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Using Text Mining and Predictive Analytics for Understanding Factors Affecting Behavior for Healthy Eating

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Abstract

Healthy eating behavior is an integral part of a healthy lifestyle, yet many individuals do not practice it despite the numerous benefits it offers. A clear understanding of the factors that influence consumers' healthy eating behavior can provide valuable insights into the adoption and non-adoption of healthy eating practices. The present study leverages text mining methods to extract meaningful insights from online textual data regarding factors affecting healthy eating behavior. This study then integrates the Theory of Planned Behavior and Stimulus-Organism-Response theories to form a comprehensive structural model. This model examines the relationships of various factors influencing consumers' healthy eating behavior using the Partial Least Squares Variance-Based Structural Equation Modeling (PLS-SEM) method. The application of predictive analytics introduces a PLS-based predictive model that identifies the key factors influencing people's healthy eating behavior. In terms of structural relationships, PLS-SEM reveals that Perceptions and Subjective Norms do not significantly influence healthy eating behavior, while Motivations and Perceived Behavioral Control are found to have a substantial impact on individuals' healthy eating behavior. Finally, the results of PLS Predict demonstrate that the PLS-based predictive model introduced in this study possesses strong predictive power, effectively forecasting future cases. This study provides a robust framework for understanding and predicting healthy eating behaviors, which can be instrumental in designing effective interventions.

Keywords: Healthy Eating, Predictive Analytics, Structural Equation Modeling, Text Mining.

Introduction

The study of how people make purchasing decisions to fulfill their needs, wants, or desires falls in the domain of consumer behavior. It examines how people are emotional, mental, and behavioral responses impact their decisions (1). Healthy eating is commonly recognized as a key component of a healthy lifestyle (2). Despite the well-documented health benefits of nutritious eating, global statistics remain concerning. According to a World Health Organization (WHO) report, non-communicable diseases (NCDs) cause at least 41 million deaths annually, accounting for approximately 71% of deaths worldwide (3). The WHO attributes the primary causes of NCDs to unhealthy lifestyle choices, including poor dietary habits. These worrying facts drive the interest of the present study as it becomes important to understand the factors affecting consumers' healthy eating behavior. The intention of studying human psychology in the context of healthy eating is to understand consumer behavior towards healthy food. This is crucial as it can help businesses to understand what factors drive and reverse consumers' buying decisions (4). The factors being studied for understanding consumers' healthy eating behavior are perceptions, motivations, subjective norm, and perceived behavioral control. Paquette described perceptions of healthy eating as the meanings, understandings, views, attitudes, and beliefs held by the public (including children, adolescents, and adults) and health professionals about healthy eating, eating for health, and healthy foods (5). He identified uniformity in people's perceptions of healthy eating across four categories: food choices, food characteristics, quality aspects, and concepts. Food choices typically include fruits and vegetables, while food characteristics focus on aspects like naturalness, fat, sugar, and salt content. Quality aspects emphasize freshness, unprocessed and homemade foods. Concepts highlight balance, variety, and moderation. More recent studies reported similar findings regarding people's perceptions of healthy eating (6–9).

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The researchers also identified additional categories such as taste, preferences, cost, and convenience. Perceptions of healthy eating are crucial because they influence individuals' food choices (10, 11). Motivations of healthy eating explore the reasons why people choose to adopt healthier eating habits. Autonomous self-regulation is principal to health behavior because an individual would give greater effort, engagement, persistence, and stability towards a given behavior when he or she is more autonomously regulated towards it (12). This is even more prominent when an individual is likely to evidence from that behavior (13). Individuals practice healthy eating due to personal drives and social influences to lose weight, maintain good health, look good and treat and prevent diseases. Therefore, individuals' motivations to eat healthy are autonomously self-regulated. Subjective norm refers to the perceived social influences or pressures to engage or not engage in a specific given behavior. It is also linked to the motivation to adhere with specific referents (14–16). Several studies reported on how family members were found to be one of the most influential factors for encouraging healthy eating behavior among adolescents (17–19). With social media usage rising enormously in the recent years, a few studies reported on how participants of the study consisting of young adults indicate that statuses and pictures posted on social media influence their food choices (20). The next factor that influences healthy eating behavior is perceived behavioral control. It is associated with one's perception of his or her own ability to perform a specific behavior. Several studies reported that healthy eating is popularly accredited as expensive and less tasty (16, 21, 22). When healthy eating is seen as expensive and not tasty, one's perception of his or her ability to engage in the behavior would be altered accordingly. The objectives for the current research are now introduced for a clear illustration of the research direction. This study seeks to explore the antecedents for consumers' perceptions, motivations, subjective norms, and perceived behavioral control for healthy eating behavior by using text mining method. The study also aims to understand the relationships between people's perceptions, motivations, subjective norms, and perceived behavioral control with healthy eating behavior by integrating the Theory of Planned Behaviour (TPB) and Stimulus-Organism-Response (SOR) theories. Additionally, the study seeks to develop a predictive model that can accurately forecast the likelihood of individuals to adopt healthy eating. The choice and interest for studying the factors affecting healthy eating behavior by using online data are due to two main reasons. The first reason is the growing number of internet data due to increasing number of internet users worldwide. The most recent statistic shows that the estimated number of internet users in 2023 is 5.3 billion people (23). The use of online data has been shown to significantly enhance organizational efficiency and profitability (24). The second reason is the availability of data mining and analytics techniques. The unprecedented volume and format of online comments today present numerous future research opportunities (25). Recent advancements in text mining and analysis techniques have enabled the transformation of information from online textual comments into more structured data (26). The contributions of the present study are now stated. Consumers of the current generations are seeking for more information on healthy food (27). Therefore, marketing must effectively communicate the health benefits of foods for healthy food products' success (2). Various studies have concluded that better understanding for factors influencing healthy eating like those proposed in this study is key success factors for successfully negotiating market opportunities for healthy food (27–29). The result from this study can help brands to redefine themselves through marketing as not just a product but also as a part of the consumer's lifestyle choices. Next, the use of text analytics in this study provides an essential avenue for analysis of subjective thoughts and latent perceptions of the public via texts and linguistic settings (25, 30). This study also offers a new perspective on predicting healthy eating behaviors by using a conceptual framework that combines TPB and SOR. The findings from the present study are hoped to provide better understanding for the behavior of people for healthy eating.

Research Hypotheses

H1: Perceptions of healthy eating influence intention for healthy eating behavior

H2: Motivations of healthy eating influence intention for healthy eating behavior

H3: Subjective norms influence intention for healthy eating behavior
H4: Perceived behavioral control influences intention for healthy eating behavior
H5: Intention to eat healthy influences healthy eating behavior
H6: Intention for healthy eating behavior mediates the influence of perceptions of healthy eating for approach healthy eating behavior
H7: Intention for healthy eating behavior mediates the influence of motivations of healthy eating for approach healthy eating behavior
H8: Intention for healthy eating behavior mediates the influence of subjective norm for approach healthy eating behavior
H9: Intention for healthy eating behavior mediates the influence of perceived behavioral control for approach healthy eating behavior

Methodology

Relying on a single theory can restrict some studies from thoroughly addressing their research questions (31). Consequently, researchers may combine two theories to achieve more comprehensive results than if they were used independently. In this study, the TPB and SOR models are integrated not because they cannot function separately but to provide a more robust foundation for predicting healthy eating behavior. The integration of TPB and SOR is based on guidelines from an article by Mayer and Sparrowe, which advises researchers on effectively combining two theories. For the present study, stimulus equates to perceptions, motivations, subjective norm, and perceived behavioral control related to healthy eating behavior, all of which are the influences that arouse an individual. Organism is defined as "internal processes and outcomes of the stimulus, usually mediating the relationship between stimulus and response" (32). For this study, organism equates to healthy eating intention. Response is the resulting individual's final behavioral outcome that can be positive (approach) or negative (do not approach) (33). For this study, response equates to people's approach behavior for healthy eating. Figure 1 below demonstrates the conceptual model of this study. The construct Attitude from TPB is absent from the proposed conceptual framework, which may possibly raise concerns. Attitude is in fact not absent when the definition by prior researchers is put forward - "An attitude can be defined as an enduring organization of motivational, emotional, perceptual and cognitive processes with respect to some aspect of the individual world, which have close relationships to people's behavior" (34,35). It becomes clear from this definition that attitude involves perceptions and motivations. Therefore, perceptions and motivations of healthy eating could also represent Attitude in this study.

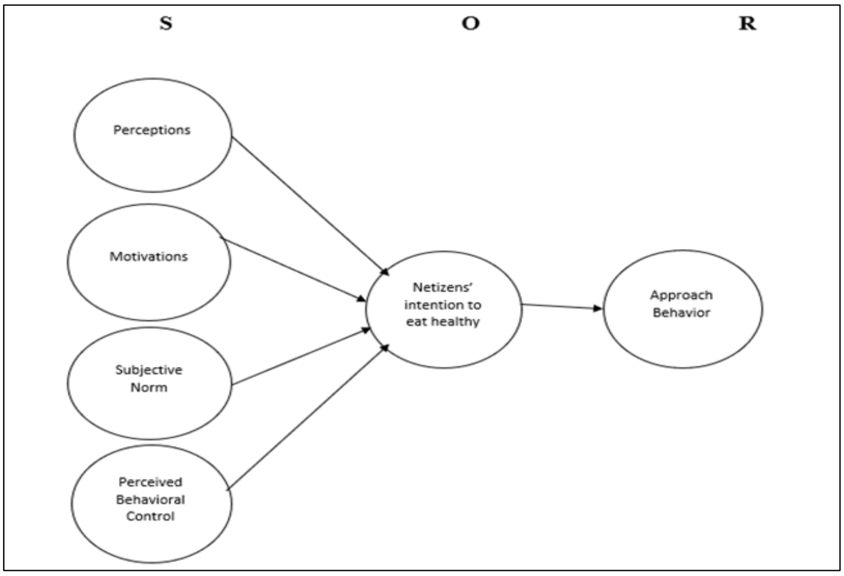

Figure 1: Conceptual Model based on TPB and SOR Integration

Data Collection

This study uses unstructured online data in the form of textual comments scrapped from three selected social media platforms being Twitter, Youtube and Reddit through data scraping method. These platforms are chosen because they provide a few of the largest feasible collection of information (36). The widespread popularity of these platforms also helps to ensure that the data collected would offer more diverse and valuable insights to healthy eating behavior. A Google Chrome web scraping extension called 'Webscraper' was used to scrape comments. The keywords used were Healthy Eating, Healthy Diet, Eat Healthy, Healthy Eating Motivation and Perceptions Healthy Eating. Several steps were taken to address potential biases, noise and incompleteness of the dataset. The data scraping process involving three different social media platforms was implemented to ensure a more diverse and representative data, hence reducing potential biases. Data cleaning process through Text Parsing process involved the removal of spam, missing comments, duplicates, irrelevant content and comments other than English language. This step was performed to reduce noise and at the same time enhance completeness in data. These steps were crucial in maintaining the integrity of the research findings. The scraping is limited to December 2019 to December 2023 due to the consideration that up-to-date data would enhance the quality and validity of the study findings (37). The scraping process from the three selected social media platforms collectively produced a total of 25,262 comments as shown in Figure 2 below.

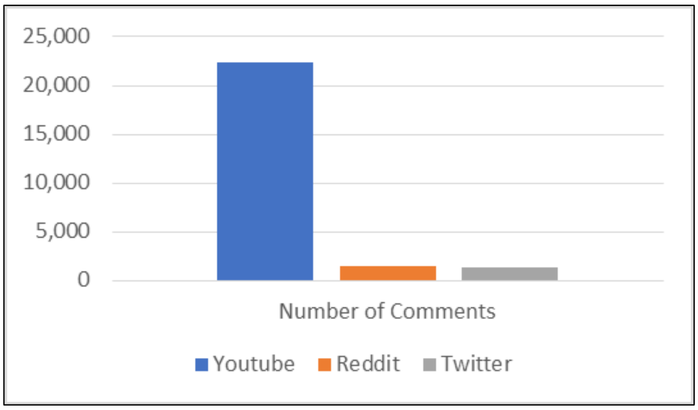

Figure 2: Number of Comments in this Study

Data Analysis

SAS Text Analytics

The dataset consisting of 25,262 online posts with a total of 820,098 words were analyzed through a computer-assisted content analysis package called SAS Text Miner. Figure 3 shows the sequential overview of the nodes in SAS in order to explain the process of the SAS Text Mining.

Figure 3: SAS Thematic Analysis Nodes

The nodes illustrate the integration of step-by-step textual and statistical analysis, emphasizing word frequency within a corpus. Homogeneous word subsets were identified based on their lexical properties. During the text parsing node, parts of speech such as prepositions, pronouns and auxiliary verbs were ignored (38,39). Text parsing enabled the systematic division of texts into manageable terms within the text corpus. These processes resulted in a comprehensive set of relevant terms for further analysis using the Term Frequency – Inverse Document Frequency (TF-IDF) algorithm. The TF-IDF algorithm is notated as: $W_{td} = tf_{td} \times log\ log\ \left(\frac{N}{df_t}\right)$ Where N depicts the total number of documents in the text corpus, W_{td} depicts the weight on the term $_t$ in document $_d$, tf depicts the frequency of the terms $_t$ in document $_d$ and df depicts the frequency of documents with the term $_t$. This algorithm retained terms that were deemed relevant to the study while removing stop words like "the", "a", "on" and "in". As for the Frequency Weighting property, the default setting is used, which is Log or Log: g(fij)= log2(fij+1). This property dampens the effect of terms that occur many times in a document. Text clustering was performed on the term-frequency document by progressively dividing the terms into mutually exclusive groups. This process utilized the Latent Semantic Indexing (LSI) method to organize the terms into higher-order semantic structures (40) notated as $A = U\sum V^T$ where A depicts the decomposed matrix of m x n. U depicts the m x m matrix, $\sum$ depicts the singular value of A, VT depicts is the matrix of n x n. The results of the clustering via SVD on the term-frequency document are set to generate enough SVD dimensions (k) for further analysis. The higher the number of dimensions (k), the higher the resolution to the term-frequency clustered. In this study, the k is set to 50, which is the default setting in SAS. The groups were constructed based on similar forms and words. The LSI procedure in this study used the Singular Value Decomposition (SVD) algorithm to reduce the terms into a set of manageable clusters (41, 42). Twenty-one clusters were derived and presented in the next section.

PLS-SEM and Predictive Modeling

A variance-based SEM path model depicting people's behavior for healthy eating is constructed on Smart PLS 3.0 software as portrayed in Figure 4. Following the findings of previous authors as detailed in the previous chapter, clusters with comments associating fruits and vegetables, breakfast concept, calorie counting concept and vegan concept to healthy eating are deemed as Perceptions. Clusters with comments regarding weight loss, weight maintenance and appearance (to look good) are regarded as Motivations. Clusters with comments about users being influenced through photo and video sharing on social media platforms for healthy eating are taken as Subjective Norm. Clusters with comments that speak why and what limit users from practicing healthy eating are placed under Perceived Behavior Control construct. Those clusters with comments that point to finding recipe and cooking ideas for healthy eating depict Intention for healthy eating. Finally, clusters with comments whereby people talk about their healthy meal preparation, meal plan, and the healthy food items that they purchase from grocery stores portray their behavior for healthy eating, thus laying them under the Behavior construct.

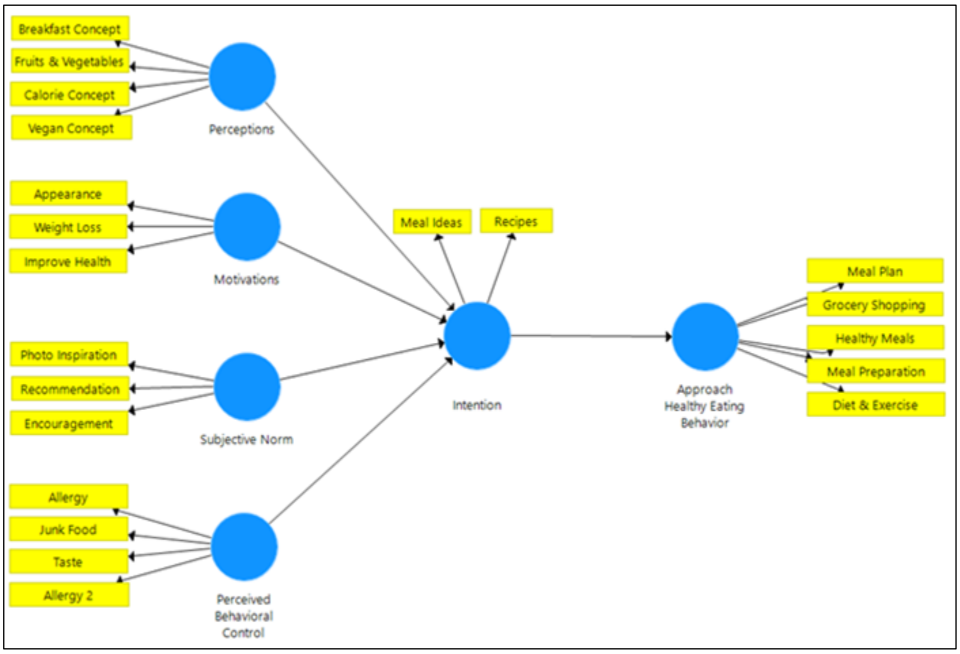

Figure 4: PLS-SEM Model

Scholars have recently put forward new evaluation procedures for PLS-SEM models that have been designed specifically according to PLS-SEM's prediction-oriented nature (43, 44). This new procedure is known as PLS Predict. They wrote that examining predictive power of a statistical model is greatly important in any study. Default settings were applied in Smart PLS 3.0.

Results

SAS Text Analytics

Table 1 illustrates that the cluster frequency root mean square (RMS) standard deviation revealed twenty-one clusters derived through SVD which were well-defined and optimal with values close to zero.

Table 1: Summary of Cluster Frequency and Root Mean Square Deviation

Cluster ID	Descriptive Terms	Cluster Label	Frequency	Percentage
9	+healthy +food +love basics +diet meals recipes healthier +'healthy food' 'healthy basics'	Healthy Meals	1827	7%
10	twitter eathealthy +know pic allergic cashews nuts +vegan 'eathealthy pic' delicious	Allergy	1358	5%
20	almonds apples +kill +apple foods +fat +top +breakfast oats bananas	Breakfast Concept	1120	4%
21	+love +meal +prep +'meal prep' video meals ideas +bread loved ingredients	Meal Ideas	1290	5%
23	twitter eathealthy pic +sweet 'eathealthy pic' healthydiet potatoes +potato +nutrition +people	Photo Inspiration	1389	6%
29	calories carbs +sugar +protein +rice +fruit +bad bars unhealthy grams	Calorie Concept	2831	11%
31	apples +apple +add +garlic chicken +doctor +oil +onion +salt +green	Fruits & Vegetables	640	3%
34	+chocolate +dark +'dark chocolate' +healthy +salad chocolate honorable +mention almonds apples	Meal Plan	444	2%
37	+good better best +food +broccoli always +thing +healthy video +love	Improve Health	914	4%
39	+food foods +eat +list health junk +milk unhealthy almonds eating	Junk Food	1231	5%
40	+water +cream +drink +yogurt +juice +nice water cashew +watch +best	Recommendation	377	1%
42	+eat eating +day +weight +want watching +lose +feel +breakfast im	Weight Loss	1746	7%
43	+salmon +avocado +vegan avocados +kale +cheese +time +garlic +toast smoked	Vegan Concept	1491	6%
47	+look +love looks +channel looking video amazing sharing +life helpful	Appearance	1225	5%
48	+broccoli +love +taste +hate loved tastes delicious raw +deal favorite	Taste	1331	5%
49	eggs +great +cook ideas cooking +egg fridge +long cooked days	Recipes	1110	4%
50	+diet +weight health loss +lose +nutrition healthydiet fitness keto +exercise	Diet & Exercise	836	3%

51	+meat +meal +day meals +week food +buy red days +dairy	Grocery Shopping	1098	4%
54	video +great +love 'great video' watching +watch awesome amazing watched helpful	Encouragement	1268	5%
55	+chicken chicken +salad +breast +'chicken breast' 'chicken salad' breasts always +big +doctor	Meal Preparation	616	2%
61	+cream cashew 'cashew cream' +long +watermelon vitamins +vitamin +milk allergic ice	Allergy 2	696	3%

The full comments extracted from YouTube videos, Reddit threads, and Twitter tweets were read through in order to provide understanding for the clusters that SAS generated. Based on the descriptions of the themes, the authors manifested them into the six different constructs in the framework.

Cluster 9 consisting of 1,827 comments is regarding people's actual choices for healthy meals.

"I love how you explain and looking forward to know more of the healthy meals that I can prepare for my family."

"Me and my friend started to eat healthy around the same time you did and we were waiting for this video."

Cluster 10 consisting of 1,358 comments is about people's difficulty inhibiting healthy eating behavior because they are allergic to certain types of healthy food.

"I am allergic to SO many things you mentioned but I too want to eat healthy"

"What about for someone who is allergic to all kinds of nuts?"

Cluster 20 consisting of 1,120 comments portrays people's understanding for healthy eating as not missing breakfast every day.

"Breakfast is the most important meal."

"My breakfast everyday are an apple, avocado, and 2 hard boiled eggs."

Cluster 21 consisting of 1,920 comments shows that people want to embark on healthy eating journey. They would like to understand the ingredients that they should include in their healthy cooking.

"There is no excuse for us not to eat healthy! I don't eat eggs and meat, but you gave me so much ideas."

"I'm trying to eat healthy and starting to meal prep, so thank you for this video."

Cluster 23 consisting of 1,389 comments suggests how people try to influence one another on healthy eating journey through photo sharing.

"This is how salad should be, pretty, healthy and delicious."

"That's your basic bowl. Brown rice, beluga lentil beans and steamed veggies dinner is served."

Cluster 29 consisting of 2,831 comments is the most frequented mentioned topic. People associate healthy eating with the number of calories in the food.

"2 cups of veggies = 80 calories. 4 oz. of salmon = 200 calories. 56 oz. of potato = 120 calories. Total = 400."

"One cup of food would be about 500 calories. If leaner like spaghetti marinara one cup is about 300 calories."

Cluster 31 consisting of 640 comments shows healthy eating is associated with fruits and vegetables.

"Please don't restrict yourself and go down a rabbit hole of bad nutrition decisions. Eat enough fruits and veggies."

"I'm allergic to alot of things and I love fruits an veg I could eat them all day."

Cluster 34 consisting of 444 comments portrays how people do meal planning to eat healthy. Meal planning in the context of healthy eating involves organizing and preparing meals ahead of time to ensure they are balanced, nutritious, and aligned with dietary goals.

"What I eat: for breakfast I start the day with coffee..at 10am I eat a brownie which contains a big amount of dark chocolate and a little bit of almonds. Im a big fan of meat so i usually eat meat for lunch .. for dinner I eat salads"

Cluster 37 consisting of 937 comments indicate the motivational aspect related to healthy eating. People associate healthy eating with general improvement of health, hence why they choose to eat healthy food.

"My obsession is eating the right foods as a preventative measure."

"Eating healthy, clean and organic is so important for our health and wellness, and helps anti-inflammation".

Cluster 39 consisting of 1,231 comments is regarding the challenge of skipping junk food eating habit.

"I've been trying to eat healthier but it's difficult to stick to 100%. I beat myself up about craving any "bad" food."

"I can eat healthy and have chocolate at the same time that makes me happy."

Cluster 40 with 330 comments is about people influencing each other to start healthy eating.

"Why not add eggs instead of salmon? Salmon is delicious, and eggs have the same benefits if not more!"

"Portion control is very important, which is why they recommending eating 6 smaller meals a day."

Cluster 42 with 1,746 comments is about people watching healthy eating related videos to 'lose weight'.

"I follow your weight loss plans and your what I eat in a day and I see progress"

"Eat less Eat less bread Eat less sugar Eat less oily food Eat less processed foods to lose weight"

Cluster 43 with 1,491 comments shows that people associate healthy eating with 'going Vegan'. They mentioned terms like avocado, kale, cheese, garlic, toast to portray their food choices in doing vegan diet.

"I follow a Whole foods plant based vegan diet. It gives me so much energy and it changed my life for the better!"

"Yep, Im Whole Foods Plant Based, vegan, low oil salt and sugar. It is the best decision of my life so far.."

Cluster 47 consisting of 1,225 comments points to the motivation of healthy eating. People shared that they eat healthy because they want to look and feel good.

"You're the reason why I have lost 87 pounds since January this year! I've been feeling great and starting to look good too!"

Cluster 48 with 1,331 comments shows that people associate healthy eating with taste. There are two contrasting views. The two comments demonstrate how people find healthy food as tasty and otherwise.

"I absolutely LOVE Vegetables. They are tasty w/ fruits."

"Kale is like chewing on a bale of hay. Yuck, no thank you!"

Cluster 49 with 1,110 comments show that the terms 'recipes', 'ideas' and 'cook' refer to people's gratitude for the recipe videos. They want to know the ingredients for healthy cooking.

"Love this one especially, so inspired! Ill definitely try out some recipes!"

"Thank you for making easy recipes with ingredients I will actually eat and can afford."

Cluster 50 with 836 comments shows that people discuss about their approach behavior of eating healthy diet as well as exercising. They shared that they practice a general healthy diet and regular exercise while some also shared on their keto diet journey.

"I eat small portions of meals every day. Exercise to me is a must also. Stay healthy everyone."

"I try to eat a clean diet 80% if the time. I exercise , lift 5 days a week."

Cluster 51 consisting of 1,098 comments represent people purchasing healthy food items. They list all the ingredients needed for the planned healthy meals. This shows their behavior for healthy eating.

"I love grocery shopping. I read labels and discern whether that is something I want to put in my body or not."

"Thank you for this video. I already wrote my shopping list."

Cluster 54 with 1,268 comments shows that people need encouragement in their healthy eating journey.

"Thank you. It felt like you came to all of our homes and sat down on a couch with us and gave us a little talk."

"I always come back to this video for some mental encouragement. It has helped me a lot!"

Cluster 55 with 616 comments shows that people discuss about healthy food that they prepare everyday.

"Every morning I have a smoothie bowl. For lunch I just eat salad. For dinner I usually eat some form of chicken."

"I have meal prepped for the week and I definitely want to try these!"

Cluster 61 with 696 comments shows people find it difficult to inhibit healthy eating behavior because they are allergic to certain types of healthy food.

"I'm allergic to carrots, almonds, nuts, snap peas and most pollen crosses allergies. I just end up eating chocolate, but I know it's not good for me."

PLS-SEM - Measurement Model Evaluation

It is compulsory to evaluate the measurement model to establish the reliability and validity of constructs before assessing the structural model. This involves testing the indicator reliability and internal consistency reliability to ensure the constructs are reliable. Additionally, the constructs' validity is assessed through convergent validity and discriminant validity. Table 2 shows the result of calculations of PLS Algorithm in Smart PLS 3.0.

Table 2: Measurement Model Result

	Items	Loadings[a]	AVE[b]	CR[c]	Rho_A[d]
Perceptions	Fruits & Vegetables	0.903	0.692	0.87	0.789
	Vegan Concept	0.796			
	Breakfast Concept	0.791			
Motivation	Weight Loss	0.740	0.536	0.775	0.602
	Improve Health	0.799			
	Appearance	0.650			
Subjective Norm	Recommendation	0.805	0.627	0.834	0.71
	Encouragement	0.798			
	Photo Inspiration	0.772			
Perceived Behavioral Control	Allergy	0.782	0.535	0.821	0.726
	Taste	0.761			
	Allergy 2	0.741			
	Junk Food	0.633			
Netizens' Intention	Meal Ideas	0.842	0.695	0.82	0.563
	Recipes	0.825			
Approach Healthy Eating Behavior	Grocery Shopping	0.813	0.539	0.777	0.604
	Healthy Meals	0.715			
	Meal Preparation	0.667			

*Items removed: Indicator items below 0.5 – Calorie Concept (Perception), Meal Plan (Behavior), Diet Exercise (Behavior)

a. All Item Loadings > 0.5 indicates Indicator Reliability (45)
b. All Average Variance Extracted (AVE) > 0.5 indicates Convergent Reliability (46,47)
c. All Composite Reliability (CR) > 0.7 indicates Internal Consistency (48)
d. All Cronbach's Alpha > 0.6 for exploratory (49–51) and > 0.5 (52) indicates Indicator Reliability

Factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were assessed. All factor loadings surpassed the recommended brink of 0.50 (45). Both Cronbach's alpha and CR were above the suggested brink of 0.50 (53). The AVE scores for each latent variable were also above 0.50 (46, 54). The Heterotrait-Monotrait (HTMT) correlation criterion was applied for discriminant validity. The values were below the brink of 0.85 as shown in Table 3 (55).

Table 3: HTMT Criterion

	Approach Healthy Eating Behavior	Motivations	Netizens' Intention	Perceived Behavioral Control	Perceptions	Subjective Norm

Approach Healthy Eating Behavior					
Motivations	0.487				
Netizens' Intention	0.56	0.701			
Perceived Behavioral Control	0.595	0.812	0.665		
Perceptions	0.396	0.609	0.458	0.841	
Subjective Norm	0.301	0.591	0.373	0.605	0.416

Hypothesis Testing

Using the Bootstrapping procedure in SmartPLS 3.0 - PLS Algorithm (Weighting scheme: path; Maximum iterations: 300; Stop criterion: 7) and Bootstrapping (Subsamples: 5000; complete boostrapping; Confidence interval method: Bias-corrected and accelerated bootstrap), the significance of estimated path coefficients would be determined. Table 4 and Table 5 display the results of the PLS estimations for the direct and indirect effects between the variables in the model. The hypothesized relationship for perceptions of healthy eating and intention shows insignificant ($\beta = 0.0486$, $p>0.05$) result. The same is observed for the effect of subjective norm on the intention for healthy eating behavior that shows that the relationship is not significant ($\beta = 0.102$, $p>0.05$). These mean that perceptions of healthy eating and subjective norm do not influence people's intention for healthy eating behavior. As for motivations of healthy eating, the hypothesized relationship with intention shows significant result ($\beta = 0.328$, $p<0.05$). The same are seen for perceived behavioral control with intention ($\beta=0.340$, $p<0.05$) and intention with approach healthy eating behavior (($\beta=0.610$, $p<0.05$). These mean that motivations of healthy eating and perceived behavioral control influence people's intention for healthy eating behavior and intention influences Approach healthy eating behavior.

PLS-SEM – Structural Model Evaluation

This analysis intends to explain the relationships between the latent variables or constructs in the model through applying Bootstrapping procedure. Both procedures follow the default SmartPLS 3.0 settings – PLS Algorithm (Weighting scheme: path; Maximum iterations: 300; Stop criterion: 7) and Bootstrapping (Subsamples: 5000; complete boostrapping; Confidence interval method: Bias-corrected and accelerated bootstrap). For the variance explained of any endogenous construct to be regarded as adequate, R^2 values should be equal or greater than 0.10 (56). Based on the value of R^2 on the intention construct from Table 4, it appears that the variables tested have explained 64 percent of variances towards people's intention to eat healthy. A model can be deemed as substantial when R^2 value is above 0.26 (57). R^2 value on Approach healthy eating behavior suggests that the variable intention explains 54 percent of the variances in behavior. This means that the model in this study is substantial. Based on the information in Table 4, the 95 percent bootstrap confidence interval (CI) for the indirect effect of perceptions (CLLL = 0.151; CLUL = 0.216), motivations (CLLL = 0.070; CLUL = 0.516), subjective norm (CLLL = 0.068; CLUL = 0.236) and perceived behavioural control (CLLL = 0.018; CLUL =0.469) towards Approach healthy eating behaviour does not straddle a 0 in between the Confidence Level Upper Limit (CLUL) and Confidence Level Lower Limit (CLLL). Therefore, this gives further evidence of the indirect effect in the model. Effect size (f^2) of 0.02 indicates a small effect, 0.15 indicates a medium effect and 0.35 indicates a large effect (58). Table 5 presents the effect size (f^2) values for the model in this study; it can be observed that intention (1.174) has a large effect in producing the R^2 for Approach healthy eating behaviour. The result further shows the effect size for perceptions (0.000), motivations (0.178), subjective norm (0.022) and perceived behavioral control (0.144) constructs. Perceptions and subjective norms have no effect in producing R^2 for Approach healthy eating behaviour while motivations and PBC have medium and close to medium effect respectively in producing R^2 for Approach healthy eating behaviour. Q^2 measures whether a model can be deemed as having predictive relevance or otherwise. It is examined through using the Blindfolding procedure. An endogenous construct in a model can be said to have a predictive relevance when the Q^2 value is larger than 0. The two Q^2 values in this model for intention (Q2 = 0.104) and Behaviour (Q2 = 0.020) are more than 0 suggesting that the model in this study has sufficient predictive relevance (59,60).

Table 4: Bootstrapping Result (Direct Effects)

Hypothesis	Relationship	Std Beta	I t-value I ^	Decision	f2	q2	95% CI LL	95% CL UL
H1	Perceptions -> Netizens' Intention	0.034	0.204	Not supported	0.000	-0.031	-0.244	0.316
H2	Motivations -> Netizens' Intention	0.381	1.974**	Supported	0.178	0.032	-0.167	0.571
H3	Subjective Norm -> Netizens' Intention	0.129	0.709	Not supported	0.022	-0.030	-0.336	0.341
H4	Perceived Behavioral Control -> Netizens' Intention	0.371	2.398**	Supported	0.144	0.037	0.061	0.539
H5	Netizens' Intention -> Approach Healthy Eating Behavior	0.735	2.295**	Supported	1.174	0.104	-0.271	0.884

- ** $p<0.01$, *$p<0.05$
- **R^2 (Netizens' Intention = 0.640; Approach Healthy Eating Behavior = 0.540);**
- **Q^2 (Netizens' Intention = 0.104; Approach Healthy Eating Behavior = 0.020);**
- Effect Size impact indicators are according to Cohen (1988), f^2 values: 0.35 (large), 0.15 (medium), and 0.02 (small)
- Predictive Relevance of Predictor Exogenous Latent Variables according to Reinartz, Haenlein and Henseler (2009), q^2 values: 0.35 (large), 0.15 (medium), and 0.02 (small)

Table 5: Bootstrapping Result (Indirect Effects)

Hypothesis	Relationship	Std Beta	I t-value I ^	Decision	95% CI LL	95% CL UL
H6	Perceptions -> Netizens' Intention -> Approach Healthy Eating Behavior	0.026	0.222	Not Supported	-0.151	0.216
H7	Motivations -> Netizens' Intention -> Approach Healthy Eating Behavior	0.233	1.998**	Supported	0.070	0.516
H8	Subjective Norm -> Netizens' Intention -> Approach Healthy Eating Behavior	0.077	1.019	Not Supported	-0.068	0.236
H9	Perceived Behavioral Control -> Netizens' Intention -> Approach Healthy Eating Behavior	0.233	1.916**	Supported	0.018	0.469

PLS Predict Predictive Modeling

Table 6 shows the result of running PLS Predict procedure on the model. PLS Predict procedure was utilized to generate case-level predictions and assess out-of-sample predictive power. As the prediction errors (RMSE or MAE) in the PLS-SEM are lower than LM analysis, this indicates that the model has a predictive power. It can be deduced from the result that the model has a high predictive power because none of the predictive errors in the indicators in the PLS-SEM analysis are higher than LM analysis (43). Therefore, it can be deemed that the model should be expected to have high accuracy in predicting the outcome value for new future cases. Additionally, a 10-fold cross-validation was divided the dataset into 10 subsets. The model was trained and tested 10 times, each time using a different subset as the test set and the remaining subsets as the training set. This approach ensures robustness and provides a reliable estimate of the model's performance. This procedure was also performed to compare the prediction error to benchmarks, ensuring the model's reliability and validity.

Table 6: PLS Predict Result

	PLS SEM			**LM**			**PLS - LM**		
	RMSE	**MAE**	**Q^2_predict**	**RMSE**	**MAE**	**Q^2_predict**	**RMSE**	**MAE**	**Q^2_predict**
Healthy Meals	0.067	0.050	0.147	0.094	0.071	-0.680	-0.027	-0.021	0.827
Meal Preparation	0.070	0.054	0.009	0.091	0.069	-0.664	-0.021	-0.015	0.673
Grocery Shopping	0.057	0.040	0.105	0.074	0.056	-0.522	-0.017	-0.016	0.627
Meal Ideas	0.052	0.039	0.265	0.062	0.049	-0.039	-0.010	-0.010	0.304
Recipes	0.048	0.034	0.168	0.056	0.043	-0.171	-0.008	-0.009	0.339

*If the PLS-SEM analysis (compared to the LM) yields higher prediction errors in terms of RMSE (or MAE) for all means (no predictive power), if majority (low predictive power), if minority or the same number (medium predictive power) or if none of the indicators (high predictive power)

Discussion

The antecedents for factors affecting healthy eating behavior are established. Through text mining procedure, perceptions of healthy eating center around Fruits and Vegetables, Breakfast Concept, Calorie Concept, and Vegan Concept. These match the previous findings by prior researchers. They reported that their study participants identified specific foods being fruits and vegetables as constituting to 'What is Healthy Eating' (9,61,62). Participants in other studies indicated that having regular meal times or three meals a day, non-avoidance of meals and avoidance of eating late at night as healthy eating (62). Participants in a study perceived healthy eating as one that embeds the necessary step of maintaining regular meal times as well as the right or moderate quantity of food (28). Similarly, another study found that the parents of school children perceive eating three square meals everyday as healthy eating (63). Balanced intake of food groups, variations in healthy food choices and eating in moderation also make up healthy eating among the participants of other studies. They also found that eating breakfast constitutes healthy eating. (64, 65). Appearance, Weight Loss, and Improve Health form people's motivations of healthy eating. Health poses as the main driver of healthy food selection especially if the risk of capturing diseases is put forward (66). They are motivated to choose to eat healthy food to prevent future potential diseases. A study with the purpose of studying healthy food motivational factors among the Lebanese consumers was carried out. It was found that people are motivated to eat healthy food for body weight management (67). Body image or to 'look good' appeared to be the individual motives for choosing to healthy food at restaurants (68). Next, the Bootstrapping procedure result shows that people's intention for healthy eating behavior mediates the relationships or influence motivations of healthy eating and perceived behavioral control for Approach healthy eating behavior. In contrary, intention does not influence the perceptions of healthy eating for Approach healthy eating behavior. It can now be said that only motivations of healthy eating ($\beta=0.233$, $p<0.05$) and PBC ($\beta=0.233$, $p<0.05$) would have the capacity of being mediated by intention construct for the approach behavior, thus establishing the significance of intention construct as a mediating variable for motivations, PBC and behavior constructs. For perceptions of healthy eating, it can now be deduced that 'people behave as they perceive' is not the case for healthy eating. There is limited study that explores the statistical links between perceptions and behavior albeit the notion that 'people behave as they perceive'. The present study has filled the vacant knowledge when perceptions of healthy eating are shown to not affect intention. As motivations comprise of reasons for performing a certain behavior, the association with behavioral intention should be positive. There are many studies that have looked at the relationship between motivations and intentions over the past years. A recent study showed positive significant relationships between the two variables (69). Studies concerning the role of motivations in driving behavioral intention in the context of healthy eating continue to be scarce. The present study has filled the gap when motivations of healthy eating are shown to affect intention. For subjective norm, although the user sharing of photo inspiration, encouragement and recommendations may positively influence one another to adopt healthy eating behavior, the limitation remains that the communication environment that they are in is in essence a 'virtual' space. Bringing in the findings of prior studies, the significance and insignificance results for the relationship between subjective norm and intention are observed. This mixed result can be related to the environment that the people are in. The study conducted within Malaysia context demonstrated how the concept of interdependency in a certain culture is proven to guide a particular behavior (70). The authors reported that food purchase intention is influenced by the collectivistic culture (SN) that exists in Malaysia. In other words, the goal of consuming certain types of food becomes in-group rather than personal. Another study showed how the peers' support in college (SN) influence the intention of the respondents to eat healthy food – fruits and vegetables (71). For the current study, the insignificant result for the effect of SN on the intention for healthy eating can also be related to and explained by the environment factor. While photo inspiration, encouragement and recommendations can entice people to practice healthy eating, the environment that they are in is a 'virtual' space that comes with no physical interaction. When reasons or motivations like weight loss, health improvement and appearance are put forward, one would intend and approach healthy eating behavior. Similarly, when one's perception of his or her ability to adopt healthy eating comes to a specific answer, the individual would either approach or avoid healthy eating behavior. This is relevant for the context of healthy eating as it has been popularly accredited as expensive and less tasty (16). It comes naturally that if healthy eating is perceived as expensive and not tasty, one's perception of his or her ability to engage in the behavior would be altered. The finding on the mediation effect of intention for motivations of healthy eating and PBC can be deemed to conform with past healthy eating studies (72, 73). From a psychological perspective, individuals are not likely to perform behavioral action without intention. This is the reason of inclusion of intention in determining behavior in Theory of Planned Behavior (TPB). The current study has further concreted the basis of intention or behavioral intention as a significant component to determine the factors that contribute to healthy eating behavior. The result shows that people are mostly influenced by their motivations and PBC for performing the behavior of interest. Intention carries a huge role for determining if behavior in question would be performed or otherwise (74). This study has confirmed the link of the two variables in the context of healthy eating whereby intention positively influences the adoption of healthy eating behavior. Finally, the result of running PLS Predict in this study is highly beneficial for future related studies. PLS Predict combats the issues mentioned with structural model assessment because it works on a holdout-sample-based procedure that ensures accuracy of prediction of outcomes for new cases. It requires attention and usage by researchers because of the availability of a clear guideline for its application that was once limited in presence. The use of PLS Predict enables the current research to establish a predictive model for healthy eating behavior.

Conclusion

A study emphasizes the necessity of a nationwide health promotion program to encourage healthier lifestyles, addressing the participants' poor dietary habits and knowledge (75). The study's findings can assist policymakers in creating and implementing more effective healthy eating campaigns, particularly online, to influence citizens' eating behaviors. The result from the predictive modeling shows that motivations of healthy eating significantly influence people's intention and thus their healthy eating behavior. As motivations of healthy eating are centered around prevention of diseases, the online campaigns can stress on the possible harmful complications arising from unhealthy eating behavior. As for businesses, the current study finding for healthy eating behavior can be the supplementary guideline for producers in designing healthy food products that appeal best to customers and their requirements. As shown in the result earlier, PBC significantly influences people's intention and their healthy eating behavior. As healthy food is often associated with not being tasty, more research and development can be carried out by food producers to come up with tastier healthy food products that can attract customers to eat healthy. The result of this study can help brands to redefine themselves (through marketing) as not just a product but also as a part of the consumer's lifestyle choices. Businesses and especially government bodies can also utilize social media for marketing, advertising, and health intervention purposes. Traditional marketing through TV commercials, newspaper ads and billboards has been used for decades prior to the development of technology. Technological advancements have made social medias to be widely used platforms in the current world. The limitation of the study lies in the number of social media platforms used to obtain the dataset. While Twitter, Reddit, and Youtube are undoubtedly powerful channels, future studies can look at both strengthening and broadening the findings obtained from this study through gathering and analysing more data from other social media platforms like Instagram and healthy eating blogs. The possibility of the n-gram algorithm also posits the limitation of this study which uses single-term parsing, filtering and clustering to derive the clusters. Future studies can replicate the methodology employed in this study while also including the training of unstructured data using the n-gram algorithm. This is where the computation of linguistics that involves more complex terms is possible.

Abbreviations

TPB: Theory of Planned Behavior, SOR: Stimulus Organism Response, PLS SEM: Partial Least Square, Structural Equation Modeling, SN: Subjective Norm, PBC: Perceived Behavioral Control.

Author Contribution

Nadia Mazlan was responsible for data collection, analysis, and writing of the manuscript. Khong Kok Wei contributed to the conceptualization of the study and reviewed the manuscript. The authors worked closely together to ensure the study was comprehensive and effectively communicated their findings. This collaboration highlights their mutual dedication to advancing knowledge in the field of data mining and analytics.

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Conflict of Interest

The authors declared that there is no conflict of interest.

Ethics Approval

The standard term for this research is 'Web-based research,' divided into non-intrusive and engaged techniques. The latter involves interacting with site users, while the former does not disturb the site's original state. This research employs the non-intrusive technique, scraping readily available data from Reddit, Twitter, and YouTube about healthy eating. In 'Web-based research' using scraping, users are generally unaware that their public or private posts may be retrieved by researchers. To counter ethical challenges, researchers rely on the terms and conditions users agree to when signing up on these platforms, which include clauses on data usage by third parties, including researchers. Once users agree to these terms, their content is treated as public data, exempting researchers from institutional ethics review. Despite minimal ethical concerns due to the public accessibility of social media data, researchers took measures to prevent ethical issues. These included discarding user IDs to ensure anonymity and avoiding the use of direct quotes and content.

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