

The Relationship of Knowledge, Risk, and Attitude in Healthcare Information Technology

Yi-Horng Lai

Department of Health Care Administration
Oriental Institute of Technology (Taiwan)
New Taipei City, Taiwan
Email: FL006 {at} mail.oit.edu.tw

Abstract—Medical and healthcare systems, both in Taiwan and internationally, are dynamic and under pressure. This study was the application of latent analysis in peoples' ideal about hospital information technology. Latent class analysis that allows large quantities of data to be processed automatically, avoiding the myths of Likert scale. Base on the result, Taiwanese ideal of e-health and m-health could be clustered to 3 groups. Group 1 was knowledge leader, and they were m-health favor. They had more knowledge in information technology than other group. They didn't think information technology was untrusted or high risk. They like new information technology, so they prefer take medical service via mobile device than traditional communication technology. Group 2 was risk percipient, and they were e-health favor. They had much information technology knowledge, but they think new information technology was high risk, unstable, and untrusted. So they prefer take medical service via traditional communication technology than mobile device. In this group, male were more than female. The mean of age of this class were younger than other classes. Group 3 was technology avoider. They had less knowledge in information technology than other group. Besides, they think new information technology was high risk. They don't like take medical service via information technology. Female were more than male. The mean of age of this class were older than other classes.

Keywords—hospital information system; e-health; m-health; latent class analysis (LCA)

I. INTRODUCTION

Medical and healthcare systems, both in Taiwan and internationally, were dynamic and under pressure. As the public demand for quality health care services was increasing, along with the cost of providing these services, growing attention was being directed towards the potential of healthcare information technology to lower health care spending and to improve the efficiency, quality and safety of medical care.

The delivery of safe and effective healthcare remains an ongoing challenge to clinicians, particularly as increased attention was being focused on the extent of medical mistake. Over the past few years, the aim of many health care systems to improve consistency and safety in patient care had prompted considerable investment in the development of evidence-based clinical guidelines. However, the effective dissemination of these guidelines had remained a challenging task, and

healthcare information technology had been proposed as an effective means to implement guidelines in practice.

Several welfares of healthcare information technology had been well known in lots of studies. While the advantages of healthcare information technology on administrative functions were readily discernible, such as decreasing paperwork and workload of health care professionals, increasing administrative efficiencies, and expanding access to affordable care, healthcare information technology had also shown effectiveness in preventing medical errors by enforcing clinical guidelines and care protocols. With the progress of information technology from PC-based internet to mobile-base connection, the healthcare information technology was built from e-health to m-health.

More and more studies were applied with latent variable, such as structural equation modeling and latent class analysis. Traditional cluster analysis was goodness for continuous variables, but weakness for categorical variables. Latent class analysis was very flexible in the sense that both simple and complicated distributional forms could be used for the observed variables within clusters. As in any statistical model, restrictions could be imposed on the parameters to obtain more parsimony and formal tests could be used to check their validity. Another advantage of latent class analysis was that no decisions have to be made about the scaling of the observed variables: for instance, when working with normal distributions with unknown variances, the results would be the same irrespective of whether the variables are normalized or not. This was very different from traditional cluster methods, where scaling is always an issue. Other advantages were that it was relatively easy to deal with variables of different scale types and that there are more formal criteria to make decisions about the number of clusters and other model features [1]. This study was the application of latent analysis in people's ideal about hospital information technology. Latent class analysis that allows large quantities of data to be processed automatically, avoiding the myths of Likert scale (no matter seven-point or five-point).

A. E-health

E-health is the use of information and communication technology for healthcare. E-health means using the power of information technology to improve public health services, such

as through the education and training of health workers, and the use of e-commerce and e-business practices in health systems management. E-health plays an important in the delivery of health information, for health professionals and health consumers, through the Internet and telecommunications [2].

E-health provides a new method for using health resources, such as information, money, and medicines, and in time should help to improve efficient use of these resources. The Internet also provides a new medium for information dissemination, and for interaction and collaboration among institutions, health professionals, health providers and the public.

B. M-health

M-health is an abbreviation for “mobile health”, a term used for the practice of medicine and healthcare supported by mobile devices, such as mobile phones, tablet computers, and PDAs, for health services and clinic information [3]. M-health broadly encompasses the use of mobile telecommunication and multimedia technologies as they are integrated within increasingly mobile and wireless health care delivery systems. The field broadly encompasses the use of mobile telecommunication and multimedia technologies in health care delivery. A definition used at the 2010 M-health Summit of the Foundation for the National Institutes of Health (FNIH) was “the delivery of healthcare services via mobile communication devices” [6].

The M-health field has emerged as a sub-segment of E-health, the use of information and communication technology, such as computers, mobile phones, patient monitors, for health services and information [4]. M-health applications include the use of mobile devices in collecting community and clinical health data, delivery of healthcare information to practitioners, researchers, and patients, real-time monitoring of patient vital signs, and direct provision of care via mobile telemedicine [5].

II. METHODOLOGY

A. Methodology of Data Analysis

Latent class analysis was initially introduced by Lazarsfeld and Henry [7] as a way of formulating latent attitudinal variables from dichotomous survey items. In contrast to factor analysis, which posits continuous latent variables, latent class models assume that the latent variable is categorical, and areas of application are more wide-ranging. The methodology was formalized and extended to nominal variables by Goodman [8, 9]. In recent years, latent class analysis have been extended to include observable variables of mixed scale type (such as continuous, and ordinal) and covariates, as well as deal with sparse data, boundary solutions, and other problem areas.

Latent class analysis assumes that each observation is a member of one and only one of T latent classes and that local independence exists between the manifest variables. Conditional on latent class membership, the manifest variables are mutually independent of each other. This model can be expressed using (unconditional) probabilities of belonging to each latent class and conditional response probabilities as

parameters [8, 9]. For example, in the case of four nominal manifest variables A, B, C, and D, it can be have

$$\pi_{ijklt} = \pi_t^X \pi_{it}^{A|X} \pi_{jt}^{B|X} \pi_{kt}^{C|X} \pi_{lt}^{D|X} \quad (1)$$

where π_t^X denotes the probability of being in latent class $t = 1, 2, \dots, T$ of latent variable X; $\pi_{it}^{A|X}$ denotes the conditional probability of obtaining the i th response to item A, from members of class t , $i = 1, 2, \dots, I$; and $\pi_{jt}^{B|X}, \pi_{kt}^{C|X}, \pi_{lt}^{D|X}$, $j = 1, 2, \dots, J$, $k = 1, 2, \dots, K$, $l = 1, 2, \dots, L$, denote the corresponding conditional probabilities for items B, C, and D, respectively.

Equation (1) can be described graphically in terms of a path diagram in which manifest variables are not connected to each other directly but indirectly through the common source X. The latent variable is assumed to explain all of the associations among the manifest variables. A goal of traditional latent class analysis is to determine the smallest number of latent classes T that is sufficient to account for the relationships observed among the manifest variables.

The analysis typically begins by fitting the T=1 class baseline model (H_0), which specifies mutual independence among the variables. Model H_0 :

$$\pi_{ijkl} = \pi_i^A \pi_j^B \pi_k^C \pi_l^D \quad (2)$$

Assuming that this null model does not provide an adequate fit to the data, a one-dimensional latent class model with T=2 classes is then fitted to the data. This process continues by fitting successive latent class models to the data, each time adding another dimension by incrementing the number of classes by 1, until the simplest model is found that provides an adequate fit.

The computer software for latent class analysis in this study was Mplus 7 and Stata/SE 13.1.

B. Research Data

The research data was got from “The integration research of network sociology” project in the Survey Research Data Archive (SRDA) provided by the Academia Sinica in Taiwan. The project leader was Tseng, S.F. [10]. The project was implemented from January 1, 2008 to December 31, 2008. The research data was collected from March 31, 2008 to April 17, 2008.

C. Research Tools

In “The integration research of network sociology” project [10], there were 6 items for healthcare information technology (as Table I). 3 items are for e-health, and 3 items are for m-health. Each part of them included knowledge of information technology, risk of information technology, and intention of using healthcare information technology. People answer these six items with “Yes” (agree) or “No” (disagree).

TABLE I. RESEARCH QUESTIONNAIRES IN THIS STUDY

		Item
1	ehealth_knowledge	Do you know e-health or tele-health that allow people take medical service via internet? With e-health, people can take medical service more convenient at home.
2	ehealth_risk	Do you concern about data leakage with e-health or tele-health?
3	ehealth_intention	Will you use e-health future?
4	mhealth_knowledge	Do you know m-health that allow people take medical service via mobile, smart phone, or tablet PC? With m-health, medical staff can get home patients' physiological information at any time.
5	mhealth_risk	Do you concern about data leakage with m-health?
6	mhealth_intention	Will you recommend friends to use m-health services?

III. RESULTS

A total of 764 feedbacks were collected without missing value. Some basic demographic information is collected, indicating approximately 360 male (47.12%) and 404 female (52.88%) in the sample population. Most of them were 41~50 years old (190; 24.87%). Most of them were under graduate (307; 40.18%) (As Table II). The descriptions of 764 feedbacks were as Table III.

TABLE II. DATA SUMMARIZE

Variable		Frequency	Percent (%)
Gender	Male	360	47.12
	Female	404	52.88
Age	21~30	111	14.53
	31~40	151	19.76
	41~50	190	24.87
	51~60	184	24.08
	61~70	98	12.83
	70~	13	1.70
	Missing	17	2.23
Education	Primary school	44	5.76
	Junior High School	91	11.91
	Senior School	280	36.65
	Under Graduate	307	40.18
	Graduate	40	5.24
	Missing	2	.26
Total		764	100.00

TABLE III. RESULTS IN PROBABILITY SCALE

Item		Frequency	Percent (%)
ehealth_knowledge	Yes	426	55.76
	No	338	44.24
ehealth_risk	Yes	492	64.40
	No	272	35.60
ehealth_intention	Yes	335	43.85
	No	429	56.15
mhealth_knowledge	Yes	334	43.72
	No	430	56.28
mhealth_risk	Yes	338	44.24
	No	426	55.76
mhealth_intention	Yes	589	77.09
	No	175	22.91
		764	100.00

The chi-square test of model fit for the binary categorical outcomes and information criteria of 2-class (T=2), 3-class (T=3), 4-class (T=4), and 5-class (T=5) were as Table IV. It could be found that the BIC of 3-class is small than others. So this study group with 3-class.

TABLE IV. MODEL FIT INFORMATION

Class (T)	X ²	G ²	AIC	BIC	df	para
T=2	166.55 (<.01)	171.49 (<.01)	5675.09	5735.39	50	13
T=3	118.90 (<.01)	123.12 (<.01)	5640.72	5733.49	43	20
T=4	76.86 (<.01)	83.89 (<.01)	5615.49	5740.73	36	27
T=5	46.58 (.02)	51.48 (.01)	5597.08	5754.79	29	34

The yes-feedback of six items of 3 classes were as Table V and Figure I. The probability scale of e-health knowledge of class-1 was highest in these 3 classes. The probability scale of e-health risk of class-3 was highest in these 3 classes. The probability scale of e-health using of class-2 was highest in these 3 classes. The probability scale of m-health knowledge of class-1 was highest in these 3 classes. The probability scale of m-health risk of class-2 was highest in these 3 classes. The probability scale of m-health using of class-1 was highest in these 3 classes.

TABLE V. RESULTS IN PROBABILITY SCALE IN 3 CLASSES

Item	Class 1	Class 2	Class 3
ehealth_knowledge	.65*	.59	.44
ehealth_risk	.44	.72	.87*
ehealth_intention	.63	.99*	.00
mhealth_knowledge	.57*	.37	.30
mhealth_risk	.00	1.00*	.78
mhealth_intention	.97*	.87	.50
	.48	.14	.38

*The highest in these 3 classes.

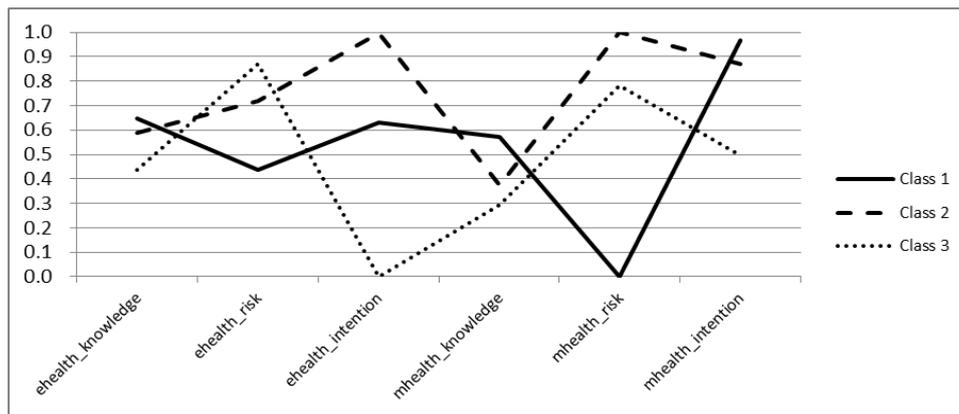


Figure 1. Results in Probability Scale in 3 Classes

TABLE VI. CLASSIFICATION OF INDIVIDUALS BASED ON THEIR MOST LIKELY LATENT CLASS MEMBERSHIP

Class	Counts	Proportions	Age		Gender	
			Mean	S.D.	Female	Male
class 1	369	48.30%	45.55	12.65	189 (51.22%)	180 (48.78%)
class 2	107	14.00%	40.97	14.20	48 (44.86%)	59 (55.14%)
class 3	288	37.70%	46.20	13.09	167 (57.99%)	121 (42.01%)
	764	100.00%	45.14	13.14	360	404

Based on the result, class-1 be named “knowledge leader”, class-2 be named “risk percipient”, and class-3 be named “technology avoider”. The counts, age, and gender of 3 classes were as Table VI.

A. Class 1: Knowledge Leader

People in this group had more knowledge in information technology than other group. They didn’t think information technology was untrusted or high risk. They were m-health favor. The mean of age of them were 45.55 years old. 51.22% of them were female, and 48.78% of them were male.

B. Class 2: Risk Percipient

People in this group think information technology was high risk and untrusted. They were e-health favor. The mean of age of them were 40.97 years old. 44.86% of them were female, and 55.14% of them were male. Male were more than female. The mean of age of this class were younger than other classes.

C. Class 3: Technology Avoider

People in this group had less knowledge in information technology than other group. They were not fever in m-health or e-health. The mean of age of them were 46.20 years old. 57.99% of them were female, and 42.01% of them were male.

Female were more than male. The mean of age of this class were older than other classes.

IV. CONCLUSION

Base on Taiwanese ideal of e-health and m-health, it could be clustered to 3 groups. Group 1 was knowledge leader, and they were m-health favor. They had more knowledge in information technology than other group. They didn’t think information technology was untrusted or high risk. They like new information technology, so they prefer take medical service via mobile device than traditional communication technology. Group 2 was risk percipient, and they were e-health favor. They had much information technology knowledge, but they think new information technology was high risk, unstable, and untrusted. So they prefer take medical service via traditional communication technology than mobile device. In this group, male were more than female. The mean of age of this class were younger than other classes. Group 3 was technology avoider. They had less knowledge in information technology than other group. Besides, they think new information technology was high risk. They don’t like take medical service via information technology. Female were more than male. The mean of age of this class were older than other classes.

Based on the result of this study, for promote people's intention for use m-health or e-health, information technology knowledge play an important role. If they have much information technology knowledge, they will take medical service via traditional communication technology (e-health). Then, if they think information technology is trustable, they would take medical service via mobile device (m-health).

ACKNOWLEDGMENT

This study is based in part on data from the Survey Research Data Archive (SRDA) provided by the Academia Sinica. The interpretation and conclusions contained herein do not represent those of Survey Research Data Archive (SRDA) or Academia Sinica.

REFERENCES

- [1] Vermunt, J.K. & Magidson, J., "Latent class cluster analysis," *Advances in Latent Class Analysis*. Cambridge University Press, 2002.
- [2] World Health Organization, "Glossary of globalization, trade and health terms," Trade, foreign policy, diplomacy and health. Retrieved on January 01, 2014 from <http://www.who.int/trade/glossary/story021/en>, 2014.
- [3] Cipresso, P., Serino, S., Villani, D., Repetto, C., Selitti, L., Albani, G., Mauro, A., Gaggioli, A., & Riva, G., "Is your phone so smart to affect your states? An exploratory study based on psychophysiological measures," *Neurocomputing*, 84, pp. 23-30, 2012.
- [4] United Nations Foundation, "Vital wave consulting. m-health for development: The opportunity of mobile technology for healthcare in the developing world," Vodafone Foundation. 2009.
- [5] Germanakos, P., Mourlas, C., & Samaras, G., "A mobile agent approach for ubiquitous and personalized ehealth information systems," *Proceedings of the Workshop on Personalization for e-Health of the 10th International Conference on User Modeling*. Edinburgh, pp. 67-70, 2005.
- [6] Torgan, C., "The mhealth summit: local & global converge," Caroltorgan.com, 2009.
- [7] Lazarsfeld, P. F., & Henry, N. W., "Latent structure analysis," Boston: Houghton Mifflin, 1968.
- [8] Goodman, L. A., "The analysis of systems of qualitative variables when some of the variables are unobservable: Part I. A modified latent structure approach," *American Journal of Sociology*, 79, pp. 1179-1259, 1974.
- [9] Goodman, L. A., "Exploratory latent structure analysis using both identifiable and unidentifiable models," *Biometrika*, 61, pp. 215-231, 1974.
- [10] Tseng, S.F., "The integration research of network sociology," *The Survey Research Data Archive*. Retrieved on December 01, 2012 from <https://srda.sinica.edu.tw/search/gensciitem/1479>, 2008.