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USE OF AN ADMINISTRATIVE DATABASE TO DEVELOP AND TEST A MODEL TO PREDICT THE ALLOCATION OF CLINICAL PHARMACY HUMAN RESOURCES

BY

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ABSTRACT

Pharmacy managers are handicapped by a lack of research in the area of resource allocation and utilization as it applies to clinical pharmacy staff. Using the decision support system at a tertiary care teaching facility in Ottawa, Ontario, two statistical models were developed and validated using over 7000 cases from each of two consecutive fiscal years. Multiple logistic regression analysis was used to identify the patient-level variables that were valid predictors of who would receive clinical pharmacy services: attending physician specialty, length of stay, complexity code, drug category. The model accurately classified 81.8% of patient encounters. A multivariate linear regression analysis was undertaken to identify the predictors of the cost of clinical pharmacy services: attending physician specialty, length of stay, drug category, drug cost, other hospital costs. These elements explained 43% of the variability in the outcome. The applicability of the models for daily operations and planning is described.

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GLOSSARY OF TERMS

CIHI – [Canadian Institute for Health Information] - a national not for profit body whose mission is to serve as the national organization to coordinate the development and maintenance of a comprehensive and integrated health information system for Canada

CLINCASE – a variable derived to identify patient cases that had received clinical pharmacy services

CLINCOST – clinical pharmacy services cost, in dollars, associated with a patient encounter

CMG™ – [Case Mix Group] – a relatively homogeneous group of patients as defined using methodology developed by the Canadian Institute for Health Information

CMG AGE GRP – standard age groups defined by CIHI for analysis purposes

COMPLEXITY – a classification developed by the Canadian Institute for Health Information, using comorbid conditions to refine the CMG grouping methodology

DRUGCOST – patient-specific dispensed medication cost, in dollars, associated with a patient encounter

ENCOUNTER – a single episode of care for a patient, from the time of admission to discharge from the facility

IDP – [Intermediate Drug Product] – a single drug entity that is orderable through the pharmacy patient care computer system, or a group of such products that have similar costs and clinical use

IDPMAX – the maximum rating of the intermediate drug products associated with a patient case, as assigned by an expert panel, with respect to the likelihood that the drug therapy would prompt action by a clinical pharmacist

IP NUMBER – a number assigned to each intermediate product within the Ottawa General Hospital decision support system, without inherent meaning

LnCLINCOST – natural log transformation of CLINCOST

LnMDRUGCOST – natural log transformation of DRUGCOST (modified by adding "1" to each case in order to allow for the transformation where the DRUGCOST was initially zero)

LOGITLOS – logit transformation of Length of Stay

LnOTHERCOST – natural log transformation of OTHERCOST

LOGITRIW – logit transformation of Resource Intensity Weight

LOS – [Length of Stay] – number of days that a patient resided in the facility during a particular encounter

MCC™ – [Major Clinical Category] – a grouping of CMG based on body systems

MDGROUP – a variable created by grouping similar Attending MD Specialties

OTHERCOST – cost of all hospital services, other than CLINCOST and DRUGCOST, in dollars, associated with a patient encounter

RIW™ – [Resource Intensity Weight] – a value assigned to each patient encounter based on expected resource use as compared to an average patient

SEXCODE – a variable derived to convert the gender assignment into numerical values during analysis

1. INTRODUCTION

1.1 CONTEMPORARY HOSPITAL PHARMACY PRACTICE

The practice of pharmacy in hospitals has both a drug distribution role and a clinical role. The former is largely accomplished through the effective use of pharmacy technicians under the supervision of a pharmacist. The latter is the professional role that pharmacists undertake within the health care team, with the objective of ensuring the appropriate use of pharmacotherapeutic agents in the delivery of patient care.

The medication cycle within a health care facility involves á large number of tasks which must be well co-ordinated in order to ensure that there is timely administration of appropriate drug therapy to patients. Typically, a physician initiates the process by ordering a medication for an individual patient. In most facilities, the pharmacy department then receives a copy of the order, and reviews it for appropriateness prior to dispensing. This is a typical central drug order review process, provided in 93% of hospitals in Canada[1]. It is unfortunately limited in usefulness because the pharmacist does not generally have access to patient-specific clinical information when assessing the orders from within the pharmacy department. For this reason, decentralised pharmacy services have evolved, whereby the "clinical pharmacists" (here referred to as "clinicians") function on the patient care units as part of the multidisciplinary teams that work together to optimise patient outcomes. Such practice varies in its degree of implementation, but is more common in teaching hospitals[1]. In facilities with a fully developed clinical pharmacy program, the clinicians provide a variety of services, including

medication history taking, pharmacotherapy monitoring, pharmacokinetic consultation, drug information provision, adverse reaction reporting and patient counselling. Often the pharmacist's actions result in a recommendation with regard to such matters as changes in drug dosage, choice of agents, lab test ordering, and other alterations in patient management. Most pharmacists document these interventions, either on the patient's chart or on forms retained within the department, in order to maintain a record of their recommendations. Such records are also useful for workload data capture.

1.2 THE MIS GUIDELINES AND PATIENT-SPECIFIC COSTING

The Guidelines for Management Information Systems in Canadian Health Care Facilities[2], more commonly referred to as the "MIS Guidelines", were introduced in 1985. These guidelines provide acute care facilities with a detailed framework and accounting structure for the reporting of financial and statistical information. One of the objectives of the MIS Guidelines is to standardise the collection of data to yield useful information for management purposes. *Functional centres* are a subdivision of an organisation used in a functional accounting system to record the budget and actual direct expenses, statistics, and/or revenues (if any) which pertain to the function or activity being carried out[2]. They are generally aligned with traditional departments within an organisation. Tracking the financial and statistical data within the many functional centres of a health care facility provides a powerful decision support tool for management purposes.

One key indicator defined in the MIS Guidelines is the cost per unit of service provided by a particular functional centre within a facility. The calculation of this

indicator is based on the accumulation of the direct and indirect operating costs, as well as the workload units generated by personnel, within that functional centre. Some facilities have gone one step further and implemented a full cost accounting system that tracks the cost of providing care to each patient, during the course of their encounter with the institution. This is primarily achieved by determining the workload units of service provided by each functional centre to the individual patients, and multiplying the units of service by the particular functional centre's cost per unit of service. Thus, the costs of running a functional centre are distributed to patients on the basis of the service that is provided to patients by the staff of that functional centre. It follows that in order to track the cost of providing clinical pharmacy services to individual patients, it is necessary to record the amount of workload time provided to each patient, and to know the cost per unit of clinical pharmacy services over that same time period.

There are two principal exceptions to this practice, as described in the MIS Guidelines. Individual supplies that have a unit value of more than $250, as well as drugs dispensed for specific patients, are to be attributed directly to the patients who receive them.

1.3 COMPUTERISED DOCUMENTATION OF CLINICAL PHARMACY SERVICES

Though the use of computer systems for documentation of clinical activities is not as yet common, this is an evolving field and one can reasonably forecast that this will become more pervasive as fully integrated hospital information systems evolve to include electronic health records. Workload activities can be captured in an aggregate form, though the tracking of clinical pharmacy activities on a patient-

specific record substantially enhances the usefulness of the data[3]. Not only does it permit the calculation of the patients' consumption of clinical services, but it allows for enhanced analysis of pharmacists' activities and the distribution of their services across the patient population. The capture of workload in an electronic system, on a patient-specific basis, is very useful for functional centre management purposes. There are a number of examples of successful implementation of computerised documentation of clinical pharmacy activities[4-22], yet manual record keeping remains the most common practice.

The clinical pharmacy staff at the Ottawa General Hospital (OGH) has been documenting patient-specific clinical services since 1993. The documented activities are listed in Table 1.

Table 1 Clinical Pharmacy Activities at the Ottawa General Hospital 1996-98

ADVERSE DRUG REACTION NOTED	MONITORING – AMINOGLYCOSIDE
DOSE ALTERED – ADMIN. ROUTE	MONITORING – CHEMOTHERAPY
DOSE ALTERED – DOSE/INTERVAL	MONITORING – FOLLOW UP PATIENT
DRUG ADMINISTRATION MODIFIED	MONITORING – NEW PATIENT
DRUG INTERACTION MANAGED	NEW NONFORMULARY DRUG REQUEST
DRUG(S) ADDED	PATIENT COUNSELLED
DRUG(S) DELETED	PHARMACOKINETIC CONSULT
DRUG(S) SUBSTITUTED	PROBLEM RESEARCHED/DRUG INFORMATION
LAB TEST(S) REQUESTED	TOTAL PARENTERAL NUTRITION MONITORING
LAB TEST(S) DELETED	OTHER CLINICAL ACTIVITY
MEDICATION HISTORY COMPLETED	

Typically, at the end of their shift, the pharmacists document the clinical activities they have provided to individual patients. There are standard workload units (expressed in minutes) associated with each of the activities. The use of these standard times is consistent with the MIS Guidelines, and simplifies the workload data capture for the pharmacists. On a quarterly basis, the pharmacists are provided with graphic profiles showing their own documentation of clinical activities in comparison with their peers, as one approach to encouraging full compliance with the department's documentation procedures. There are a number of approaches one can take in the analysis of the workload data, and these often involve the grouping of patients into meaningful units for analysis.

1.4 CASE MIX GROUPS AND RESOURCE INTENSITY WEIGHTS

The Canadian Institute for Health Information (CIHI) has developed and maintains a methodology to group patients that are relatively homogeneous both clinically and in expected resource use. There are approximately 475 Case Mix Groups (CMG™), and these are revised on an annual basis to reflect current clinical opinion. The grouping methodology is largely based on the most responsible diagnosis or procedure as documented in the patient's health record. The CMGs are themselves grouped, essentially by body system, into 25 Major Clinical Categories (MCC).

In April 1997, CIHI introduced a *Complexity Overlay* on top of the CMG categories, to provide a refinement of the classification based on comorbid conditions for which prolonged length of stay or more costly treatment might be reasonably expected[23]. It is only applied to Case Mix Groups where it would result

in improved homogeneity of the groups, as assessed by CIHI. There are five possible Complexity assignments:

1. No Complexity
2. Complexity related to chronic conditions
3. Complexity related to serious/important conditions
4. Complexity related to potentially life-threatening conditions
9. Complexity not applied

The Resource Intensity Weights (RIW™) are also a product of CIHI. They are a measure of the relative value of expected resource use, originally applied at the level of the CMGs[24]. With the advent of the Complexity Overlay, as well as an age adjustment, the resource intensity weights are now calculated for individual patients in an even more refined process. For atypical cases (deaths, transfers, sign-outs, length of stay outliers) there is another adjustment to the resource intensity weight at the patient case level. For interpretation, an RIW of 1.000 represents a case with average resource consumption. An RIW of 1.500 would indicate expected resource use of one and a half times the average patient. It is this resource intensity weight that is currently built into the acute care funding formula of Ontario hospitals, to help adjust for differences in case mix between facilities[25]. Although the RIW has been found to be useful for funding at the facility level, it has not been demonstrated to provide a meaningful estimate of relative workload requirements of individual functional centres within a facility.

The resource intensity weights were historically calculated on the basis of Maryland State case-specific charge data provided to CIHI, with adjustments based

on Canadian case mix and length of stay information. With cost data arising out of Ontario and Alberta projects, CIHI has recently revised the resource intensity weight methodology to incorporate only Canadian data. The RIW values in the data sets used for this study are based on the Maryland methodology.

1.5 DECISION SUPPORT SYSTEM AT THE OTTAWA GENERAL HOSPITAL

The Ontario Case Cost Project[26] is an initiative in which 13 hospitals were initially supported in the implementation of cost accounting systems in order to obtain better estimates of hospitalisation costs, commencing in 1993. Since then, a second generation of 17 facilities has implemented the systems. As one of the inaugural sites, the OGH implemented a decision support system to capture information on resource consumption for all inpatient admissions and selected day surgery cases. The level of detail is such that the specific service provided by each functional centre, including the clinical pharmacy service, is known for each day of stay. The quantity of each of the services received, the workload units, and the associated costs, are retained in the database. The costs are further broken down into direct and indirect components as well as fixed and variable costs. For a functional centre such as clinical pharmacy, the direct cost component is primarily the labour expense of the clinical staff. Except for a small portion of the staffing budget identified as fixed direct management costs, the staffing costs are classified as a variable direct expense. Overhead costs allocated to the clinical pharmacy functional centre are classified as fixed indirect operating expenses.

The real strength of decision support systems such as the one implemented at the OGH comes from the merging of financial and statistical information with the

clinical information contained in the health record abstract. This abstract is prepared at the time of patient discharge, and is submitted to CIHI by most acute care facilities in Canada. At CIHI, these abstracts are integrated into the national Discharge Abstract Database. At the OGH, there is an electronic interface through which the clinical abstract is brought into the decision support system. Patient demographic information, diagnostic and procedure codes, medical staff involvement with the case, length of stay information, and CMG/RIW assignments are just some of the components of the abstract. To ensure the comparability of data across fiscal years from a clinical perspective, the CMG grouping methodology is applied to historical data for analysis purposes. Thus, at OGH the 1997/98 grouper algorithm had been used to regroup the 1996/97 cases into the same CMG structure using a consistent methodology.

Facilities that have fully implemented decision support systems with integrated financial, workload and clinical data have a powerful tool for managing the use of resources. Department management, utilisation review, quality improvement initiatives, budgeting, planning, and general administrative activities are facilitated with this information. Facilities with these systems are in a position to use them for research purposes and disseminate the findings for the broader benefit of health service providers.

1.6 LITERATURE REVIEW

A literature search was conducted in an effort to identify published articles that addressed the issues related to the allocation of clinical pharmacy services in hospital practice settings. Using the Medline (1966 - 1997), and HealthSTAR

(1975 – 1997) databases, an online search was conducted using the following terms: *[hospital costs/,*OR *health resources/,* OR *health priorities/,* OR *health care rationing/,* OR *health services research/,* OR *health manpower/,* OR *health services needs* OR *demand/], combined with pharmacy.af.* An online review of the 253 abstract citations revealed only four that might have relevance to clinical pharmacy services allocation. Those that were of potential interest were retrieved and found not to be of particular value in the context of the current study[27-30]. The published literature regarding clinical pharmacy services in hospital settings is currently limited to descriptions of approaches to documenting activities and estimating cost savings of pharmacists' interventions using elementary methods. There is a need for research on the analysis of clinical pharmacy resource utilization and use of this information to optimise the delivery of service. An updated search was conducted during the preparation of this manuscript, for the period 1998 to Feb 2000, using the same parameters. An additional 72 abstracts were identified, though none was applicable to the research questions being addressed in this study.

2. OBJECTIVES

2.1 GENERAL

My personal experience, as well as the wanting literature search, led to confirmation that further research is needed in the area of planning for clinical pharmacy services. Pharmacists are often assigned to groups of patients, as they are at the OGH, yet staffing levels are such that not all patients receive the services available. Pharmacists select the patients to whom they provide service, and the difficulty pharmacy managers struggle with is how to best direct the pharmacists' services to the patients most in need. Similarly, during recent fiscal constraint exercises in many jurisdictions, staff reductions precipitated a review of the allocation of retained personnel. Undoubtedly, if the manager directs more staff hours to a particular patient group then more of those patients could be expected to receive more services. Unfortunately, such allocation decisions are by necessity being made on a visceral rather than scientific basis. Learning more about the patient-level variables that are associated with the provision of clinical pharmacy services may lead to an improved capacity to plan for such services and evaluate the appropriateness of the allocation decisions made by managers.

In addition to internal management needs, comparative reporting between facilities through report cards and benchmarking exercises is growing in popularity. My experience with the Professional Pharmacy Advisory Group of the Joint Policy and Planning Committee in Ontario reaffirmed that the underlying assumptions for comparative reporting are problematic. The denominators of comparative indicators are frequently counts of cases, patient days, or weighted cases[31]. The weighted

cases, based on the resource intensity weights, may be the best but need to be further evaluated. It has yet to be demonstrated, however, that the use of weighted cases is a valid approach to benchmarking of clinical pharmacy service delivery. The implied assumption that pharmacy service delivery should correspond to the hospital's overall expected resource intensity has not been validated, to my knowledge. Research that provides insight into the factors associated with the delivery of clinical pharmacy services will enlighten those involved in the planning and funding of this important component of health service delivery.

The aim of this research project was to develop valid models that would identify the patient level variables most strongly associated with the provision of clinical pharmacy services, using epidemiologic methods applied to a large database. In doing so, a small but useful contribution to this field is made, as it will serve as a starting point for debate about the allocation of pharmacy staff, and a launching point for hypothesis generation and future research initiatives.

2.2 MODEL #1 – PATIENTS RECEIVING CLINICAL PHARMACY SERVICES

The first objective was to identify and validate the variables in terms of a model's ability to correctly classify patients into groups according to whether they would receive clinical pharmacy services. Because many of the variables of interest (ie. length of stay, resource intensity weight, CMG, attending physician) are only known at the point of discharge, the model development and validation was based on the ability to retrospectively classify the patients correctly into either group. The identification of such variables can then be discussed in terms of appropriate

benchmark indicators for pharmacy services and conceptual adjustments to funding methodologies.

2.3 MODEL #2 – COST OF CLINICAL PHARMACY SERVICES RECEIVED

The second objective was to identify and validate the patient level variables that would estimate the extent of the clinical pharmacy services received.

2.4 RESEARCH ETHICS BOARD APPROVAL

The research protocol was initially approved for a one year period by the Research Ethics Board of the Ottawa General Hospital Research Institute (Protocol No. OGH-98-045) on June 9, 1998. The approval was subsequently renewed on July 11, 1999 for a second year. A statement of termination of the research project was submitted to the institute in July, 2000.

3. METHODS

This section describes the methods used in the development and validation of the mathematical models. Though the statistical methods were different, there were similarities in the strategies undertaken so a similar format has been used to present the two models in a consistent manner. Statistical analyses were carried out with SPSS for Windows Release 8.0.0.

3.1 MODEL #1 – PATIENTS RECEIVING CLINICAL PHARMACY SERVICES

3.1.1 MODEL DEVELOPMENT

3.1.1.1 CHOICE OF ANALYSIS

In selecting a method of analysis for the data, four considerations should enter into the choice[32]: the purpose of the investigation; the mathematical characteristics of the variables involved; the statistical assumptions made about these variables; and how the data are collected. Model #1 is intended to describe how the patient level variables are related to the probability of receiving any amount of clinical pharmacy services. The dependent variable is dichotomous in that the patient either does or does not have a record of clinical pharmacy activity within their workload activity summary. The independent variables that will be considered are a mixture of continuous and discrete variables. The study has a cross-sectional design, and the model development is based on all qualifying discharges in one complete fiscal year (1996/97). Logistic regression analysis is an appropriate approach under these circumstances[32-35], albeit with some limitations which will be detailed in the discussion section. The model was validated using another complete fiscal year of data (1997/98) based on the same inclusion/exclusion criteria.

3.1.1.2 CASE SELECTION

The selection of cases from the decision support system has important implications for the validity and generalizability of the results. The target population was the group of adult inpatients to whom the pharmacy department allocated staff for routine clinical services. Within this population, the pharmacists themselves typically made the determination of who they would actually provide service to.

It was known that clinical pharmacy services were provided to surgical patients almost exclusively on a consultation basis. That is, the pharmacists did not provide routine coverage to surgical patients but rather responded to a specific request by medical or other health personnel. The surgical cases were therefore excluded, by specifying the inclusion of only CMG categories identified as either "medical" or "both" ("CMG TYP = M or B"). It was also recognised that the Major Clinical Categories that grouped Pregnancy & Childbirth (MCC 14) and Newborns & Neonates (MCC 15) had little pharmacy involvement. These were predominantly healthy individuals with very short lengths of stay and little requirement for pharmacy services. Encounters classified into these MCCs were also therefore excluded from the study.

In order to focus the analysis on the inpatient population, only those cases meeting that requirement ("INOUT CODE = I") were included. Adults were defined as individuals having an age greater than 12 ("AGE YEAR is gt 12"), as this was considered the usual minimum age for admission to OGH other than neonates. The abstracting information was required to be complete ("ABSTRACT STATUS = C"), though this would have little if any impact due to the retrospective nature of the

study. Abstracts are typically completed within a month or two of a patient's discharge.

In order to ensure consistent costing across all patients for the resource utilisation, only those patients with an admission and discharge within the fiscal year were included. Changes to the OGH cost accounting structure and service descriptions between fiscal years had been found to cause data quality problems in the costing of cases that transcended the fiscal year. This has since been resolved, but was a valid concern for the years of data considered for this analysis. In order to consider whether excluding patients already in hospital as of March 31 would compromise the external validity of the results, a brief analysis was conducted of those cases which otherwise met the inclusion criteria. It was likely that some of them would be length of stay outlier cases with extended hospitalisations. A simple descriptive comparison was conducted of these cases against the group that underwent further detailed analysis in the model building. Parameters compared were the average length of stay and the percent of cases receiving clinical pharmacy services.

3.1.1.3 VARIABLE SELECTION

The selection of patient-level potential predictor variables was another important consideration in the study design. These are summarised in Table 2. The first step in the variable selection was to identify those that might have a sound scientific basis for being associated with the outcome variable. The Canadian Society of Hospital Pharmacists' White Paper on the Establishment and Elaboration of Clinical Pharmacy Services[36] includes guidelines for the prioritisation of clinical activities.

It suggests some criteria that might be used by pharmacists to identify patients who require in-depth evaluation of their drug therapy. The onus is placed on the practitioners to establish criteria for selective monitoring (eg. certain medical services, certain drugs, certain diseases). Priority situations cited in the paper include:

- elderly or very young patients (< 6 months, > 65 years)
- patients taking many medications (>7)
- patients taking medications with a narrow therapeutic index (eg. digoxin, theophylline, gentamicin, nitroprusside)
- patients receiving excessively high doses
- patients whose disease state predisposes them to toxicity or decreased efficacy

An OGH pharmacy resident's administration project[37] suggested a number of other variables that might be used to screen patients upon admission for those most likely to benefit from pharmacotherapy monitoring. In addition to the White Paper criteria, these included patients receiving medications for infections, medications with severe adverse effects, non-formulary medications, and specific laboratory test results.

Table 2 Variables Considered as Potential Predictors for Clinical Pharmacy Services

VARIABLE	COMMENTS	VARIABLE IN OGH DECISION SUPPORT SYSTEM
AGE (> 65 years)	- age considered as continuous variable and categorical variable	AGE YEAR CMG AGE GROUP
POLYPHARMACY (>7 medications)	- clinical pharmacists' opinion was that this was important, yet secondary to the nature of the medication(s) prescribed	None
NARROW THERAPEUTIC INDEX	- the 847 different "intermediate drug products" were classified into three categories by five clinical pharmacists	IP NUMBER
ANTI-INFECTIVES	- the categorisation of the 847 intermediate drug products included consideration of the use of the drug	IP NUMBER
ADVERSE EFFECTS	- the categorisation of the 847 intermediate drug products included consideration of the adverse effect potential of the drug	IP NUMBER
NON-FORMULARY STATUS (ie. not approved for routine use in the hospital)	- the categorisation of the 847 intermediate drug products included consideration of the formulary status of the drug	IP NUMBER
DOSAGE	- the individual dosage prescribed for a patient would more likely be addressed during the central drug order review process, though the matter might be referred to a decentralised clinical pharmacist	None
LAB TEST RESULTS	- abnormal results may flag the attention of a clinical pharmacist - the categorisation of the 847 intermediate drug products included consideration of the potential impact on lab parameters and need for serum drug level monitoring	IP NUMBER (proxy)
CMG	- the CMGs are the basis for much inpatient data analysis and comparative reporting	CMG
LENGTH OF STAY	- length of stay is a known driver of resource utilisation and is often used in comparative reporting	LENGTH OF STAY (LOS)
COMPLEXITY LEVEL	- the Complexity overlay to the CMG assignments is intended to provide further refinement of the grouping methodology to account for comorbidities	COMPLEXITY
RIW	- the Resource Intensity Weight is a calculated measure of expected resource use, as compared to an average case	RIW
SEX	- sex is a standard inclusion in data analysis and may be required for comparability with other studies	SEX
ATTENDING PHYSICIAN SPECIALTY	- the clinical pharmacists at the OGH are assigned to medical teams, based on the attending physician specialty coding	ATTENDING MD SPECIALTY
MCC	- Major Clinical Categories are a higher level summary of the CMGs that could reasonably be expected to relate to clinical pharmacy activities	MCC

Other variables of potential importance based on hospital funding methodology were the MCC group, the CMG assignment, length of stay, complexity level, and resource intensity weight. Sex was considered as a standard item for data analysis, and the attending physician specialty was included since that was the basis upon which the clinical pharmacy staff was assigned to patient groups.

The physician specialty is assigned to the patient case based on the health record tables that associate each attending physician with a particular specialty code. There were 22 possible codes in fiscal 1996/97.

For analysis purposes, sex was recoded into a new variable SEXCODE as follows: 1 = Female ; 2 = Male ; 3 = Transsexual.

Age was analysed as both a continuous and categorical variable (based on the CIHI age categories), in order to assess the most appropriate strategy. CIHI established three age groups (0-17, 18 – 69, 70+) based on statistical analysis of the Discharge Abstract Database when developing the Complexity Overlay and age adjustment methodology. These definitions were used for the categorical analysis of age (CMG AGE GRP) because they were considered to be a national guide and less arbitrary than the 65+ suggested in the White Paper. Age was also considered as a continuous variable, to ensure there was no meaningful loss of information by using the categories.

As noted, there were a number of possible predictor variables that were related to the specific medications dispensed for the patients. A Delphi-like process was used to obtain agreement from an expert panel of five clinical pharmacists on how they would respond to information that a patient had been prescribed a particular

medication. Volunteers were sought from the clinical pharmacy staff at the OGH, and selected to ensure that a variety of clinical services (eg. general medicine, family medicine, psychiatry, cardiology, neurology) were covered by the respondents. One of the five was a clinical specialist, that is, a pharmacist with primarily clinical and research responsibilities with little involvement in drug distribution. The other four were representative staff pharmacists who provided decentralised clinical services for approximately 60% of their worked hours. They were each provided with an introductory letter (Appendix A), and a list of all of the 847 "intermediate drug products" (IDP) that could potentially have been dispensed to patients during the 1996/97 fiscal year.

When computer support staff enter specific medications into the pharmacy system data tables, the drugs are uniquely identified as "orderable services". There are over 3000 such services in the OGH pharmacy computer system. In order to reduce this number to a manageable quantity for management reporting purposes, these services are grouped in the decision support system into the IDPs. The IDPs may have a 1:1 relationship with an orderable service, or a many:1 relationship. In the latter case, the services are grouped based on therapeutic use and cost of the medication. This yields relatively homogeneous groups of medications from a financial and clinical perspective. An excerpt of the list is attached as Appendix B.

The task the panel was given was to categorise each of the IDP into one of three drug category groups:

- Group 1 : the drug is not likely to prompt a pharmacist to provide clinical service
- Group 2 : it is somewhat probable that a pharmacist would provide service

- Group 3 : it is highly probable that a pharmacist would provide service

The list of IDPs was provided to the panel with the suggested grouping assignment, and rationale for the selected category, in order to facilitate their review of this large number of items. As a practising clinician with 15 years of experience, I felt justified in creating the first draft and seeking feedback from the panel. In the instructions, the pharmacists were encouraged to make their own determination of what category the IDP should be assigned to. As evidenced by the number of suggested changes to the IDP assignment, the pharmacists did not feel restricted by the presentation format.

When the responses were received, they were entered into a spreadsheet for analysis. The category assigned by each clinician was entered for each of the intermediate products. The criterion for the final assignment of the code to the IDP was that at least 3 of the 5 experts had to agree on the code. To achieve this, the first responses were analysed, and the IDPs for which there was not unanimous agreement on the coding were extracted. If four of the five respondents agreed on the coding, then this assignment was accepted. If only three clinicians had selected the same code, then the pharmacists who differed from the majority were provided with a list of those particular IDPs, indicating their original coding as well as the proposed assignment from three of the other respondents. The pharmacists therefore each received a list customised to their initial responses. Once again, they were asked to either confirm their original response or adjust it to another category. The result of this process was that there was agreement on the coding

of the IDPs either unanimously (556/847, 65.6%), by four clinicians (268/847, 31.6%), or by three of the experts (23/847, 2.7%).

With the IDPs categorised by the panel, the patients' drug therapy was reviewed in detail. All of the IDP usage was downloaded for each of the patient encounters, and a lookup done of the categorical assignment for each IDP. At the patient case level, a new variable representing the drug category assignment (IDPMAX) was created. The value assigned to this variable was the highest of the individual IDP categories on that patient record. The case may have had one or more IDPs within that grouping. The net result of this process was that each patient was assigned a value of 1, 2 or 3 for the likelihood that they would receive clinical pharmacy services based on the patient-specific drug therapy they had received during the course of their admission. Note that medications available on the patient wards as stock, which are typically nonprescription drugs that are needed on a frequent basis, are documented in the pharmacy computer system but not captured as patient-specific medications because they are not dispensed to individuals by the pharmacy staff.

The Attending MD Specialties were regrouped into a smaller number of categories, on the basis that many practitioners would have had similar education and training and were likely to be similar in their approaches to patient management. General medicine, nephrology and rheumatology for example, were combined as the patients were often cross-covered by physicians from either of these specialties. Cancer patients are typically managed at the OGH by the haematology, oncology, and radiotherapy specialists. The grouped physician

specialties variable was created, with each of the physician specialty codes assigned to one of the groups as shown in Table 3. This recoded variable was considered in the analysis, as was the original physician specialty assignment.

The outcome of interest was whether there had been clinical pharmacy services provided to that patient. From the decision support system, the quantity of intermediate products associated with the clinical pharmacy functional centre was downloaded for each patient (CLIN PHM QTY). A new dependent variable CLINCASE was created and assigned to each encounter, based on whether the patient's CLIN PHM QTY was >0 (CLINCASE = 1) or there was no documented activity (CLINCASE = 0).

3.1.1.4 UNIVARIATE ANALYSIS

Having selected the variables of potential interest, the next step in the model development was a descriptive analysis of the variables, to gain information about their characteristics, to identify missing data, and to detect any other problems prior to proceeding. The variables were then analysed individually, to determine their association with the outcome variable CLINCASE. To accomplish this, a univariate logistic regression approach was undertaken. The Likelihood Ratio Test (LRT) chi-square statistic was used as the basis for considering whether the variable had a statistically significant association with the outcome. A p-value <0.25 for this chi-square statistic was considered significant, to ensure that potentially important variables were not removed at this early stage of the model building[35].

Table 3 Attending Physician Specialty Regrouped for 1996/97 Cases

MDGROUP	Number of Patients	% Clinical Pharmacy Cases	Attending MD Specialty Codes Included in this MDGROUP		Number of Patients	% Clinical Pharmacy Cases
			CODE	DESCRIPTION		
Family Medicine	338	74.9	1	Family Medicine	338	74.9
General Medicine	2319	85.4	10	General Medicine	2067	85.8
			16	Nephrology	116	68.1
			19	Rheumatology	97	99.0
			57	Anaesthesia	13	53.8
			72	Geriatrics	26	100.0
Cardiology	718	59.6	12	Cardiology	718	59.6
Neurology	722	81.6	17	Neurology	722	81.6
Surgery	1801	37.8	30	General Surgery	538	30.1
			32	Neurosurgery	166	51.8
			34	Orthopedic Surgery	191	73.8
			35	Plastic Surgery	77	18.2
			36	Thoracic Surgery	94	23.4
			39	Urology	208	14.4
			50	OBS/GYN	315	60.3
			60	Otorhinolaryngology	114	9.6
			62	Ophthalmology	34	20.6
			95	Vascular Surgery	64	26.6
Psychiatry	789	49.2	64	Psychiatry	789	49.2
Haematology/ Oncology	910	81.2	66	Haematology	315	76.8
			74	Medical Oncology	425	86.6
			81	Radiotherapy	170	75.9
TOTAL	7597	66.6			7597	66.6

Physician specialty, grouped physician specialties, CMG, MCC, CMG age group, drug category, complexity level and sex were each analysed as nominal variables. For these nominal independent variables, a set of dummy variables was created to represent the multiple categories of these variables, as described by Hosmer and

Lemeshow[35]. It would be inappropriate to include nominal variables in a model as if they were interval scaled. A reference group was identified for each of the nominal variables. Age, length of stay and resource intensity weight were treated as continuous variables. With the continuous variables, the assumption of linearity with the logit was tested by creating decile groups of the independent variables and plotting the midpoint of each range against the logit of the group mean. A straight line confirmed that the scaling of the variable was appropriate.

The variables were then analysed for any associations between them. As it was known that length of stay was a factor in the RIW methodology, that physicians would tend to manage a similar group of patients (CMG, MCC) in their specialty areas, and that more complex patients could be expected to have longer lengths of stay, there was good reason to believe that there might be strong correlations between some of the variables. The square of the Pearson correlation coefficient (R^2) was used to assess the strength of the association between continuous variables, the Contingency Coefficient was assessed for categorical variables, and the Eta coefficient (squared) was examined where there was a mix of the two[38]. Correlation between independent variables is a necessary, but not sufficient, indicator of the degree of multicollinearity between independent variables[33]. Values greater than 0.90 were considered to be potentially problematic in terms of this correlation[32].

3.1.1.5 MULTIPLE LOGISTIC REGRESSION ANALYSIS

Having identified the variables that would be further considered in the model development, the next step was to build a model, using a standard approach to

variable selection. For this set of data the forward stepwise logistic regression procedure was selected. The principle of this approach is that for each step of the procedure the next most important variable is identified as that which produces the smallest p-value associated with the LRT chi-square statistic. The criteria used for variable inclusion were a $p_{entry} = 0.15$ and a $p_{removal} = 0.20$, in order to strike a balance between a complete model and an excessively large model[35]. The assessment of the model performance, after consideration of interactions and confounding, would ultimately determine the final appearance of the model. The standard errors associated with the regression coefficients were reviewed for evidence of instability in the estimates, and potential problems of multicollinearity.

Once the main variables were identified through the forward stepwise regression, interaction terms were considered for inclusion in the model. The interaction terms that were tested included all of the first order two-factor product terms of the independent variables. This was done so as to consider all possible interactions. Higher order interactions were not considered, in the interest of keeping the model relatively small to minimise potential collinearity problems[34]. Each of these interaction terms was added to the main effects model one at a time, and a p-value < 0.15 for the step LRT chi-square was considered significant with respect to retaining the term for further consideration. The nominal variables were once again handled with the use of dummy variables, and analysed as a set of interaction terms. Once all of the significant interactions were identified through individual analysis, they were added in a forward stepwise regression process to the main effects model, using the same p-value criteria as for the main effects model

building. Those that were found to be significant at this point were included in the final model. In order to ensure that the model was hierarchically well formulated, all lower order components of the included interaction terms were required to be retained in the model[34].

After the identification of the significant interaction terms, and ensuring that their lower order variables were included, the remaining variables were assessed for the potential to be removed. The criteria used in this assessment were the model performance (using the Goodness-of-fit chi-square statistic and the classification table), as well as any evidence of confounding. Confounding is assessed without the use of statistical testing[34]. The procedure involves determining whether the regression coefficients meaningfully change when the potential confounders are removed from the model. If there was no real difference in the coefficients, and the model performance was maintained, then the variable was excluded.

3.1.1.6 ASSESSING THE MODEL PERFORMANCE

The performance of the model was assessed using two approaches: the Hosmer-Lemeshow Goodness-of-fit statistic and the classification table. The Hosmer-Lemeshow Goodness-of-fit statistic is obtained by calculating the Pearson chi-square statistic from the decile table of observed and estimated expected frequencies in the two outcome groups[35]. It can be evaluated as a chi-square with 8 degrees of freedom. The advantage of using it is that it provides a single, easily interpretable, value which can be used to assess fit. The classification table is a 2x2 matrix from which the percent of correctly classified cases can be calculated. Estimated probabilities are used to predict group membership. A cutpoint of 0.5

was used for this analysis, as it is the most commonly used value[35]. Accuracy of classification is appropriately used as an adjunct measure for goodness of fit, supplementing the Hosmer-Lemeshow test.

3.1.2 MODEL VALIDATION

3.1.2.1 CHOICE OF VALIDATION APPROACH

The purpose of model validation is to evaluate whether the model chosen has a good chance of fitting new samples of data from similar populations. The reason for considering this type of assessment of model performance is that the fitted model always performs in an optimistic manner on the developmental data set[35]. In this study, the approach taken was to select a population from a contiguous fiscal year (1997/98). In doing so, there was a high degree of confidence that the costing methodology, patient characteristics, clinical pharmacy service delivery, and other considerations would be similar to the data upon which the model was developed. Despite the fiscal pressures, the pharmacy department had managed to maintain its staffing level between the two fiscal years. There had been no major changes within the structure of the clinical pharmacy services functional centre in terms of the allocation of clinical staff to patient groups.

In the validation process, the variables and their regression coefficients from the 1996/97 model were used to estimate the probability of the 1997/98 patients having received clinical pharmacy services. The patient encounters were subsequently classified as either expected cases or non-cases, based on a probability cutpoint of 0.50. A classification table was then constructed using the

information about the actual cases and non-cases in fiscal 1997/98. The sensitivity and specificity were compared with the developmental data set.

The cases were chosen for the validation data set based on the same criteria used for the model development.

3.1.2.2 VARIABLE CODING

In order to ensure comparability with the 1996/97 data, some modification of the coding was required. There had been some minor changes in the definitions of the physician specialty categories between the two fiscal years which had to be accounted for. Vascular Surgery (code 95) had been reassigned to a new physician specialty code 37. For the validation process, these cases were back-coded to 95 to ensure comparability to the 1996/97 data. Similarly, Radiation Oncology had been changed from code 81 to 75, but for the purpose of validation the 1997/98 cases were back-coded to 81. Lastly, the obstetrics/gynecology (OBS/GYN) specialty (code 50) had been subdivided in the new fiscal year into OBS/GYN (code 50) and Gynecological Oncology (code 76). The cases were therefore regrouped back into code 50 for the validity testing.

The other large component of the data that required review was that of the intermediate drug products. During the course of a year, there are many new drugs that are added to the pharmacy computer system data tables. On an annual basis, the IDP structure is reassessed and new products are defined in order to distinguish the unique drugs added during the past year.

Similarly, the accuracy with which the costing methodology estimates the actual utilisation of different drugs is reviewed annually. Where there is evidence of a

need to further refine the costing process, some IDPs are further broken down to produce more discrete, and therefore more homogeneous, groups of agents. As the system has been in place at the OGH since 1993, and the number of intermediate drug products had increased from approximately 300 in 1993/94 to 847 for fiscal 1996/97, this refinement process was largely complete by the time of this study. The total number of IDPs available in 1997/98 was 913.

The categorisation of the 1996/97 IDPs by the expert panel was applied to the 1997/98 IDP structure. Drugs for which a code had been agreed upon for 1996/97 were assigned the same code in the 1997/98 data set. New drugs were assigned a code by me, based on the expert panel's coding of comparable IDPs from 1996/97. There were no IDPs for which a return to the expert panel was felt necessary, as they were all easily categorised based on what had been learned in the initial coding exercise.

3.2 MODEL #2 – COST OF CLINICAL PHARMACY SERVICES RECEIVED

3.2.1 MODEL DEVELOPMENT

3.2.1.1 CHOICE OF ANALYSIS

Model #2 is intended to identify the patient level variables that have a significant association with the extent of the clinical pharmacy services received by patients. The dependent variable is continuous, and could be expressed in either minutes of workload or monetary terms. As the cost per unit of service is constant across all patients in the same reporting period, the choice of using workload or cost is immaterial. The clinical pharmacy services cost was selected as the outcome variable as it was the more easily interpretable in the context of other available

information. The independent variables considered were once again a mixture of continuous and discrete variables. This study has the same cross-sectional design as Model #1, with the model development based on all qualifying discharges in fiscal 1996/97. Multiple linear regression analysis is an appropriate approach for this research question[32]. The model was validated using the fiscal 1997/98 data from the OGH decision support system.

3.2.1.2 CASE SELECTION

The cases selected for the development of Model #2 were a subset of the qualifying cases used in Model #1. The focus shifted to those inpatients that had any documented record of having received clinical pharmacy services. Factors that were important in determining the amount of service received, after the decision had been made to provide service, would therefore be identified with this strategy.

3.2.1.3 VARIABLE SELECTION

The variables to be considered in studying the extent of clinical pharmacy services received were similar to those postulated to be associated with the decision to provide any amount of service. Other variables that were perceived as potentially important were those relating to other costs. Drug costs were a reasonable inclusion since patients consuming greater amounts of expensive medication are likely to receive more thorough reviews and monitoring by the clinical pharmacists. The sum of the other costs (ie. total patient cost excluding the dependent variable clinical pharmacy cost, and the isolated drug cost) was considered as another potential predictor.

3.2.1.4 UNIVARIATE ANALYSIS

Descriptive analyses of the new variables were conducted and transformations were considered for the dependent and independent variables based on their patterns of distribution and other logical considerations. The association between each independent variable and the dependent variable was analysed using analysis of variance (ANOVA). A p-value of <0.25 for F was considered adequate for inclusion of a variable in the multiple variable regression stage of the model building, as per Model #1. The variables that demonstrated a statistically significant association with the outcome were further analysed for strong correlations between each other.

3.2.1.5 MULTIPLE LINEAR REGRESSION ANALYSIS

The significant variables identified through the univariate analysis were subjected to a manual forward stepwise linear regression analysis[32]. The variable most highly correlated with the dependent variable, and with the most significant F statistic, was selected first. The approach that was taken was to conduct repeated analyses of the impact of adding a variable, or block of dummy variables representing a single variable, on the model in terms of the significance of the F-statistic and the change in R^2. At each step, a partial F test was made for each of the variables included in the model, and any that were found to be nonsignificant were removed.

At any step, if the largest partial F statistic for variables not yet included was not significant (at $p<0.15$), then the model building process was stopped. In addition, the increase in the R^2 was assessed to ensure that the addition of the

variable made a meaningful addition to the model along with its statistical significance. Variables for which the change in R^2 was <0.005 were not included in the model, in order to obtain a parsimonious result. Some authors suggest that a change in R^2 should be a few percent for any one variable[38], but I opted for less stringent criteria due to the exploratory nature of this research. It was my intent to identify meaningful predictor variables, which could lead to further hypothesis generation and testing. To be too restrictive with regard to the contribution to R^2 may confine further hypothesis generation and testing. It has been recommended that stepwise regression procedures using statistical criteria for entry of variables be regarded primarily as an exploratory strategy to investigate possible relationships to be verified on a second set of data[38]. Such was the approach in this research project.

As in Model #1, interaction terms were considered for inclusion in Model #2. Meaningful interaction terms that were statistically significant at $p<0.15$ when added one at a time to the main model were further assessed for their value in inclusion in the final model.

3.2.1.6 ASSESSING THE MODEL PERFORMANCE

The model performance was evaluated based on the square of the multiple correlation coefficient (R^2). There was no predefined target for explaining the variability in the clinical pharmacy services cost, as there were no comparable models identified through the literature search. Regression diagnostic tests were conducted, including a normal probability plot, histogram of residuals, and analysis of Cook's distance to detect outliers. Variance inflation factors and eigenvalues

were assessed, to identify potential problems of multicollinearity. The validity of the model was tested using the 1997/98 set of data.

3.2.2 MODEL VALIDATION

3.2.2.1 CHOICE OF VALIDATION APPROACH

In order to assess the validity of the chosen model a recommended approach is to use the estimated prediction equation from the first model and compute predicted values for the second group of data[32]. The new cross-validation correlation R_{-}^2 is determined, and the difference between R^2 and R_{-}^2, the *shrinkage on cross-validation*, is assessed. Shrinkage values less than 0.10 are deemed to indicate a valid model[32].

3.2.2.2 VARIABLE CODING

Consideration was given to making an adjustment for the changes in cost per unit of service between the two fiscal years, but this was found to be unnecessary. Although the cost per unit of service would change between the fiscal years, the relative amount of service received by patients in the validation data set would be equally well measured. There had been no changes to the relative workload values assigned to the clinical pharmacy services provided to patients.

4. RESULTS

4.1 GENERAL DESCRIPTIVE ANALYSIS

There were 19,936 inpatients admitted after March 31, 1996 and discharged by March 31, 1997 at the OGH. When the inclusion criteria for this study were applied, there remained 7597 cases for analysis and development of Model #1. Of the 7597 cases, 5058 (66.6%) had a record of receiving clinical pharmacy services. These 5058 cases formed the study population for Model #2 development.

In the 1997/98 validation data set, there were 7304 cases in the database that met the study criteria. Of these, 4915 cases (67.3%) had a documented record of receiving clinical pharmacy services.

When 1996/97 data were broken down by physician specialty, the percent of patients identified as cases ranged from a low of 9.6% (Otorhinolaryngology) to highs of 99% for Rheumatology and 100% for Geriatrics (Table 3). The number of cases within the specialties ranged from 13 (Anesthesia) to 2067 (General Medicine).

The mean age of the 1996/97 study population was 55.0 (std dev = 19.4) with a range from 13 to 100 (shown in Figure 1 with a normal curve). By CMG age group, the breakdown was as follows: 0-17 years, 60 cases (0.8%); 18-69 years, 5359 cases (70.5%); 70+ years, 2178 cases (28.7%). For the 1997/98 data, the mean age was 56.1 (std dev = 19.6) with a range from 14 to 102. CMG age group breakdowns for this fiscal year were: 0-17 years, 38 cases (0.5%); 18-69 years, 4950 cases (67.8%); 70+ years, 2316 cases (31.7%). The trend was toward an older population in the validation data set.

Figure 1 Age Distribution of Patients 1996/97

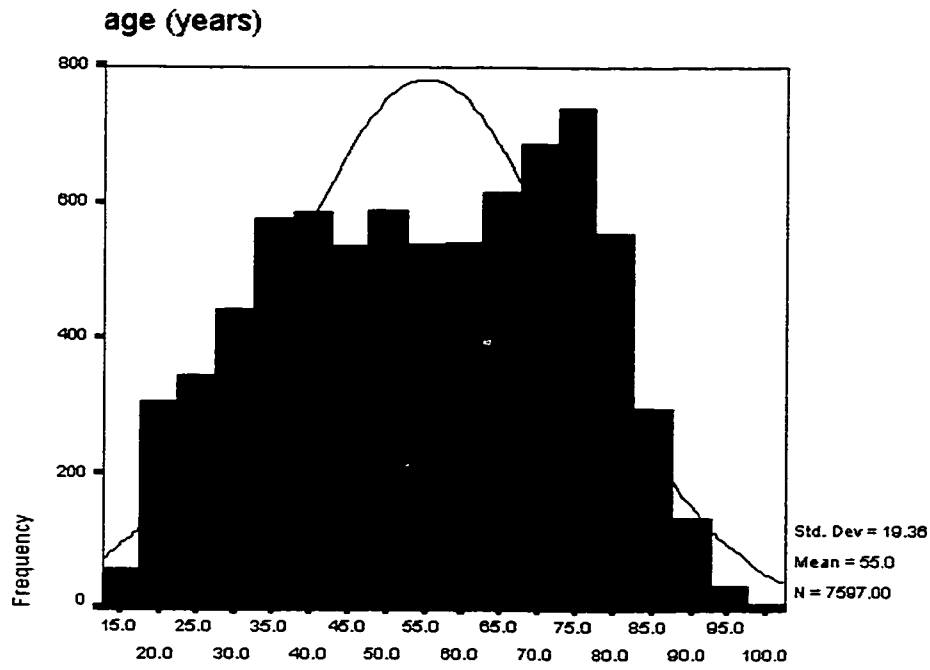

Table 4 IDPMAX Assignments for Encounters in Both Data Sets

	1996/97		1997/98	
IDPMAX CATEGORY	**Number of Patients**	**% Patients**	**Number of Patients**	**% Patients**
0	467	6.1	350	4.8
1	997	13.1	979	13.4
2	3015	39.7	2745	37.6
3	3118	41.0	3230	44.2
TOTAL	7597	100.0	7304	100.0

The drug category assignments were distributed unevenly across the two data sets. Table 4 summarises the frequency distribution for each.

The 1996/97 encounters had been coded to 201 different CMG categories. The number of patients in each CMG ranged from 1 (several CMGs) to 319 (CMG 294: Esophagitis, Gastroenteritis, Miscellaneous Digestive Diseases). The 1997/98 encounters were distributed across 198 different CMG categories, with CMG 294 retaining its status as the category with the largest number of cases (n=343).

By Major Clinical Category, the number of encounters included in the 22 categories to which the 1996/97 patients had been assigned ranged from 11 (MCC 12: Diseases and Disorders of the Male Reproductive System) to 1148 (MCC 5: Diseases and Disorders of the Circulatory System). For the 1997/98 data set, there were 23 different MCC assignments, with a range in case volume from 1 (MCC 99: Ungroupable Data) to 1076 (MCC 5).

The length of stay distribution was severely skewed to the right (Figure 2) and was remarkably consistent between the two fiscal years. The median length of stay of all 1996/97 patients was 4.0 days. The mean* length of stay for this fiscal year was 7.4 days (std dev = 9.7), with a range from 1 to 162 days. In the 1997/98 data set, the median length of stay was also 4.0 days, and the mean length of stay remained at 7.4 days (std dev = 10.5), with an identical range of 1 to 162 days. In both fiscal years, 80% of the cases had a length of stay of 10 days or less.

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* Mean LOS is reported for reference, to facilitate comparisons with other studies on hospital resource utilisation

Figure 2 Length of Stay Distribution of Patients 1996/97

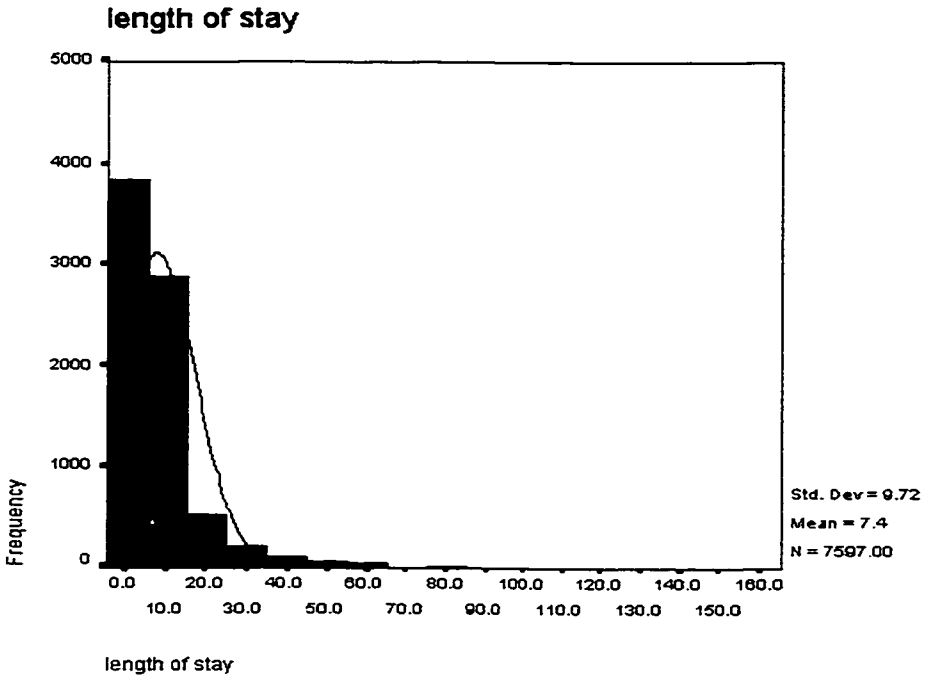


Table 5 Complexity Levels for Encounters in Both Data Sets

		1996/97		1997/98	
Complexity Level	**Complexity Level Description**	**Number of Patients**	**% Patients**	**Number of Patients**	**% Patients**
1	No complexity	4995	65.7	4459	61.0
2	Complexity: Chronic Conditions	753	9.9	855	11.7
3	Complexity: Serious/Important Conditions	468	6.2	576	7.9
4	Complexity: Life-threatening Conditions	325	4.3	455	6.2
9	No Complexity Applied	1056	13.9	959	13.1
TOTAL		7597	100.0	7304	100.0

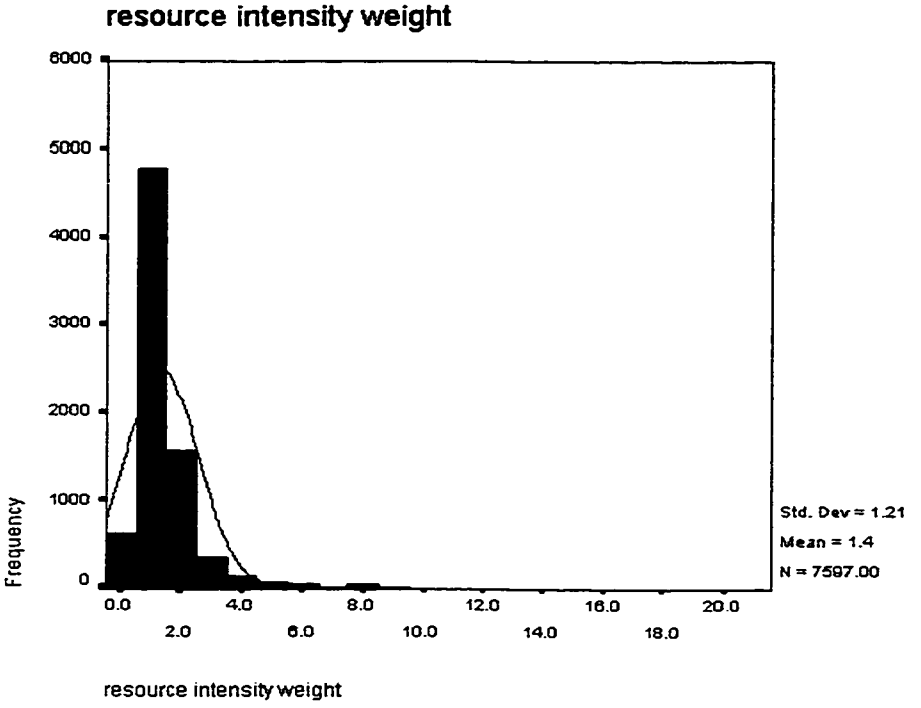
Analysis of the complexity level assignments revealed that over 60% of the patients had no complexity, and another 13 to 14% of encounters had not been classified due to CIHI's exclusion criteria for the application of the complexity overlay methodology. The frequency distribution showed a pattern of somewhat higher complexity in 1997/98 (Table 5).

The resource intensity weights (RIWs) for the 1996/97 encounters had a mean value of 1.3517 (SD = 1.2143) and a range from 0.1137 to 21.4149. The RIW distribution was moderately skewed to the right (Figure 3). The mean value in 1997/98 was somewhat higher at 1.4421 (SD = 1.393) and the range slightly wider (0.1137 to 22.585).

The 1996/97 study population was approximately evenly split between males (47.4%) and females (52.6%), with one transsexual patient. The proportion of males was similar in 1997/98 (47.7%) and there were no transsexual cases in that data set.

There were no missing data points for any of the variables in the data set. All of the cases that were identified based on the inclusion and exclusion criteria for each model were included in each stage of the stepwise regression model building, to ensure comparability of the statistical results. The edit checks that are built into the clinical abstracting and decision support processing assure the completeness of the records that reach the database.

Figure 3 Resource Intensity Weight Distribution of Patients 1996/97



Prior to commencing the model development, a brief descriptive analysis was undertaken of the 182 cases which had been excluded based on the admit date criterion (ie. admit after March 31, 1996). The average length of stay was 24.7 days for these patients, compared with 7.4 days for the included patients. The percent receiving clinical pharmacy services was approximately the same at 64.3%, compared with 66.6% of those that met the admission criterion.

4.2 MODEL #1 – PATIENTS RECEIVING CLINICAL PHARMACY SERVICES

4.2.1 MODEL DEVELOPMENT

4.2.1.1 UNIVARIATE ANALYSIS

The results of the univariate analyses are summarised in Table 6, revealing that all variables except sex were associated with clinical pharmacy cases at a high level

of statistical significance. Sex was retained at this stage, however, as the p-value for the LRT chi-square statistic was < 0.25 for this variable.

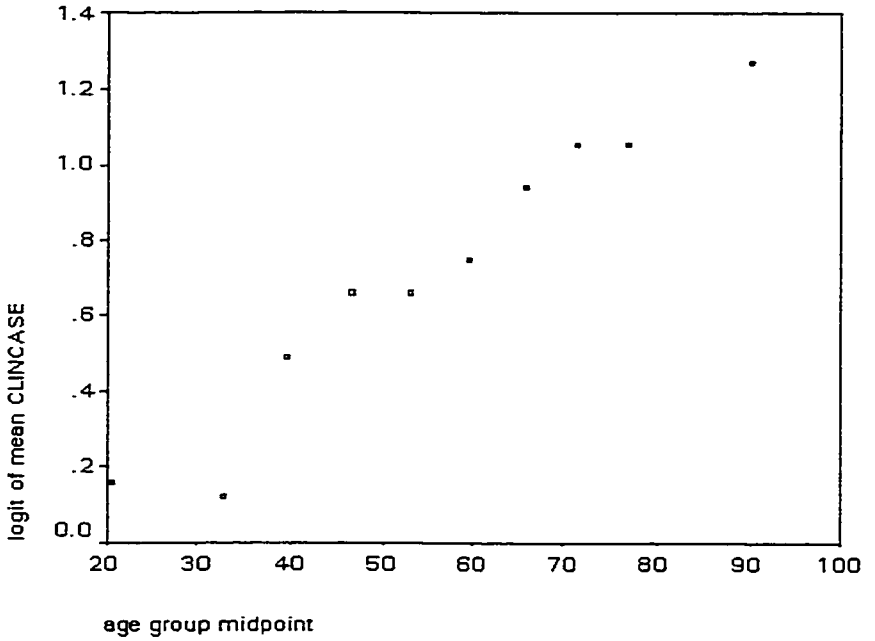
Table 6 Results of Univariate Analyses for Model #1 1996/97

VARIABLE	TYPE OF VARIABLE	-2 LOG LIKELIHOOD	LRT CHI-SQUARE STATISTIC	DEGREES OF FREEDOM	P-VALUE FOR LRT CHI-SQUARE
INITIAL (with constant)		9680.412			
ATTENDING MD SPECIALTY	NOMINAL	7921.418	1758.994	21	0.0000
MD GROUP	NOMINAL	8326.338	1354.074	6	0.0000
AGE (YEARS)	CONTINUOUS	9475.431	204.981	1	0.0000
CMG AGE GROUP	NOMINAL	9566.802	113.610	2	0.0000
IDPMAX	NOMINAL	8512.665	1167.747	3	0.0000
CMG	NOMINAL	7957.693	1722.719	200	0.0000
MCC	NOMINAL	9101.391	579.021	21	0.0000
LOS	CONTINUOUS	8704.631	975.781	1	0.0000
COMPLEXITY	NOMINAL	9186.591	493.821	4	0.0000
RIW	CONTINUOUS	8686.788	993.624	1	0.0000
SEXCODE	NOMINAL	9673.899	6.513	2	0.0385

When age was analysed as a continuous variable, using decile groups based on case volumes, a plot of the logit of the proportion of clinical pharmacy cases in the

age group (ie. logit of mean CLINCASE) versus the midpoint of the age group (Figure 4) supported the use of this variable without scaling transformation.

Figure 4 Logit of Mean CLINCASE vs. Age Group Midpoint 1996/97



A corresponding review of the plot of the logit of the outcome versus the midpoint of similarly created length of stay groups revealed that there was not a linear relationship in this case (Figure 5). A logit-type transformation was chosen as more appropriate for linear relationship, and a new variable LOGITLOS [= lnLOS/(1 + lnLOS)] was created. The transformed variable (hereafter referred to in the text merely as length of stay) had a near linear relationship when the logit of the proportion of clinical pharmacy cases within the group was plotted against the group midpoint (Figure 6), confirming the statistical appropriateness of the strategy.

Figure 5 Logit of Mean CLINCASE vs. LOS Group Midpoint 1996/97

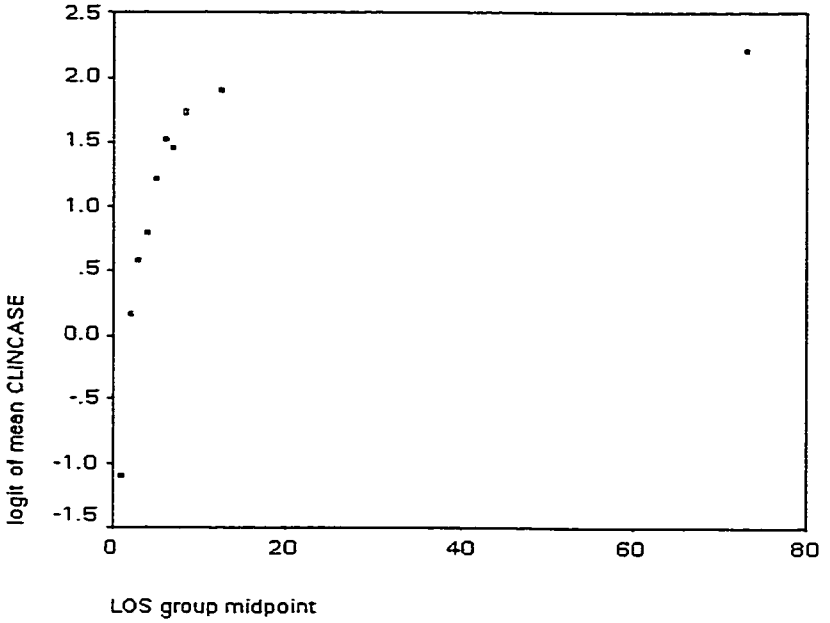
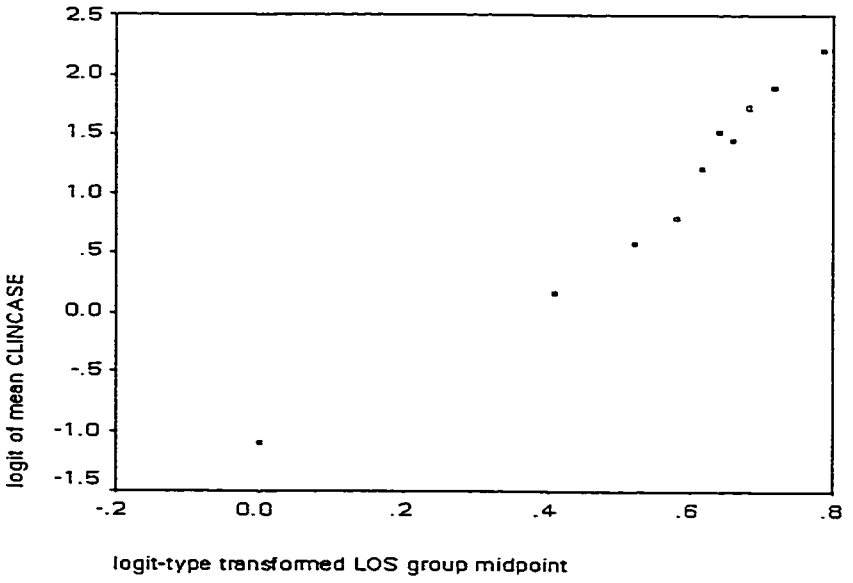
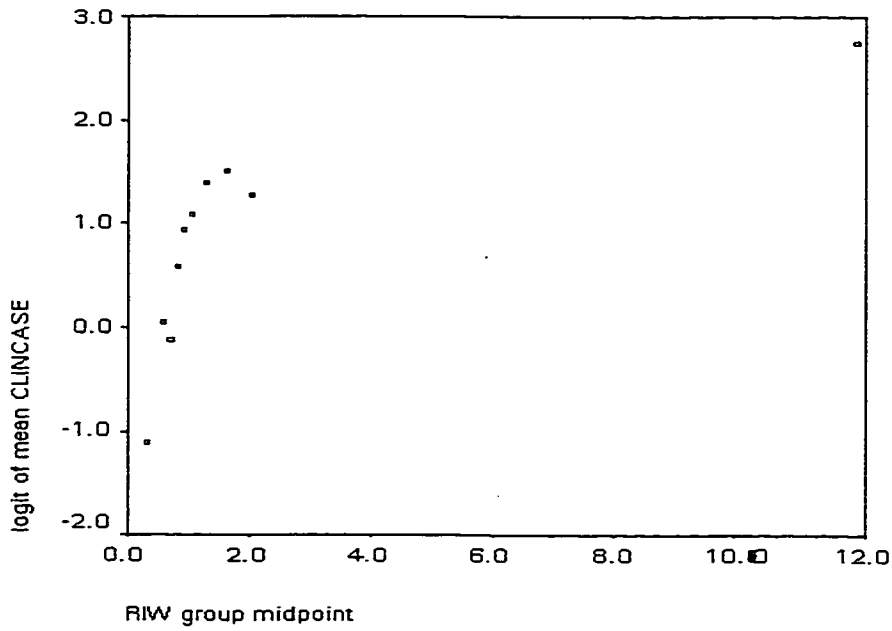


Figure 6 Logit of Mean CLINCASE vs. Transformed LOS Group Midpoint 1996/97



As with length of stay, the resource intensity weight showed a nonlinear relationship with the logit of the outcome (Figure 7). The same logit-type transformation of RIW was undertaken and LOGITRIW [= lnRIW/(1 + lnRIW)] was created as a new variable that was used in subsequent analyses.

Figure 7 Logit of Mean CLINCASE vs. RIW Group Midpoint 1996/97



The correlations between the independent variables were examined prior to the next stage of model development. The results of these analyses are summarised in Table 7. As was expected, there was a strong correlation (>0.90) between the physician specialty and the covariate MD GROUP. Physician specialty was also seen to be highly correlated with CMG (0.95) and MCC (0.91), which is plausible since physicians within the same medical specialty would tend to care for patients with similar clinical conditions. As well, CMG was found to be very highly

correlated with MCC (0.98), which was also as expected as the former groups are rolled up into the latter categories.

Table 7 Correlations Between Independent Variables in Model #1 1996/97

	ATTENDING MD SPECIALTY	MD GROUP	AGE (YEARS)	CMG AGE GRP	IDPMAX	CMG	MCC	LOS	COMPLEXITY	RIW	SEXCODE
ATTENDING MD SPECIALTY	1.00	**.93**	.16	.31	.49	**.95**	**.91**	.13	.67	.09	.25
MD GROUP		1.00	.13	.27	.47	.88	.84	.09	.66	.04	.09
AGE (YEARS)			1.00	.59	.07	.31	.14	.01	.10	.03	.00
CMG AGE GRP				1.00	.19	.45	.27	.01	.19	.03	.04
IDPMAX					1.00	.62	.47	.03	.36	.04	.07
CMG						1.00	**.98**	.26	.75	.28	.72
MCC							1.00	.10	.72	.05	.21
LOS								1.00	.15	.61	.00
COMPLEXITY									1.00	.25	.04
RIW										1.00	NA
SEXCODE											1.00

Correlations between continuous variables represented by R^2
Correlations between continuous and categorical variables represented by $(Eta)^2$
Correlations between categorical variables represented by Contingency Coefficient

Based on the univariate analyses and the assessment of the correlations, the decision was made to exclude some of the independent variables. The grouped physician specialties variable was not found to be more useful than the physician specialty from which it was derived. They both were statistically significant predictors, and they were highly correlated, so inclusion of both was redundant. Physician specialty was retained in order to avoid the loss of information that came with the regrouping. The trade off was that there would be more degrees of freedom used up with the increase in the number of categories, but with the large number of cases this was acceptable.

Similarly, CMG age group was a significant predictor but if retained in lieu of age, there would be loss of information for no benefit in the model. Both CMG and MCC were highly correlated with physician specialty. The latter variable, however, made the greatest contribution to the model as evidenced by the LRT chi-square statistic and its associated p-value, and it was a necessary inclusion since the deployment of pharmacy staff at the OGH was based on this factor. The decision was made to exclude CMG and MCC from further analysis. My experience in planning of hospital resources is that the impact of physician staffing additions is analysed at the physician specialty level, not at a CMG or MCC level.

The variables that were therefore retained for the multiple variable model building process were: physician specialty, age, drug category, length of stay, complexity level, resource intensity weight, sex.

4.2.1.2 MULTIPLE LOGISTIC REGRESSION ANALYSIS

The stepwise summary of the regression is provided in Table 8. The only variable that did not produce a statistically significant improvement in the LRT chi-square statistic was sex and it was therefore eliminated from further analysis. It was recognised at this stage that other variables (age, resource intensity weight) had statistical significance ($p<0.05$) but were producing little in terms of improvement in the classification of cases. Once the interaction terms were finalised, confounding and the fit of the model were assessed more rigorously to test the value of retaining these variables.

Table 8 Forward Stepwise Multiple Logistic Regression Model #1 1996/97

STEP	VARIABLE IN	-2 LOG LIKELIHOOD	MODEL CHI-SQUARE	MODEL df	MODEL CHI-SQUARE SIG.	CORRECT CLASSIFI-CATION (%)	SIG OF STEP IMPROVEMENT IN CHI-SQUARE
0	None	9680.41				66.58	
1	ATTENDING MD SPECIALTY	7921.42	1758.99	21	.000	74.69	.000
2	LOGITLOS	6409.68	3270.74	22	.000	80.81	.000
3	IDPMAX	6165.22	3515.19	25	.000	81.49	.000
4	COMPLEXITY	6137.43	3542.98	29	.000	81.57	.000
5	LOGITRIW	6130.94	3549.47	30	.000	81.57	.011
6	AGE	6126.37	3554.05	31	.000	81.65	.032

The results of the assessment of interaction terms are shown in Table 9. Based on a p-value < 0.15, the terms retained for further analysis are highlighted.

Table 9 Assessment of Interaction Terms in Model #1 1996/97

INTERACTION TERM	IMPROVEMENT IN CHI-SQUARE	df	p-VALUE	COMMENTS
ATTENDINGMDSPECIALTY*LOGITLOS	47.292	21	0.0009	
ATTENDINGMDSPECIALTY*IDPMAX	94.454	61	0.0039	Loss of 2 df due to design redundancies
ATTENDINGMDSPECIALTY*COMPLEXITY	83.830	77	0.2782	Loss of 7 df due to design redundancies
ATTENDINGMDSPECIALTY*LOGITRIW	26.797	21	0.1777	
ATTENDINGMDSPECIALTY*AGE	27.482	21	0.1555	
LOGITLOS*IDPMAX	3.627	3	0.3047	
LOGITLOS*COMPLEXITY	33.817	4	0.0000	
LOGITLOS*LOGITRIW	0.463	1	0.4963	
LOGITLOS*AGE	0.157	1	0.6922	
IDPMAX*COMPLEXITY	16.430	11	0.1259	Loss of 1 df due to design redundancies
IDPMAX*LOGITRIW	0.917	3	0.8214	
IDPMAX*AGE	7.599	3	0.0551	
COMPLEXITY*LOGITRIW	9.551	4	0.0487	
COMPLEXITY*AGE	8.953	4	0.0623	
LOGITRIW*AGE	0.004	1	0.9468	

The results of forward stepwise regression analysis of the interaction terms are shown in Table 10. The significant interaction terms identified at this stage were:

ATTENDINGMDSPECIALTY*LOGITLOS

ATTENDINGMDSPECIALTY*IDPMAX

COMPLEXITY*LOGITLOS

Table 10 Stepwise Logistic Regression of Interaction Terms in Model #1 1996/97

STEP	VARIABLE IN	-2 LOG LIKELIHOOD	MODEL CHI-SQUARE	MODEL df	MODEL CHI-SQUARE SIG.	CORRECT CLASSIFI-CATION (%)	SIG OF STEP IMPROVEMENT IN CHI-SQUARE
0	ATTENDING MD SPECIALTY LOGITLOS IDPMAX COMPLEXITY LOGITRIW AGE	6126.37	3554.05	31	.000	81.65	
2	ATTENDINGMDSPECIALTY* LOGITLOS	6079.08	3601.34	52	.000	81.93	.001
3	ATTENDINGMDSPECIALTY* IDPMAX	5980.47	3699.95	113	.000	82.31	.002
4	COMPLEXITY*LOGITLOS	5965.67	3714.74	117	.000	82.28	.005

While assessing the interaction terms, it became evident that there were some redundancies in the design matrix. A cross-tabulation of physician specialty and drug category revealed that two cells had a count of zero, and 7 others were less than 5. An examination of the Step 4 model after the removal of

ATTENDINGMDPSECIALTY*IDPMAX showed a slight degradation in the classification accuracy (from 82.28% to 81.98%), with a slight improvement in the Hosmer-Lemeshow Goodness-of-fit test (p-value changed from 0.6386 to 0.7469). I decided at this point to include only ATTENDINGMDSPECIALTY*LOGITLOS and COMPLEXITY*LOGITLOS in the final model.

Following the hierarchy principle, physician specialty, length of stay, and complexity level were mandatory inclusions for the final model since they were components of the interaction terms. The other three variables (age, resource intensity weight, drug category) could potentially be removed, if their contribution to the model was of little value and there was no evidence of confounding. The removal of both age and resource intensity weight produced no appreciable change in the regression coefficients or their confidence intervals. In addition, the classification accuracy without these variables was comparable at 81.83%. The decision was made to exclude these two variables as nonconfounders that were adding little to the model performance.

When drug category was removed from the model, there were many changes to the coefficients that were considered meaningful, the confidence intervals were not improved, and the classification accuracy decreased to 81.1%. The p-value of the Goodness-of-fit chi-square also became significant at 0.0011. The variable drug category was therefore judged to be required for inclusion in the model as an important confounder of the other effects, as its elimination produced undesirable results. The final model (Table 11; Appendix C) had a −2 Log Likelihood value of 6075.02, with a chi-square of 3605.39 and 54 df ($p=0.000$).

There were two variables that were associated with very high standard errors, the specialty Geriatrics and the interaction term of this same specialty with length of stay. The unstable estimates were due to the fact that all patients assigned to this specialty had received clinical pharmacy services. A repeat of the logistic regression analysis excluding this specialty produced a very similar model as when all cases were included. Thus, though this particular dummy variable was problematic, the group of physician specialties as a whole was a valuable predictor.

Table 11 Odds Ratios and Confidence Intervals for Final Model #1

VARIABLE	CATEGORY	ODDS RATIO	95% CONFIDENCE INTERVAL
ATTENDING PHYSICIAN SPECIALTY	Family Medicine	(reference)	
	General Medicine	1.5947	.7891, 3.2227
	Cardiology	.5034	.2300, 1.1018
	Nephrology	.4708	.1515, 1.4632
	Neurology	2.0489	.9402, 4.4651
	Rheumatology	21.4833	.4156, 1110.7
	General Surgery	.0921	.0311, .2726
	Neurosurgery	.3298	.1094, .9942
	Orthopedic Surgery	1.5222	.5825, 3.9781
	Plastic Surgery	.0740	.0091, .5991
	Thoracic Surgery	.0005	.0000, .0709
	Urology	.0749	.0210, .2676
	OBS/GYN	1.0406	.4658, 2.3247
	Anaesthesia	.9489	.0971, 9.2767
	Otorhinolaryngology	.0270	.0024, .3011
	Ophthalmology	.4785	.0577, 3.9672
	Psychology	.0416	.0075, .2294
	Haematology	1.3045	.5355, 3.1821
	Geriatrics	3.0×10^{6}	.0000, 3.1×10^{135}
	Medical Oncology	1.3840	.5711, 3.3538
	Radiotherapy	1.1948	.2700, 5.2871
	Vascular Surgery	.1566	.0229, 1.0725
LENGTH OF STAY (transformed)		20.4665	6.1804, 67.7758

IDPMAX (drug category)	No drug therapy	(reference)	
	Not likely to prompt service	1.7666	1.2263, 2.5449
	Somewhat probable to prompt service	3.3318	2.3661, 4.6918
	Highly probable to prompt service	6.5484	4.6018, 9.3182
COMPLEXITY	No complexity	(reference)	
	Complexity: chronic conditions	.4831	.2244, 1.0401
	Complexity: serious/important conditions	1.3426	.4772, 3.7774
	Complexity: life-threatening	.6393	.0943, 4.3355
	No complexity applied	.5429	.1824, 1.6157
ATTMDSP*LOS (Interaction term)	Family Medicine * Length of Stay	(reference)	
	General Medicine * Length of Stay	3.5277	.9538, 13.0469
	Cardiology * Length of Stay	1.9470	.4668, 8.1215
	Nephrology * Length of Stay	4.1912	.4452, 39.4539
	Neurology * Length of Stay	1.4328	.3382, 6.0709
	Rheumatology * Length of Stay	2.5983	.0014, 4960.6
	General Surgery * Length of Stay	3.2533	.4930, 21.4678
	Neurosurgery * Length of Stay	6.9533	.8537, 56.6327
	Orthopedic Surgery * Length of Stay	2.2135	.3163, 15.4916
	Plastic Surgery * Length of Stay	2.6769	.0657, 109.1258
	Thoracic Surgery * Length of Stay	7674.3584	2.3960, 2.5×10^{7}
	Urology * Length of Stay	.7832	.0756, 8.1186
	OBS/GYN * Length of Stay	.9253	.1916, 4.4676
	Anaesthesia * Length of Stay	4632.1346	.0000, 6.7×10^{16}
	Otorhinolaryngology * Length of Stay	3.1360	.0380, 259.1019
	Ophthalmology * Length of Stay	.0422	.0008, 2.2631
	Psychology * Length of Stay	10.5631	.6601, 169.0412
	Haematology * Length of Stay	.5670	.1029, 3.1247
	Geriatrics * Length of Stay	.0000	.0000, 3.4×10^{160}
	Medical Oncology * Length of Stay	2.4838	.4484, 13.7585
	Radiotherapy * Length of Stay	.4918	.0426, 5.6764
	Vascular Surgery * Length of Stay	.7954	.0316, 19.9994
COMPLEXITY*LOS (Interaction term)	No complexity * Length of Stay	(reference)	
	Complexity: chronic conditions * Length of Stay	5.9757	1.6336, 21.8593
	Complexity: serious/important conditions * Length of Stay	1.3302	.2383, 7.4255
	Complexity: life-threatening * Length of Stay	17.1004	.7721, 378.7526
	No complexity applied * Length of Stay	7.1139	1.0250, 49.3736

4.2.1.3 ASSESSING THE MODEL PERFORMANCE

The Hosmer-Lemeshow Goodness-of-fit chi-square statistic in the final model [physician specialty, length of stay, drug category, complexity level, ATTENDINGMDSPECIALTY*LOGITLOS, COMPLEXITY*LOGITLOS] was 6.6134 with 8 degrees of freedom (p = 0.5789). The classification matrix (Table 12), based on a cutpoint of 0.5 for group assignment, shows an overall accuracy of 81.8%. The sensitivity (true positive rate) was 90.3% while the specificity (true negative rate) was 65.0%.

Table 12 Classification Accuracy for Model #1 1996/97 Developmental Data Set

	PREDICTED 0	**PREDICTED 1**		**PERCENT CORRECT (%)**
OBSERVED 0	1651	888	2539	65.03 (SPECIFICITY)
OBSERVED 1	492	4566	5058	90.27 (SENSITIVITY)
	2143	5454	7597	81.83 (OVERALL)

The impact of selecting a different cutpoint was also assessed. Classification is sensitive to the relative sizes of the two component groups and will always favour classification into the larger group[33]. As two-thirds of the cases had received clinical pharmacy services (CLINCASE = 1), a probability cutpoint of 0.67 was considered. The result was that the specificity increased to 78.9% while the sensitivity decreased to 80.9% and the overall classification accuracy was lower at 80.2%.

The final model was judged to fit the data well, to be plausible, and to provide a reasonably accurate classification of cases in terms of clinical pharmacy services. The validation of the model in a second data set was undertaken to confirm the findings.

4.2.2 MODEL VALIDATION RESULTS

Using the regression coefficients from the final 1996/97 model, the probability of having received clinical pharmacy services for each of the 7304 patients in the 1997/98 data set was calculated. Using a cutpoint of 0.5, the patients were assigned to a predicted group. The classification results (Table 13) were then compared between the two fiscal years. There was no change in the specificity (65.0%), but a small decrease in both the sensitivity (from 90.3% to 88.8%) and the overall classification accuracy (from 81.8% to 81.0%). The results provided evidence that the model was valid in a second set of similar data.

Table 13 Classification Accuracy for Model #1 1997/98 Validation Data Set

	PREDICTED 0	**PREDICTED 1**		**PERCENT CORRECT (%)**
OBSERVED 0	1553	836	2389	65.01 (SPECIFICITY)
OBSERVED 1	549	4366	4915	88.83 (SENSITIVITY)
	2102	5202	7304	81.04 (OVERALL)

4.3 MODEL #2 – COST OF CLINICAL PHARMACY SERVICES RECEIVED

4.3.1 MODEL DEVELOPMENT

4.3.1.1 UNIVARIATE ANALYSIS

The clinical pharmacy services cost (outcome variable CLINCOST) was examined for its frequency distribution and was found to be skewed to the right (Figure 8). The mean value was 111.68 (std dev = 117.03) and the range was 8 to 1371. As the dependent variable, it should follow an approximately normal distribution and a log transformation (lnCLINCOST) was undertaken to achieve this (Figure 9).

Figure 8 Clinical Pharmacy Services Cost Distribution 1996/97

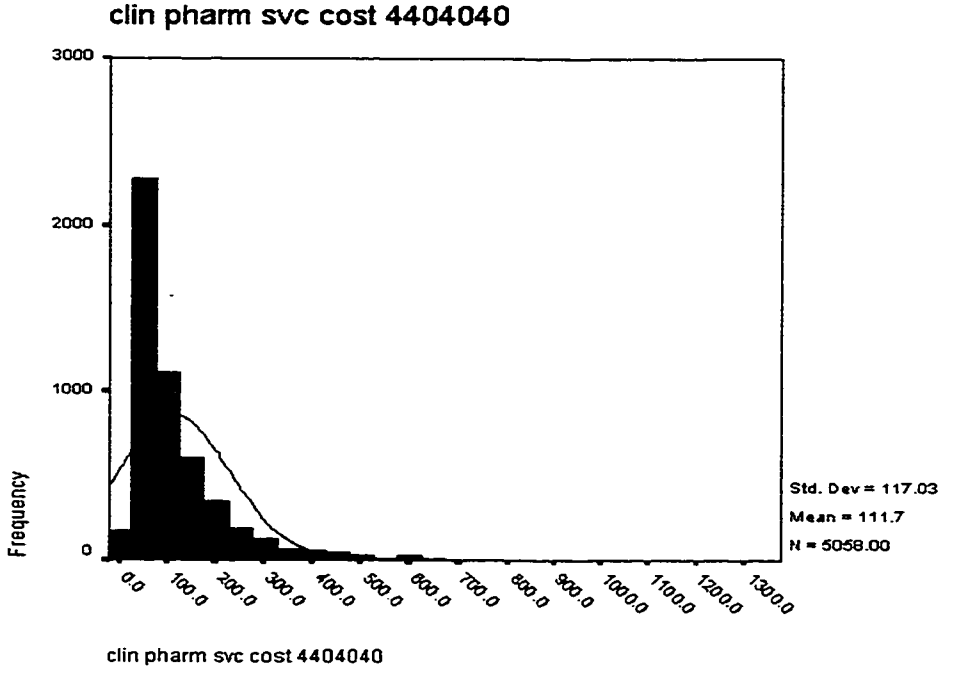
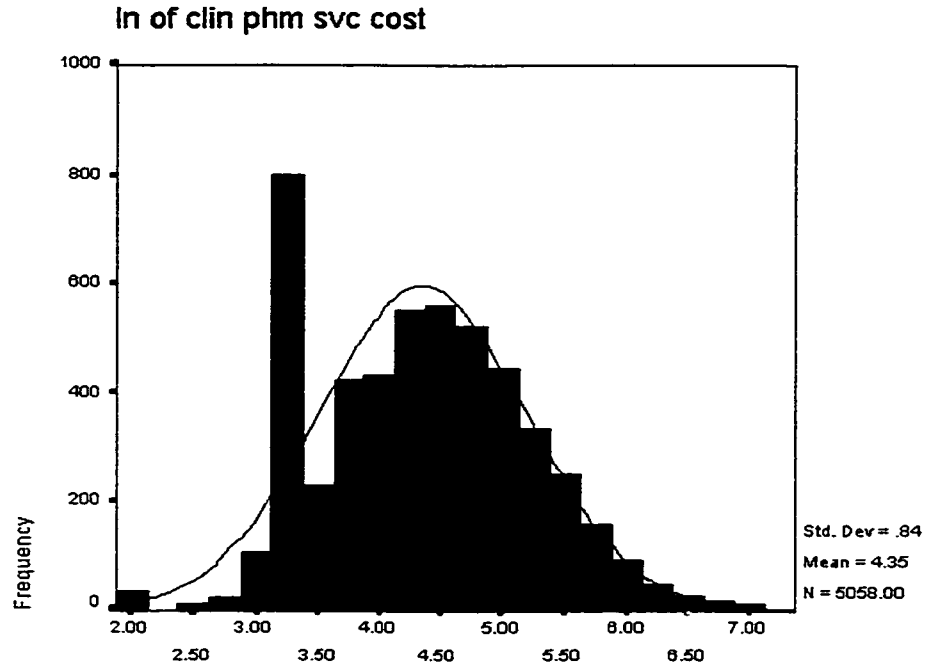


Figure 9 Log Transformation of Clinical Pharmacy Services Cost 1996/97

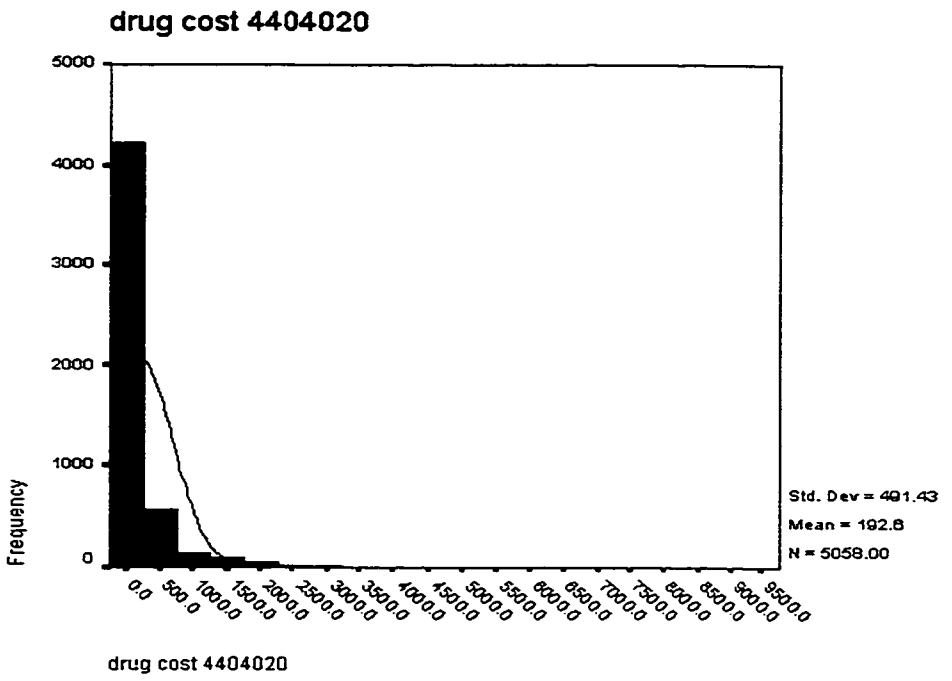


New independent variables that were considered in Model #2 development were drug cost and other cost. Drug cost is the dollar value of all drugs dispensed to the patient during their course of stay. For this study population, the mean was $192.60 (std dev = $491.43) with a range from $0 to $9301. Drug cost had a similar distribution (Figure 10) to clinical pharmacy services cost.

A scatter plot of the transformed clinical cost versus drug cost confirmed the nonlinear relationship with the dependent variable (Figure 11). As the cost variables are both expressed in monetary terms with similar scales, and clinical pharmacy services cost had been transformed, it was reasonable to consider a corresponding log transformation of drug cost. In order to transform drug cost, the value of $1 was added to each encounter so that there would be no $0 values. This new

derived variable for the modified drug cost (MDRUGCOST) was used in subsequent steps of the analysis.

Figure 10 Drug Cost Distribution for Patients Receiving Clinical Services 1996/97



The scale of the two cost variables after transformation was comparable, with a range of 2.08 to 7.22 for lnCLINCOST and 0.00 to 9.14 for lnMDRUGCOST. A better approximation of a linear relationship between the outcome and independent variable was confirmed (Figure 12).

"Other cost" is the cost of all hospital services provided to the patient less those amounts for drugs (the other new independent variable) and clinical pharmacy services (the dependent variable). The mean value of other cost was $2443.27 (std dev = $3205.45) and the range was from $78 to $43195. The frequency distribution was once again skewed to the right (Figure 13).

Figure 11 Ln[Clinical Pharmacy Services Cost] vs. Drug Cost 1996/97

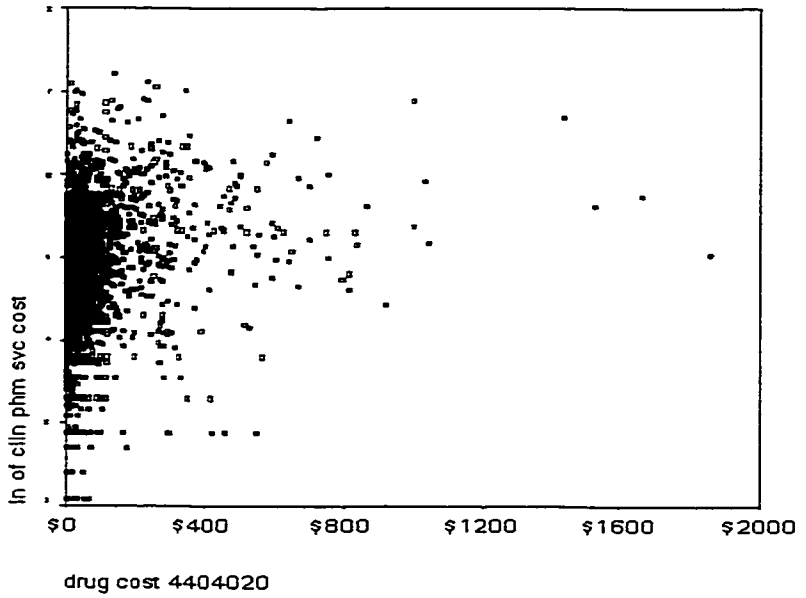


Figure 12 Ln[Clinical Pharmacy Services Cost] vs. ln[Drug Cost] 1996/97

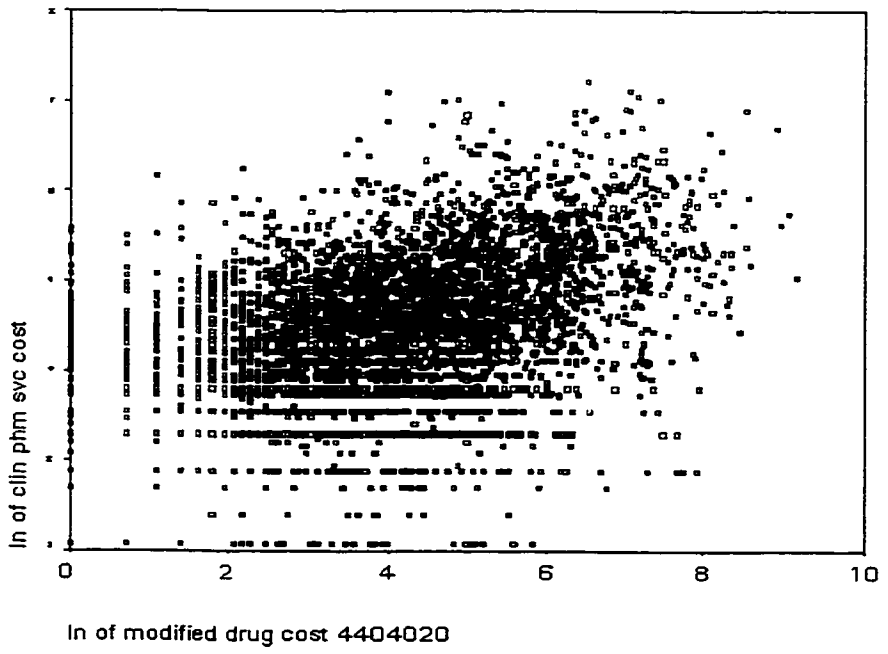
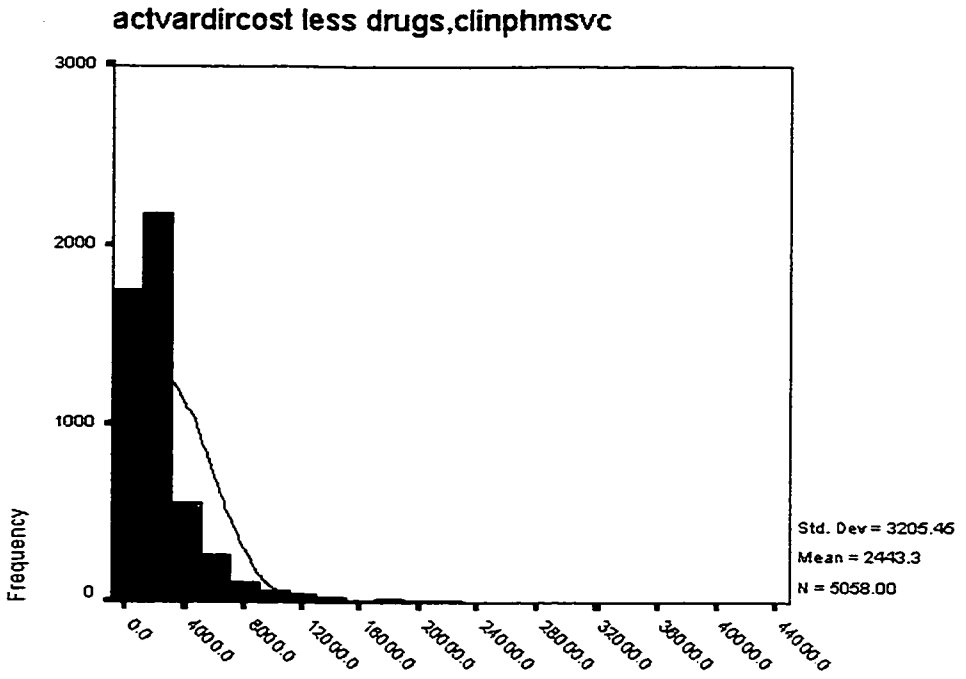


Figure 13 Other Costs Distribution for Patients Receiving Clinical Services 1996/97



The log transformation of the variable representing all other costs was undertaken and it showed improved linearity with the log transformed dependent variable (Figures 14, 15).

The ANOVA results are summarised in Table 14. From this univariate analysis, only sex was excluded from further consideration due to statistical non-significance (p-value for $F > 0.25$). The variable which has the strongest association with the outcome variable is lnOTHERCOST.

Figure 14 Ln[Clinical Pharmacy Services Cost] vs. Other Costs 1996/97

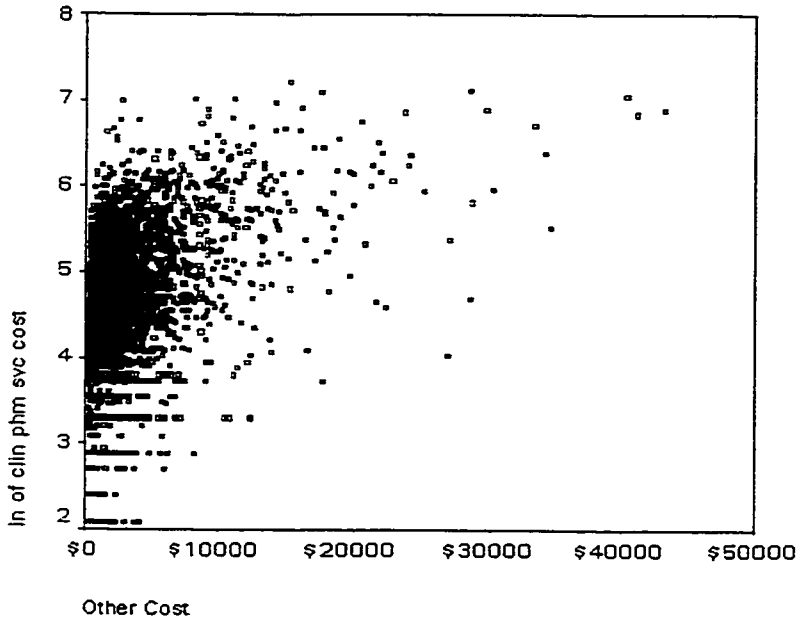


Figure 15 Ln[Clinical Pharmacy Services Cost] vs. Ln[Other Costs] 1996/97

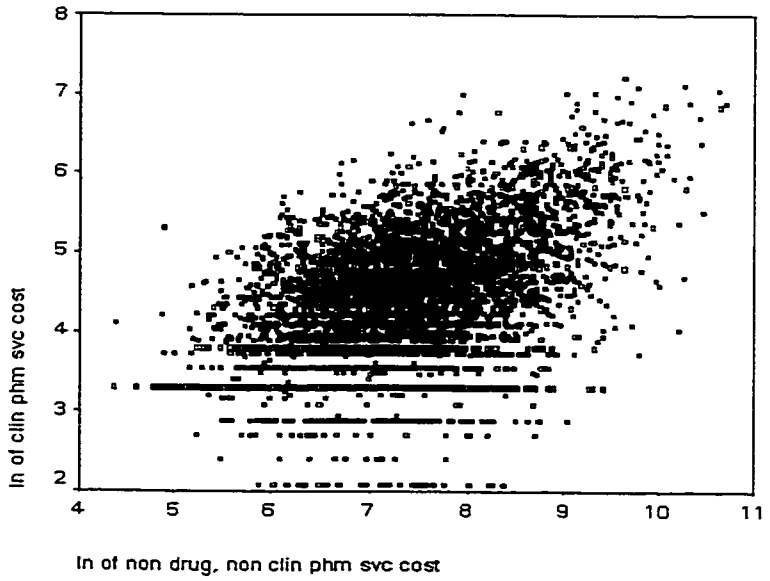


Table 14 Results of Univariate Analyses for Model #2 1996/97

VARIABLE	F STATISTIC	p-VALUE for F	R^2
ATTENDING MD SPECIALTY	22.302	.000	.085
AGE	17.028	.000	.003
IDPMAX	269.279	.000	.138
LOS	1111.352	.000	.180
COMPLEXITY	145.394	.000	.103
RIW	895.794	.000	.151
SEXCODE	.178	.673	.000
LnMDRUGCOST	1632.679	.000	.244
LnOTHERCOST	1733.101	.000	.255

The assessment of the correlations between the variables (Table 15) revealed no correlations >0.90 so there were no major concerns identified at this time. The variables that were considered in the next stage of model development were: physician specialty, age, drug category, length of stay, complexity level, resource intensity weight, drug cost, and other cost.

4.3.1.2 MULTIPLE LINEAR REGRESSION ANALYSIS

Having identified the variables of interest from the univariate analysis, the model was built in a stepwise fashion (Table 16). The variable indicated in bold is that which was assessed as most significant, and therefore included in the model for the next step. Complexity level was judged to add insufficient value to the model to justify its inclusion, based on a change in R^2 <0.005.

Table 15 Correlations Between Independent Variables in Model #2 1996/97

	ATTENDING MD SPECIALTY	AGE	IDPMAX	LOS	COMPLEXITY	RIW	lnMDRUGCOST	lnOTHERCOST
ATTENDING MD SPECIALTY	1.00	.11	.43	.15	.64	.07	.14	.07
AGE		1.00	.03	.01	.07	.02	.00	.02
IDPMAX			1.00	.01	.29	.02	.39	.05
LOS				1.00	.16	.61	.12	.53
COMPLEXITY					1.00	.24	.11	.22
RIW						1.00	.11	.39
LnMDRUGCOST							1.00	.24
LnOTHERCOST								1.00

Correlations between continuous variables represented by R^2
Correlations between continuous and categorical variables represented by $(Eta)^2$
Correlations between categorical variables represented by Contingency Coefficient

Consideration of the interaction of variables identified for inclusion in the main model was complicated by the fact that the two most significant predictors had undergone a log transformation in order to maintain a linear relationship with the log-transformed dependent variable. Aside from the difficulties surrounding the interpretability of complex interaction terms including the financial terms, the

experience in Model#1 development had identified difficulties in analysing interactions between categorical variables.

When the more easily interpretable interaction terms were included, the change in R^2 was 0.018 (LOS*ATTENDINGMDSPECIALTY) and .006 (LOS*IDPMAX), and all other variables remained significant when these were added individually to the main terms. To include the interaction terms would add to the model complexity and improve the explanatory power, but yield little in terms of the research objective of identifying the important variables. I decided that the final model (Table 17; Appendix D) would be assessed using just the terms identified in the forward stepwise analysis: other cost, drug cost, length of stay, drug category, physician specialty.

Table 16 Stepwise Building of Model #2 1996/97

STEP	VARIABLES INCLUDED	VARIABLES NOT INCLUDED	PARTIAL F STATISTIC	P-VALUE OF F STATISTIC	CHANGE IN R^2
1	none	AGE	17.028	.000	.003
		RIW	895.794	.000	.151
		LOS	1111.352	.000	.180
		LnOTHERCOST	**1733.101**	**.000**	**.255**
		LnMDRUGCOST	1632.679	.000	.244
		COMPLEXITY	145.394	.000	.103
		IDPMAX	269.279	.000	.138
		ATTENDING MD SPECIALTY	22.302	.000	.085
2	lnOTHERCOST	AGE	1.02	.312	.000
		RIW	60.327	.000	.009
		LOS	47.573	.000	.007
		LnMDRUGCOST	**612.373**	**.000**	**.080**
		COMPLEXITY	27.410	.000	.016
		IDPMAX	201.510	.000	.080
		ATTENDING MD SPECIALTY	39.518	.000	.105
3	LnOTHERCOST LnMDRUGCOST	AGE	.101	.751	.000
		RIW	52.323	.000	.007
		LOS	56.161	.000	.007
		COMPLEXITY	11.862	.000	.006
		IDPMAX	52.317	.000	.020
		ATTENDING MD SPECIALTY	**29.359**	**.000**	**.072**
4	LnOTHERCOST LnMDRUGCOST ATTENDING MD SPECIALTY	AGE	.371	.543	.000
		RIW	26.849	.000	.003
		LOS	32.873	.000	.004
		COMPLEXITY	7.717	.000	.024
		IDPMAX	**50.889**	**.000**	**.017**
5	LnOTHERCOST LnMDRUGCOST ATTENDING MD SPECIALTY IDPMAX	AGE	.124	.725	.000
		RIW	30.364	.000	.003
		LOS	**44.223**	**.000**	**.005**
		COMPLEXITY	5.679	.000	.003
6	LnOTHERCOST LnMDRUGCOST ATTENDING MD SPECIALTY IDPMAX LOS	AGE	.003	.953	.000
		RIW	2.976	.085	.000
		COMPLEXITY	6.152	.000	.003

Table 17 Regression Coefficients and Standard Errors for Final Model#2

VARIABLE	CATEGORY	UNSTANDARDIZED COEFFICIENT	STANDARD ERROR
ATTENDING PHYSICIAN SPECIALTY	Family Medicine	(reference)	
	General Medicine	-.09741	.043
	Cardiology	-.274	.052
	Nephrology	-.158	.083
	Neurology	-.04335	.048
	Rheumatology	1.022	.077
	General Surgery	-.435	.065
	Neurosurgery	-.318	.081
	Orthopedic Surgery	.113	.067
	Plastic Surgery	-.666	.176
	Thoracic Surgery	-.814	.142
	Urology	-.660	.124
	OBS/GYN	-.042	.062
	Anaesthesia	.139	.246
	Otorhinolaryngology	-.867	.197
	Ophthalmology	-.953	.245
	Psychology	-.102	.054
	Haematology	.137	.059
	Geriatrics	.245	.133
	Medical Oncology	.106	.053
	Radiotherapy	-.008	.069
	Vascular Surgery	-.529	.160
OTHERCOST (transformed)		.291	.016
DRUGCOST (transformed)		.0805	.008
IDPMAX (drug category)	No drug therapy	(reference)	
	Not likely to prompt service	-.138	.088
	Somewhat probable to prompt service	.0042	.085
	Highly probable to prompt service	.274	.088
LENGTH OF STAY		.0086	.001

4.3.1.3 ASSESSING THE MODEL PERFORMANCE

The R^2 value of 0.431 for the final model (Appendix D) means that approximately 43% of the variability in the outcome variable is explained by the model. There was no benchmark comparison for this value found in the literature search, but it was considered to be a meaningful result. The more important consideration at this time was whether the regression diagnostic test results were satisfactory, and whether the model would perform equally well with a new set of data.

The normal probability plot (Figure 16), histogram of the standardised residuals (Figure 17) and plot of the standardised residuals versus predicted values (Figure 18) confirmed the appropriateness of the standard regression assumptions of normality and homoscedasticity[32]. The maximum Cook's distance was 0.035, which is well below the value of 1.0 at which one might become concerned about outlier influence[32].

The variance inflation factors (VIF) and eigenvalues were assessed to identify problems of multicollinearity. There were no two independent variables (or groups of dummy independent variables) for which the VIF values were greater than 10.0. A review of the eigenvalues and the associated condition index values (no two were greater than 30.0) confirmed that multicollinearity was not a problem in the model.

A summary table of the variables included in the two final models (Table 18) provides a concise overview of the similarities and differences.

Figure 16 Normal Probability Plot of Standardised Residuals for Model #2 1996/97

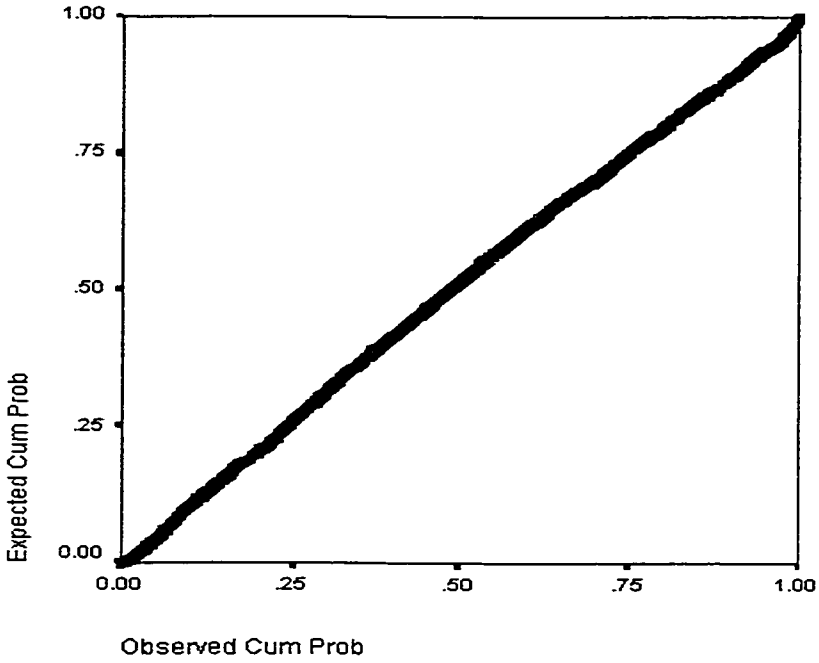


Figure 17 Histogram of Standardised Residuals for Model #2 1996/97

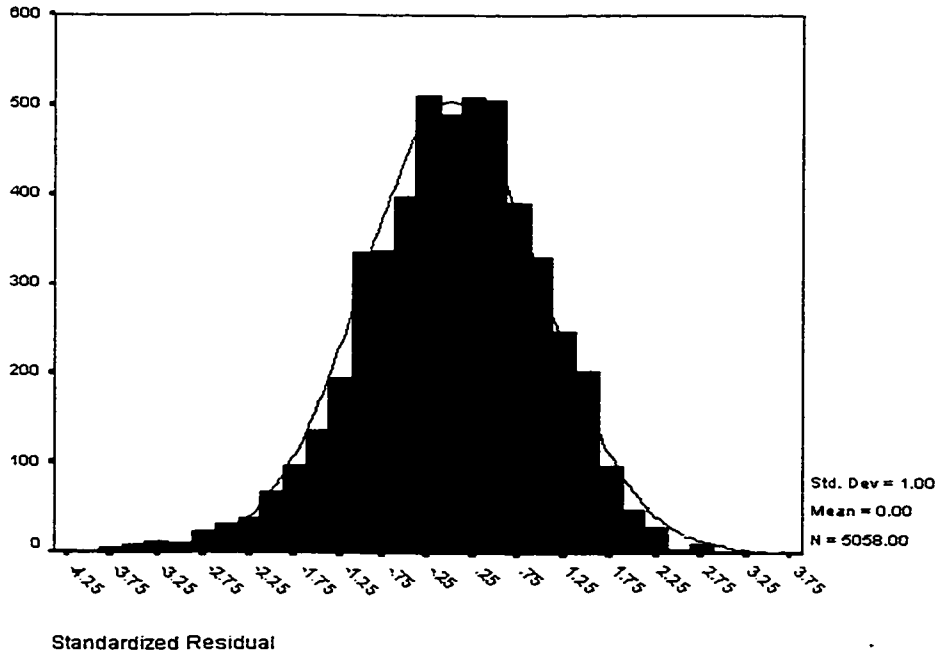
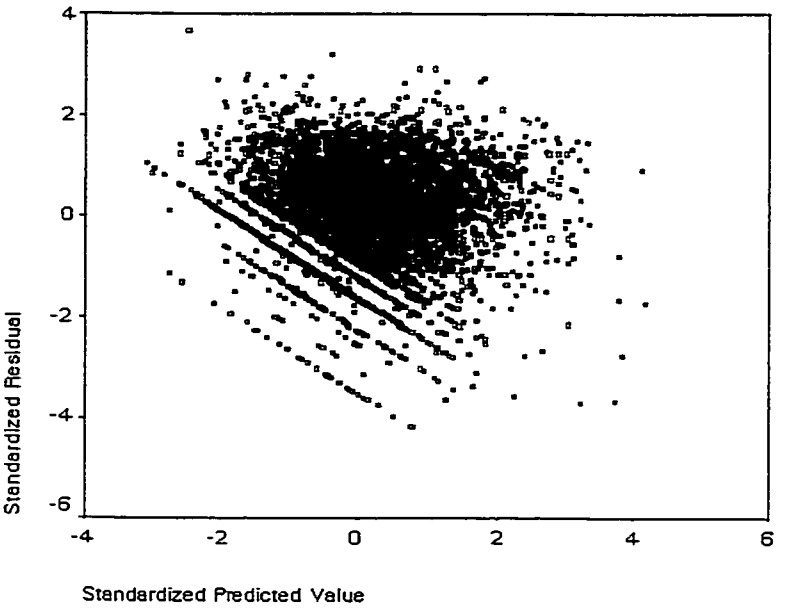


Figure 18 Standardised Residuals vs. Predicted Value Model #2 1996/97



4.3.2 MODEL VALIDATION RESULTS

The variables and coefficients identified in the model development using the 1996/97 data set were used to predict the clinical pharmacy services cost for the encounters in 1997/98. Analysis of the association between the predicted costs and the actual costs in 1997/98 revealed an R^2 value of 0.399. The change in R^2 between the two data sets was calculated as 0.032 (0.431 - 0.399). This shrinkage value, being less than 0.10, provided evidence of the reliability of the model.

Table 18 Summary Table of Variables Included in Final Models #1, #2

Model #1	Model #2
Length of Stay	Length of Stay
Drug Category	Drug Category
Physician Specialty	Physician Specialty
Complexity Level	Other Costs
Interaction term [Physician Specialty and Length of Stay]	Drug Costs
Interaction term [Complexity Level and Length of Stay]	

5. DISCUSSION

5.1 GENERAL

The aim of this research project was to develop valid models from administrative data in order to identify the patient level variables most strongly associated with clinical pharmacy services, using epidemiologic methods. Two models were successfully developed and validated, one to classify patients as to whether they would receive any clinical pharmacy services and the other to estimate the extent of services received. The models have some commonality in their predictor variables, as well as some differences.

5.2 MODEL #1 – PATIENTS RECEIVING CLINICAL PHARMACY SERVICES

The model that was developed to classify patients in terms of their probability of receiving clinical pharmacy services included the following independent variables: Physician specialty, length of stay, drug category and complexity level. The analysis of interaction terms demonstrated that there was significant interaction between physician specialty and length of stay as well as complexity level and length of stay. The effect of these three variables cannot therefore be described without the consideration of the level of the interacting variable. The large number of categories resulting from the dummy variable creation for the three nominal variables, and the required transformation of length of stay, defy a simple summary interpretation of the coefficients associated with the many terms in the model. An assessment of the clinical plausibility of the interaction terms is, however, an important step in the model development process.

Regarding the interaction of physician specialty and length of stay, it is conceivable that for some physician specialties, length of stay would be a less important predictor of clinical pharmacy services than for other specialties. For Hematology, for example, where 76.8% of cases are seen by the pharmacist, length of stay does not increase the odds of receiving clinical services in the same manner as it does for General Surgery. This is plausible, as General Surgery cases are less closely monitored by the pharmacists than the hematology patients, and receive services only when issues arise during the course of their stay. It is reasonable to expect that the longer the patient stays in the facility, the more likely it is that they will have pharmacotherapy related issues that prompt a pharmacist's intervention. For the Hematology cases, the delivery of pharmacy services is more proactive and routine, and length of stay would thus be a less important predictor.

Similarly, it is feasible to consider that patients with different levels of complexity might reveal different patterns of the impact of length of stay on the outcome of receiving clinical services.

The final model had an overall accuracy of 81.8% in the developmental data set. Upon validation, this performance remained high at 81.0%. With a classification cutpoint of 0.5, the model overestimates the need by 7.8% (5454/5058), but yields a high sensitivity at 90.3%. When the cutpoint is increased to 0.67, reflecting the observed prevalence among the study population, the need is underestimated by 8.5% (4627/5058) and fewer patients who received clinical services were accurately classified in this group. From the point of view of erring on the side of

caution, it would be preferable to use the 0.5 cutpoint for the model so that the patients likely needing services would be classified in the correct group.

The confirmation of the significance of the physician specialty assignment was important, as this is the basis upon which the pharmacists are deployed to the patient areas. Other large teaching hospitals follow a similar practice, as the unique demands of the patients admitted to specialty services in tertiary care centres require specialised knowledge from the pharmacists as well as the physicians and other health care professionals.

The statistical significance of length of stay is also an important finding, as this is perhaps the most commonly referenced variable when reporting resource utilisation. The nonlinear relationship of length of stay with the outcome necessitated the transformation of this variable. It is sufficient to say at this time that length of stay is an important determinant and that it must be considered in similar model building activities that pertain to clinical pharmacy resource allocation.

The importance of drug category is consistent with the pharmacists' perception that the patient's drug regimen is one of the most critical factors in their decision to provide clinical services. The rating process employed in this study proved to be valuable in predicting patients who would receive pharmacists' attention. With all other variables constant, the odds ratios of receiving clinical services were 1.77 (95% CI 1.23 to 2.54), 3.33 (95% CI 2.37 to 4.69) and 6.55 (95% CI 4.60 to 9.32) for IDPMAX categories of 1, 2 and 3 respectively when compared to patients who received no patient-specific drug therapy. Although there is a slight overlap in the confidence intervals, it is clear that the categorisation of the intermediate drug

products provides a solid foundation upon which one might develop a flagging system during the order entry process.

The inclusion of complexity level in the final model is also important from the perspective of confirming that the complexity overlay methodology from CIHI, which assists in the refinement of the grouping methodology, is actually useful in terms of differentiating patients with regard to the delivery of pharmacy services.

One of the most significant findings of this research is that the Resource Intensity Weight is not statistically significant once the other variables are included in the model. Resource intensity weights are used to express the resource needs of cases relative to an average case, but this study suggests this may not apply to the delivery of clinical pharmacy services. The findings are further substantiated in the development of Model #2. As the RIWs have been recently re-calibrated based on Canadian data, this relationship should be re-examined to see if there is a stronger association with the new weights.

Age was not found to be a strong predictor in the final model. This is a reasonable finding, as the other determinants are more important to the clinicians than would be the consideration of age. In the univariate logistic regression analysis, virtually all patients (99.2%) were predicted to receive clinical services when using the CMG age group categories. This was clearly not a useful factor to consider in differentiating the outcome groups. Similarly, sex was not an important predictor.

Though Case Mix Groups and Major Clinical Categories were found to be highly associated with the outcome, the physician specialty is so closely aligned with

these variables, and with fewer possible categories, that the latter was identified as the more important factor. For facilities that do not deploy their staff on the basis of medical specialties, it is conceivable that CMG could be found to be a more important predictor. This would be another area for future research and validation in another facility.

Model #1 was found to be a valid, parsimonious model that was successful in classifying over 80% of patients in terms of whether they would receive clinical pharmacy services.

5.3 MODEL #2 – COST OF CLINICAL PHARMACY SERVICES RECEIVED

The model created to predict the amount of clinical pharmacy services received, measured in dollars, was successful in explaining 43.1% of the variability in the outcome. This was only slightly lower in the validation step (39.9%). The most important predictor variables were: drug cost, other cost, length of stay, drug category and physician specialty.

The association that was identified between the clinical pharmacy costs and drug costs is consistent with the concept that as drug therapy costs increase there is likely to be more intensive service by the clinicians. We have heightened the awareness among the pharmacists of the need to use the most cost-effective approach to drug therapy. Staff is aware of the high cost drugs, and these are often associated with the need for careful monitoring for such outcomes as adverse reactions and abnormal laboratory tests.

The explanatory contribution of OTHER costs was also more confirmatory than remarkable as it was expected that patients using more hospital resources in

general would have a similar demand for clinical pharmacy services. The R^2 value is the highest of any of the variables (0.26), and there is a strong statistical significance.

Length of stay is a known driver of hospital costs, for each day of stay results in the delivery of services to patients in the nature of basic nursing services, and other direct operating expenses such as medications, lab tests, and therapeutic services. Though patients often have higher intensity of services early in their hospital stay, due to active investigation activities and interventions, maintenance costs persist even for long term stable patients.

Once again, the drug category was found to have an important association with the delivery of pharmacy services. It is understandable, since pharmacists would tend to track patients more closely if they are receiving the medications identified as important factors for the clinicians. The physician specialty remained a significant predictor in Model #2, consistent with the staff allocation strategy at this facility.

Variables that were considered but not included in the final model were: age, complexity level, resource intensity weight, and sex. Though age and sex are readily accepted as necessary considerations that were not likely to play a key role, complexity level and resource intensity weight warrant further comment.

The patients who are more complex in terms of comorbid conditions could reasonably be expected to receive more clinical pharmacy services due to more complex drug therapy. From the univariate analysis, complexity explained only 10.3% of the variability in the outcome. This is due to the categorical nature of the

variable, and the fact that there is a high degree of variability with respect to the amount of pharmacy services received, within each category.

The RIW has an even more solid rationale for having an association with the outcome. As previously noted, hospitals in Ontario are funded using a formula that incorporates the resource intensity weight. Across a group of patients, the sum of the RIWs yields the total weighted cases. When comparing resource allocation between institutions, it is often the weighted cases value that is used as the denominator for benchmarking indicators, at both the facility and functional centre levels. This is intended to help ensure some consideration of the variation in mix of cases between facilities. Because the resource intensity weights are shown in this study to be of little value, in both models, there is convincing evidence that managers and policy makers should consider other approaches to benchmarking exercises at the functional centre level, at least in the case of pharmacy.

Though Model #2 explains just less than half of the variability in the cost of clinical pharmacy services, revealing information is provided by the model in terms of the variables that are identified as being significant (or notably non-significant) predictors.

5.4 ADMINISTRATIVE DATABASE AT THE OTTAWA GENERAL HOSPITAL

This study was unique in its approach to using an administrative database for the analysis of clinical pharmacy services. The strengths and limitations of such an approach must be considered.

Administrative databases usually originate from systems that provide or finance medical care and contain computerised records of encounters between patients and

health care providers. Four major problems have been noted when administrative databases are used in some types of retrospective studies for policy and program analysis: poor data quality, lack of concurrent controls, inability to ascertain essential study outcomes, and incomplete data on case mix[39]. For the purposes of the two research questions being addressed by this study, the decision support system at the Ottawa General Hospital was found to be of high quality and did not reveal these same issues. Considerable effort had been invested in implementing and maintaining the database that merges clinical, financial and statistical data. There are sufficient data quality checks built into the data processing steps of the database maintenance, that there were no missing data or invalid entries.

The study outcomes were definable with the data set, but there were limitations cited in terms of data elements that might otherwise have been confirmed as useful predictors had they been included in the data set (eg. >7 concurrent medications, unusual dosage, abnormal lab test results). The development of clinical data repositories is an active area of systems development in hospitals, and will provide these types of details in the future.

Case mix data were available in the decision support database in the form of CMGs, MCCs and resource intensity weights. The coding of these data elements is validated through processing edit checks at CIHI before being finalised in the OGH's data set, thus there is an external as well as internal review process.

It is acknowledged that the database is only as complete as the clinical activity documentation completed by the pharmacy staff. If the clinical staff fail to document fully then there is the risk of underestimating the population that received

clinical services, as well as the amount of services received. This could be a potential source of bias if it is not consistent across the study population. The likelihood of under-reporting is minimised by providing feedback to pharmacists in the form of graphical comparisons of their documented activities vis-à-vis peer clinicians and subsequent discussions of these profiles with their supervisors. It is also conceivable that over-documentation might occur, in an effort by staff to embellish their clinical workload. The likelihood of this being a factor is perceived as small, for the documentation serves as a legal record of the involvement of the professional staff with the patients and the implications of falsifying the information are significant.

The costing methodology used at the OGH is based on relative workload values for the different services provided by the various functional centres. If these are not founded on good information, then there will be a misallocation of the costs of services provided. In the case of clinical pharmacy, actual time studies were conducted just prior to the decision support system implementation, in order to establish standard times for each of the clinical activities. As a matter of routine practice, these are validated on a regular basis to ensure their ongoing relevance. The calculation of the standard workload units for each activity is less critical than the relative values between activities, as it is this latter consideration that determines the allocation of the resources studied in this type of research.

The use of the decision support system for epidemiologic studies is supported by this research. There is considerable potential to develop similar models for other disciplines, and to elaborate on this research in the area of clinical pharmacy. If

clinical results are incorporated into the system at a future date, and clinical outcomes are documented in the database, the value of such a system in quality management and resource utilisation will increase dramatically.

5.5 VALIDITY ISSUES, GENERALIZABILITY AND USE OF THE RESULTS

Since the outcome of interest and the potential predictor variables were assessed at the same point in time using the administrative database, observational studies of this type do not distinguish the temporal relationship between the pharmacist's clinical activity and the other variables[40]. For example, the pharmacist may have seen the patient because of a profile listing a medication ranked in a high IDP category, or the patient may have been switched to this medication subsequent to the pharmacist's monitoring activities. Cross-sectional studies such as this are therefore useful for descriptive analyses, and for formulating rather than for testing hypotheses. It is expected that the reported results will achieve this purpose.

As alluded to in the methods, there are limitations to using logistic regression in cross-sectional studies, due to the fact that the constant value is not meaningful[34]. The regression coefficients and odds ratios can still be estimated, however, so the approach is valid in terms of estimating the exposure-outcome association[34]. In terms of the objective of identifying the important predictor variables, therefore, the use of logistic regression was scientifically valid.

The study population had been restricted by admission and discharge criteria, to account for the changes to the IDP tables between fiscal years. Cases that were in-hospital on March 31 and stayed over into the new fiscal year were excluded for this reason. The number of excluded cases was relatively small, at 2.4% of those

that were fully analysed. Though a comprehensive comparison of the excluded cases with the retained cases was not conducted, it is reasonable to expect that the profile of cases would have been very similar between the two groups. The distribution pattern for length of stay and costs could be expected to have more extreme values due to a few long stay outliers. Most of the patients, however, would still be expected to have a normal length of stay since the fiscal year end is merely a defined cutpoint for accounting purposes. It is reasonable to conclude that the removal of these encounters would have no appreciable impact on the study.

The large number of cases in both fiscal years and the consistency of both the data collection and resource costing provided a solid basis for the model validation process. Using data from the same facility in a contiguous fiscal year ensured the comparability of the patient population and service providers since it was known that there had been no major changes in clinical pharmacy staff deployment. The generalizability of the study may be limited to facilities that offer a similar extent of clinical pharmacy services, specifically those that are larger teaching hospitals that focus these services on medical patients.

The assignment of categories to the IDPs by the clinical pharmacy staff was found to be feasible and valuable. Though there was not unanimous agreement of the codes for each IDP, the majority (65.6%) reached this level of consistency. In retrospect, it would be desirable to provide more stringent definitions of the categories used for the intermediate drug products to ensure their consistent interpretation by the pharmacists. In terms of categorising patients, it might also be desirable to develop an index that considers the mix and volume of IDPs that the

patient uses during the course of their stay. The sum of the drug category codes was not felt to be useful, since a patient may have received a number of IDPs that refer to the same drug with slightly different dosages. The complexity of the regimen would not have changed, though the sum of the codes would imply that it had. If concurrent drug therapy was analysed, then it is conceivable that an index considering the weighted value attached to each of the IDPs the patient was receiving at that time may prove useful.

The focus of this research was on the allocation of clinical pharmacy human resources. It would be ideal to ensure that the needs of patients are considered when allocating resources. Defining need is a major challenge for policy makers and others.

The White Paper[36] cites a number of criteria that might be used as a measure of patient need. Several of these factors were proven to be valid predictors of utilization, while others were not found to have a strong association in this study. Whether the guidelines should change, whether this facility's practice should change to be more compliant with the guidelines, or whether it is a matter of further prioritizing the criteria in light of limited resources remain open for debate.

Other researchers have proposed that health care need can be identified through different types of health and health care information, including health services actually used[41, 42]. Common statistics include: number of health services, number of persons receiving services, and services-per-patient rate.

Moves toward formula allocation of resources are in principle to be welcomed[43]. The basic problem in deciding allocation of health resources, however, is to find a

combination of factors reflecting dimensions of need and then to develop a set of "appropriate" weights to combine these factors into an overall measure of need. With the development of well-validated models using methodologies as done for this study, future research efforts might focus on the process of combining the variables into that overall measure. One must bear in mind that an allocation model should only play a contributing role in the allocation of resources, as it cannot explain 100% of the variability in the outcome. The application of such models in actual practice must be done with full consideration of the inherent strengths and limitations.

Whether one interprets the reported distribution of clinical pharmacy services as a measure of need, or whether it is merely descriptive of actual patterns of use, it is reasonable to consider such information as a starting point for policy development as it pertains to resource allocation for this discipline. Other approaches to more specifically defining patient need in terms of clinical pharmacy services would be complementary to studies of utilisation patterns such as this. Each of the models in this study could have their own practical applications with further supporting evidence from other practice settings.

The first model provides solid evidence that there are patient-level variables that can be used to predict patients who will receive clinical pharmacy services. The model forms the foundation for developing approaches to the identification of patients that will benefit from the clinical services. Ultimately, developments in this area may prove to have applicability at both an operational level, in concurrently identifying patients in need, as well as at a planning level. The attending physician

specialty is known at the time of admission, the drug category assignment can be identified upon entering medication orders into the pharmacy information system, the complexity level would be known in a facility with concurrent abstracting, and the length of stay can be monitored on a daily basis. The model suggests the feasibility of establishing an automated notification system for pharmacists, for patients likely to benefit from service, when all of the variables are incorporated into an integrated system with the appropriate algorithms built in. Pharmacy computer systems currently generate warnings associated with excessive dosages, therapeutic duplications, drug interactions and allergy checks. It is conceivable that the drug therapy itself, or patient's complexity level, could also be incorporated into these systems as an automated flag to prompt the action of a clinical pharmacist. More work would obviously be required in order to implement and test such an approach, but if it were successful it would enhance the efficiency of staff deployment, help ensure patients in need are not overlooked, and allow for quality assurance processes to be built into the information system.

The findings of the second model will be of considerable interest to those involved in the budgeting of pharmacy services and the development of comparative indicators. The resource intensity weights may perform quite well at the facility level, but this study suggests the need for caution when applying the same approach to the management of pharmacy, and perhaps other, services. These findings should be confirmed and validated in other institutional settings, and also reviewed in light of the re-calibration of the RIWs with Canadian data. Length of stay is also often incorporated into benchmark indicators for service delivery but

this study demonstrates the limited usefulness of this parameter in terms of the magnitude of the association with pharmacy costs. This research also demonstrates the importance of building consideration of the drug therapy regimen of patients into a resource allocation model. More work is required in this area, but there is now some good evidence that this is an important predictor.

Pharmacy managers are looking for models upon which to base their staffing strategies, to budget their resources, and to engage in benchmarking exercises with other peer institutions. The second model suggests that at least some of the factors that should be considered in these discussions include the attending physician specialty, the cost of other hospital services, the length of stay, and the drug therapy provided to the patients.

As future research efforts are directed to patient outcomes associated with the delivery of pharmacy services, the results of this study will also inform researchers about possible control variables which should be considered in their study design.

5.6 CONCLUSION

As this research is the first to examine the association between patient level variables and the delivery of clinical services using an administrative database, it will be important to replicate the findings in other settings. The models that were developed and validated provide pharmacy managers with information about what variables are useful in predicting which patients receive clinical pharmacy services (physician specialty, length of stay, drug category, complexity level) and to what extent (physician specialty, drug cost, other costs, length of stay, drug category). The future challenge is to determine which pharmaceutical services should be

provided for specific patients and where resources should be allocated to provide maximum cost-benefits[27]. It is believed the findings of this study will contribute to that effort.

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PRIORITIZATION OF DRUGS FOR DETERMINING WHETHER A PHARMACIST WILL PROVIDE CLINICAL SERVICE TO A PATIENT

OBJECTIVE:

The aim of this exercise is to assign a rating to 847 different "intermediate drug products" in terms of the likelihood that a pharmacist would provide clinical activities to patients receiving these medications.

BACKGROUND:

The General Campus has had a case costing database in place for over five years. This database includes all of the medications dispensed to patients, as well as all of the documented clinical pharmacy activities provided to patients. In terms of the drugs, all of our 3000 + services available in our patient care system have been grouped into what are called "intermediate drug products". You will see by their descriptions that some are merely 1:1 mappings with the services that are selected in the patient care system. Others are groupings of services which are clinically and financially similar, in order to reduce the volume of data to be analysed on a routine basis. Merging these pharmacy data with the patient clinical and demographic data provides many opportunities for research. This particular project involves the creation of a model to predict the patients who are likely to receive the attention of a clinical pharmacist. If all patients were seen, then the model would not be necessary. However, our data show that two thirds of our patients who are categorised as "medical" or "combined medical-surgical" are seen by the pharmacist. The identification of patient-specific variables that may be associated with the decision of a pharmacist to provide clinical pharmacy services is fundamental to this research. One variable which could likely determine whether the patient will receive our attention is the medication regimen the patient is receiving. In order to test this hypothesis, it is necessary to classify the different medications in terms of their likelihood that they would prompt a pharmacist to provide clinical service. The variable will then be put into the model to test its statistical association with the outcome (ie. Whether the pharmacist did indeed provide any service).

PROCESS: I have created three categories into which the drugs are to be assigned:

Rating of 1 = the drug is not likely to prompt a pharmacist to provide clinical service
Rating of 2 = it is somewhat probable that a pharmacist would provide service
Rating of 3 = it is highly probable that a pharmacist would provide service

Based on my expert panel (yourselves), I hope to reach consensus on the ratings of the intermediate drug products. I have made a preliminary "stab" at the classification based on the following principles:

Rating 1 – by default, all drugs, unless otherwise qualified, are given this rating
Rating 2 or 3 – specific drugs are classified as either 2 or 3 for one or more of the following reasons:

A. The drug is listed in those which have "Criteria for Use"
B. The drug is included in the IV to PO conversion program
C. The drug has prescribing restrictions
D. The plasma concentration of the drug is commonly monitored
E. Specific agents felt to likely result in clinical services, including:

- TPN
- Anti-infectives
- Study/investigational agents
- Replacement agents (or removing agents)
- Antidiabetic agents
- Antiepileptics
- Unusual and expensive agents

The rationale for rating the drugs as either category 2 or 3 is included on the sheets under the "reason" column for your edification. These data come from the fiscal year 1996/97, and the formulary status of agents at that time was used in the ratings (though there has been surprisingly little change in the last two years). NOTE THAT THE REASON IS NOT GOING TO BE CONSIDERED IN THE MODEL, IT IS STRICTLY THE RATING OF THE DRUG (as 1, 2 or 3) THAT IS IMPORTANT FOR THIS PROJECT.

Your are asked to review these preliminary ratings, indicate any suggested changes right on the sheets you have been provided with, and return them within a time frame of two weeks if at all possible. I will then review the responses, and determine if we need a meeting to discuss any apparent discrepancies.

THANK YOU FOR YOUR PARTICIPATION IN THIS EXERCISE. IT IS MUCH APPRECIATED AND CAN BE VIEWED AS JUST ANOTHER OF YOUR CONTRIBUTIONS TO RESEARCH ON CLINICAL PHARMACY SERVICES.

APPENDIX B EXCERPT OF LIST OF INTERMEDIATE DRUG PRODUCTS 1996/97

IP NUMBER	IP DESCRIPTION
4558	CLINDAMYCIN 900 MG INJECT
4563	CYCLOSPORIN 25 MG CAP INPT
4573	EPIRUBICIN > 100 MG INJECT
4574	EPO INJECT > 10 KU INPT
4575	ERYTHROMYCIN 1 G INJECT
4578	PAMIDRONATE INJECT 15-30 MG
4585	FLUCONAZOLE 100 MG TAB
4586	FLUCONAZOLE 200 MG INJECT
4589	GANCICLOVIR 0-500 MG INJECT
4591	FILGRASTIM 300 MCG
4629	TOBRAMYCIN < 100 MG INJECT
4631	VANCOMYCIN < 400 MG INJECT
4634	GENTAMICIN < 100 MG INJECT
4640	ERYTHROMYCIN ORAL SOLID
4643	PENICILLIN < 10 MU INJECT
4646	AMPICILLIN < 500 MG INJEC
4649	CLOXACILLIN 0-200 MG INJE
4650	CLINDAMYCIN ORAL CAP
4652	CIPROFLOXACIN 201-400 MG
4655	CIPROFLOXACIN 250 MG TAB
4656	PEN G PROCAINE 5 MU/BENZ 1.2MU
4658	METRONIDAZOLE INJECT
4662	ACYCLOVIR <= 200 MG ORAL
4600	INTERFERON A-2B 10 MU VIAL
4601	IPRATROPIUM RESP SOLN 5 MG
4603	LEUCOVORIN CA <= 50 MG INJECT
4605	LEUPROLIDE INJECT
4607	THYROID AGENTS INJECT
4608	MELPHALAN INJECT
4610	MIDAZOLAM 5 MG/1 ML VIAL
4738	LISINOPRIL TAB
4739	COAL TAR PREPARATIONS
4748	ETHAMBUTOL
4789	FLUCONAZOLE 400MG INJECT
4790	GANCICLOVIR 501-1000 MG I
4792	FILGRASTIM 480 MCG
4795	IMIPENEM 500 MG INJECT
4797	IPRATROPIUM 0.5MG/2ML UD

```
      Number rejected because of missing data:  0
      Number of cases included in the analysis: 7597

Dependent Variable..   CLINCASE   clinical pharmacy case
Beginning Block Number  0.  Initial Log Likelihood Function

-2 Log Likelihood    9680.4119
* Constant is included in the model.

Variable(s) Entered
          ATTMDSP   attending md specialty
          LOGITLOS  ln LOS/(1+ ln LOS)
          IDPMAX    IDP MAX RATING AT ENCTR LEVEL
          COMPLEX   complexity level
          ATTMDSP * LOGITLOS
          COMPLEX * LOGITLOS

Estimation terminated at iteration number 5 because
Log Likelihood decreased by less than .01 percent.

 -2 Log Likelihood          6075.021
 Goodness of Fit            8124.199

                     Chi-Square     df Significance

 Model                  3605.391     54         .0000
 Block                  3605.391     54         .0000
 Step                   3605.391     54         .0000

---------- Hosmer and Lemeshow Goodness-of-Fit Test-----------

    CLINCASE = 0                CLINCASE = 1

Group    Observed    Expected    Observed    Expected     Total

    1     704.000     710.447      50.000      43.553   754.000
    2     603.000     587.535     166.000     181.465   769.000
    3     414.000     422.318     344.000     335.682   758.000
    4     309.000     297.193     455.000     466.807   764.000
    5     195.000     200.410     565.000     559.590   760.000
    6     132.000     135.516     629.000     625.484   761.000
    7      94.000      86.810     661.000     668.190   755.000
    8      50.000      53.952     697.000     693.048   747.000
    9      29.000      32.237     731.000     727.763   760.000
   10       9.000      12.716     760.000     756.284   769.000

                     Chi-Square     df Significance

Goodness-of-fit test      6.6134      8         .5789
------------------------------------------------------------

Classification Table for CLINCASE
The Cut Value is .50
                 Predicted
                 0         1      Percent Correct
                  0  I    1
Observed      +-------+--------+
   0      0   I  1651 I   888 I   65.03%
              +-------+--------+
   1      1   I   492 I  4566 I   90.27%
              +-------+--------+
                       Overall   81.83%
```

---------- Variables in the Equation ----------

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
ATTMDSP			146.5369	21	.0000	.1039	
Gen Med	.4667	.3590	1.6903	1	.1936	.0000	1.5947
Cardiology	-.6864	.3997	2.9493	1	.0859	-.0099	.5034
Nephrology	-.7534	.5786	1.6955	1	.1929	.0000	.4708
Neurology	.7173	.3975	3.2572	1	.0711	.0114	2.0489
Rheumatology	3.0673	2.0130	2.3217	1	.1276	.0058	21.4833
Gen Surgery	-2.3847	.5535	18.5633	1	.0000	-.0414	.0921
Neurosurgery	-1.1092	.5630	3.8821	1	.0488	-.0139	.3298
Ortho Surgery	.4202	.4901	.7350	1	.3913	.0000	1.5222
Plast Surgery	-2.6037	1.0671	5.9540	1	.0147	-.0202	.0740
Thorac Surgery	-7.6666	2.5611	8.9607	1	.0028	-.0268	.0005
Urology	-2.5919	.6498	15.9122	1	.0001	-.0379	.0749
OBS/GYN	.0398	.4101	.0094	1	.9227	.0000	1.0406
Anaesthesia	-.0525	1.1633	.0020	1	.9640	.0000	.9489
ENT	-3.6110	1.2300	8.6191	1	.0033	-.0261	.0270
Ophthalmology	-.7370	1.0791	.4664	1	.4946	.0000	.4785
Psychiatry	-3.1800	.8713	13.3208	1	.0003	-.0342	.0416
Haematology	.2665	.4546	.3437	1	.5577	.0000	1.3054
Geriatrics	14.9048	151.5570	.0097	1	.9217	.0000	2972083.9
Med Oncology	.3250	.4516	.5178	1	.4718	.0000	1.3840
Radiotherapy	.1780	.7588	.0550	1	.8145	.0000	1.1948
Vas Surgery	-1.8538	.9816	3.5670	1	.0589	-.0127	.1566
LOGITLOS	3.0188	.6109	24.4159	1	.0000	.0481	20.4665
IDPMAX			205.8260	3	.0000	.1437	
Not Likely	.5690	.1863	9.3344	1	.0022	.0275	1.7666
Somewhat prob	1.2035	.1746	47.4902	1	.0000	.0686	3.3318
Highly prob	1.8792	.1800	109.0165	1	.0000	.1051	6.5484
COMPLEX			5.1709	4	.2702	.0000	
CPLX: chronic	-.7275	.3913	3.4576	1	.0630	-.0123	.4831
CPLX: serious	.2946	.5278	.3115	1	.5768	.0000	1.3426
CPLX: life-thr	-.4474	.9767	.2098	1	.6469	.0000	.6393
CPLX not appld	-.6108	.5564	1.2049	1	.2723	.0000	.5429
ATTMDSP * LOGITLOS			27.7084	21	.1486	.0000	
Gen Med * LOS	1.2606	.6673	3.5688	1	.0589	.0127	3.5277
Cardiol * LOS	.6663	.7287	.8361	1	.3605	.0000	1.9470
Nephro * LOS	1.4330	1.1440	1.5691	1	.2103	.0000	4.1912
Neuro * LOS	.3596	.7367	.2383	1	.6254	.0000	1.4328
Rheum * LOS	.9549	3.8544	.0614	1	.8043	.0000	2.5983
Gen Sur * LOS	1.1797	.9627	1.5015	1	.2204	.0000	3.2533
Neurosur * LOS	1.9392	1.0701	3.2840	1	.0700	.0115	6.9533
Ortho * LOS	.7946	.9927	.6407	1	.4235	.0000	2.2135
Plastic * LOS	.9847	1.8918	.2709	1	.6027	.0000	2.6769
Thoracic * LOS	8.9456	4.1184	4.7182	1	.0298	.0168	7674.3584
Urology * LOS	-.2444	1.1932	.0420	1	.8377	.0000	.7832
OBS/GYN * LOS	-.0776	.8033	.0093	1	.9230	.0000	.9253
Anaesth * LOS	8.4408	15.4576	.2982	1	.5850	.0000	4632.1346
ENT * LOS	1.1429	2.2522	.2575	1	.6118	.0000	3.1360
Opthalm * LOS	-3.1653	2.0317	2.4273	1	.1192	-.0066	.0422
Psych * LOS	2.3574	1.4147	2.7766	1	.0956	.0090	10.5631
Haematol * LOS	-.5674	.8708	.4245	1	.5147	.0000	.5670
Geriat * LOS	-14.5601	196.0279	.0055	1	.9408	.0000	.0000
Med Onc * LOS	.9098	.8734	1.0850	1	.2976	.0000	2.4838
Radiother * LOS	-.7096	1.2479	.3233	1	.5696	.0000	.4918
Vas Sur * LOS	-.2290	1.6453	.0194	1	.8893	.0000	.7954
COMPLEX * LOGITLOS			13.7465	4	.0081	.0244	
Chronic * LOS	1.7877	.6617	7.2989	1	.0069	.0234	5.9757
Serious * LOS	.2854	.8773	.1058	1	.7450	.0000	1.3302
Life-thr * LOS	2.8391	1.5805	3.2267	1	.0724	.0113	17.1004
Not appld * LOS	1.9620	.9885	3.9400	1	.0472	.0142	7.1139
Constant	-1.9929	.3728	28.5756	1	.0000		

APPENDIX D - MODEL FOR COST OF CLINICAL PHARMACY SERVICES RECEIVED

Model Summary

Model	R	R Square	Adjusted R Square
1	.656[a]	.431	.428

a. Predictors: (Constant), length of stay, attending md dummy 1 (=60), attending md dummy 1 (=35), attending md dummy 1 (=16), attending md dummy 1 (=57), attending md dummy 1 (=95), attending md dummy 1 (=62), attending md dummy 1 (=36), attending md dummy 1 (=39), attending md dummy 1 (=32), attending md dummy 1 (=19), attending md dummy 1 (=34), attending md dummy 1 (=81), attending md dummy 1 (=30), idpmax dummy (idpmax=2), attending md dummy 1 (=50), attending md dummy 1 (=72), attending md dummy 1 (=17), attending md dummy 1 (=66), attending md dummy 1 (=74), idpmax dummy (idpmax=1), attending md dummy 1 (=12), attending md dummy 1 (=64), ln of modified drug cost 4404020, ln of non drug, non clin phm svc cost, attending md dummy 1 (=10), idpmax dummy (idpmax=3)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.767	.131		13.537	.000
	ln of non drug, non clin phm svc cost	.291	.016	.325	18.453	.000
	ln of modified drug cost 4404020	8.052E-02	.008	.175	10.434	.000
	attending md dummy 1 (=10)	-9.741E-02	.043	-.055	-2.257	.024
	attending md dummy 1 (=12)	-.274	.052	-.090	-5.307	.000
	attending md dummy 1 (=16)	-.158	.083	-.023	-1.913	.056
	attending md dummy 1 (=17)	-4.335E-02	.048	-.016	-.898	.369
	attending md dummy 1 (=19)	1.022	.077	.165	13.323	.000
	attending md dummy 1 (=30)	-.435	.065	-.091	-6.732	.000
	attending md dummy 1 (=32)	-.318	.081	-.049	-3.946	.000
	attending md dummy 1 (=34)	.113	.067	.022	1.676	.094
	attending md dummy 1 (=35)	-.666	.176	-.041	-3.783	.000
	attending md dummy 1 (=36)	-.814	.142	-.063	-5.720	.000
	attending md dummy 1 (=39)	-.660	.124	-.060	-5.334	.000
	attending md dummy 1 (=50)	4.191E-02	.062	.009	.673	.501
	attending md dummy 1 (=57)	.139	.246	.006	.564	.573
	attending md dummy 1 (=60)	-.867	.197	-.048	-4.405	.000
	attending md dummy 1 (=62)	-.953	.245	-.042	-3.889	.000
	attending md dummy 1 (=64)	-.102	.054	-.032	-1.905	.057
	attending md dummy 1 (=66)	.137	.059	.035	2.304	.021
	attending md dummy 1 (=72)	.245	.133	.021	1.840	.066
	attending md dummy 1 (=74)	.106	.053	.033	1.982	.047
	attending md dummy 1 (=81)	8.302E-03	.069	.002	.120	.904
	attending md dummy 1 (=95)	-.529	.160	-.036	-3.301	.001
	idpmax dummy (idpmax=1)	-.138	.088	-.046	-1.563	.118
	idpmax dummy (idpmax=2)	4.170E-03	.085	.002	.049	.961
	idpmax dummy (idpmax=3)	.274	.088	.163	3.111	.002
	length of stay	8.611E-03	.001	.111	6.650	.000

a. Dependent Variable: ln of clin phm svc cost