



The use of classification algorithms and partial least squares for patient satisfaction

Hung-Pin Hou^{1,2*}, Ping-Feng Pai³, Hsin-Mei Lin¹

¹Dept. of International Business Studies, National Chi Nan University, Taiwan

²PuLi Christian Hospital, Nantou, Taiwan

³Dept. of Information Management, National Chi Nan University, Taiwan

Abstract After customer satisfaction investigation has been widely applied in many countries, the medical insurance payment system has change from pay by service to pay by quality, even pay by satisfaction. Therefore, how to collaborate with medical professionals and patient experiences have revealed the important issue for both medical providers and patients. Using partial least squares (PLS) and classification algorithms to examine 237 patients interviewed on Maternal in clinics and hospitals of Taiwan. Firstly, we proposed a measurement structure of patient satisfaction index (PSI) model based on direct and indirect experiences of medical service form patient. Our study shows that the continued medical treatment of patients and the accountability of medical staffs perceived by patients play fully mediating effect between medical institute's reputation, comprehensiveness, and accessibility and patient satisfaction. Among the routes, the medical institute's reputation has the highest influence upon patient satisfaction through continued medical treatment of patients and the accountability of medical staffs that patients perceived. Secondly, using classification algorithms exploring the majority influence factors which correlative with the patient satisfaction we proved that decision tree result shows consistence with PSI model. Thirdly, we proposed the Confusing-Satisfaction Matrix for pruning skewed distribution and poor data to strengthen the PSI model from a weak one to a strong one. For some of the weak structure of exploratory research, we provide an effective way for data cleaning and sampling.

Keywords patient experience, classification algorithms, structural equation model

1. Introduction

As the popularity of internet and the rise of social media networks, the attitude of hospital choice of patients has rapidly developed into a diversified interactive mode. Under the government health insurance, Taiwan medical industry, as resembling other industries counting on the large-scale production and consumption in the past, is facing the differentiation, individualization and refinement of industry. Therefore, the relationship between the patient satisfaction for doctors and patients' choices of medical services has been an important issue in administrating medical institutions.

In recent years, by the encouragement of success of Swedish Customer Satisfaction Barometer (SCSB) and American Customer Satisfaction Index (ACSI) on methods and models for assessing the consumer satisfaction resulting from the gap between the expectations and the actual consumption experience, almost all developed countries are studying or establishing a convenient method and model for the National Customer Satisfaction Index (NCSI). In addition, ACSI models (Figure 1) have demonstrated some variations for different industries [1-3]. The framework based on ACSI for patient satisfaction has been widely applied to health services. However, the ASCI model is aimed for consumption. Further discussions on whether it is fully applicable for the healthcare industry are needed. Batbaatar et al. [4-5], for example, stated the satisfaction architecture based on the marketing theory is not entirely applicable to the medical service industry. Therefore, some revisions of the satisfaction architecture so as to learn how the patient assesses medical care leads patients satisfaction are



worthy for further exploration. The differences of country policies, cultural and other global factors should take into consideration for a general patient satisfaction measurement.

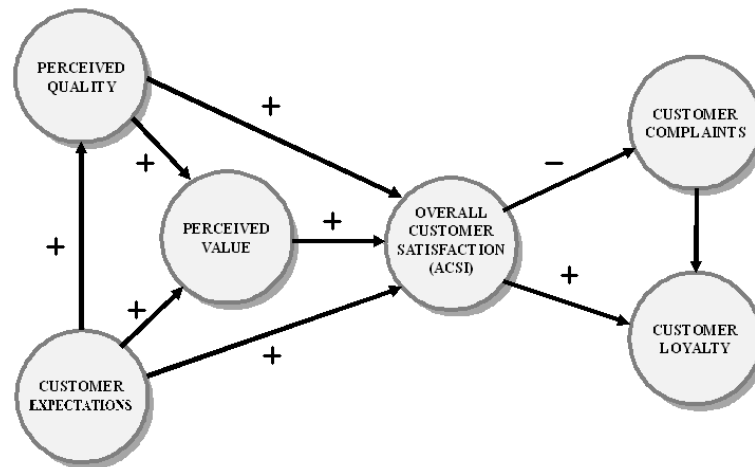


Figure 1: The American Customer Satisfaction Index (ACSI) Model (Fornell et al., 1996)

The satisfaction with a medical service for patients should be correlated with the service quality of structure, process, and outcome they perceived, but literature has either focus on the expectation to satisfaction without the involvement of quality or lack of an integrated framework to illustrate a complete explanation of the relationship between quality and satisfaction [6-7]. In practice, the patient can choose freely preferred medical institutions across different levels because there is a lack of an effective medical referral system for some countries, including Taiwan. To better understand attitudes and behaviors of patients so as to improve medical quality and patient satisfaction through good communication, the study, we adopt the NCSI model with some cultural characteristics when applying to Taiwan's NHI care system. Our model attempts to develop an effective model measuring patient satisfaction. The rest of this study is organized as follows: Section 2 reviewed the literature. The hypotheses development is provided in Section 3. Section 4 contains the methodology and results for revised NCSI model as well as the Confusing-Satisfaction Matrix for methodology improvement. Discussion and Conclusions are depicted in Section 5. Following section (section 6) states the important implications and directions for future research.

2. Related work

Anderson et al. [1] indicated that the objective customer satisfaction is an indicator that summarizes the overall experience of purchasing and consuming products or services [8]. Customer satisfaction can measure the difference between customer expectations and perceived values of products or service [9]. In the study of consumer purchase behavior, Woodside et al. [10] pointed out customer satisfaction, mostly based on the expectancy confirmation theory and rational expectancy theory [11], is the main factor influencing customer behaviors. Literature debates that the customer satisfaction has mixed results when applying to diverse industries [12].

NCSI model, based on pre-consumer customer expectation for satisfaction, measures the overall customer satisfaction and the followed loyalty by perceives the value of experience, such as product reliability, degree of standardization and defect level, the price perception, and the sense from customer experience of recent consumption [13]. The extant literature of NCSI models usually focuses on shortening the gaps between patient expectation and experience, and thus, maybe limited in applying to medical industry. For instance, some researchers study the patient satisfaction only by the monofactor regarding to the patient expectation of medical services [4]. Some other studies [14] suggested customization can be an added factor in determining customer satisfaction in NCSI model. Consequently, using patient satisfaction scores to evaluate the performance of physicians may lead to ineffective care due to patient's not having capability of evaluating care quality [7]. Bowling, et al. [15] revealed that NCSI model should incorporate more measurements which the patients concern mostly, such as information about service flow, convenient and punctual appointments, helpful



reception staff, knowledgeable clinicians, clear and understandable instructions, participation in treatment decisions, and experiencing symptom relief. Accordingly, not only the pretreatment expectation but also quality of healthcare is the key factors for patient satisfaction. It is worthy to taking the two key factors affecting the patient satisfaction model for medical industry.

3. Hypotheses development

We offer a research frame work illustrating the antecedent, mechanism, and result of the patient satisfaction model. The antecedents include the reputation, comprehensiveness, and accessibility of health institution. The mechanisms are the expectation from quality, which presented in the concept of continued medical treatment and accountability of medical staff. The result is showed in patient's satisfaction (see Figure 2).

3.1 Continued medical treatment and patient satisfaction

Cohen et al. [16] presented an adequacy-importance e model measuring the importance of every attribute, which provides more appropriate predictability for consumer satisfaction. Mazia et al. [17] also employed the adequacy-importance model for quantitative examination for predicting the patient's continuing medical treatment. The frequent experience or medical information obtained through actual participation has a more realistic expectation of medical quality and, thus, a better prediction of patient satisfaction. On the contrary, patients who do not often seek medical treatment have less direct access to relevant medical information, and thus, lesser patients' continued medical treatment expectations of care quality which eventually reduces the patient satisfaction [18]. Accordingly, respectable patient satisfaction should be affected by the continued interaction between health care provider and patient. Therefore, hypothesis is proposed as follows:

H1: Continued medical treatment of patients has a positive relationship with patient satisfaction.

3.2 Accountability of medical staffs and patient satisfaction

Patient's experience of accountability of medical staff is the best evidence of the health quality [19]. Patient-centered care is a critical aspect of accountability of medical staff, promoting provider's response to patient expectation and providing needed services with care of patient's respect and dignity [20]. Accountability can have a good result of better clinic outcomes, culture of patient safety, and patient satisfaction [21]. Close communication has more information between physician and patient, leading to better satisfaction of diagnosis and treatment. Empirical study for undesirable events using quality as indicator found a negative impact on patient satisfaction when there is no good communication skills, irresponsible for delayed treatment, poor personally diagnose patients and less preparation for patient discharge [22-23]. Another study shown physicians expressed their concern about how clinicians could meet the needs of patients to facilitate the provision of evidence based medical services can effectively reduce the incidence of complications, and thus, improves patient satisfaction [24]. Thus a hypothesis is stated as follows:

H2: There is a positive relationship between the accountability of medical staffs perceived by patients and patient satisfaction.

3.3 The reputation of a medical institution and the expectation of care quality

Varkevisser et al. [25] found that patient will choose the medical institution according to the published hospital quality rating report in Dutch where the rate approximates the hospital with well-known better care quality. Bundorf et al. [26] found that public reports of medical institution quality is an important source of reputation which significantly affected patient's choices of the medical institution in the study of fertility clinics. However, the public hospital quality reports only part of the medical institution's reputation. The patients will still choose to stop the continued medical treatment and turn to other well-known medical institutions when the delivered information is different from the patient's own personal experience [27]. The reputation of a medical institution is good indicator for the continued medical treatment of patients [28-30]. Thus, a hypothesis could be made.



H3-1: The reputation of a medical institution has a positive relationship with the continued medical treatment of patients.

The NCSI model reveals the relationship between perceived value and expectation. Literature finds that customer tends to comfort with the value judgment of word-of-mouth and the assessment of the cure quality of others [31-33]. Varkevisser et al. [25] reported that the published hospital quality rating encourages clinician to be in charge of better care quality. Bundorf et al. [26] investigated fertility clinics found that public quality report positively affected the behavior of accountability of medical staffs. Reputation brings a superior patient experience because health care providers incline to show greater extent of accountability when they perceive reputation of their own affiliations [34-36]. Based on above argument, the following hypothesis could be made.

H3-2: The reputation of a medical institution has a positive relationship with the accountability of medical staffs perceived by patients.**3.4 The comprehensiveness of medical care and the expectation of care quality**

The comprehensiveness of medical service of primary care should include patient-centered integrated care, accessibility of health care services, sustainable patient partnership, and practices for family and community [37]. Bostan et al. [38] pointed out that patients tend to ask for more medical service quality when they trust the comprehensiveness of medical service. Safran et al. [39] found physicians can build physician-patient trust relationship and make the compliance with physician advices when the physicians are equipped with splendid medical knowledge and acknowledged patient rights of 'whole person'. Thus, the hospital should provide wide-arranged specialist for effectively keeping the continuing medical treatment in the same hospital. For example, in of maternal health and neonatal health, not only the completed maternal health education guidelines but also complete obstetric and neonatal services are important factors for ensuring the continuity of medical treatment. Therefore, the following hypothesis is depicted.

H4-1: Hospital comprehensiveness has a positive relationship with the continued medical treatment of patients.

The comprehensiveness of the medical institution can be understood via the example of mother intervention. A decent mother intervention includes the pregnancy warning, production safety education, and the prenatal care [40]. It should also includes good nutrition promotion, acute neonatal illness diagnosis, and childhood diseases care. Canada's healthcare system identified the comprehensiveness services across the continuum of healthcare is a key of successful accountability of medical staffs [41]. Bostan et al. [38] pointed out that accountability is driven by peer review, monitor, mimic, and imitate whenever the medical institution has completed sub-special services. Safran et al. [39] found physicians had a comprehensive knowledge of 'whole person' can build sense of responsibility of the physician-patient relationship and make physician prefer to following evidence-based medicine. The hospital should provide completed specialist and treatment guidelines so as to effectively avoid malpractice in accountability. Thus, we provide hypothesis 4-2.

H4-2: Hospital comprehensiveness has a positive relationship with the accountability of medical staffs perceived by patients.**3.5 The accessibility of medical service and the expectation of care quality**

The accessibility of medical service is defined by the feasibility of medical resources, such as frequent physician visits, consultation of specialists, and hospitalization [42-43]. Mason [23] suggests that accessibility offered through adequate staffing and cleaning can reduce delay of treatment and the incidence of complications. The accessibility is essential factor of effective care. Fisher et al. [44] found that the accessibility of medical service, measured by expenditures spending, leads to a good quality care of health outcomes and patient satisfaction. Iversen et al.[45] found the insufficient accessibility in Swedish healthcare is resulted from the long waiting time. Ghorbani et al. [46] revealed that the continued medical treatment was mainly derived from components of



accessibility medical service such as waiting time, cost, welfare facilities, accessibility and teams providing services. The expectation of quality care is jeopardized and risk of patient safety is increased simply because long-waited patients are forced to turn to other hospitals. Based on the above argument, this study suggests that, through providing the patient convenience and effective medical experience, the continued medical treatment could be strengthened by accessibility of medical treatment. Thus a hypothesis could be derived.

H5-1. Hospital provides accessibility medical service has a positive relationship with the continued medical treatment of patients.

The accessibility of medical service also influences the accountability of the physicians because enough treatment time without the stress from keeping the patient waiting too long can provide the physician will for adequate expression of medical resources by physicians and nurses. Ghorbani et al. [46] revealed that the expression of accountability of the family physician services is mainly derived from components of services such as waiting time, cost, welfare facilities, accessibility and teams providing services. After comparing the different regions health expenditures, Fisher et al. [44] found that having medical treatment, measured by expenditures spending, is sensitive to the professional, complete consultation of specialists, i.e. the accountability of the physicians. Based on the above study, we suggest the accessibility of medical treatment could strengthen accountability of medical staffs.

H5-2. Hospital provides accessibility medical service has a positive relationship with accountability of medical staffs perceived by patients.

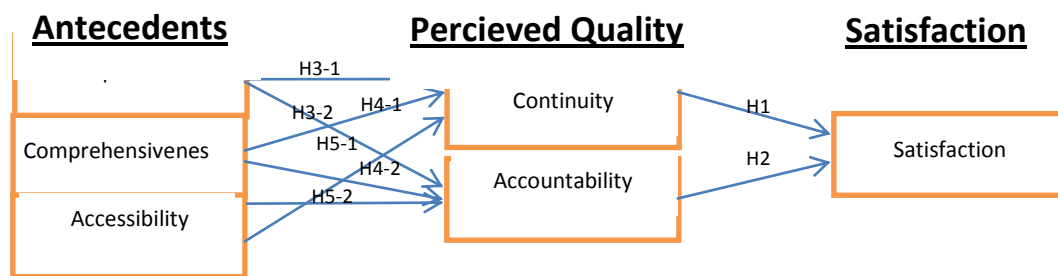


Figure 2: Patient Satisfaction Index Model

4. Methodologies and Results

Prior study usually suffered from limited information when investigating the hospital choice of the pregnant women. To fix the problem by exploring different models for practical factors for patient satisfaction in outpatient department, our study incorporate the category of data according to the concept of patient-centered care [39-43] of a secondary dataset.

4.1 Data collection

This study was mean to investigate the influencing factors of the patient satisfaction of medical care in outpatient department. A secondary dataset adopted from Academia Sinica Survey Research Data Archive [50] of Taiwan was collected through questionnaires. The questionnaire was pre-tested by 56 pregnant women then collected from the five obstetrics and gynecology hospital or clinic outpatient department in Taiwan. There is a sample of 237 observations (59.25% responsive rate). After excluding some of the missing data, the sample number of this study was 212(53% effective responsive rate).

The conceptualization of the factors is structuralized as: Q1-Q5 for Reputation, Q6-Q12 for Accessibility, Q13-Q17 for Accountability, and Q18-Q25 for Comprehensiveness service. Reorganized constructs shown as Table 1. In addition, we confirmed each latent variable by Confirmatory Factor Analysis (CFA) of Amos. Due to the small sample size, the PSI model was rechecked by the Smart PLS-SEM and compared with the original research [50]. Furthermore, the importance of the PSI model in hospital selection by decision tree provided by WEKA [51-52] was discussed in this study.



Table 1: Classification of survey questions before confirmatory factor analysis

Survey Questions	Reputation	Accessibility	Accountability	Comprehensiveness
1. Fame of the hospital	V			
2. Reputation of the hospital	V			
3. Recommended by professionals	V			
4. Recommended by people around	V			
5. Recommended by public information	V			
6. Short waiting time		V		
7. Simple formalities		V		
8. Clinic time meets require		V		
9. Reasonable charge for different ward		V		
10. Convenient location that can be easily accessible		V		
11. Convenient parking		V		
12. With Acquaintance health care staff		V		
13. Ethic of the doctor			V	
14. Skills of the doctor			V	
15. Friendliness of the doctor			V	
16. Friendliness of the nurse			V	
17. Friendliness of the staff			V	
18. Good follow up				V
19. Good parent-child education				V
20. Good prenatal health education				V
21. Complete and new ward facilities				V
22. Complete and advanced medical devices				V
23. With Complete divisions				V
24. With Pediatric division				V
25. With Postpartum care center				V

4.2. Data analysis

A better model exploration should control the influence of the patient characteristics [47-49]. Our study employed the Partial least squares (PLS), structural equation modeling (SEM), cluster analysis and classification algorithm to explore the PSI model explaining the patient satisfaction. Then, the hypothetical factors of the PSI model are shown in Figure 2.

In general, SEM uses a maximum likelihood (ML) function to minimize covariance between samples to confirm latent variables (LVS) [53]. The sample data must follow the normal distribution. In contrast, PLS has been applied to model causal paths among numbers of LVS as a variance-based method [54]. Similar to the covariance-based approach, PLS is suitable for small sample, imbalanced distribution, complex models and exploring relationship of SEM [55-56]. The PLS-regression model is only suitable for the simple analysis of independent blocks and dependent blocks. Contrary to the PLS-SEM as path model structure, can be applied to complex SEM with a large number of constructs [55]. Therefore, this study used the PLS-SEM for examining model analysis and prediction [57].

After item analysis (independent t test $\alpha=0.000$), explore factor analysis (KMO = 0.884 and Bartlett's Test $\alpha=0.000$), and internal consistency reliability analysis (The Cronbach's α value were all above 0.8), the secondary data shows good reliability and validity. Due to the imbalance skews and poor of data, the results of prior study were limited [50]. Furthermore, the Adequacy-Importance Model [16] was utilized to form the patient perceived quality to seek medical attention continuity. Each construct indicators was verified by CFA. After remove high collinear items, each indicator reaches the threshold with good prediction as shown in Fig.3.



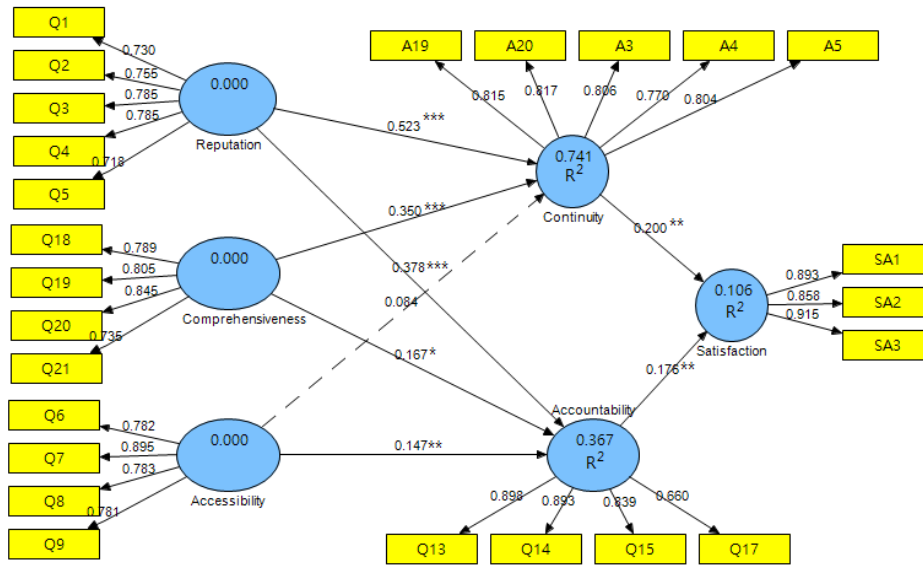


Figure 3: PSI model exam result of Smart PLS Analysis (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Most of the skewed distribution or abnormal data are not easy to test significance [58-59]. Thus, data with skewness or outlier data influence correlation analysis and statistical test. To verify it structure by CFA is a must since the LVS consists of different measures. This verification indicates that variable represents a more effective latent variable, and therefore, solidifies the model validation. After CFA, some of the measurements are excluded from the model due to low factor loadings or high covariance with others. The unidimensional test results were shown in Table 2, and are within acceptable ranges [60].

Table 2: Latent variables confirmatory factor analysis

Latent Variable	Reputation	Accessibility	Comprehensiveness	Accountability	Continuity
Measures	Q:1,2,3,4,5	Q:6,7,8,9,10,11,12	Q:18,19,20,21	Q:13,14,15,16	A:5,7,9,10,17,18,20,21,23,25
Chi-square	46.425	31.223	7.337	11.5	60.109
p_value	0.000	0.005	0.026	0.003	0.005
df	5	14	2	2	35
GFI	0.91	0.96	9.83	0.974	0.945
AFGI	0.731	0.92	9.14	0.87	0.914
RMSEA	0.198	0.76	0.112	0.15	0.058

The root mean square error of approximation (RMSEA); Goodness of fit index (GFI) and adjusted goodness of fit index (AGFI)
 Q: Survey Question; A: Continuity Attitude

4.3 Assessment of the measurement model and the structure model

After the LVS construct quality has been assessed, the Smart PLS was employed to estimate model parameters for checking the hypothesis of the PSI model. Evaluation of the model adequacy through internal consistency, convergent and discriminant validities was conducted [61]. After performing PLS algorithms, all data quality criteria were validated listed in Table 3. The results of convergence were obtained in five iterations [62-65].

Table 3: Validation of latent variables data quality

Latent Variable	AVE	Composite Reliability	R Square	Cronbachs Alpha	Communality	Redundancy
Accessibility	0.658	0.885		0.827	0.658	
Accountability	0.686	0.896	0.355	0.841	0.686	0.090
Comprehensiveness	0.631	0.872		0.804	0.631	
Continuity	0.644	0.901	0.742	0.862	0.644	0.298
Reputation	0.570	0.869		0.811	0.570	
Satisfaction	0.791	0.919	0.106	0.873	0.791	0.047



After all measurements meet the criteria, structural path coefficients (loadings), illustrated in Fig.3, the path diagram after running PLS Algorithm, are the path coefficients for the structure model [66-67].

The significance of the paths within structure model is determined by bootstrap resampling method (5000 resamples). The overall results of structure model test are shown in Fig.3, Patient Satisfaction is significantly associated with continued medical treatment of patients (path coefficient = 0.2, t- statistic = 2.386), the accountability of medical staffs perceived by patients (path coefficient = 0.176, t-statistic = 2.297), only 10.6% of the variance in the patient satisfaction variable is explained. Accordingly, hypotheses H1 and H2 are supported. The competing model shows no direct relationship between Reputation (path coefficient = 0.004, t-statistic = 0.031), Comprehensiveness (path coefficient = 0.051, t-statistic = 0.452), and Accessibility (path coefficient = -0.025, t-statistic = 0.346) on patient satisfaction. Instead, Reputation (path coefficient = 0.540, t-statistic = 10.596) and Comprehensiveness (path coefficient = 0.386, t-statistic = 7.276) have significantly fully mediating effect by continued medical treatment of patients as a mediator. Thus, hypotheses H3-1, H4-1 are supported. Accessibility (path coefficient = 0.084, t-statistic = 1.774) has no significant correlation with Continuity. Therefore, hypotheses H5-1 is not supported. Reputation (path coefficient = 0.376, t-statistic = 4.246) and Comprehensiveness (path coefficient = 0.165, t-statistic = 1.832) and Accessibility (path coefficient = 0.154, t-statistic = 2.040) also have significantly fully mediating effect by the accountability of medical staffs perceived by patients as a mediator. Therefore, hypotheses H3-2, H4-2, H5-2 are supported. As Fig.3 shown, 60% of the standardized path coefficients range exceeds 0.2; the model fitness is good as shown in Table 4, in spite the model could be considered as weak effect [62].

Table 4: Summary of structural equation model test result

	Satisfaction			Continuity			Accountability		
	Path Coefficient	f ² Effect Size	q ² Effect Size	Path Coefficient	f ² Effect Size	q ² Effect Size	Path Coefficient	f ² Effect Size	q ² Effect Size
Accessibility					0.019	0.000	0.154	0.027	0.011
Accountability	0.176	0.027	0.018						
Comprehensiveness				0.386	0.216	0.060	0.165	0.022	0.009
Continuity	0.200	0.031	0.025						
Reputation				0.540	0.440	0.143	0.376	0.100	0.062

5. Analysis the structure model with classification algorithms

5.1 Decision tree classifier

In this study, the PSI model of accuracy of the classification of patient satisfaction factors was analyzed by decision tree classifier using the latent variable data generated by PLS-SEM for the reason that decision trees are easy to understand and easy to converted to a set of production rules [68]. This study found that all classifiers have Accountability as root with leaf of Comprehensiveness and Reputation on the judgement of patient satisfaction. However, the correct classification rate of the classifier is only between 59.4% and 82.2% (except Random Tree 99.1%) as shown in Table 5. Many imbalanced data occur in real-world. For example, medical discussions are often concerned about the positive cases which belong to minority in real-world as most people health status is normal. In competitive markets, the satisfaction and quality ratings is often a negative skew distribution [12]. The data in this study showed that the proportion of respondents and strongly agree is 70.6%, and the proportion of disagree and strongly disagree is only 2.59%. This phenomenon shows imbalanced distribution (Fig. 4). In this case, for the easily overlooked minority's opinion, the classification algorithm would become unable to produce a correct classification or have an overfitting problem [69]; thus, fail to provide more accurate classification information.

To deal with this problem, we summation each of the questionnaire answer scales as a respondent rating scale. From the quartile of the rating scale, those above 75 percentile are defined as high rating group and those below the 25th percent as lower rating group. Besides, we categorize the satisfaction scale into higher or lower groups by WEKA [51-52] cluster algorithm. Then, we use these two kinds of group to generate a Confusing-Satisfaction Matrix (Fig. 5) to assess the respondent type in order to improve data quality and minority sampling problem. According to the Confusing-Satisfaction Matrix, we can have 4 groups of respondents: low rating and



high satisfaction, i.e. false satisfied, as Group A; high rating and high satisfaction, i.e. true satisfied, as Group B; low rating and low satisfaction, i.e., true dissatisfied, as Group C; and high rating and low satisfaction, i.e. false dissatisfied, as Group D.

Table 5: Classification results for various decision trees

Classifier	TP Rate	FP Rate	Specificity	Sensitivity	AUC	Root	Leafs
J48	0.651	0.35	0.65	0.651	0.668	Accountability	Comprehensive 、 Reputation
RandomTree	0.991	0.009	0.991	0.991	1	Comprehensive	Accountability
DecisionStump	0.594	0.419	0.581	0.594	0.588	Accountability	
ADTree	0.703	0.289	0.711	0.703	0.762	Accountability	Comprehensive
BFTree	0.642	0.378	0.828	0.822	0.669	Accountability	Reputation
SimpleCart	0.637	0.363	0.637	0.637	0.645	Accountability	Comprehensive

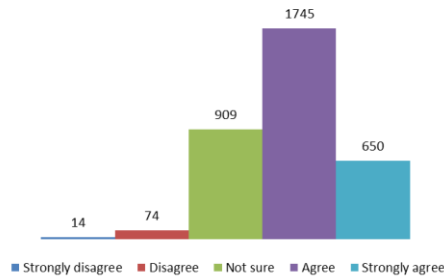


Figure 4: Category of respondents answer negative skew distribution

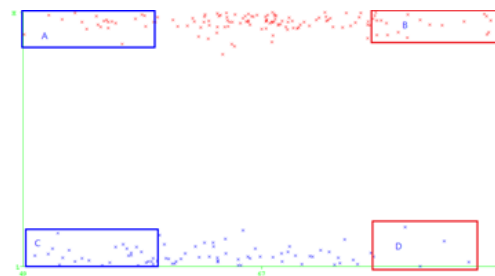


Figure 5: Confusing-Satisfaction Matrix. (Red as Satisfied, Blue as Dissatisfied)

5.2 The corrected result

In general, imbalanced or abnormal data may result in difficulty in classification [56-57]. In this study, we analyzed different combination of datasets by classifier Tree J48 and Random Tree with 10-fold cross-validation. The specificity (SP), Sensitivity (SE) and area under the ROC curve (AUC) of each datasets are shown in Table 6, the true satisfied and true dissatisfied (Group B,C) dataset has a higher SP, SE, AUC and a better classification, the AUC of Random Tree is very close to 1, indicates an accurate classification result. However, the whole dataset (original dataset) are negative skew distribution and poor quality. It leads to an unfavorable classification result both using Classifier Tree J48 and Random Tree explored. This is consistent with the fact that most of the studies have shown that data quality influences the accuracy of classification [70].

Thus, we analyze Group B and C only by the Random Tree classifier. The result shows the measurement factors that affect the patient satisfaction of medical treatment are mainly due to the recommendation of the professional (Reputation), the convenience of the medical process (Accessibility), whether the physician is friendly and the physician's expertise (Accountability) as shown in Fig. 6. It is different with PLS-SEM assessment finding, due to the reason that highly path coefficient of reputation may be weighted its impact on classification algorithm. Consequently, reputation of the healthcare institutes strongly affects the patient perceived quality care and satisfaction. Moreover, only ignoring Group A and D of the whole dataset, classification results showed that more than half classifiers take Continuity (perceived quality from recommended by professionals) as primary factor that determine patients satisfaction, another primary factor classified by J48 is Accountability (perceived quality from doctor's skills), and reputation of the hospital, recommended by public information (Reputation); maternal health education, newborn health education, perfect ward facilities (Comprehensiveness); less waiting time, reasonable charges (Accessibility) are others important influence factors as Table 7, same as PLS-SEM assessment finding.

Table 6: Performance of classification algorithms with different datasets analysis

Datasets	Classifier	TP Rate	FP Rate	Specificity	Sensitivity	AUC
Whole Samples	J48	0.566	0.52	0.48	0.566	0.495
	RandomTree	0.59	0.496	0.504	0.59	0.547
Exclude A, D	J48	0.681	0.373	0.627	0.681	0.688
	RandomTree	0.654	0.385	0.615	0.654	0.635
Group B, C	J48	0.822	0.172	0.828	0.822	0.803
	RandomTree	0.933	0.063	0.937	0.933	0.935



Table 7: Performance and classified of classification algorithms for satisfaction analysis

Classifier	TP Rate	FP Rate	Specificity	Sensitivity	AUC	Root	Leafs
J48	0.91	0.132	0.868	0.91	0.932	Accountability-Q14	Continuity-A5、Comprehensive-Q19
RandomTree	1	0	1	1	1	Continuity-A20	Continuity-A4、Reputation-Q5
DecisionStump	0.691	0.346	0.654	0.691	0.673	Continuity-A3	
ADTree	0.798	0.268	0.732	0.798	0.876	Continuity-A3, A19	Reputation-Q2、Accessibility-Q6,Q9、Comprehensive-Q19,Q21
BFTree	0.883	0.179	0.828	0.822	0.923	Continuity-A3	Accessibility-Q9、Comprehensive-Q19
SimpleCart	0.637	0.363	0.637	0.637	0.645	Continuity-A3	Accessibility-Q9

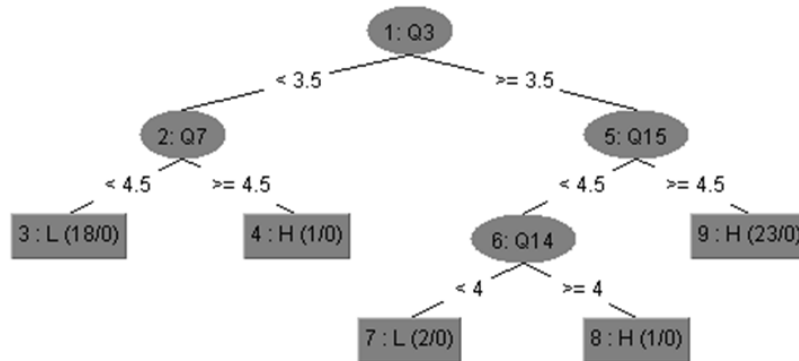


Figure 6: Random Tree for patient satisfaction factors using group (B, C) data only

Prior studies are based on factors affecting satisfaction of medical service according to the NCSI structure. The verification of NCSI model did not reach significant because the poor quality and the imbalanced skewed distribution of the data, leading to the result that it only the correlation between the attitude of pregnant women toward hospitals and satisfaction is significantly positive [50]. This study tries to find appropriate constructs between essential factors of patient choices and satisfaction via PSI model. The results showed that Reputation does not influence satisfaction of medical service directly; however, Reputations indirectly mediated by Continuity and Accountability to affect Satisfaction, therefore, Reputation is the most important factor to the patient satisfaction in Taiwan. This result is consistent with TCSI study which investigating indirect effect of perceived value on satisfaction based on NCSI structure as well as results of analysis of ‘with or without recommendation from experts’ [14].

Similarly, Comprehensiveness of service does not have a direct impact on satisfaction but indirectly correlates with satisfaction through Continuity of the willingness of a patient to seeking medical attention. In addition to patient satisfaction factors, customers concern about relevant factors of fetal services. Therefore, besides the obstetric professional, the expectation of the neonatal services is also an important factor for medical choice. This phenomenon is consistent with the analysis of ‘with or without maternal and child education’.

Accessibility has no direct influence on satisfaction either. This result may be due to the near 100% penetration rate of special medical institutions in Taiwan for many years. Except mountain and island areas, the accessibility of health service in metropolitan is not a significant problem. However, the convenience of medical treatment, such as the short waiting time factor obtained by the classification calculus analysis, still influences the satisfaction of medical service indirect-only mediation effect by Accountability.

Due to the transparency of the internet, users can collect information about the experiences of the relevant users. Most of them have selected the medical institutions through the information in advance. Thus, the organization will have majority data from user satisfaction questionnaire as satisfied or false satisfied, showing an imbalance skewed distribution. However, it is the unsatisfactory of the minority should be concerned by the manager. Thus, this study attempted to use the classification algorithm to improve the imbalance and poor data problem by cleaning and optimization sampling strategies for ensuring that minority data are not ignored and that poor data is removed. Analyzing the measurement factors influencing satisfaction of medical service, the classification algorithms results is consistent to the PSI model. If we analyze the conformity of PSI model by PLS-SEM after removing the poor data (mask Group A,D) first, the explanatory power for satisfaction of medical service, R^2 , will rise from 0.106 to 0.273. If we analyze the PSI model by optimal sampling data (proper Group B, C), R^2

will rise to 0.819, making the PSI model transform from weak structure to strong structure. This method proposes that PSI model is indeed suitable for use in test of satisfaction of medical services.

6. Conclusions

For manufacturing industries, price competition dominated by general brands and retail discounts is the price-driven satisfaction, while for non-consumer industries, quality is the core factor for satisfaction of the customers [71]. Measurement of the patient experience provides the opportunity for improving medical service and health outcomes. The proper communication, respectable medical experiences, and low incidence of complication, patient thoughts of care quality are key performance factors for medical choices [72]. Although many hospitals seek to improve patient satisfaction through the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS), and several studies have shown some improvements in the HCAHPS score through various interventions. A more effective assessment of the patient satisfaction model, especial for outpatient is still in need to improve patient satisfaction. In this study, by using secondary data, a comparison between PSI model and NCSI model was conducted.

Due to the uncertainty of medical outcome and medical knowledge disparity, researches of the NCSI models investigate patient satisfaction, in the past decade, have rarely assert the measurement structure that takes both the medical profession opinions and the patient satisfaction into account. We propose a PSI model based on prior patient experiences studies and medical profession arguments by using PLS-SEM to verify the strength of the PSI model.

The result shows that patient satisfaction is mainly affected by the continued medical treatment of patients and the accountability of medical staffs perceived by patients as mediators that the institute's reputation, accessibility and comprehensive services indirectly affect patient satisfaction. Among the rest, Reputation, the highly explanatory power, is the most important factor to the patient satisfaction; the classification algorithm also consistently finds reputation is the key factor which affects patient satisfaction as well. As a result of PSI model, the construction of the satisfaction index transformed into patient satisfaction through healthcare systems' quality. Therefore, comparing to the NCSI model, the PSI model is more appropriate for healthcare industry to examine patient satisfaction. Due to the overall explanatory power of satisfaction of the PSI model is only 10.6%, for further investigation, this study propose a Confusing-Satisfaction Matrix to identify the relationship between the robust of model structures and the quality of data. We found that poor data (false satisfied and false dissatisfied), in addition to impacting the significance of PSI model, can improve the performance of the PSI model in terms of the explanatory power. For the negative skew distribution data analysis, Confusing-Satisfaction Matrix can provide sampling strategies; qualify the relationship between the significance of the research model and the facets.

This study use obstetrics and gynecology outpatient patients as the investigation population. It is still much more needs to be examined. Subsequent studies can use the PSI model to assess the suitability of the research framework for inpatients, different departments and different levels of medical institutions and the interaction between PSI model constructs. In addition, the classification accuracy of patient satisfaction factors can be compared by different classification algorithms to find the better algorithm for analyzing patient satisfaction.

Reference

- [1]. Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer Satisfaction, Market Share, and Profitability: Findings from Sweden. *The Journal of Marketing*, 58(3): 53-66.
- [2]. Fornell, C. (1992). A National customer satisfaction barometer: The Swedish experience. *The Journal of Marketing*, 56(1):6-21.
- [3]. Johnson, M. D., & Fornell, C. (1991). A framework for comparing customer satisfaction across individuals and product categories. *Journal of Economic Psychology*, 12(2):267-286.
- [4]. Batbaatar, E., Dorjdagva, J., Luvsannyam, A., & Amenta, P. (2015). Conceptualisation of patient satisfaction: a systematic narrative literature review. *Perspectives in Public Health*, 135(5): 243-250.
- [5]. Batbaatar, E., Dorjdagva, J., Luvsannyam, A., Savino, M. M., & Amenta, P. (2017). Determinants of patient satisfaction: a systematic review. *Perspectives in Public Health*, 137(2): 89-101.



- [6]. Kupfer, J., & Bond, E. (2012). Patient satisfaction and patient-centered care: Necessary but not equal. *The Journal of the American Medical Association*, 308(2):139-140.
- [7]. Price, R., Elliott, M., Cleary, P., Zaslavsky, A., & Hays, R. (2014). Should health care providers be accountable for patients' care experiences? *Journal of General Internal Medicine*, 30(2):253-256.
- [8]. Czepiel, J. A., Rosenberg, L. J., & Akerele, A. (1974). *Perspectives on consumer satisfaction*. New York University, Graduate School of Business Administration, 119-123
- [9]. Ostrom, A., Iacobucci, D. (1995). Customer trade-offs and the evaluation of services. *Sloan Management Review*, 59(1): 17-28.
- [10]. Woodside, A.G., Frey, L.L., Daly, R.T. (1989). Linking service quality, customer satisfaction, and behavioral intention. *Journal of Health Care Marketing*, 9(4): 5-17.
- [11]. Kotler, P. (2006). *Marketing Management*, New York, NY: Prentice Hall, 12th Ed., 144-169.
- [12]. Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., & Bryant, B. E. (1996). The American customer satisfaction index: nature, purpose, and findings. *The Journal of Marketing*, 60(4): 7-18.
- [13]. Karatepe, O. M., Yavas, U., & Babakus, E. (2005). Measuring service quality of banks: Scale development and validation. *Journal of Retailing and Consumer Services*, 12(5): 373-383.
- [14]. Hu, H. Y., Chiu, S. I., Cheng, C. C., & Hsieh, Y. F. (2010). A study on investigating patient satisfaction of medical centers using Taiwan customer satisfaction index in Taiwan. *African Journal of Business Management*, 4(14): 3207-3216.
- [15]. Bowling, A., Rowe, G., & McKee, M. (2013). Patients' experiences of their healthcare in relation to their expectations and satisfaction: a population survey. *Journal of the Royal Society of Medicine*, 106(4): 143-149.
- [16]. Cohen, J. B., Fishbein, M., & Ahtola, O. T. (1972). The nature and uses of expectancy-value models in consumer attitude research. *Journal of Marketing Research*, 9(4): 456-460.
- [17]. Mazis, M. B., Ahtola, O. T., & Klippel, R. E. (1975). A comparison of four multi-attribute models in the prediction of consumer attitudes. *Journal of Consumer Research*, 2(1): 38-52.
- [18]. Howard, J. A. (1977). *Consumer behavior: Application of theory*. McGraw-Hill Companies.
- [19]. Lyu, H., Wick, E. C., Housman, M., Freischlag, J. A., & Makary, M. A. (2013). Patient satisfaction as a possible indicator of quality surgical care. *The Journal of the American Medical Association, surgery*, 148(4):362-367.
- [20]. Anhang Price, R., Elliott, M. N., Zaslavsky, A. M., Hays, R. D., Lehrman, W. G., Rybowski, L., ... & Cleary, P. D. (2014). Examining the role of patient experience surveys in measuring health care quality. *Medical Care Research and Review*, 71(5):522-554.
- [21]. Wolfe, A. (2001). Institute of Medicine Report: crossing the quality chasm: a new health care system for the 21st century. *Policy, Politics, & Nursing Practice*, 2(3):233-235.
- [22]. Agoritsas, T., Bovier, P. A., & Perneger, T. V. (2005). Patient reports of undesirable events during hospitalization. *Journal of General Internal Medicine*, 20(10):922-928.
- [23]. Diana J. Mason (2015 JAMA Forum) <https://newsatjama.jama.com/2015/06/17/jama-forum-does-linking-payment-to-patie>
- [24]. O'leary, K. J., & Cyrus, R. M. (2015). Improving patient satisfaction: timely feedback to specific physicians is essential for success. *Journal of Hospital Medicine*, 10(8):555-556.
- [25]. Varkevisser, M., van der Geest, S. A., & Schut, F. T. (2012). Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands. *Journal of Health Economics*, 31(2):371-378.
- [26]. Bundorf, M. K., Chun, N., Goda, G. S., & Kessler, D. P. (2009). Do markets respond to quality information? The case of fertility clinics. *Journal of Health Economics*, 28(3):718-727.
- [27]. Dranove, D., & Sfekas, A. (2008). Start spreading the news: a structural estimate of the effects of New York hospital report cards. *Journal of Health Economics*, 27(5):1201-1207.
- [28]. Pope, D. G. (2009). Reacting to rankings: evidence from "America's Best Hospitals". *Journal of Health Economics*, 28(6):1154-1165.



- [29]. Siddiqui, Z. K., Zuccarelli, R., Durkin, N., Wu, A. W., & Brotman, D. J. (2015). Changes in patient satisfaction related to hospital renovation: experience with a new clinical building. *Journal of hospital medicine*, 10(3), 165-171.
- [30]. Mukamel, D. B., Weimer, D. L., Zwanziger, J., Gorthy, S. F. H., & Mushlin, A. I. (2004). Quality report cards, selection of cardiac surgeons, and racial disparities: a study of the publication of the New York State Cardiac Surgery Reports. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 41(4):435-446.
- [31]. Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy*, 74(2), 132-157.
- [32]. Festinger, L., & Carlsmith, J. M. (1959). Cognitive consequences of forced compliance. *Journal of Abnormal Social Psychology*, 58(2), 203- 210.
- [33]. Holloway, R. J. (1967). An experiment on consumer dissonance. *The Journal of Marketing*, 31(1): 39-43.
- [34]. Pope, D. G. (2009). Reacting to rankings: evidence from "America's Best Hospitals". *Journal of Health Economics*, 28(6):1154-1165.
- [35]. Howard, D. H. (2005). Quality and consumer choice in healthcare: evidence from kidney transplantation. *The BE Journal of Economic Analysis & Policy*, 5(1): 1349-1366
- [36]. Mukamel, D. B., Weimer, D. L., Zwanziger, J., Gorthy, S. F. H., & Mushlin, A. I. (2004). Quality report cards, selection of cardiac surgeons, and racial disparities: a study of the publication of the New York State Cardiac Surgery Reports. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 41(4):435-446.
- [37]. Institute of Medicine. 1994. Defining Primary Care: An Interim Report. Washington, DC: The National Academies Press. <https://doi.org/10.17226/9153>.
- [38]. Bostan, S., Acuner, T., & Yilmaz, G. (2007). Patient (customer) expectations in hospitals. *Health policy*, 82(1):62-70.
- [39]. Safran, D. G., Taira, D. A., Rogers, W. H., Kosinski, M., Ware, J. E., & Tarlov, A. R. (1998). Linking primary care performance to outcomes of care. *Journal of Family Practice*, 47(3):213-221.
- [40]. Perry, H. B., Rassekh, B. M., Gupta, S., Wilhelm, J., & Freeman, P. A. (2017). Comprehensiveness review of the evidence regarding the effectiveness of community based primary health care in improving maternal, neonatal and child health: 1. rationale, methods and database description. *Journal of Global Health*, 7(1):010901
- [41]. Suter, E., Oelke, N. D., Adair, C. E., & Armitage, G. D. (2009). Ten key principles for successful health systems integration. *Healthcare Quarterly* (Toronto, Ont.), 13(Spec No):16-23.
- [42]. Genteis, M., Edgman-Levitan, S., Dalay, J., & Delbanco, T. L. (2003). Through the Patient's Eyes: Understanding and Promoting Patient-Centered Care. *Journal for Healthcare Quality*, 25(3):47-47.
- [43]. Laine, C., & Davidoff, F. (1996). Patient-centered medicine: a professional evolution. *The Journal of the American Medical Association*, 275(2):152-156.
- [44]. Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., & Pinder, E. L. (2003). The implications of regional variations in Medicare spending. Part 1: the content, quality, and accessibility of care. *Annals of Internal Medicine*, 138(4):273-287.
- [45]. Iversen, C., Johansson, L., Sandén, L., Vosough, T., Widerberg, V., & Jacobsson, T. (2014, November). Increasing patient accessibility to a surgery department through operations management principles. In The 6th Swedish Production Symposium.
- [46]. Ghorbani, A., Raeissi, P., Saffari, E., & Reissi, N. (2016). Patient Satisfaction with the Family Physician Program in Sabzevar, Iran. *Global Journal of Health Science*, 8(2): 219-229.
- [47]. Anand, S., & Sinha, R. K. (2010). Quality differentials and reproductive health service utilisation determinants in India. *International Journal of Health Care Quality Assurance*, 23(8):718-729.
- [48]. Xesfingi, S., & Vozikis, A. (2016). Patient satisfaction with the healthcare system: Assessing the impact of socio-economic and healthcare provision factors. *BMC Health Services Research*, 16(1):94-100.



- [49]. Fenton, J. J., Jerant, A. F., Bertakis, K. D., & Franks, P. (2012). The cost of satisfaction: a national study of patient satisfaction, health care utilization, expenditures, and mortality. *Archives of Internal Medicine*, 172(5):405-411.
- [50]. Hsu, Y.-H. (2003). A Study on the Key Factors of Patients' Choosing Hospital and Their Decision-making Behavior (E89076) [data file]. Available from Survey Research Data Archive, Academia Sinica. doi:10.6141/TW-SRDA-E89076-1.
- [51]. Hall, M.A., "Correlation-based feature subset selection for machine learning", Ph.D. thesis, Department of Computer Science, University of Waikato, New Zealand, 1999.
- [52]. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H. (2009) The WEKA data mining software: an update. *SIGKDD Explorations*, 11(1):10-18.
- [53]. Baumgartner, H., & Homburg, C. (1996). Applications of structural equation modeling in marketing and consumer research: A review. *International Journal of Research in Marketing*, 13(2):139-161.
- [54]. Wold, H. (1985). *Partial least squares*. *Encyclopedia of Statistical Sciences*, Wiley, New York, 6: 581-591
- [55]. Urbach, Nils & Ahlemann, Frederik (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology and Theory*, 11(2): 5-36.
- [56]. Chin, W. W., & Newsted, P. R. (1999). Structural equation modeling analysis with small samples using partial least squares. *Statistical Strategies for Small Sample Research*, 1(1):307-341.
- [57]. Garson, G. David (2016). *Partial Least Square: Regression & Structural Equation Models*. Asheboro, USA: Statistical Publishing Associates.
- [58]. Chen, W., Zhou, K., Yang, S., & Wu, C. (2017). Data quality of electricity consumption data in a smart grid environment. *Renewable and Sustainable Energy Reviews*, 75:98-105.
- [59]. Japkowicz, N., & Stephen, S. (2002). The class imbalance problem: A systematic study. *Intelligent data analysis*, 6(5): 429-449.
- [60]. Markus KA. Principles and Practice of Structural Equation Modeling by Rex B. Kline. *Structural Equation Modeling: A Multidisciplinary Journal*, 19(3):509-512.
- [61]. Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal*, 20(2): 195-204.
- [62]. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2):295-336.
- [63]. Hock, M. and Ringle, C.M. (2006), "Strategic networks in the software industry: an empirical analysis of the value continuum", paper presented at the IFSAM VIIIth World Congress, Berlin, September 28-30.
- [64]. Daskalakis, S., & Mantas, J. (2008). Evaluating the impact of a service-oriented framework for healthcare interoperability. *Studies in Health Technology and Informatics*:285-290
- [65]. Fornell, C. & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1): 39-50.
- [66]. Henseler, J., Ringle, C. M., & Sarstedt, M. (2012). Using partial least squares path modeling in advertising research: basic concepts and recent issues. *Handbook of Research on International Advertising*: 252-274.
- [67]. Hair, J. F. Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage Publications, Thousand Oaks, CA, 91-107
- [68]. Zhao, Y., & Zhang, Y. (2008). Comparison of decision tree methods for finding active objects. *Advances in Space Research*, 41(12):1955-1959.
- [69]. Barros, R. C., Basgalupp, M. P., De Carvalho, A. C., & Freitas, A. A. (2012). A survey of evolutionary algorithms for decision-tree induction. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(3):291-312.
- [70]. He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9):1263-1284.



- [71]. Buzzell, R. D., & Quelch, J. A. (1990). The costly bargain of trade promotion. *Harvard Business Review*, 68(2):141-149.
- [72]. Stein, S. M., Day, M., Karia, R., Hutzler, L., & Bosco III, J. A. (2015). Patients' perceptions of care are associated with quality of hospital care: a survey of 4605 hospitals. *American Journal of Medical Quality*, 30(4):382-388.

