on the novel hybrid MCDM model method; therefore, the method may be applicable to the development of strategic plans.

The SEM technique has many advantages, including dealing effectively with multicollinearity and settling the causal relationship between latent variables. However, a particular structure cannot be confirmed as being the right model, even though the fit may be acceptable since a data set will fit other alternative structures in addition to the one under consideration. All perspectives of the SEM technique should be conducted through theory, which is critical for model development and modification. An explicit mishandling of SEM may occur when data are merely consistent with the model and then the theory is extended from the analytical result.[18,19,21,78,79]

DEMETAL provides another tool for examining the accuracy of researchers' initial hypotheses. A model may be revised based on the analysis result of the DEMATEL technique, and a better model may be acquired. In addition, the DEMATEL technique may offer reasonable bases for modification of SEM to avoid overfitting and the above-mentioned misuses.

Causal analysis largely influences the effectiveness of decision-making and marketing actions. Only correct causal analysis helps manager make right decision. The results of the study demonstrated that the DEMATEL method may be an efficient, complementary, and effective approach for reprioritization of the amended modes in a SEM model. Therefore, the model-fit and causal analysis could be meaningful, affecting the efficiency of decision-making.

7. Recommendation for Future Study

SEM includes one or more linear regression equations that express how the endogenous variables depend upon the exogenous variables by using the standardized data set. It can be shown as the matrix $[z_{ij}]_{q\times q}$ and$z_{ij} = (x_{ij} - \overline{x_i})/s_i$, where variable i, $i = 1, 2, \ldots, q$ and sample j, $j = 1, 2, \ldots, n$; the correlation coefficient r_{ik} can be represented as follows:

$$r_{ik} = r(x_i, x_k) = \frac{1}{(n-1)} \sum_{j=1}^{n} [(x_{ij} - \bar{x}_i)/s_i][(x_{kj} - \bar{x}_k)/s_i]. \tag{7}$$

The correlation coefficient $r(Y, X_j)$ between the dependent variable (Y) and independent variables $(X_i, i = 1, 2, \ldots, q)$ is considered as these weights show the effect of the independent variables $(X_i, i = 1, 2, \ldots, q)$ on the dependent variable (Y). Therefore, these weights (correlation coefficients) can be used to infer the degree of influence. However, the correlation coefficient only indicates the relative degree of relationship among variables. It cannot measure the true degree of influence and is unable to quantify the relation intensity among various constructs. SEM uses standardized regression coefficients to infer the comparative magnitude of the impact of the independent variable on the dependent variables. However, SEM does not measure with mathematical precision the relation intensity among various dimensions. Because of an already existing relation between the dimensions, the magnitude of influence is not the same, and the relative weights of criteria are not necessarily equal. For example, in the current model under study, though the WAE is influenced by PIL and ATWA, the importance and influences of the two dimensions on WAE is not the same. SEM assumes that if the criteria weights are equal, they may distort the results, and is thus unable to describe the intensity of the relation that exists among dimensions. Using DEMATEL along with an analytical network process (ANP), the relative weights of criteria can be decided. DEMATEL technique is applied to illustrate the interrelations among the criteria, thus facilitating finding of the central criteria to represent its effectiveness. Subsequently, the ANP method derives the weights of criteria and obtains the effective score of each Web advertising, so that the WAE could be measured more efficiently. Thus, DEMATEL could be used to overcome the problem of evaluation and could be applied with an ANP to construct a new measurement model for WAE, which may be worth pursuing in further researches. It is helpful in alternative selection when these weights are used with one of the techniques of MCDM.[87]

Appendix A. Literature Review

The main measurement method for advertising effects is classified into sales effects and communication effects reflecting advertising as a means to increase product sales. The sales conditions may be direct determined by advertising effects (known as sales effects). Advertising viewing rate, listening rate, product popularity, and various other factors are indirect means to promote sales (known as communication results).[88] Because actual sales cannot be acquired, in terms of Web-advertising effect measuring, this study based its measuring dimensions on the communication effects.

During earlier times, the effectiveness of Web advertising used to be determined by a data of numbers of click-through users however, there is no way to know the effects of cognition, attitude, and purchase intention after consumer contact. Thus, click-through has its shortcomings and insufficiencies when used only as a measurement tool for advertising effects. Hoffman and Thomas[89] suggest observing the mental aspect of consumers through Internet user browsing behavior is similar to traditional advertising where user attitude was used to measure attitude of brand, purchase intention, recall and confirmation, etc. Lohtia *et al.*,[90] uses three output variables — click-through-rate, attitude toward the ad, and recall — to measure the efficiency of banner advertisements. Since there is no consistent Web advertising to affect measurement variables in use at the moment, and traditional media often use recall effects, attitude of brand and purchase intention in measuring advertising effects. Thus, the traditional method is used as a measurement indicator for Internet advertising effect in this study. Moreover, when considering the features of web advertising, many scholars also take click-through number into account in determining whether web advertising is effective.

A.1. *Web-Use Extent*

There is a conflict of opinion among scholars in terms of the subject, how one's the length of the time one the Internet affect Web-advertising effect and the attitude toward Web advertising Some studies were done which showed that light web users have an adverse effect on the Web advertising, more experienced and heavier web users are more used to advertisements being broadcast.[91] Korgaonkar and Wolin[92] explore user's level of Web advertising interest and level of interest in clicking on the site and how they are significantly correlated with the attitude toward Web advertising. The differences between heavy, medium, and light web users in terms of their beliefs about Web advertising, attitudes toward Web advertising, purchasing patterns, and demographics lead to a more positive attitude toward Web advertising, which likely leads to more frequent web purchasing and higher dollar amounts spent on these purchases.

However, for many Web users, Web advertising disrupts flow on web sites, potentially leading to an interruption in the hierarchy-of-effects sequence.[93] Napoli and Ewing[94] indicate that people dislike having advertising while checking or reading e-mail. Web users often have to be interfered by Web advertising while collecting information, checking e-mail, and reading newspaper through the Internet. The longer the time of Web usage, the more the advertising is encountered. For this reason, people feel annoyed about the forced and frequently interfering Web advertising.

A.2. *Attention toward Web Advertising*

Consumers' attention for Web advertising has a great impact on his the advertising attitude and purchase behavior. The position appears to be supported by Nua Internet Surveys[95] notes 32% of online trades result from viewing online advertising.

Rethans *et al.*[96] believe that through repeated occurrence or increasing the occurrence frequency of advertising; the consumer's ability to recall is also enhanced. After exposed to advertising, through attention, understanding and memory, a consumer learns about the message content the advertisement transmits. He then develops interest and preference for the product. At last, through advertising attitude and product assessment, his purchase intention and behavior are influenced. There is a hierarchy effect existing among advertising attention level, advertising attitude, attitude of brand, and purchase intention and they present positive relation to each other.[97] Therefore, by increasing the opportunity and the willingness for consumers to contact with advertising and attracting consumer attention to Web advertising, it leads to a positive Attitude toward Web advertising and improves Web-advertising effects.

A.3. *Web-ad Design*

Advertising content presentation is an important driver factor in Web-advertising effects.[98] Advertising values form in consumers' mind by transmitting advertising messages, which affect their consumption pattern. If messages in advertising help consumers make decisions, their attitude and willingness of making purchases will be influenced.

Bayles and Chaparro[99] comparison between static and dynamic banner advertising recall and confirm effects show that animated advertising is more likely to be correctly recalled. Researchers have also found that website complexity influences consumer attitudes.[100] Norris and Colman[101] study the effects of advertising content on advertising recall effects and pointed out that different types of advertising design will cause different degrees of involvement, which further affects the recall effects of advertising. Wu *et al.*[2] further point out that the greater the importance placed on Web-advertising content design by consumers, the greater the degree of product involvement. After consumers are attracted by the Web-advertising design, they become better informed about the advertising content and the product, which deepens the product-involvement level and further produces Web-advertising effects.

A.4. *Attitudes toward Web Advertising*

Attitudes toward Web advertising is a significant mediator for advertising effects. This opinion has been held by many scholars.[2,102–105]

Advertising attitude will affect the purchase intention toward a particular brand.[106] Perception of advertisements direct affects the consumers' attitudes toward brands and then purchases intention.[107] Moore *et al.*[108] report a positive linear relationship exists between advertising attitude and the attitude of brand. The advertising attitude will direct affect brand cognition. Consumer cognition toward advertising source forms the advertising attitude, which in turn elicits brand cognitions and affective reactions.[102–106] Wu *et al.*[2] state that the more positive a consumer's attitude toward an advertisement is, the greater the effect of the advertisement is.

A.5. *Product-Involvement Level*

McWilliams and Crompton[109] find that different involvement segments have different media choices, information processing, and behavior patterns. Ray[110] proposes that different degrees of involvement will produce different product adoption processes. Korgaonkar and Moschis[79] point out that after consumers have read about related product messages, those with low product involvement are likely to change their minds as results of changes in messages and their attitudes are maintained for shorter periods of time. Therefore, brand-switch is a frequent occurrence for these people. Those with higher Product-involvement level are likely to carefully think over messages being advertised and they are less likely to change their attitudes during advertised messages exposure.

It has been determined in past studies that the level of Product involvement is an important mediator for the Web-advertising effects.[2,108,112–114] Cho[99] finds that when the consumers' product-involvement level is high, consumer intention to click-through advertising also increases. Yoon and Kim[115] have also proved that product-involvement level is a very important crux for web purchase.

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