



Brand personality factors affecting purchasing decision for bottled drinking water in Bangkok and Bangkok peripheral area: Supervised machine learning approach

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Abstract

The study of brand personality factors affecting purchasing decision for bottled drinking water in Bangkok and Bangkok peripheral area aimed to investigate brand personality factors that affect purchasing decision for bottled water in Bangkok and Bangkok peripheral area by utilizing a supervised machine learning approach from data science discipline. The objective of the study was to develop and evaluate the most suitable and practical purchasing decision label prediction model from brand personality features. The samples were drawn from people living in Bangkok and Bangkok peripheral area experienced in consuming bottled drinking water. Research tools were questionnaire with rating scale, and convenience sampling method was applied. The analysis of results showed that 5 brand personality features positively and significantly affected the level of purchasing decision label. Furthermore, this well-developed prediction model from train set maintained a moderate level of generalization as per supervised machine learning model evaluation by unseen set. As per the results, bottled drinking water manufacturer should not ignore the importance of promoting drinking water brand personality to match target consumers' various personality traits as all 5 brand personality traits had a significant effect on the decision to buy bottled drinking water. Predicting purchasing decision for bottled drinking water by adopting Supervised Machine Learning approach from data science discipline is considered as a contribution of this study. Future research should possibly broaden the results of this study by utilizing unsupervised machine learning technique to develop the classification algorithm to classify an unknown target label.

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Introduction

The bottled drinking water industry in Thailand is continuously growing regardless of economic conditions. From 2017 to 2019, the market value of bottled drinking water in Thailand increased from 36,600 million baht to 45,300 million baht (Marketeer, 2019). Even if the Metropolitan and Provincial Waterworks Authority of Thailand have certified the quality of produced water, consumers still prefer to buy bottled drinking water for daily consumption. This indicates a positive sign in Thai consumer behavior towards buying bottled drinking water. This phenomenon provides a business opportunity in this industry, and presently there are many bottled drinking water manufacturers fighting out there in the business battle field. The main reason why bottled water business is growing continuously is that consumers perceive and believe that bottled water is clean and free of impurities, and they feel more confident to consume it.

According to the basic economic theory, bottled drinking water is considered as one of the commodity goods in a near perfect competitive market, that is to say, there are many manufacturers in the market and the core features of products are exactly the same. Moreover, there is no obstacle to enter or leave the competition, and both manufacturer and consumer have full knowledge and information towards the product (Ferrier, 2001). Because of this, a problem brought to the researchers' attention was how to survive in this highly competitive market and gain more profitable income sustainably. Fortunately, marketing and its elements are considered as powerful weapons in the fight in the business war, especially branding. Owing to bottled water having the same core feature, some consumers consider buying bottled water which has a brand personality that is associated with their personal traits and identity. The product brand and its personality can be associated with human personality traits through perception, recognition, learning and experiences and this can improve demand towards the product. The main objective of branding strategy is to increase consumption beyond basic needs and, by this strategy, growth in sales can be expected. Thus, branding can be one of many marketing strategies to help bottled drinking water manufacturers maintain a strong fighting stance in the ring. Furthermore, this powerful marketing tool and technique can possibly bring an advantage in this highly competitive business industry.

Nowadays, there are many academic researches that shed light on branding perspective towards consumer behaviors. Nevertheless, there are few studies that mainly

focus on the brand personality traits towards purchasing decision in most common commodity goods like bottled drinking water context. According to those reason aforementioned, this study aimed to answer the question: By adopting a machine learning approach, how do 5 aspects of brand personality features, namely, sincerity, excitement, competence, sophistication and ruggedness affect the level of purchasing decision label? Therefore, this study aimed to scrutinize brand personality factors that affect purchasing decision for bottled water in Bangkok and Bangkok peripheral area by utilizing a supervised machine learning approach. The objective of the study was to develop and evaluate the most suitable and practical purchasing decision label prediction model from brand personality features.

Literature Review

Supervised Machine Learning Concept

Supervised Machine Learning (SML) has been utilized to analyze various content in many fields of studies (Burscher, Vliegenthart & De Vreese, 2015). Quintessentially, according to data science concept of SML, the computer tries to replicate the coding decision that was formerly coded by human. The main objective of this technique was to automatically code a number of texts into a previously defined function. Hence, a set of pre-coded or pre-fitted prediction or classification model for the content categories was a main precondition of SML. This set was considered as a training set for the SML procedure. Generally, SML involved three main steps (Burscher, Odijk, Vliegenthart, De Rijke, & De Vreese, 2014). First, the datasets would be randomized into two sets, which were train set and test set in certain ratio. Second, the train set would be put into a prediction model or classification model development. In this process, a SML algorithm would statistically analyze features from each content category from train set and generated a predictive model or classification model depending upon the research question whether to predict or to classify the target outcome. Finally, after fitting a predictive model or classification model by train set, a test set would be put into a model to evaluate the prediction of classification performance. SML provided several advantages over legacy manual model development analysis. Primarily, SML would allow researcher to expand the scope of their analysis by determining the effectiveness of the prediction or classification model by using test set to test and evaluate

an effectiveness or performance of the developed model, unlike classical statistical analysis. Additionally, once the model was trained to code the content categories and features, it could be applied to other unseen datasets.

To generalize, supervised machine learning was the search for several algorithms that reason from external instances to generate general hypotheses, which placed prediction about future instances or classified things into several groups. The main objective of supervised machine learning was to construct a concise model of the distribution of class labels (dependent variables) in terms of predictors or classifier features (independent variables). This resulted in the classifier being then used to assign class labels to testing instances where the values of the predictor or classifier features were known, but the value of the class label was unknown (Kotsiantis, Zaharakis & Pintelas, 2007).

An Overview of Purchasing Decision Process

Generally, the purchasing decision process can be divided into 5 stages, namely, problem recognition, information search, evaluation of alternative, purchase decision and post purchase behavior (Kotler & Keller, 2016). However, there are many conceptualizations that have been developed so as to describe the purchasing decision process. For instance, the purchase decision process could be divided into three elements of the buying group construct (McCabe, 1987). These elements were participation, which portrayed an involvement of various members, formalization, which described a reliance on formal procedure, and centralization, which showed a degree of hierarchy of authority. Moreover, purchasing decision process could be divided into another five dimensions according to the buying center, namely, vertical involvement, lateral involvement, extensivity, connectedness and centrality (Johnston & Bonoma, 1981). The purchasing decision process was the stage where the consumer actually purchased the products or services for consumption. This was considered as an action committed by a consumer to make a decision in the form of selection, the selection of the brand, the condition and features of products or services such as promotion, discount, rebate and allowance, and the amount of the purchase. These could possibly be measured by cognitive, affective and conative items of the purchase decision label (Schiffman, Kanuk & Wisenblit, 2010).

Brand Personality

In accordance with brand personality theories and concepts, the brand and its personality could be linked

with human personality traits through perception, learning and experiences. Seeing that consumers had tried to articulate perceived differences between several brands based on the physical attributes and function, brand personality had been a vital part of a marketing campaign. The task of differentiating brands can be facilitated when consumers relate brand personality to actual human traits and characteristics. Therefore, communicating a crystal-clear definition of brand image and personality would allow consumers to identify the needs that the brand provided (Park, Jaworski, & MacInnis, 1986). However, not every brand had a clear personality of its own. Hence, it is quintessential for consumers to experience the brand first before they form any subjective recognition about and personality characteristics associated with the perceived brand. The effect of such experiences is the creation of a brand with a personality of its own. The total mix of marketing communication factors and every other exposure that the brand received would provide brand personality from time to time (Aaker, 1996).

Brand personality was considered as a beneficial tool for marketer as a brand personality was considered as an integrative component of brand image and brand equity. Besides, it was also associated with the brand value in the consumer's mind (Keller, 1993). A brand personality would be clear and solid if the personality elements were distinctive and consistent over time (Batra, Lehmann, & Singh, 1993). Brand personality could build a strong bond with consumers, especially when the personality was clear, strong, distinctive and constant. Therefore, many marketing practitioners perceived brand personality as an efficient way to distinguish the brand from its competitors. By promoting the distinction of these elements, brand personality would supply self-expressive benefits for the consumer (Aaker, 1999) now that consumers always stipulated brand to build and communicate their own traits and personality. For instance, consumers utilized brands to form connections between their self-concepts and brand images as self-brand connection. This phenomenon played a crucial role in creating and maintaining long term relationship between consumer and brand. Furthermore, consumers always value the mental benefits of linking their traits with brand as they could form and identify their self-concepts and portray themselves to others in various social context (Escalas & Bettman, 2003). Thereby, a well-built brand personality was determined as a psychological linkage with brand, which increased patronage and sense of loyalty.

Big Five: The Brand Personality Elements and Human Personality

The five-factor model of human personality, namely, neuroticism, extraversion, openness, agreeableness and conscientiousness could be utilized to apprehend and link to five brand personality factors (Aaker, 1997). For example, sincerity, excitement and competence resembled three human personality dimensions of agreeableness, extraversion and conscientiousness while other two human personality traits were correlated among various mixed dimensions of brand personality element. It seemed that these personalities were correlated and generalizable. As discussed before, because brand personality was built and maintained in the consumer's mind as a perception of the brand, it could have a significant impact on brand trust and its effect. Moreover, brand personality improved emotion and affected levels in consumption the same way as trust and loyalty level (Fournier, 1998). Brand personality was said to be related to cognitive level of brand evaluation.

There were a number of past studies that signified an effect of brand personality on purchasing decision. For example, there was a study that focused on effect of brand personalities on purchasing intention of Aquafina bottled water, and this study utilized a structural model and paths analysis as a tool. The results showed that all elements of brand personalities indirectly affected purchasing intention through brand preference (Maymand & Razmi, 2017). Apart from that, past research that studied factors affecting Ghana consumer's purchasing decision of bottled water implied that personality, perception toward brand and belief affected buying behavior of bottled water (Quansah, Okoe, & Angenu, 2015). Moreover, several past studies suggested that brand personality was a significant antecedent of consumer purchasing behavior in various contexts. (Anggraeni, 2015; Bouhlel, Mzoughi, Hadjji, & Slimane, 2011; Wang, Yang, & Liu, 2009).

According to the review of related literature aforementioned, it could be hypothesized that, by utilizing a machine learning technique, the purchasing decision label of prediction model, in which predictors were 5 aspects of brand personality features, were statistically significant, and the developed prediction model by train set was fitted with empirical data.

Methodology

This research was determined as a survey with a quantitative methodology and cross-sectional design. The population of the study was anyone that bought

bottled water. A convenience sampling method was applied and anyone living in Bangkok and Bangkok peripheral area with an experience in buying bottled water was considered as sampling frame and inclusion criteria. According to machine learning procedure, samples in datasets were divided into 2 groups as per holdout validation method, which were training set and testing set with 75:25 ratio. According to previous studies, there was no fixed rule for separation ratio and these could range from 60:40 to 90:10 depending upon data characters (Acampora, Herrera, Tortora, & Vitiello, 2018). Several self-administered survey questionnaires in hard copy format and online soft copy format were distributed by researchers due to the nature of samples, and the questionnaire was classified into 2 parts, which were demographic and rating scale. For the rating scale part, 5 rating scale of brand personality consisted of sincerity, excitement, competence, sophisticate and ruggedness brand personality. After cleaning duplicated data, detecting outlier, imputation for missing value and eliminating noisy information, only 500 samples qualified for the statistical analysis. According to the holdout validation method, 375 samples were randomized into training set and 125 samples were randomized into testing set. Questionnaires and rating scale were administrated as per actual social context, tradition and local Thai social and cultural context. Therefore, all the measurements were translated and back-translated from English to Thai. Supervised machine learning technique adopted from data science discipline was the technique that analyzed several algorithms from external instances to generate prediction model, which predicted about future instances. This technique constructed a concise prediction model from training set to predict outcomes, and its prediction performance could be evaluated by data from testing set. This technique allowed evaluation of the prediction performance of the model via absolute fit and relative fit indices generated by testing set (Handelman et al., 2019). This is the main difference between supervised machine learning technique and classic statistical analysis methods.

For the number of samples (Cochran, 1977), infinite population mean formula was calculated as Equation (1).

$$n = \frac{p(1-p)z_{\alpha/2}^2}{d^2} \quad (1)$$

In this formula, proportion (p) is 0.5, error (d) was 0.05, alpha was 0.05 and Z at 0.975 was 1.96. Therefore the minimum number of samples would be 385 or more as per calculation.

For the measurements scale, this research adopted the five point Likert scale of big 5 aspects for brand personalities and purchasing decision from past research (Aaker, 1997; Sung, Choi, Ahn, & Song, 2015). There were five personality factors in this study, which were sincerity, excitement, competence, sophistication and ruggedness. Items indicating sincerity factor were down-to-earth, honest, wholesome and cheerful. Items indicating excitement factor were daring, spirited, imaginative and up-to-date. Items indicating competence factor were reliable, intelligent and successful. Items indicating sophistication factor were reliable and intelligent. And items indicating ruggedness factor were outdoorsy and tough. Example items for purchasing decision factor were 'While going to the store, I decide to buy bottled drinking water' and 'If possible, I decided to buy bottled drinking water again'.

Data Analysis

For the data analysis, the cleaned and screened data of 500 samples were put into a multiple regression prediction model analysis with supervised machine learning approach. The main purpose behind the utilization of this technique was that it provides for evaluating the prediction performance of the fitted prediction model. According to the objective of the research, first, basic descriptive statistics of each scale were calculated to portray overall snap-shot of the data and assumption requirement such as normality and correlation. Second, linear multiple regression was fitted to hypothesize the study. After that, testing dataset was put into the model to evaluate the prediction performance. The analysis process from data preprocessing to model evaluation was entirely conducted by R, a powerful yet free-of-charge statistical computer language (R Core Team, 2020).

Results and Discussion

According to data analysis, the results were separated into 2 sections consisting of descriptive statistics and inferential statistics. Cleansed and screened

500 samples were input into the statistical analysis. For the descriptive statistic part, most of the samples were female (61.8%), holding bachelor degree (69.6%), working in private organization (46.6%) and monthly income THB 15,000–25,000 (31.8%). The mean age of the sample was 32.86 years with standard deviation of 9.84 years.

From Table 1 to 3, descriptive statistics for scales, from main dataset, train set and test set, are described including means, standard deviation, skewness, kurtosis and correlation matrix among continuous variables. All variables from main dataset were internally inconsistently reliable as alpha for sincerity, excitement, competence, sophistication and ruggedness were 0.85, 0.84, 0.84, 0.85 and 0.88 respectively, and data were distributed normally as skewness and kurtosis were within range of plus and minus two. Besides, all variables were moderately and significantly correlated. Variable Importance-the most important predictor determining a level of purchasing decision- of Sincerity, Excitement, Competence, Sophistication and Ruggedness from main dataset was 3.49, 2.13, 3.47, 3.20, 6.72 respectively.

In accordance with Table 4 shown below, by utilizing an ordinary least square estimation, a linear multiple regression model could be developed from train set. In this model, all predictors were statistically significant and the entire model was overall significant.

After fitting the model, the regression function is described as following: Purchasing Decision = $1.291 + 0.159(\text{SIN}) + 0.097(\text{EXC}) + 0.146(\text{COM}) + 0.096(\text{SOP}) + 0.187(\text{RUG})$

After fitting the model, model diagnosis was analyzed by checking multicollinearity and autocorrelation. According to Table 5, predictors variance inflation factor (VIF) was not more than 5 indicating no multicollinearity (Robinson & Schumacker, 2009). Moreover, the most important predictor determining a level of purchasing decision was ruggedness in accordance with variable importance of 5.862 (Grömping, 2009). The Durbin-Watson Test of Autocorrelation indicated a non-significance. This implied that there was no autocorrelation problem in this developed model (Savin & White, 1977).

Table 1 Descriptive Statistics for Scale, Skewness, Kurtosis and Correlation Matrix of Main Dataset

Scale	<i>M</i>	<i>SD</i>	Skew	Kur	SIN	EXC	COM	SOP	RUG
SIN	3.96	0.72	-0.84	0.64	1	0.65**	0.64**	0.52**	0.42**
EXC	3.68	0.90	-0.64	0.32	0.65**	1	0.65**	0.66**	0.41**
COM	3.99	0.77	-0.70	0.53	0.64**	0.65**	1	0.64**	0.46**
SOP	3.62	0.99	-0.50	0.01	0.52**	0.66**	0.64**	1	0.38**
RUG	4.08	0.88	-0.95	0.68	0.42**	0.41**	0.46**	0.38**	1

Note: SIN = Sincerity; EXC = Excitement; COM = Competence; SOP = Sophistication; RUG = Ruggedness; *N* = 500.

** *p* < .01.

Table 2 Descriptive Statistics for Scale, Skewness, Kurtosis and Correlation Matrix of Train Set

Scale	<i>M</i>	<i>SD</i>	Skew	Kur	SIN	EXC	COM	SOP	RUG
SIN	3.97	0.70	-0.77	0.64	1	0.64**	0.65**	0.50**	0.38**
EXC	3.66	0.88	-0.61	0.39	0.64**	1	0.63**	0.64**	0.39**
COM	3.99	0.75	-0.68	0.52	0.65**	0.63**	1	0.62**	0.47**
SOP	3.64	0.97	-0.50	0.03	0.50**	0.64**	0.62**	1	0.37**
RUG	4.10	0.89	-0.98	0.72	0.38**	0.39**	0.47**	0.37**	1

Note: $N = 375$, ** $p < .01$.

Table 3 Descriptive Statistics for Scale, Skewness, Kurtosis and Correlation Matrix of Test Set

Scale	<i>M</i>	<i>SD</i>	Skew	Kur	SIN	EXC	COM	SOP	RUG
SIN	3.94	0.78	-0.96	0.45	1	0.67**	0.60**	0.58**	0.53**
EXC	3.73	0.95	-0.74	0.13	0.67**	1	0.68**	0.72**	0.47**
COM	3.93	0.82	-0.70	0.41	0.60**	0.68**	1	0.68**	0.44**
SOP	3.56	1.03	-0.49	0.19	0.58**	0.72**	0.68**	1	0.42**
RUG	4.01	0.84	-0.85	0.53	0.53**	0.47**	0.44**	0.42**	1

Note: $N = 125$, ** $p < .01$.

Table 4 Fitting a Multiple Linear Regression Model from Train Set

Term	Estimate	Beta	Standard Error	t value	<i>p</i> -value
Intercept	1.291	-	0.160	8.050	.000***
SIN	0.159	0.172	0.050	3.146	.001**
EXC	0.097	0.132	0.042	2.283	.022*
COM	0.146	0.169	0.050	2.866	.004**
SOP	0.096	0.144	0.035	2.704	.007**
RUG	0.187	0.256	0.032	5.862	.000***

$R^2 = 0.46$, Adjusted $R^2 = 0.45$, F-statistics = 64.26, *p*-value < .00***

Note: * $p < .05$, ** $p < .01$, *** $p < .00$.

Table 5 Variance Inflation Factor, Variable Importance and Autocorrelation Test from Train Set

Variable	Variance Inflation Factor (VIF)	Variable Importance	Durbin Watson Autocorrelation Test
Sincerity	2.063	3.146	Autocorrelation = -0.003
Excitement	2.313	2.283	D-W Statistic = 2.004
Competence	2.403	2.866	<i>p</i> -value = .912
Sophistication	1.964	2.704	
Ruggedness	1.320	5.862	

Note: Variable Importance of Sincerity, Excitement; Competence, Sophistication and Ruggedness from Test Set was 1.500, 0.174, 1.876, 1.863, 3.275 respectively.

According to the supervised machine learning concept, after fitting the regression prediction model and diagnosing it, the model needed to be tested to an unseen dataset or test set (Flach, 2012). In this research, 25 percent of main dataset were randomized and stored as an unseen dataset or test set to evaluate a prediction performance of the model. For a regression model predicting a continuous value, there were 4 necessary metrics evaluating prediction performance, which were Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and R-squared (R^2). These metrics ranged from 0 to 1. The first 3 metrics were determined as an absolute measure of fit as the lower number, the better absolute fit with empirical data while R-squared was determined as a relative measure of fit as the higher the number, the better relative fit with empirical data (Chen, de la Torre, & Zhang, 2013).

These fit measures are shown in **Table 6** and indicated the moderate level of generalizability.

Eventually, the purchasing decision prediction model based on training datasets could be visualized as portrayed in **Figure 1**.

According to the results stated above, all 5 brand personality predictors were significant and could determine 46 percent of variability of purchasing decision. There were no autocorrelation and multicollinearity in

Table 6 Prediction Evaluation Performance Metrics from Test Set

Mean Absolute Error (MAE)	Mean Square Error (MSE)	Root Mean Square Error (RMSE)	R-squared (R^2) -unseen dataset
0.370	0.230	0.480	0.429

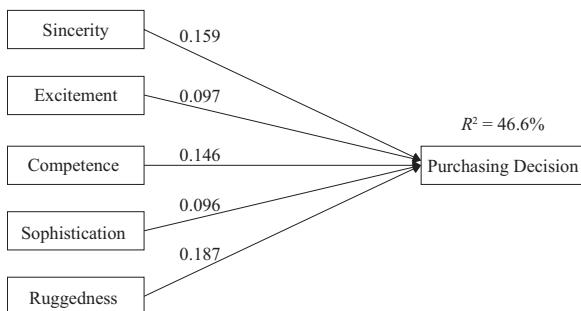


Figure 1 Multiple Linear Regression Model

the model. As per prediction performance evaluation metrics, the model indicated the moderate level of generalizability. These results could be broadened more than the traditional statistical analysis method since supervised machine learning technique evaluated and determined model prediction performance that the traditional statistical analysis could not provide.

Conclusion and Recommendation

As primarily discussed, this study aimed to answer the question: By adopting a machine learning approach from data science discipline, this approach allowed us to answer the question: how do 5 aspects of brand personality, which are sincerity, excitement, competence, sophistication and ruggedness, affect the level of purchasing decision? The objective of the study was to develop and evaluate the most suitable and practical purchasing decision label prediction model from 5 brand personality features. In accordance with an analysis of results, the objective of the study was achieved, and the study analysis result also portrayed that all 5 brand personality features positively and significantly affected a level of purchasing decision label. Supervised machine learning approach adopted from data science discipline allowed us to evaluate the performance of prediction accuracy by separating main dataset into train set, which was used to train and fit the prediction model, and test set, which was used to evaluate prediction performance. The results portrayed that this well-developed prediction model maintained a moderate level of generalizability.

The concept of supervised machine learning in this study was adapted from data science discipline. Supervised machine learning process involved three main steps (Burscher et al., 2014). First, the datasets would be randomized into two separate sets, which were train set and test set in certain ratio. Second, the train set would be put into a process of model development and the train set would train the model to learn about logic and algorithm

behind these data. Then the performance of the model would be evaluated by test set or unseen set to determine performance and a level of generalizability. According to the supervised machine learning process stated above, it could be found that overall trained prediction model was significant and all 5-brand personality features affected purchasing decision label significantly. There were no autocorrelation and multicollinearity. The most important predictor determining a level of purchasing decision was ruggedness, according to variable importance coefficients. After the process of model performance evaluation by test set, the model showed a moderate level of generalizability to the unseen data. This indicated that this model could be used to predict a level of purchasing decision label in other contexts regarding brand personality features. A model evaluation process and prediction performance metrics made supervised machine learning different from the traditional statistical method. The results in this study were consistent with prior studies about supervised machine learning technique in education context from Majeed (Majeed & Junejo, 2016) and in marketing context from Florez (Florez-Lopez & Ramon-Jeronimo, 2009). This implied that the supervised machine learning method, which primarily stemmed from data science discipline, could be utilized in other fields of studies like business and social science as well. By adopting this technique from data science field of study, the result of the analysis could be broadened more than the traditional statistical analysis method as this technique had the process of model evaluation to determine model prediction performance and level of generalizability that the classical statistical analysis did not directly provide for this type of outcome. Therefore, regarding analysis of results in this study, all 5 brand personality features had a significantly positive effect on purchasing decision label. Bottled drinking water manufacturer should not ignore the importance of promoting drinking water brand personality to match target consumers various personality traits as all 5 brand personality traits had a positive effect on the decision to buy bottled drinking water. In order to survive in this highly competitive industry, a marketing tool such as brand personality could be adopted to gain more space in market share and could help the company to survive in this market in the long run.

Even though this study employed the supervised machine learning technique borrowed from data science field of study, there were several limitations. First, this study only fitted the prediction model. Supervised machine learning technique also included a classification model. Future study could possibly extend and broaden the result of this study by employing a classification technique for categorical data. Second, the samples used in this study were drawn from Bangkok and Bangkok peripheral area. Future study should

focus on different sample size from different sampling frame to check whether the result could be generalized to other contexts.

Conflict of Interest

There is no conflict of interest.

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