Applying structural equation model in HBM theory: Case of nutraceutical intake behavior

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ARTICLE INFO

Article history:

Received 18 August 2020

Received in rev. form 05 Sept. 2020

Accepted 08 Sept 2020

Keywords:

Structural Equation Model, Model fit, Diabetic Mellitus, Health Belief Model, Nutraceutical

JEL Classification:

O15, P36

ABSTRACT

Diabetic Mellitus (DM) is a widespread chronic disease around the world, among which type 2 DM (T2DM) shared the majority. It caused multiple severe complications and consequently a high mortality rate. DM complications overwhelm jeopardize the patient's quality of life. In response to the threats of such complications, some nutraceuticals were developed, including the highly praised bitter melon peptide (BMP). This study aims to apply the structural equation model in HBM. A theoretical model had been developed on the health belief model (HBM), and to test with the structural equation model (SEM) technique to examine the fitness of the theory and the data gathered in this research. A structural questionnaire was developed and used to collect 292 valid responses from DM patients. The SEM results indicated the fitness of the theory and the data were acceptable. Perceived susceptibility of DM complications and perceived benefits of nutraceutical were major predictors of intake behavior, and the association of perceived benefits and behavior was mediated by the patient's self-efficacy on nutraceutical intake behavior.

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Introduction

Despite that DM is a horrible health problem, it can be manageable, especially for those caused mainly by dietary and living style, so called type 2 DM. Although effective medications had been developed and applied to help DM patients controlling their blood sugar for years, death count caused by DM remain as high as the top 5 cause (Egede & Ellis, 2008; Zhuang, Ma, Pan & Lu, 2020). In addition, severe DM complications, such as kidney diseases, neurological, circulatory, oral, ophthalmic and skin complications, and other unspecified diabetic conditions can jeopardize the quality of life of the patients and their families. Despite that death is an end to the life, the severe complications are even more tremble than mortality.

The word "nutraceutical" refers to the words "nutrition" and "pharmaceutical", named in 1989 by Stephen L. De Felice. In USA, it is also called 'dietary supplement' or 'food additive', and some other countries 'functional food'. It is generally a pharmaceutical alternative that claims to be beneficial to human's physiological status (Sarris et al., 2016). In addition to the basic nutritional value, nutraceutical is a product that generally extracted or derived from human's food sources to provide extra health benefits. Nutraceutical products can be found in the market to claim to prevent chronic diseases, improve health, delay the aging process, increase life expectancy, or support the structure or function of the body (Sarkar, 2007; Sarris et al., 2016).

In response to the threat of DM complications and its associated deteriorated quality of life, a plethora of nutraceutical were developed to help managing this particular health disorder. Bitter melon peptide is one of the most noticeable products with good market share (Hsu, Pan & Hsieh, 2020). Research question incurred from the observation is what are the factors behind such a demand of BMP. We choose HBM as a theoretical background to explain this phenomenon since HBM is one of the most notable theories in predicting health behavior (Noh, Cho, Lee & Yun, 2020).

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This study aims to apply structural equation model in HBM. A theoretical model had been developed on the health belief model (HBM), and to test with the structural equation model (SEM) technique to examine the fitness of the theory and the data gathered in this research. A structural questionnaire was developed and used to collect 292 valid responses from DM patients.

Literature Review

Theoretical background and Conceptual Framework

Health belief model (HBM) was developed to understand people were reluctant to receive the government's health prevention campaigns in the 1950s. HBM is known as an effective theory to explain and predict the human's health behavior, including disease prevention and health promotion (Janz & Becker, 1984; Rosenstock, Strecher & Becker, 1988) since it was introduced (See Noh et al., 2020 for detailed review).

According to HBM (Rosenstock, 1974), the likelihood of taking recommended preventive health actions can be predicted by perceived threats of certain diseases, as well as the value of perceived benefits of preventive actions minus perceived barriers of taking preventive action. In the later model, self-efficacy from social learning theory (Bandura, 1977) was adopted as a new variable in predicting the preventive action with a better predicting power, or higher levels of variance explained (Janz & Becker, 1984; Rosenstock, Strecher & Becker, 1988). The new variables of self-efficacy supersede other original variables and almost dominate the major part of variance explained of the new model. The current research raises a question regarding the role of self-efficacy in the new model of HBM.

Figure 1: Theoretical framework of the study

Purpose of the current study is to apply structural equation model (SEM) to examine fitness of the data and the theoretical model, in particular to verify the role of respondent's self-efficacy plays in the entire model (Bandura, 1977). The theoretical framework of the current study was shown as figure 1.

Research and Methodology

Samples and code of ethics

Subjects are at least 20 years old, were diagnosed as a Type II Diabetic Mellitus (T2DM), and were recruited on a volunteer basis. 292 responses were gathered and analyzed in this study. In response to the requirement of code of academic study ethics, the study was approved by the Institutional Review Board (IRB) of Pingtung Christian Hospital (PCH; Pingtung City, Taiwan) with approval number IRB552B.

Variables measurement

The perceived susceptibility is a term to inquire the subject's perception toward the possibility of diabetic complications, including diseases with the cardiovascular system, kidney, eyes, feet, and sexual function. In addition, the perceived severity construct inquires the respondent's perception of the consequences of these diabetic complications.

Perceived benefit was used as a construct to measure how the respondents believed the nutraceutical could be beneficial to prevent the progress of complications. Perceived barrier was used as a predictor to reflect how difficult the respondents perceived when taking nutraceutical, such as cost, accessibility, and other expected barriers.

The self-efficacy construct inquires the respondents how confident they estimate to take the nutraceutical.

Research instrument

A structured questionnaire was developed based on the HBM and revised with a pre-test with 50 subjects with good levels of reliability and validity. A five-point scale was applied to measure the responses to the items of each construct.

The questionnaire contained four main constructs of the HBM, i.e. perceived susceptibility and perceived severity of DM complications, perceived benefits and perceived barriers to taking BMP in addition to other medication, and self-efficacy.

Data were analyzed using AMOS / SPSS 20.0 (Armonk, NY: IBM Corp). All significance levels were set at $p \leq 0.05$.

Measurement model

Convergent validity

A two-step approach of structural equation modeling (SEM) suggested by Anderson and Gerbing (1988) is used to measure the structure of the model. In the first step, a confirmatory factor analysis (CFA) is used to examine the construct reliability and validity of the measurement model. The second step is to test the path effects and their significance of the structural model. By using the maximum likelihood estimation (MLE) in terms of factor loadings, reliability of measurement, convergent validity, and discriminant validity, the measurement model was assessed.

As suggested by Fornell and Larcker (1981), Table 1 presented unstandardized factor loadings, standard errors, significance tests, standardized factor loadings, square multiple correlations, composite reliability, as well as average variance extracted (AVE) to show the features of each construct in this study.

As what table 1 has shown, all standardized factor loadings of questions are from 0.592 to 0.944 falling into a reasonable range. This demonstrate all questions have convergent validity. All the composite reliability of the constructs ranging from 0.901 to 0.978, exceed an acceptable level at least 0.7 indicating all constructs have internal consistency.

All values of average variance extracted (AVE) are ranging from 0.609 to 0.85, and exceeding the standard level of 0.5 that was suggested by scholars (Fornell & Larcker, 1981). This means all constructs of the study have adequate convergent validity.

Table 1: Results for the measurement model.

Constructs	Item	Significance of estimated parameters				Item Reliability		Construct	
		Unstd.	S.E.	Unstd./S.E.	<i>p</i>	Std.	SMC	Reliability	Validity
SP	SP01	1.000				0.856	0.733	0.961	0.690
	SP02	1.060	0.050	20.997	0.000	0.882	0.778		
	SP03	1.052	0.049	21.451	0.000	0.895	0.801		
	SP04	1.056	0.055	19.373	0.000	0.851	0.724		
	SP05	0.840	0.049	17.184	0.000	0.798	0.637		
	SP06	0.897	0.054	16.566	0.000	0.780	0.608		
	SP07	1.072	0.058	18.417	0.000	0.834	0.696		
	SP08	1.042	0.060	17.226	0.000	0.800	0.640		
	SP09	1.045	0.056	18.819	0.000	0.842	0.709		
	SP10	0.953	0.056	17.035	0.000	0.797	0.635		
	SP11	0.990	0.058	16.938	0.000	0.794	0.630		
SS	SS01	1.000				0.887	0.787	0.969	0.742
	SS02	1.018	0.044	23.326	0.000	0.896	0.803		
	SS03	1.056	0.046	22.975	0.000	0.890	0.792		
	SS04	1.015	0.043	23.833	0.000	0.907	0.823		
	SS05	0.884	0.042	21.192	0.000	0.860	0.740		
	SS06	0.982	0.051	19.210	0.000	0.819	0.671		
	SS07	1.041	0.053	19.801	0.000	0.833	0.694		
	SS08	1.048	0.057	18.327	0.000	0.799	0.638		
	SS09	1.017	0.052	19.738	0.000	0.830	0.689		
	SS10	1.020	0.047	21.781	0.000	0.871	0.759		
	SS11	1.014	0.046	21.969	0.000	0.876	0.767		
BE	BE01	1.000				0.906	0.821	0.978	0.775
	BE02	1.062	0.043	24.803	0.000	0.895	0.801		
	BE03	1.108	0.044	25.335	0.000	0.903	0.815		
	BE04	1.087	0.041	26.555	0.000	0.919	0.845		
	BE05	1.025	0.052	19.640	0.000	0.812	0.659		
	BE06	0.980	0.046	21.327	0.000	0.843	0.711		
	BE07	1.035	0.041	25.417	0.000	0.905	0.819		
	BE08	1.014	0.048	21.283	0.000	0.844	0.712		
	BE09	1.064	0.043	24.516	0.000	0.892	0.796		
	BE10	1.027	0.041	25.159	0.000	0.901	0.812		
	BE11	1.060	0.045	23.336	0.000	0.877	0.769		

Table 1: Cont'd

	BE12	1.032	0.042	24.475	0.000	0.893	0.797		
	BE13	1.042	0.049	21.471	0.000	0.848	0.719		
BA	BA01	1.000				0.607	0.368	0.901	0.609
	BA02	0.992	0.112	8.873	0.000	0.592	0.350		
	BA03	1.534	0.137	11.186	0.000	0.831	0.691		
	BA04	1.370	0.130	10.548	0.000	0.761	0.579		
	BA05	1.629	0.140	11.613	0.000	0.907	0.823		
	BA06	1.658	0.142	11.665	0.000	0.919	0.845		
SE	SE01	1.000				0.881	0.776	0.952	0.799
	SE02	1.201	0.048	24.775	0.000	0.925	0.856		
	SE03	1.178	0.067	17.575	0.000	0.794	0.630		
	SE04	1.254	0.051	24.547	0.000	0.931	0.867		
	SE05	1.305	0.054	24.377	0.000	0.931	0.867		
BH	BH01	1.000				0.907	0.823	0.958	0.850
	BH02	0.988	0.035	28.111	0.000	0.944	0.891		
	BH03	1.001	0.037	27.305	0.000	0.935	0.874		
	BH04	0.931	0.038	24.780	0.000	0.900	0.810		

Unstd.: Unstandardized factor loadings; Std: Standardized factor loadings; SMC: Square Multiple Correlations; CR: Composite Reliability; AVE: Average Variance Extracted.

Discriminant validity

Comparing the square root of the average variance extracted (AVE) of a given construct with the correlations between the construct and the other constructs is the discriminant validity (Fornell & Larcker, 1981). The indicators are more closely related to the construct than the others if the square root of the AVE of a construct is greater than the off-diagonal elements in the corresponding rows and columns.

Table 2: Discriminant validity for the measurement model.

	AVE	SP	SS	BE	BA	SE	BH
SP	0.690	0.831					
SS	0.742	0.792	0.861				
BE	0.775	0.429	0.347	0.88			
BA	0.609	0.046	0.023	-0.078	0.78		
SE	0.799	0.259	0.209	0.603	-0.047	0.894	
BH	0.850	0.495	0.383	0.608	-0.074	0.685	0.922

Note: The items on the diagonal on bold represent the square roots of the AVE; off-diagonal elements are the correlation estimates

As shown in table 2, the bold numbers in the diagonal direction represent the square roots of AVEs. Because all the numbers in the diagonal direction are greater than the off-diagonal numbers, discriminant validity appears to be satisfactory for all constructs.

Results and Discussion

Structural model analysis

This study performed structural model testing to examine the hypothesized relationships of the proposed model with the maximum likelihood method. Model fit indicators determines whether the sample data fit the structural equation model proposed. A variety of standards were recommended by Schumacker and Lomax (2010) to determine model fit of a structural model. In addition, a review study has also suggested to create model fit report (Jackson, Gillaspay & Purc-Stephenson, 2009). These indices are χ^2 , d.f., χ^2 /d.f. ratio, GFI, AGFI, RMSEA, SRMR, CFI and TLI(NNFI) etc.

Table 3 presents several model fits indicators as well as the recommended thresholds. Except for χ^2 , all model fits indicators exceed the recommended levels (Schumacker & Lomax, 2010). Because χ^2 is very sensitive to a large sample, the ratio of χ^2 to its degree of freedom was computed, and the ideal ratio should be below three for a good model fit. Hu and Bentler (1999) suggested that instead of evaluating each index independently, a stricter combination rule should be applied to model fit indices to control types I error.

Table 3: Model fit

DV	IV	Unstd	S.E.	Unstd./S.E.	p-value	Std.	R ²
SE	BE	0.569	0.052	10.999	0.000	0.603	0.364
BH	SP	0.322	0.075	4.284	0.000	0.319	0.599
	SS	-0.035	0.072	-0.486	0.627	-0.034	
	BE	0.207	0.063	3.284	0.001	0.178	
	BA	-0.065	0.054	-1.209	0.227	-0.051	
	SE	0.617	0.070	8.792	0.000	0.500	

Table 4: Regression Coefficient

Model fit	Criteria	Model fit of research model
ML χ^2	The small the better	3909.003
DF	The large the better	1163.000
Normed Chi-sqr. (χ^2/DF)	$1 < \chi^2/DF < 3$	3.361
RMSEA	<0.08	0.090
SRMR	<0.08	0.070
TLI (NNFI)	>0.9	0.841
CFI	>0.9	0.849
GFI	>0.9	0.798
AGFI	>0.9	0.787

The table 4 shows the results of path coefficients. Perceived benefits (BE) has significantly impact on self-efficacy (SE) ($b=0.569$, $p < 0.001$). Perceived susceptibility (SP) ($b=0.322$, $p < 0.001$), perceived benefit (BE) ($b=0.207$, $p=0.001$), and self-efficacy (SE) ($b=0.617$, $p < 0.001$) have significantly impacts on intake behavior (BH).

The results support the research question regarding the validity of the research model. 36.4% of SE can be explained by BE ($\beta=0.569$) constructs. 59.9% of BH can be explained by constructs of SP ($\beta=0.322$), SS ($\beta=-0.035$), BE ($\beta=0.207$), BA ($\beta=-0.065$) and SE ($\beta=0.617$), as shown as well in figure 2. On the other hand, the total effect of BE on the BH is 0.557, of which is composed by a direct effect of BE (0.207) and an indirect effect through SE ($0.569 \times 0.617 = 0.350$).

Figure 2: Regression coefficient

Model fit correction

In the SEM analysis, good model fit demonstrates that the covariance matrix generated by the sample is consistent with the expected covariance matrix produced by the model in study. A structural equation modeling (SEM) generally uses maximum likelihood (ML)

estimation to analyze data that is featured with multivariate normality. Original model fit is shown as in Table 5. Indices such as RMSEA and SRMR should be lower than 0.08, the SRMR of the current study is 0.07, and the RMSEA is 0.090, are lower or close to the good levels. Other indices such as TLI, CFI, GFI, and AGFI are better to be higher than 0.9 to show the good levels of fitness. In this study, TLI=0.841, CFI=0.849, GFI=0.898, and AGFI=0.887 are very close to the good, denotes that the fitness level is acceptable.

Table 5: SEM model fit

Model fit	Criteria	Model fit of research model
$ML\chi^2$	The small the better	3909.003
DF	The large the better	1163.000
Normed Chi-sqr (χ^2/DF)	$1 < \chi^2/DF < 3$	3.361
RMSEA	<0.08	0.090
SRMR	<0.08	0.070
TLI (NNFI)	>0.9	0.841
CFI	>0.9	0.849
GFI	>0.9	0.898
AGFI	>0.9	0.887

If the data is not multivariate normally distributed, parameter estimation will be biased, yet the chi-square will cause poor model fit. That is a type I error, and that wrongly rejects null hypothesis (Curran, West & Finch, 1996; Kaplan, 2000). In response to this problem, Satorra and Bentler (1994) developed a process that can correct the bias caused by the data that is not multivariate normally distributed. The scaling correction factor (c) is the averaged difference of biased chi-square in multivariate kurtosis. Dividing the original chi-square by the scaling correction factor (c) is the corrected chi-square. The process is called Satorra-Bentler (SB) scaled chi-square.

Table 6: Model fit processed by Satorra-Bentler scaled chi-square

Model fit	Criteria	Model fit of research model
Satorra-Bentler χ^2	The small the better	2697.525
DF	The large the better	1163.000
Normed Chi-sqr (χ^2/DF)	$1 < \chi^2/DF < 3$	2.319
RMSEA	<0.08	0.067
SRMR	<0.08	0.071
TLI (NNFI)	>0.9	0.868
CFI	>0.9	0.875
GFI	>0.9	0.921
AGFI	>0.9	0.932
Scaling correction factor	>1	1.449

During the process of scaling correction, RMR and SRMR can't be modified because they are calculated by residuals but not chi-square. After Satorra-Bentler scaled chi-square process, all the model fit indicators have been significantly improved, both RMSEA and SRMR are lower than 0.08, and all TLI, CFI, GFI, and AGFI are improved or higher than 0.9, as shown in Table 6.

Common method variance

Common method variance (CMV) may appear if variations in responses are caused by the instrument rather than the actual predispositions of the respondents (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In other words, it is possible to produce a CMV if a quantitative research adopted a measurement in investigation, especially self-reported questionnaires.

We adopted ULMC (Unmeasured Latent Method Construct) to detect and control the CMV when CMV produce an impact of CMV in the current study. ULMC using a latent construct with no unique observed indicators represents the shared variance (Williams,

Cote & Buckley, 1989). In table 7, the chi-squared difference of congeneric and non-congeneric model is 652.931, the difference in degrees of freedom is 49, and p-value is 0, indicating a significant difference between these two models. Congeneric model is obviously better than non-congeneric model, because Chi-square of congeneric model is lower than non-congeneric one. CMV has effect on the congeneric model.

Table 7: congeneric and non-congeneric model fit comparison

	χ^2	d.f.	$\Delta\chi^2$	Δ d.f.	p-value
Non-congeneric	3878.742	1159	652.931	49	0
Congeneric	3225.811	1110			

Congeneric model is the model that performed CFA after removing CMV. Constrained model covariance is affected by CMV.

In table 8, the chi-squared difference of congeneric and constrained model is 3.788, the difference in degrees of freedom is 15, and p-value is 0.998, indicating no significant difference between these two models. CMV has no impacts on model constructs. Model does not need to do CMV corrections.

Table 8: congeneric and constrained model fit comparison

	χ^2	d.f.	$\Delta\chi^2$	Δ df	p-value
Constrained model	3229.599	1125	3.788	15	0.998
Congeneric model	3225.811	1110			

Mediation Effects

In a research model, 'Me' is a mediator if the independent variable (X) affects the dependent variable (Y) through (Me). Because the mediator is closer to the outcome variable than the predictor variable, the mediator becomes a causal or endogenous variable. When the independent variable affects the dependent variable through the mediator, it is called mediation effect. The indirect effect of the mediator can be examined by several methods, such as the prevailed method proposed by Baron and Kenny (1986) (B-K method), product of coefficients, and bootstrapping mediation analysis among many others.

Using B-K method to test indirect effects

The B-K method suggested by Baron and Kenny (1986) is the most common approach for testing indirect effects. Me is a mediator between X and Y if both paths of a ($X \rightarrow \text{Me}$) and b ($\text{Me} \rightarrow Y$) in a model are statistically significant and 'c' ($X \rightarrow Y$) is closer to zero than 'c' does, as shown in figure 3.

The B-K method is weak in the power of the test (Fritz & MacKinnon, 2007; MacKinnon, Lockwood, Hoffman, West & Sheet, 2002). Another weakness of this method is that it is also lack of quantitative verification of the indirect effects.

Figure 3: Mediator of dependent and independent variables

Using product of coefficients to test indirect effects

Sobel's z test (Sobel, 1986) is often used to test mediation effects by determining the significance of regression analyses and the product of coefficient.

The unstandardized regression weight and standard error of indirect effect from path 'a' and path 'b' were estimated by the Sobel's z test (Preacher & Hayes, 2004). The null hypothesis: the indirect effect equals to zero, was tested by calculating the ratio of indirect effect 'a*b' to its unstandardized regression weight standard error.

Sobel's z test works as a supplement of the B-K method. It is assumed that the indirect effects are normally distributed in the Sobel's z test. However, if skewness and kurtosis are not zero, the distribution of indirect effect 'a*b' tends to be asymmetric (Bollen & Stine, 1990; Stone & Sobel, 1990). Therefore, at 95% confidence level, even if $z > 1.96$, the indirect effect might not be significant.

Using Bootstrapping to test indirect effects

When examining the indirect/mediation effects, prior literature believed using bootstrapping mediation analysis is better than B-K method or product of coefficient (MacKinnon, Lockwood & Williams, 2004; Williams & MacKinnon, 2008). Using bootstrapping mediation analysis has the advantage over the other two methods because the assumption of normalized distribution of indirect effect can be ignored when analyzing.

Bootstrapping is a statistical method about random sampling with replacement. The product coefficient of 'a' and 'b' is estimated for each sampling. Standard errors and confidential intervals can be derived from the distribution of the product of 'a' and 'b'. The sampling processes will repeat at least 1000 times, although 5,000 times are more desirable (Hayes, 2009).

Table 9: The analysis of indirect effects

Effect	Point estimate	Product of coefficients			Bootstrap 1000 times	
		S.E.	Z-value	p-value	Bias-corrected 95%	
					Lower bound	Upper bound
Total effect						
(BE→BH)	0.558	0.081	6.912	0.000	0.397	0.709
Total indirect effect						
(BE→BH)	0.351	0.089	3.937	0.000	0.193	0.532
Direct effect						
(BE→BH)	0.207	0.123	1.686	0.092	-0.031	0.440

Bootstrapping mediation analysis is better than other mediation testing methods because it can provide confidential intervals to examine the indirect effects. Bias corrected bootstrapping is one of the preferable bootstrapping mediation analysis methods (Williams & MacKinnon, 2008).

As shown in Table 9, the total effect BE→BH, $p < 0.05$, bias-corrected confidence interval (CI) does not include 0 (CI of BE→BH = [0.397 0.709]). The existence of total effect was supported.

Discussion and Implications

Perceived susceptibility and perceived severity are two components of perceived threats of diabetic complications for DM patients, both of which generally have impacts on any prevention measures including medications. The current study revealed that perceived susceptibility is the only factor that significantly affect the respondent's taking behavior of the nutraceutical. Unlike other studies that inquired general population of adults, the respondents in this study were those already diagnosed by physician as DM patients. These people are suffering health problems caused by DM when they were recruited. Possibility of the development of severe DM complications in any human organs or internal systems may be a more urgent issue than how severe of these complications may cause for this particular respondent group.

Self-efficacy as an independent construct that was introduced by Bandura in 1977, later than the inauguration of HBM, can be found to be included as part of an HBM in many studies. However, these HBM-based studies frequently find that self-efficacy become the major predictor in the new model. In other words, self-efficacy can be used as a sole predictor without any effects of other variables such as perceived threat of health problems, perceived benefits and barriers of health improvement measures. We are not in a position to argue that self-efficacy was not effective in explaining health promotion or disease prevention. On the contrary, self-efficacy is important in help explaining the disease prevention activities, yet just in the positions of mediation or moderation and may not be a decisive factor.

Both B-K method and bootstrapping mediation analysis support the mediation effects of self-efficacy in the association of perceived benefits of nutraceutical and the patient's intake behavior. This further support our proposition that the mediating roles of self-efficacy in the HBM model.

Conclusions

The data of nutraceutical intake behavior among T2DM patients conform to the theoretical model of the current research at a good level. We conclude that perceived severity of perceived threats and perceived barrier nutraceutical were not significantly affect the nutraceutical intake behavior. On the contrary, perceived susceptibility of potential DM complications and the perceived benefits of nutraceutical may work in promoting health as the major predictors of the likelihood of taking nutraceutical. As far as the perceived benefit concerned in the intake behavior of nutraceutical, self-efficacy on such behavior indeed acts a significant mediator. The results from the current research shed more light on the role of self-efficacy acts in the HBM theory. Results from the current research provide clear guidance to the nutraceutical business when making marketing plans.

Acknowledgement: We are grateful to Dr. Joe Hsu for his assistance in guiding the SEM analysis. We also thank to Dr. Ente Hsu of Tunghail University, and Mr. T. Y. Lee of former president of San Fu Motors y for their valuable comments on the earlier draft.

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