

A medication-estimated health status measure for predicting primary care visits: the Long-Term Therapeutic Groups Index

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Accepted 1 September 2009

Background Managed care is one of the means advocated for health care reforms. The Malaysian government has proposed managed care for its citizens. In the Malaysian private health care sector, managed care is practised on a small scale with crude risk adjustment. The main determinant of an individual's health service utilization is their health status (HS). HS is used as a risk adjuster for capitation payment. Prescribed medications represent a useful source for HS estimation. We aimed to develop and validate a medication-based HS estimate and to incorporate it in the Andersen model of health service utilization. This is a preparatory step in studying the feasibility of developing a model for risk assessment in the Malaysian context.

Methods Data were collected retrospectively from an academic year from computerized databases in University Sains Malaysia (USM) about users of USM primary care services. A user is a USM health scheme beneficiary who made at least one visit in the academic year to USM-assigned primary care providers. Socio-demographic variables, enrolment period, medications prescribed and number of visits were also collected. Chronic illness medications and some non-chronic illness medications were used to calculate the Long-Term Therapeutic Groups Index (LTTGI) which is an estimate of the HS of users. Using a random 50% of users, weighted least square methods were used to develop a model that predicts a user's number of visits. The other 50% were used for validation.

Results Socio-demographic variables explained 15% of variability in number of primary care visits among users. Adding the LTTGI improved the explanatory power of the model to 36% ($P < 0.001$). A similar contribution of the LTTGI was noted in the validation.

Conclusions The Long-Term Therapeutic Groups Index was successfully developed. Variability in number of primary care visits can be predicted by LTTGI-based models.

Keywords Long-Term Therapeutic Groups Index, primary care, service utilization, medication-based health status measures, risk assessment, risk adjustment, University Sains Malaysia

KEY MESSAGES

- A medication-based health status estimate, called the Long-Term Therapeutic Group Index (LTTGI), is developed and validated in this study.
- Managed care in Malaysia, as proposed, could benefit from this method and the findings of this work for risk assessment and risk adjustment for fair capitation payment.

Introduction

Since the evolution of Managed Care Organizations (MCOs), health care service researchers have continually tried to find ways to better match payments to the needs of beneficiaries. Risk adjustment serves the health care funder, the service provider and the patient. Risk adjustment is one tool to improve the payment fairness and to decrease adverse risk selection, and it improves the quality of care. Risk adjustment using demographic data of individuals is insufficient to account for the variance in health service utilization and cost (Ash *et al.* 1989; Newhouse *et al.* 1989). The inclusion of the health status of individuals improves risk adjustment models.

Several ways are used to measure individuals' health status, such as self-reporting, diagnoses-based methods and medication-based methods. After Von Korff *et al.* (1992), health service researchers have used dispensing data as risk adjusters in risk adjustment. Von Korff *et al.* developed a Chronic Disease Score (CDS) from automated pharmacy data and demonstrated that CDS was a stable and valid measure of the presence and the severity of chronic diseases. CDS uses medications as a proxy for chronic diseases and thus it can be used to measure the health status of individuals. Two studies confirmed the validity of the CDS to reflect health status (Johnson *et al.* 1994; Clark *et al.* 1995).

In the above-mentioned studies, each medication class was given a weight derived either from analysis of previous health care utilization and cost or empirically by expert judgement. CDS was developed for an adult population 18 years and above. Fishman and Shay (1999) extended the CDS and developed a version to be used in a paediatric population, called CPDS. Kuhlthau *et al.* (2005) confirmed the good performance of the pharmacy-based risk adjustment model in a Medicaid paediatric population in the United States. Malone *et al.* (1999) developed an unweighted CDS and called it Chronic Disease Index (CDI). CDI was validated against CDS and the results were similar. Wahls *et al.* (2004) compared Adjusted Clinical Groups, a diagnoses-based method, and CDI in predicting outpatient and inpatient utilization in a veterans population and the prediction powers of both tools were comparable. Gilmer *et al.* (2001) adopted and combined CDS and CPDS to develop CDS for Medicaid subpopulations. They found that the performance of this combined CDS was better than the demographic model. Two studies revised, expanded and validated a new version of the CDS and called it the RxRisk model (Fishman *et al.* 2003; Sloan *et al.* 2003). Recently, Zhao *et al.* (2005) have used medications as a risk adjuster to develop their RxGroups system.

Outside the United States, risk adjustment methodologies were called to be applied in Australian health system policy

as part of health system reforms (Donato and Richardson 2006). In the Netherlands, pharmacy costs groups were developed, validated (Lamers 1999; Lamers and van Vliet 2004) and introduced in 2003 for reimbursing sickness funds.

The Malaysian government provides health care services to the public throughout a network of hospitals and primary care clinics. The public sector is funded from the central treasury of the government. The care providers in these facilities are government servants who are paid salaries on a monthly basis. Beneficiaries of these services pay substantially reduced fees. The private sector contributes in offering health care via hospitals and private clinics. It is funded mainly by out-of-pocket payments by consumers or by money from insurance companies for care provided to the companies' clients. In the latter case, the payment by the insurance companies is either fee-for-service or capitation based. In the case of capitation-based payment, crude methods of risk adjustment are implemented.

Due to the escalation of health care costs, The 8th Malaysian Plan proposed a capitation-based national health care financing scheme (Economic Planning Unit 2001). The Malaysian Ministry of Health is the authority responsible for scheme implementation. This study provides a preparatory step in studying the feasibility of developing a model for helping in risk assessment and risk adjustment in the Malaysian context.

In this study we develop and validate a medication-based risk assessment score. To reflect the origins of our classification of prescribed drugs into Long-Term Therapeutic Groups (LTTGs), we call the score the Long-Term Therapeutic Groups Index (LTTGI). This nomenclature is meant to emphasize the importance of long-term disease conditions when choosing medications for risk assessment and prediction of primary care visits. The LTTGI of an individual reflects his/her health status. The LTTGI was calculated for University Sains Malaysia (USM) health system beneficiaries. Data about this population served as a platform to calculate the LTTGI and to test the applicability of the developed score. However, the methodology of developing the LTTGI can be applied in different populations after appropriate validation.

Overview of the USM health care system

Apart from hospital services which are offered by the Malaysian government for all Malaysians, University Sains Malaysia (USM) offers primary health care services to its beneficiaries through its health centre (USMHC) located at the university campus, and through a panel of private clinics (USMPC) and pharmacies. USM beneficiaries consist of USM staff, their

spouses and children as well as USM students, their spouses and children. All beneficiaries have equal access to the health care services in USMHC. However, their access to the panel clinics is not the same; staff and their dependants have unlimited access while students have limited access of six visits per year, and students' dependants and pensioners do not have access to the USMPC.

USMHC is owned by USM, and the health care providers are employees of USM. Panel clinics (USMPC) are private entities and are reimbursed by USM on the basis of fee-for-service. This fee-for-service is capped to a ceiling according to the service provided.

While dispensing takes place in the pharmacy unit of the USMHC, most prescriptions issued by USMPC are dispensed by those clinics, since the Malaysian regulations allow private clinics to dispense prescriptions. However, if the patient chooses to get the prescribed medications from a pharmacy outside the clinic, dispensing takes place in one of the panel pharmacies. Pharmacies send claims to USM which reimburses them for the prescriptions they dispense.

The details of beneficiaries' visits to USMHC are maintained as electronic medical records (EMR) in a computerized database called e-klinik. Panel clinics' claims are maintained in another computerized database called e-panel. Both e-klinik and e-panel are located in the USM computer department. These two databases contain data about each visit, including visit date, beneficiary's identity number (IC), the prescribed medications (each is expressed as a unique code) with the dose and the duration. In the case of e-panel, the cost of the visit is also included. Diagnoses are coded in e-klinik according to a modified version of the International Classification of Diseases version 9 (ICD-9) but this is not coded in e-panel. A visit to either USMHC or USMPC results in the generation of a record in the corresponding database including the medication(s) prescribed and dispensed.

Study objectives

The objective of this study is to develop a measure of health status of USM beneficiaries using prescription data, and to use this measure to develop and validate a model that predicts the number of primary care visits of the beneficiaries.

Methods

We retrospectively collected data from the academic year 1 July 2004 to 30 April 2005. In this academic year there were 30 466 beneficiaries, of whom 3015 were staff, 20 712 were students and 6736 were dependants.

We collected data in an academic year rather than a fiscal or calendar year because students are not at university from March to July each year, and thus their utilization is not captured by the USM health databases. The study subjects are USM beneficiaries who made at least one visit to USMHC or to USMPC in the study period. Users' socio-demographic data were obtained from the human resources computerized database that is maintained at USM. Anonymity of users was guaranteed by assigning a unique number to each user.

From e-klinik and e-panel, the prescribed medications in each visit were obtained.

Ages were calculated from the birth date until the first date of the study period (i.e. 1 July 2004). For those whose birth dates are after 1 July 2004, their ages were calculated from their birth dates until the date of the first visit. We adopted the WHO convention in categorizing age into bands. WHO convention categorizes age into 19 bands. The first band includes children less than 1 year; the second band includes those from 1 to 4 years. Subsequent bands are of 5 years each. The last band includes those 85 years and older. However, ages below 1 year were banded with ages between 1 and 4 years due to the small number of individuals in these bands. Similarly, people older than 60 years were banded in one group for the same reason. Age categorization allowed us to overcome the assumption of linear regression that the relationship between the number of visits (the dependent variable) and age (the explanatory variable) must be linear. It was found that the relationship between age and the number of visits was strong but it was not linear (results are not shown). Presenting age in categories (called dummy variables) allowed us to include age as a variable in the linear regression analyses.

We calculated the number of visits per user in the study period. In the USM health care system, the beneficiary cannot renew his/her prescription without seeing a USM-assigned doctor, thus we excluded visits for prescription renewal as well as visits for administrative purposes. We then annualized the number of visits of each user. It was noted that there is a negligible difference between annualized and unannualized number of visits because the vast majority of users were eligible for the service for the entire academic year.

From e-klinik and e-panel, we extracted a list of prescribed medications that are used to treat diseases that need long-term treatment, i.e. a long-term disease. We define a long-term disease as any disease condition that goes through remission and exacerbation or is not curable or needs continuous treatment or repeated courses of treatment. The extracted list was confirmed to be used for chronic diseases by checking the literature: the 2004 Drug Formulary (called the Blue Book) of the Ministry of Health of Malaysia, the online version of the British National Formulary (March 2005, <http://bnf.org/bnf/>) and *Martindale: The Complete Drug Reference*, edition 34 (Sweetman 2005).

Then the medications in the list were classified according to the disease(s) they treat or the body system they affect. Medications for the same disease/body system were classified into groups called Long-Term Therapeutic Groups (LTTGs). In assigning medications to one of the LTTGs, we took into account whether these medications can be a replacement of each other or are add-on treatments. If two medications for the same disease can be added to each other in the clinical scenario (like hydrochlorothiazide and furosemide, both are diuretics), these two medications were assigned to two different LTTGs. Taking hydrochlorothiazide and furosemide as an example, hydrochlorothiazide was assigned to an LTTG called diuretics1 and furosemide was assigned to another LTTG group called diuretics2. If two medications for the same disease are replacements of each other, like furosemide and

bumetanide, both medications were assigned to the same LTTG; in this case both furosemide and bumetanide were assigned to the same LTTG, diuretics2. Thus, diuretics1 is an LTTG and diuretics2 is another LTTG.

Then, the number of LTTGs per user was calculated. The resulting number is the Long-Term Therapeutic Groups Index (LTTGI) of that particular user. LTTGI reflects not only the presence of long-term diseases but also the severity of these diseases, and subsequently the health status. For example, a user on nifedipine (a calcium channel blocker, an LTTG), captopril (an ACE inhibitor, an LTTG) and lovastatin (a statin, an LTTG) would have an LTTGI of 3, and another user on felodipine (a calcium channel blocker) and enalapril (an ACE inhibitor) would have an LTTGI of 2; and the first user's health status would be worse than that of the second user. It should be noted that LTTGs do not have risk weights.

Some LTTGs that are not classically used in the treatment of chronic diseases, and those that are used for acute illnesses in addition to their use for chronic diseases, were included in the calculation of LTTGI. The former were included if prescribed on more than three occasions, and the time between the first and the last prescription of that LTTG for that particular user was 3 months or more during the study period. Similarly, the latter were included if the same two criteria were met in addition to the fact that the LTTG is used to treat diseases that undergo a pattern of recurrence. We did this to avoid the inclusion of incidental use of these groups, and thus these groups were more likely to treat a condition that is consistent with our definition of long-term disease mentioned above. This inclusion criterion was found effective in choosing regular users of such LTTGs (Lamers 1999).

We calculated the enrolment period for each user in the study period. The enrolment period is the number of days a user was eligible for health care services in the study period. We used this enrolment period as a weighting variable in the regression analysis to account for users who joined the system late in the study period. This weighting variable was calculated as the number of days from the first date of enrolment until the end of the study period in that academic year. If the date of enrolment was before the date of the beginning of the study (i.e. before 1 July 2004), the enrolment period was fixed to 303 days (which is the study duration in that academic year). If the date of enrolment was after the beginning of the study (i.e. after 1 July 2004), the enrolment period was calculated as the number of days between the date of enrolment (the date of the first visit in 2004/2005 academic year) and the date of the end of the study (i.e. 30 April 2005).

Two ways to overcome the effect of different enrolment periods have been reported. The first one is to annualize the utilization. We follow this approach. We have annualized the number of visits of users because a part of our goal is to develop a risk adjustment model for capitation payment. In our analysis, we use the annualized number of visits. Hereafter, the number of visits refers to the annualized number of visits.

The second way is to include the enrolment period as an adjuster in the risk adjustment model (Roblin 1998). We do not find it suitable to include the enrolment period in the model because it is not a relevant predictor in Andersen's model of

health service utilization. Instead, we included the enrolment period as a weighting variable in our model after we have annualized the number of visits. For the same reason, another study used the same weighting method (Gilmer *et al.* 2001). Models by Zhao *et al.* (2005) are weighted by the fraction of year two that eligible users stayed in the system.

Study variables and statistical analyses

We selected the variables according to the Andersen–Newman behavioural model of health care utilization. This behavioural model conceptualizes the utilization of health care services as a function of predisposing factors, enabling factors and need factors. Predisposing factors include age, gender and race, enabling factors include income and insurance, while need factors include disability and health status.

Employing the user as the unit of analysis, we conceptualize the utilization of a user *i* as a function of age, gender, race, service access, marital status and the health status of that user:

$$\text{Utilization}_i = f(\text{age, gender, race, access, marital status, health status})_i$$

The number of primary care visits per user is used to represent the primary care service utilization of users. The LTTGI was used as a proxy for the health status of individuals. The relationship between the LTTGI and the number of visits was linear (results not shown).

Users were randomly divided into two groups. The first group was used to develop the model and is called the development dataset. This dataset was used to estimate the regression weights of predictors. The other dataset of users is called the validation dataset. It was used to test the model accuracy in predicting the number of visits. We validated the model in different datasets of users to avoid over-fitting.

We used weighted ordinary least squares (WLS) to predict the number of visits for each user (the dependent variable). Step-wise regression was used. The predictors are age, gender, race, marital status, access type (limited or unlimited) and the LTTGI. The enrolment period is used as a weighting variable. Marital status is added to the framework as a potential predictor.

We used SPSS version 13.0 to analyse the data. We described the socio-demographic characteristics of the users. We compared the model predictive power before and after adding the LTTGI by calculating R^2 , mean prediction error (MPE), mean absolute prediction error (MAPE) and predictive ratios (PR).

Results

Socio-demographic characteristics of users

Table 1 shows the distribution of beneficiary type, gender, race, marital status and age categories of the users. Some LTTGI statistics are also included. Students represented the majority of users; there were more females than males; and more than half of users were of Malay race. Because students were the majority, 79% of users were non-married and 57% of users were 20–24 years old.

Model development

The distribution of the visits and the number of users in the three utilization categories is shown in Table 2. The high utilization group represented 19% of users but they made 48%

Table 1 Users' socio-demographic characteristics in the development and validation datasets

	Development dataset (<i>N</i> = 8379) <i>n</i> (%)	Validation dataset (<i>N</i> = 8328) <i>n</i> (%)
Type		
Students	5591 (66.7)	5508 (66.1)
Staff	1442 (17.2)	1439 (17.3)
Dependants	1346 (16.1)	1381 (16.6)
Gender		
Male	3019 (36)	3093 (37.1)
Race		
Chinese	2531 (30.2)	2407 (28.9)
Indian	466 (5.6)	465 (5.6)
Malay	4927 (58.8)	5006 (60.1)
Other	455 (5.4)	450 (5.4)
Marital status		
Not married	6649 (79.4)	6602 (79.3)
Access		
Limited	5765 (68.8)	5688 (68.3)
Age category		
0–4	167 (2)	200 (2.5)
5–9	232 (2.8)	277 (3.3)
10–14	236 (2.8)	229 (2.7)
15–19	450 (5.4)	458 (5.5)
20–24	4802 (57.3)	4666 (56)
25–29	559 (6.7)	528 (6.3)
30–34	332 (4)	348 (4.2)
35–39	292 (3.5)	291 (3.5)
40–44	393 (4.7)	384 (4.6)
45–49	358 (4.3)	375 (4.5)
50–54	297 (3.5)	278 (3.3)
55–59	149 (1.8)	160 (1.9)
≥60	112 (1.4)	124 (1.5)
LTTGI		
Mean (SD)	0.57 (1.86)	0.54 (1.71)
Min.	0	0
Max.	23	20

of visits. Both the mean and the median of LTTGI were greater in the high utilization group.

Regression analyses

In Table 3, the socio-demographic model (model 1) explained 15% of the variability in the number of visits among the users in the development dataset. Adding LTTGI (model 2) to the socio-demographic model improved the explanatory power by 20%; the resulting R^2 became 36%.

Validation of the model for utilization prediction

Table 3 also shows that the pattern of R^2 increase and the contribution of adding the LTTGI in the validation dataset is similar to that in the development dataset. In the validation dataset, the socio-demographic model (model 1) explained 14% of the variability in the number of visits among users. Adding the LTTGI to the socio-demographic model improved the explanatory power of the model (model 2); the resulting R^2 became 34% and the contribution of the LTTGI was 20%.

Model accuracy

The validation dataset was used to examine the accuracy of the model in three different utilization levels: those who made 3 visits or fewer (the low utilization group), those who made between 4 and 6 visits (the medium utilization group) and those who made more than 6 visits (the high utilization group). In this study, the added risk adjuster is the LTTGI. From Table 4 we can see the following: (1) both models are similar in all accuracy criteria in the low and medium utilization groups except in R^2 ; (2) in the high utilization group, model 2 was more accurate than model 1 by MAPE and R^2 ; and (3) in model 2, the changes in R^2 are parallel to the utilization level.

Discussion

This study aims at developing a tool (the LTTGI) to estimate health status. In doing so it takes into account three types of therapeutic group that might reflect health status. The first type is medications used exclusively for chronic diseases; the second is medications used for chronic as well as acute illnesses; and the third is medications used to treat diseases that are not classically chronic but are of recurrence pattern. The later two types are used in health status estimation if the criteria stated in the methodology section are met.

Furthermore, this study applies the developed LTTGI to develop a model of primary care service utilization for USM

Table 2 Utilization levels and their statistics in the development dataset

Utilization category	Definition	No. users (%)	No. visits (%)	LTTGI mean (SD)	LTTGI median
Low	1–3 visits	4694 (56)	8433 (23)	0.09 (0.44)	0
Medium	4–6 visits	2099 (25)	10 240 (29)	0.77 (1.41)	0
High	>6 visits	1586 (19)	17 115 (48)	2.61 (2.36)	2
Totals		8379 (100)	35 788 (100)	0.57 (1.86)	0

Table 3 Changes and significance of adding the LTTGI into the socio-demographic model in the development and the validation datasets

	Model	R	R ²	Adjusted R ²	Std. error of the estimate	Change statistics		
						R ² change	F change	Sig. F change
Development dataset	1	0.387	0.150	0.148	66.208	0.150	5.540	0.019
	2	0.595	0.355	0.353	57.689	0.205	2653.864	<0.001
Validation dataset	1	0.375	0.141	0.139	67.962	0.141	6.166	0.013
	2	0.579	0.336	0.334	59.763	0.195	2437.960	<0.001

Table 4 Comparison of the two models in terms of the accuracy parameters in the validation dataset

	Model 1				Model 2			
	R ²	MPE	MAPE	PR	R ² (R ² changes)	MPE	MAPE	PR
1–3 visits	0.007	0.013	0.723	1.007	0.014 (0.007)	0.012	0.724	1.006
4–6 visits	0.003	0.005	0.693	1.001	0.014 (0.011)	0.005	0.698	1.002
>6 visits	0.12	0.022	3.423	1.003	0.218 (0.097)	0.021	3.18	1.003

MPE = mean prediction error; MAPE = mean absolute prediction error; PR = predictive ratio.

beneficiaries. The developed model has good explanatory and predictive power.

As we stated in the introduction, dispensing data is a good source to reflect the presence of chronic diseases. This is especially true when we talk about primary health care facilities in which the health care providers are either government employees or private practitioners enrolled in fee-for-service reimbursement systems. Such providers are not reimbursed for the diagnosis they treat (Gilmer *et al.* 2001). Consequently, there are no incentives for them to document the diagnoses, but the medications that are prescribed and will be dispensed to patients are certainly documented. Thus dispensing data become a more useful source of information about the presence of chronic illnesses.

Another advantage of medication-based health status measures is that they create less perverse incentives from the provider's perspective than other health status measures. For example, it might be thought that a capitated provider could prescribe more LTTGs than necessary to obtain higher payment. Obviously, such behaviour will affect the health care funder financially and will put the patient at greater risk of adverse drug reactions. It is worth noting the following points: (1) most LTTGs are therapeutic groups for chronic diseases, which means their usage is continuous, sometimes lifelong; (2) the capitated provider is responsible for providing drugs to the patient, depending on the negotiations between the funder and the provider. With these two points in mind, the provider's perverse incentives will also adversely affect the provider him/herself in two ways: (1) the provider must provide more drugs to the patient, which is a financial burden on the capitated provider; (2) there are possibilities of harming the patient, and it is the provider who is responsible for offering the required care if such harm occurs. It is clear from this that such malpractices are less likely to occur. Furthermore, if there is a quality assurance programme, it is feasible to audit the provider in terms of good prescribing practice and drug consumption of beneficiaries under that provider. Since medication prescribing auditing is easier to perform, such measures can mitigate such malpractices.

The severity of the chronic disease in a patient has an impact on the level of his/her utilization (Demers 2004). It should be noted that the severity reflected by the LTTGI is not specific to a particular disease but to all long-term diseases a user is suffering from. In other words, the LTTGI reflects the level of the health status of users regardless of the disease conditions responsible. For example, a user with an LTTGI of 3 may have one disease (treated with three different LTTGs) or may have two diseases (one is treated with one LTTG and the other with two other LTTGs). The higher the LTTGI of the user, the poorer his/her health status is. This allowed us to overcome one of the difficulties in estimating health status as it does not take into account the specificity of a medication to a disease only that the disease treated with this medication is a long-term disease. For example, detecting a beta blocker in the record of a user will add a value of one to the LTTGI of that user regardless of the indication of that beta blocker (hypertension, CHF, migraine). We see this as a reasonable approach, especially when we could not validate our score against a diagnoses-based scale, as is mentioned in the limitations below.

Three studies have concluded that the number of dispensed medications performed better than the CDS in predicting health care utilization and other outcome measures (Schneeweiss *et al.* 2001; Perkins *et al.* 2004; Farley *et al.* 2006). In this study, counting the number of medications would overestimate health status because e-klinik and e-panel do not contain information about a physician order to stop a medication for a particular patient. Thus the number of medications as a measure of health status would not have face validity if applied in this study. For example, a patient who was on propranolol and then was changed to atenolol would have a score of 2 while he/she was on only one of these two medications at any time point. Another argument against using the number of medications to estimate health status is that not all medications can be used to reflect the health status of the patient, and thus measuring health status by counting the number of medications obviously would overestimate health status. For example, amoxicillin would be counted if all medications are considered in calculating the LTTGI. A medication such as

amoxicillin is used for acute illnesses and for a limited period of time, and therefore should not be included in estimating the health status of individuals. A medication such as amoxicillin was not represented in any LTTG in this study.

It may be thought that the inclusion of some LTTGs which are not classically used to treat chronic diseases, and those LTTGs which are used for acute as well as for chronic diseases, will overestimate a user's health status. However, we were conservative in including such LTTGs via the three selection criteria mentioned in the methods section. With these criteria, we believe it is unlikely that the LTTGI overestimates the user's health status. For example, we included anti-fungals because fungal diseases in the primary care setting are mainly dermatophytoses and nail fungal infections. Fungal skin diseases are recurrent and, though not disabling, are disturbing. We believe that a user in a free access health care system like that of USM will make a visit for a fungal skin infection. We also included some antihistamines that are used in chronic as well as acute allergic conditions.

It may be argued that the explanatory power of the model is far from the ideal where the model at its best can explain only 36% of utilization variance. It should be emphasized here that when we look at the performance of the model, we should not look at the value of the R^2 achieved, but at its value after the addition of the proposed 'new' adjuster. This study evaluates the effect of adding the LTTGI on the explanatory power of the model. Newhouse *et al.* (1989) found that R^2 could not explain more than 30% of the utilization variance in any of the models they examined, and thus they questioned the role of risk adjustment in capitation payments. However, another study concludes that including risk adjusters other than the demographic variables is still a valuable tool (van de Ven *et al.* 1994). Diehr *et al.* (1999) state that it is difficult to estimate individual utilization, but regression gives the reasonable utilization average of people with the same covariates. Demers (2004) found that the persistence of high use of primary care was low and she concludes that this low persistence of the high use can partly explain the low predictive power of risk adjustment methods in primary care settings.

The results of this study confirm the findings of many previous studies that adding a health status measure improves the predictive power of risk adjustment models. The value of R^2 in our study is relatively high. This high value is attributed to several factors. In addition to the relevance of predictors, the model in our study is concurrent rather than prospective. Furthermore, the model predicts primary care visits. Relevant literature has documented better prediction in concurrent models compared with prospective models (Cumming *et al.* 2002; Winkelman and Meymud 2007). Similarly, prediction of visits is better than prediction of cost, and prediction of outpatient services is better than prediction of inpatient services.

Because the prediction power of a model can differ from one utilization level to another, we examined the performance of the model in three different levels of primary care visits. As mentioned earlier, the relation between number of visits and the LTTGI was linear in most of its parts and it was strong, which means there is a positive linear relationship between these two variables. In other words, users with poorer

health status made more visits. Furthermore, the mean of the LTTGI rises as the level of utilization increases. Then, we can explain the noticed variability in the accuracy criteria in the three utilization levels. The effect of adding LTTGI is more obvious in the high utilization group as this group of users have poorer health status. Model 2 is 0.34 visits per high utilization user more accurate than model 1. For the same reason R^2 was higher in model 2, especially in the high utilization group. Predictive ratio (PR) is the same in both models and across all utilization levels. This is because PR assesses the accuracy in the whole group, not individual-by-individual, while mean prediction error (MPE), mean absolute prediction error (MAPE) and R^2 are individual-based measures of accuracy (Cumming *et al.* 2002; Winkelman and Meymud 2007).

The PRs were higher than 1 which means that the model over-predicts the utilization. This can happen when the population under study are healthy (Kuhlthau *et al.* 2005). Sixty-six per cent of our study subjects are university students and 65% are aged between 20 and 35 years, which imply that they are healthy individuals. Because PRs are similar in both models and across all utilization groups, we can conclude that the observed over-prediction is not due to the addition of the LTTGI.

Limitations

Our study has some limitations. First, we could not confirm our LTTGs list through peer review. We tried to minimize this limitation by consulting the literature on the use of medications in these groups. All medications of LTTG were confirmed to be used in long-term diseases.

Second, we could not capture medications that were dispensed in the panel pharmacies as these dispensing data are not computerized. Nonetheless, dispensing from the panel pharmacies is so small that this would not affect the LTTGI.

Third, we used the number of visits as a measure of health care utilization. It is appealing to use the cost of each user, but we could not reasonably estimate cost data in USMHC. Liu *et al.* (2003) used the number of visits as a measure of utilization. Furthermore, measuring the number of visits reflects patient behaviour rather than system characteristics, while cost measurement does the reverse, i.e. to visit or not is related to the user him/herself, then once the visit has occurred, it is the provider who determines how to treat and the extent and the cost of the treatment.

Fourth, we did not compare the performance of our pharmacy-based model with a diagnoses-based model. We have a good reason for this. USMPC do not use a coding system for the diagnosis, thus diagnoses cannot be captured in e-panel. Although the International Classification of Diseases (ICD) is implemented in the USMHC, the ICD coding of diagnoses is not followed, which makes it an unreliable source on the presence of chronic diseases. This devalues the ICD codes as the gold standard against which comparison is made. For example, the number of diabetic patients discovered by medications and ICD were 323 and 252, respectively. Similarly, the number of patients with gout/hyperuricaemia was 154 and 80 by medications and ICD, respectively.

Fifth, the developed LTTGI in this study is unweighted. This was unavoidable, due to incompleteness of diagnoses data in

our databases and the use of an expert panel not being feasible. However, one study has reported the validity of an unweighted index (Malone *et al.* 1999).

Conclusion

The Long-Term Therapeutic Groups Index (LTTGI) was successfully developed. Variability in number of primary care visits can be explained and predicted by LTTGI-based models. A LTTGI-based model of USM beneficiaries' primary care visits was developed and validated. The model has good prediction power and can be used in risk adjustment for capitation payment in a primary care setting.

Acknowledgements

We wish to acknowledge the assistance provided by Mr Zulham Hamdan and Mrs Fawziah from the research and development department (PPKT), USM, in making this work a success. We would also like to thank Ahmed Awaisu of the Clinical Pharmacy Department, School of Pharmacy, USM, for his contribution in checking the intellectual content of the revised manuscript.

References

- Ash A, Porell F, Gruenberg L, Sawitz E, Beiser A. 1989. Adjusting Medicare capitation payments using prior hospitalization data. *Health Care Financing Review* **10**: 17–29.
- Clark DO, Von Korff M, Saunders K, Baluch WM, Simon GE. 1995. A chronic disease score with empirically derived weights. *Medical Care* **33**: 783–95.
- Cumming RB, Knutson D, Cameron BA *et al.* 2002. A comparative analysis of claims-based methods of health risk assessment for commercial populations. Final report to the Society of Actuaries. Symmetry Health Data Systems.
- Demers M. 2004. The predictability of individual primary care costs and its impact on managed care plans. *Health Policy* **68**: 345–52.
- Diehr P, Yanez D, Ash A, Hornbrook M, Lin DY. 1999. Methods for analyzing health care utilization and costs. *Annual Review of Public Health* **20**: 125–44.
- Donato R, Richardson J. 2006. Diagnosis-based risk adjustment and Australian health system policy. *Australian Health Review* **30**: 83–99.
- Economic Planning Unit. 2001. Eighth Malaysia Plan 2001–2005. Kuala Lumpur: Economic Planning Unit, Prime Minister's Department.
- Farley JF, Harley CR, Devine JW. 2006. A comparison of comorbidity measurements to predict healthcare expenditures. *American Journal of Managed Care* **12**: 110–9.
- Fishman PA, Shay DK. 1999. Development and estimation of a pediatric chronic disease score using automated pharmacy data. *Medical Care* **37**: 874–83.
- Fishman PA, Goodman MJ, Hornbrook MC *et al.* 2003. Risk adjustment using automated ambulatory pharmacy data: the RxRisk model. *Medical Care* **41**: 84–99.
- Gilmer T, Kronick R, Fishman P, Ganiats TG. 2001. The Medicaid Rx model: pharmacy-based risk adjustment for public programs. *Medical Care* **39**: 1188–202.
- Johnson RE, Hornbrook MC, Nichols GA. 1994. Replicating the chronic disease score (CDS) from automated pharmacy data. *Journal of Clinical Epidemiology* **47**: 1191–9.
- Kuhlthau K, Ferris TG, Davis RB, Perrin JM, Iezzoni LI. 2005. Pharmacy and diagnosis-based risk adjustment for children with Medicaid. *Medical Care* **43**: 1155–9.
- Lamers LM. 1999. Pharmacy costs groups: a risk-adjuster for capitation payments based on the use of prescribed drugs. *Medical Care* **37**: 824–30.
- Lamers LM, Van Vliet RC. 2004. The Pharmacy-based Cost Group model: validating and adjusting the classification of medications for chronic conditions to the Dutch situation. *Health Policy* **68**: 113–21.
- Liu CF, Sales AE, Sharp ND *et al.* 2003. Case-mix adjusting performance measures in a veteran population: pharmacy- and diagnosis-based approaches. *Health Services Research* **38**: 1319–37.
- Malone DC, Billups SJ, Valuck RJ, Carter BL. 1999. Development of a chronic disease indicator score using a Veterans Affairs Medical Center medication database. IMPROVE Investigators. *Journal of Clinical Epidemiology* **52**: 551–7.
- Newhouse JP, Manning WG, Keeler EB, Sloss EM. 1989. Adjusting capitation rates using objective health measures and prior utilization. *Health Care Financing Review* **10**: 41–54.
- Perkins AJ, Kroenke K, Unutzer J *et al.* 2004. Common comorbidity scales were similar in their ability to predict health care costs and mortality. *Journal of Clinical Epidemiology* **57**: 1040–8.
- Roblin DW. 1998. Physician profiling using outpatient pharmacy data as a source for case mix measurement and risk adjustment. *Journal of Ambulatory Care Management* **21**: 68–84.
- Schneeweiss S, Seeger JD, Maclure M *et al.* 2001. Performance of comorbidity scores to control for confounding in epidemiologic studies using claims data. *American Journal of Epidemiology* **154**: 854–64.
- Sloan KL, Sales AE, Liu CF *et al.* 2003. Construction and characteristics of the RxRisk-V: a VA-adapted pharmacy-based case-mix instrument. *Medical Care* **41**: 761–74.
- Sweetman S (ed.). 2005. *Martindale: The Complete Drug Reference*. 34th edition. New York: Pharmaceutical Press.
- Van de Ven WP, Van Vliet RC, Van Barneveld EM, Lamers LM. 1994. Risk-adjusted capitation: recent experiences in The Netherlands. *Health Affairs (Millwood)* **13**: 120–36.
- Von Korff M, Wagner EH, Saunders K. 1992. A chronic disease score from automated pharmacy data. *Journal of Clinical Epidemiology* **45**: 197–203.
- Wahls TL, Barnett MJ, Rosenthal GE. 2004. Predicting resource utilization in a Veterans Health Administration primary care population: comparison of methods based on diagnoses and medications. *Medical Care* **42**: 123–8.
- Winkelman R, Meymud S. 2007. A comparative analysis of claims-based tools for health risk assessment. A research study sponsored by the Society of Actuaries. Schaumburg, IL: Society of Actuaries. Online at: <http://www.soa.org/research/health/hlth-risk-assessment.aspx#>.
- Zhao Y, Ash AS, Ellis RP *et al.* 2005. Predicting pharmacy costs and other medical costs using diagnoses and drug claims. *Medical Care* **43**: 34–43.