An *a priori* Resource-Based Classification Methodology for Specialty/Secondary Ambulatory Patients

by

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ABSTRACT

The World Bank [1993] identifies several problems that health care systems in the world in general, and in developing countries in particular, face. Escalating costs of health care and misallocation of health resources are prominent among these - suggesting that a better understanding of the resources required by a client prior to the rendering of services might help address the problem. The resultant pressures imposed by an increasingly resource-constrained environment have encouraged efforts to adapt and apply manufacturing management techniques relating to cost control, forecasting, and quality assurance for application in the medical field.

This study proposes an approach to predict the health care resource requirements of speciality ambulatory patients at a micro (clinic) level. It employs cluster analysis and learning tools to develop a generalized methodology based on a health provider's patient discharge data to spawn a patient classification system which, on the basis of information available prior to a patient receiving health care service, predicts the clinic resources that a patient may use on the appointment date.

To evaluate its robustness, the methodology has been field-tested at seven secondary/tertiary low vision ambulatory clinics in North America and Sub-Saharan Africa. A minimum of 25% of all available data was collected from each site. After collection, the data were analyzed (by clinic) using the methodology by first employing cluster analysis to develop iso-resource groups, then applying a variety of techniques (decision trees, non-parametric discriminant analysis, nearest neighbour, and neural networks) on data that are available at appointment time. Additionally, the study attempted to determine the generalizable iso-resource variables or groupings which are systemic across clinics/centres in the speciality ambulatory setting of low vision and, therefore, which could, along the lines of length of stay (in acute and long-term health care settings), form the basis for a standard set of measures for resource planning and scheduling in speciality ambulatory low vision settings.

Estimates of apparent and true errors were used in gauging the predictive performance of each learning technique at the sites. Chance criterion served as the benchmark in this evaluation. No learning technique emerged as the universally superior one (and hence the

method of choice), however, they typically outperformed the benchmark's predictive ability (frequently doubling or tripling it). This suggests that their usage would make significant contributions to the decision making process.

This research broadens previous work done in this area into a variety of low vision clinical settings to determine 1) the robustness of the proposed methodology, 2) potential additional complexity issues that the proposed methodology must attend, and 3) the generalizable and systemic iso-resource variables across low vision settings that may form the basis for a standard set of measures for ambulatory resource planning and scheduling in speciality low vision settings. It also discovered that an *a priori* classification can indeed be successfully achieved in this speciality setting.

The implications of this research include the contribution of an aggregate planning tool that may find useful application in equating a health provider's resource capacity to the expected demand for the same in a manner that is apparent to the user. The demonstration that a patient classification system can be applied to a patient (on an individual basis) to determine his/her expected resource requirements, and that the latter can subsequently serve as input information for such planning functions as patient- and resource-scheduling, has the theoretical significance of paving the way for future research in the suitability of using patient resource classification systems as a basis for resource prediction in addition to being used for reimbursement or after-the-fact cost allocation purposes. The methodology proposed in this research can be extended to resource-intensive high customer-contact service organizations (outside of health care) in which reservation/referral systems are used and where significant delays may exist between booking and actual service delivery. In aiding to identify specific components that go into the end-product, the methodology may be useful as a components-to-forecast tool.

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Dedication

I dedicate this dissertation to my mother Rece Osita Khamalah (1933 - 1985), my mother-in-law Mary Naliaka Wamalwa, my father Johnstone Khamalah, and my father-in-law William Wamalwa (1922 - 1976). As the days turn into months and the months into years, I get to appreciate more and more the many things that are possible today largely due to the foundations you laid and the sacrifices you made. I thank the Almighty for the honor of being called your son/son-in-law.

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CHAPTER 1

INTRODUCTION

1.1 Thesis Motivation

The motivation for this research derives from two of the four key problems that health care systems in the world in general, and developing countries in particular, currently face - exploding health care costs and misallocation of health care resources [World Bank 1993; Schieber 1990]. Not only have these been said to frustrate attempts aimed at delivering adequate health care for all, but also, they hamper the ability to meet new health challenges. It has been suggested that poor and uninformed resource decisions by governments and health care providers are some of the root causes for these problems [World Bank 1993]. This implies that an understanding of the resources (services, facilities, or time to be expended) required by the health care provider (prior to rendering services to patients) would help ameliorate part of the problem.

This study proposes the APRCM (*a priori* Resource-Based Classification Methodology) - a grouping/placement approach that seeks to determine the health care resource requirements of patients prior to their utilization of resources by placement of in-coming patients into appropriate patient iso-resource groups. The study is limited to scheduled specialty/secondary ambulatory (out-patient or non-bed) health care - wherein the development of patient resource classifications has not received as much attention as in other settings. The proposed approach builds on Fetter's [1980, 1991a] "product" concept that has been applied to the medical field by different researchers [for examples see Bay 1982; Fries 1985; Shaffer 1986; Tenan 1988; Ashcraft 1989; Young 1991; Harada 1993; Pink 1994a & b].

The point of departure for this study is its focus on the clinic level (individual care provider). It commences from the same basis as other classification systems, i.e. that a patient, having a set of complaints which defines the reason (and goal) for the visit, interacts with the health care provider who formulates a diagnosis and prescribes a treatment [Caro 1990]. This encounter involves the patient utilising a set of resources (physician time, equipment, etc). As confirmed by several studies, the level of resources used is a function of both patient characteristics and practice (provider) variation [for instance Lion 1982, 1985, Stuart 1988, 1993, Gold 1988, Eckerlund 1989, Longo 1993, Weiner 1996]. This study avoids the hitherto common macro approach, and instead focuses on the individual clinic as the level for which the resource utilisation of patients in specialty/secondary ambulatory care can be determined. This is based on the premise that decisions on capacity planning, financial budgeting and workload scheduling can be made more precisely if estimates of patient resource requirements are known by the clinic prior to the actual therapy. In doing so, an attempt is made to avoid the common but inaccurate supposition that specialty/secondary ambulatory patients are a homogeneous group with regard to resource demands [Dilts 1994]. It should be noted that the study does not set out to determine the "right" set of resource requirements for a patient, but rather, it seeks to predict the patient's most likely resource requirements given the clinic's current practice. Further, it assumes that whatever difference in practise that may exist between individual practitioners within the clinic are 'managed' (i.e. there is a standard practice within a clinic, but not necessarily among a group of clinics).

1.2 Background

Escalating health care costs and the related misallocation of resources, appear to be global phenomena [Schieber 1990]. In most developing countries, however, they are far more momentous and harder to solve plights than is the case elsewhere [Gesler 1984, Phillips 1990, World Bank 1993]. The case of Kenya, and other Sub-Saharan countries, is typical [Roemer 1991]. Highly centralised and inefficient decision-making and wide fluctuations in budgetary allocations have been identified as some of the reasons behind the problem [World Bank 1993]. Very high population growth rates and the exigencies of the latest economic recession [IMF 1994, World Bank 1994], over and above unstable political climates make the situation worse than it would otherwise have been.

In the developed world, this issue has been approached from various angles, including adapting and applying to the medical sector those techniques that have worked successfully in the manufacturing field. Examples of these include the "product" concept in the definition of a hospital's output, the product line management (PLM) method in the organizational structure of hospitals, and total quality management (TQM) and continuous quality improvement (CQI) approaches in the management of hospital operations [Fottler 1988; Berwick 1990; Fetter, 1991a].

Applying the "product" concept has engendered iso-resource patient groups, that is, the identification of patients as classes or groups, with members of each class making similar resource demands on the health care provider. Such efforts have yielded a number of in-patient (acute and long-term) and ambulatory classification schemes that, to varied degrees of success, undertake to determine the resource utilisation of patients [for examples, see Tenan 1988; Starfield 1991; Harada 1993; Freeman 1995]. Whereas the duration (in days) of a patient's stay in the hospital (length of stay or LOS) has been accepted as the standard measure of a patient's resource utilisation (as a predictor of total charges) in in-patient schemes, no such single measure of resource use has been developed and standardised for use in the ambulatory schemes to date. This implies that the problem is more protracted in ambulatory care.

Medical literature suggests that the grouping of patients into homogeneous classes on the basis of the health care resources they use (resource-based classification) has been more extensively investigated in the in-patient rather than the ambulatory health care setting. For instance, a recent search through MEDLINE using the search terms 'patient care classification' over the past ten years (1987 -1997) had 879 hits out of which only 37 were in ambulatory care (the remainder are in the inpatient environment). Further, existing schemes in both settings fall short of adequately grouping patients on a basis that can usefully be employed in the determination of the health care resource requirements of patients before the appointment date. This is especially evident in the ambulatory setting where no scheme, so far, has attempted a per visit patient pre-classification (or in other words, a resource-based grouping of the patients before actual treatment commences). Instead, methods post-classify patients (i.e. group the patients after they have left the health care provider) without relating them directly to incoming patients. Thus, whereas these schemes may be useful in such activities as health care expenses billing or reimbursement, they do not have as much utility when used as forward-planning tools [Bay 1982].

The foregoing is not unique to the health care sector, it is a task encountered by service managers in general when doing aggregate (and disaggregate) planning. Like their manufacturing counterparts, service managers have to plan and make decisions aimed at equating available capacity to variable demand. The former is controlled and managed, whereas the latter can be established through a variety of forecasting techniques [MacStravic 1984, Murdick 1990]. Equating the two can be achieved through either yield management strategies (i.e. strategies focused on smoothing the demand and thus permitting a fuller utilisation of a fixed service capacity) or strategies that adjust capacity to fit the demand [Fitzsimmons 1994].

Both types of strategies presuppose that resources required to meet demand are not only known, but also identifiable in advance. This is normally the case in manufacturing - where clear standards and criteria pertaining to the 'bill of materials' and process flows (the utilisation of materials, labour, and equipment) are present, and where design quality, production quality, and performance are continually subject to monitoring, measurement, feedback, and control. The same, however, can not be said of the health care sector, where the determination of 'inputs' is either unknown or frequently made through some cost allocation manner after the fact [Fetter et al, 1991b]. What is required to effectively manage capacity and demand (hence avoid the drawbacks that attend mismatches between these two) [Murdick 1990] is a prior determination of demand characteristics.

As pointed out earlier, patient resource classification efforts have, hitherto, concentrated on the in-patient setting, and only made occasional forays into ambulatory care. More than ever before, there is a need for patient resource-based classification schemes that are not only focused on specialised ambulatory health care settings, but which also classify patients on the basis of the health care resources before such resources are demanded. Although the necessary tools for this pre-classification of patients exist, no such undertaking has been attempted in any per visit ambulatory health care setting. This seems to be due to a variety of reasons, not least of which is the fact that the parameters of the patient and provider interaction are so varied that no standardised measure similar to LOS for in-patients exists which can be used as an accepted basis for classification in ambulatory settings [Tenan 1988; Berlowitz 1995]. A robust methodology to effect this is, therefore, necessary.

Preliminary work in this direction has shown that such a methodology is possible and distinct patient resource groups can be identified in a low vision specialty/secondary clinic setting [Dilts 1994]. This work suggests that it is possible to go a step further and pre-classify the patients therein on data obtainable before actual treatment commences. Since the characteristics of the groupings obtained are largely determined by the type of health care setting (service delivery, funding, provider management and organizational practices, the available resources, and patient characteristics, among others) it is safe to assume that the patient groupings so obtained may be unique to a clinic. So far, there are no indications ruling out the possibility of obtaining equally distinctive groupings (albeit with different profiles) when the same general method is followed in other specialty/secondary ambulatory settings [Dilts 1995].

1.3 Statement of the Problem

This research study addresses two questions. The primary question is: To what extent can management in a specialised ambulatory health care clinic conduct an *a priori* determination of patient resource needs and use this 'forecast' to predict future resource loads on the clinic? To address this problem, the study proposes a generalised methodology for establishing health care resource requirements for incoming patients in a non-emergency specialty/secondary ambulatory setting. Towards this end, the study's unit of analysis is the clinic. The proposed methodology is based on a grouping/placement model which consists of the following set of tasks:

I. collecting data on the (biographic, diagnostic, treatment, and resource usage) characteristics of discharged patients;

II. applying available clustering tools on these data to group patients on the basis of the resources utilised;

III. developing a predictive (pre-classification) iso-resource patient classification system based on relevant sets of the profiles of the groups obtained;

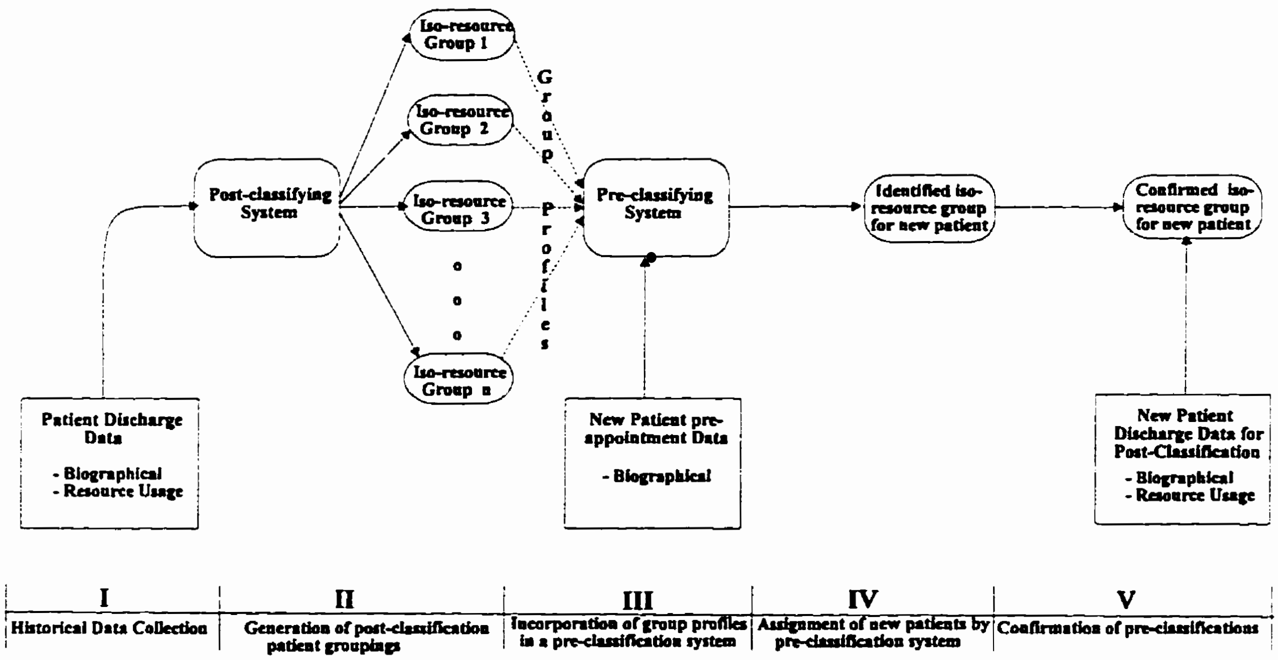
IV. incorporating the pre-classification in a learning system that places in-coming patients into relevant iso-resource groups; and

V. validating the output obtained and the approach used.

These five tasks correspond to activities I through V respectively in Figure 1.1. It is envisioned that the resulting assignments (placements realised at Stage IV) can be employed in the scheduling of resources to in-coming patients in a manner that assures the delivery of suitable and more resource-effective health care. This approach calls for the utilisation of the target patient population's demographic features and the relative sizes and distributions of identified patient groups as a logical planning underpinning for appropriate resource allocations.

Regrettably, practical considerations make it impossible for this study to use actual new patients at stages III through V in the model. Instead, discharged patients (from whose profiles all resource and other information that is not obtainable before 'admission date' have been stripped) are used in the place of 'new patients'.

Figure 1.1: The Proposed a priori Resource-Based Classification Methodology (APRCM)



The second research question is: Are there generalizable iso-resource variables or groupings which are systemic across all low vision sites? To address this supplementary question, the study will attempt to identify common or systemic variables and groupings in activities II and III in Figure 1.1. It is envisioned that once identified, such variables could help, along the lines of LOS in acute- and long-term health care environments, form the basis for a standard set of measures for ambulatory resource planning and patient-scheduling in specialty low vision settings.

1.4 Objective and Expected Contributions

Focusing on the determination of patient health care resource requirements before the fact, this study is primarily aimed at developing a tool to use in aiding the equating of a health provider's resource demands to its resource capacity. This may assist in efforts geared towards matching the supply of health care services to their predetermined demand without compromising quality or patient satisfaction. The tool attempts to foster the placement of patients in appropriate resource groupings which in turn should lead to more effective aggregate resource utilisation in this age of constrained resources.

It is worth pointing out at this juncture that the focus of the study is on resource use rather than on the best possible treatment of the patient, hence, it is not based on the patient's disease/condition state. Our orientation considers the patient's condition as part of the available information that may or may not feature prominently in the iso-resource profiles that are obtained and used.

This study extends preliminary work done in this area [Dilts, 1994] along two lines. First, the results of the previous work suggest that while the dynamics of the patient/provider interaction and the encompassing health care system produces patient groupings that may be unique to each provider and health care system, the general methodology used can be extended into other settings. This dissertation research broadens the approach into a variety of low vision clinical settings to determine:

1. the robustness of the methodology;
2. potential additional complexity issues which the methodology must attend (for example different local practices or unique population characteristics); and
3. potential key iso-resource variables or groupings which are systemic across low vision sites and, which could form the basis for standard sets of measures for ambulatory resource planning and patient-scheduling in specialty low vision settings.

Second, this study seeks to determine whether an *a priori* classification can indeed be achieved and the extent to which the resultant groupings can be used in determining a patient's expected resource requirements. Once the classification is realised, the study evaluates a variety of learning systems which can incorporate the knowledge for predicting the expected resource requirements of 'new' patients. The theoretical significance of this is the demonstration that a patient classification system can be applied to a patient (on an individual basis) to determine his/her expected resource requirements which can then serve as input information to such planning functions as patient- and resource-scheduling.

1.5 Extent of the study

Previous research has found that patient resource utilisation is a complex function of provider and patient characteristics [Buczko 1986; Stuart 1988; Wouters 1991]. This may help to explain why it has hitherto been difficult to develop patient resource classifications that cut across provider types in ambulatory care. To overcome this difficulty, this study takes a micro approach that is restricted to individual clinic settings. It is, therefore, limited to specialty/secondary low vision clinics in North America (US) and Sub-Saharan Africa (Kenya)[1]. At each study site covered, this methodology is implemented and evaluated.

1.6 Outline and Structure of Thesis

This thesis is divided into six chapters. Chapter 2 covers the theoretical framework and provides a review of the relevant literature on patient resource classification schemes and methods. It also reviews learning systems applications in classifications, discusses the validation framework for the proposed methodology, and presents the propositions of interest for the study. Chapter 3 addresses the research design and methods adopted in the study. The results obtained at the various sites are examined in Chapter 4. Chapter 5 covers the analyses done on the amalgamated data and discusses the findings therefrom. Finally, Chapter 6 provides a discussion of the findings, conclusions drawn, points out the limitations of the study and concludes with recommendations for further work.

[1] The extension of this study to the Sub-Saharan African setting was a precondition for the study-leave and award for graduate studies by the Commonwealth Scholarship Agency in Kenya (from where the researcher hails).

CHAPTER 2

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Overview

Attempts to determine a hospital's 'product' or output are rooted in the desire to measure and evaluate (with the intent to better manage) hospital activities in a manner akin to production in a factory. This has been of interest to professionals in the health care field from the early parts of this century [Codman 1914]. Towards this end, however, little was achieved until the late 1960s and early 1970s when rising costs focused attention on efforts aimed at curbing runaway health care costs [Fetter 1991b]. Since then, hospitals and other health care providers have endeavored to control escalating costs through a variety of ingenious methods while simultaneously generating revenues to offset their operating costs [Gutis 1989]. Numerous attempts have been made to apply (and reap the benefits of) management techniques that have successfully been utilized in manufacturing operations [Fetter 1991b]. These techniques were, however, designed for situations where the final 'product' and the inputs that go into the process that generates that output are known [Fetter 1986]. Hence considerable attention has revolved around defining the 'product' of hospitals and other health care providers [for instance Codman 1914, CPHA 1976, Schneider 1979, Fetter 1980, 1986, 1991b, Fries 1985, Stimson 1986, Tenan 1988, Young 1991, Harada 1993, Freeman 1995].

The foregoing tasks are not unique to the health care sector; they have to be performed by service organizations in general. They are driven by a service capacity that is 'perishable' [Fitzsimmons 1994]. On the one hand, unutilized capacity represents idle servers and facilities -

a potential service that is lost forever. On the other hand, periods of consumer waiting result when capacity is outstripped by demand. Like their manufacturing counterparts, therefore, service managers have to plan and make decisions aimed at equating available capacity to demand. Whereas the former can be a given, the latter has to be established through a variety of forecasting and yield management techniques [MacStravic 1984; Murdick 1990; Fitzsimmons, 1994].

Several strategies (falling under two broad categories) can be used to equate capacity to demand or, in other words, to produce enough 'products' to meet the demand. First, attention can be focused on smoothing the demand and thus permitting a fuller utilization of a fixed service capacity (e.g. pricing incentives, promoting off-peak use, developing complementary services, reservation systems, etc.). This is what is normally done in clinical settings [Dilts 1994]. Alternatively, capacity can be 'adjusted' to fit the demand, for instance through workshift scheduling, cross-training of employees, closing and opening certain areas of operations, use of part-timers, subcontracting, etc. [Fitzsimmons 1994]. This second alternative does not find ready application in specialty/secondary clinical settings. For instance cross-training of employees to provide medical treatment or subcontracting in a setting like the low vision clinic is generally infeasible.

As pointed out earlier, equating capacity to demand (or vice versa) presupposes that the various inputs into the process that produces each unit of the end-product are not only known but are also identifiable in advance. Whereas this is normally the case in manufacturing - where clear standards and criteria pertaining to the 'bill of materials' (i.e. utilization of materials, labor, and equipment) are present, and where design quality, production quality, and performance are continually subject to monitoring, measurement, feedback, and control [Fitzsimmons 1994], the same can not be said for the service sector in general (and health care in particular). Hence the need for a methodology that identifies patient resource demands (inputs) prior to their actual use.

To effectively devise clinical and financial management strategies for patients, health care providers must be able to associate resource use with specific patients and be able to identify the mix of clinic patients in terms of a useful case-mix classification system [Cameroun 1990]. This implies relating patients' sociodemographic, diagnostic and therapeutic features to the resources they 'consume' in such a manner that the patients are differentiated only by those features (like age and surgical operation) that affect the patient's utilization of the provider's facilities [Fetter 1980]. This would, in essence, mean that the care provider would have defined its output or "product" as classes or groups of patients, with members of each group making similar resource demands on the provider [Fetter 1991b].

From a management sciences perspective, the foregoing efforts (patient resource classifications in general) are all attempts to determine the demand side of aggregate planning. The non-inventorability, perishability, nontransferability, and the individualized nature of the service (among other reasons) make service aggregate planning especially challenging [Murdick 1990], but once the output and the required inputs have been determined, it is then feasible to adapt and apply some management techniques that have been effectively used in the manufacturing field [Fetter 1991b]. As in manufacturing, the main task here involves determining and equating the firm's resource capacity to its determined demand.

Time-perishability, idle servers and facilities when capacity outstrips demand, consumer waiting when the opposite holds true, a 'fixed' capacity (over the short term), and a fluctuating demand due to a variety of reasons/conditions, are typical of many areas in the service sector. Attempting to maintain full utilization of capacity in these conditions is an extremely challenging management problem [Murdick 1990; Fitzsimmons 1994]. The problem addressed in this research is, therefore, not unique - it is frequently confronted in the service sector. The conventional approach in tackling this problem is to commence with long-range forecasts that are subsequently broken down into aggregate plans from whence detailed schedules can be drawn. APRCM suggests an alternate approach that commences with a prediction of the specific 'product' components which, when summed, yield demand forecasts that can be factored into capacity management decisions. From this general perspective, APRCM lends itself to resource-intensive settings in the service sector where reservations/referral systems are used, where there can be a long delay between booking and service delivery, and where the utilization of specific resources varies widely across classes or categories of clients served.

2.2 Background to Patient Pre-Classification

A review of the health care literature leads to the conclusion that patient resource classification efforts have concentrated on the in-patient (acute and long term care) setting, and only made occasional forays into ambulatory care. Further, existing ambulatory schemes have some notable shortcomings [Gold 1988; Tenan 1988; Berlowitz 1995]. First, the vast majority are invariably high level, that is, focusing on primary care and ignoring secondary or tertiary settings that provide specialty care, for instance low vision services. Secondly, they are, in large part, post-classificatory in nature, i.e. they classify patients after discharge rather than before treatment commences and offer little by way of linkages between the two. The majority utilize a single index (total charges) as a measure of the resources utilised. Further, most of them are period-based (e.g. one year) rather than visit-based. The combination of these attributes compromises their utility as forward planning tools especially in resource and patient scheduling.

The methodology proposed in this study is primarily intended for a specialised ambulatory care setting such as low vision. As with diagnosis-related groups (DRGs) [Fetter 1991b] and most patient resource classification schemes in general, the iso-resource groupings generated should consist of patients demonstrating similar levels and patterns of resource utilisation. The groups should also be resource-meaningful, that is, when a group is described to a clinician, for instance, s/he should be able to relate to it and to identify a generic patient management process for members of this group. Again, the groups need to be reasonable in number, i.e. not so detailed as to consist of a few patients (with some groups rarely being seen), and not so few as to be meaningless (with some groups being too large and general). Finally, the purposes of this study require that the groupings be capable of being used predictively.

The foregoing implies that the groupings obtained should be capable of being applied on incoming patients in a manner that facilitates the making of informed operational decisions in such areas as capacity planning, budgeting, and workload and patient scheduling. This implies that the resultant groupings can be embodied in a learning system[1].

---

[1] A learning system is defined here as any computer-based program that leads to the making of a decision based on the accumulated experience contained in successfully solved cases. It could be either a simple look-up table, linear discriminant, nearest neighbor, decision tree, or neural network application whose fundamental goal is to extract a decision rule from historical data that will be applicable to new data [Weiss, 1991]. This definition implies that 'intelligent' systems are a subset of learning systems.

What is outlined above calls for the usage of a number of clustering and learning systems tools for which no common 'across-the-board' validation 'tools' have so far been unearthed in the available medical or management sciences literature. To overcome this difficulty, an approach that involves the validation of each step or tool in the methodology is adopted in this study to ascertain the extent to which the *a priori* determination of patient resource utilisation has been achieved.

2.3 Previous Research

The modern history of the health care field is replete with classification schemes, the majority of which, however, focus on grouping various dimensions of disease, including their codes, etiology, pathology, pathophysiology, prognosis, or combinations of these [for instance Hurtado 1971, Schneider 1979, Bay 1982]. Due to the etiological (or causal) inadequacy of certain diseases, problems associated with co-morbidity, and the wide variations of therapeutic or care requirements within a disease category, the ability of most of these schemes to address patient care requirements, or resource utilization, has been questioned [Bay 1982]. Several schemes specifically address the issue of resource utilization, including Patient Classification by Type of Care [Bay 1982], Diagnosis Related Groups [Fetter 1980, 1991; Freeman 1995], Case Mix Groups [Pink 1994a, b], Resource Utilization Groups [Fries 1985], Psychiatric Patient Classification [Ashcraft 1989], Functional Related Groups [Harada 1993] and a plethora of nursing and home health care schemes [Shaffer 1986]. These schemes, however, focus on long-term or acute-care patients and use LOS as the basic measure of resource utilization (and hence basis for the classification) - see Table 2.1 for a summary of some of the classification systems.

The introduction of DRGs, the most widely used scheme today, paved the way for the development of many of the resource-based classification systems in in-patient care, and fostered the development of similar schemes for application in ambulatory care. The diversity of ambulatory care has, however, proven nearly impossible to fit into a systematic, universal scheme, hence ambulatory care lags behind in-patient care in the number and comprehensiveness of resource utilization schemes developed [Hornbrook 1985; Gold 1988; Tenan 1988; Berlowitz 1995]. Again, unlike the in-patient setting where LOS defines an episode of care, the parameters of the patient and provider interaction in ambulatory care are so complex that no single measurement exists that is as standardized and as widely used as LOS [Gold 1988; Tenan 1988; Starfied 1991].

Some previous studies have used the National Ambulatory Medical Care Survey (NAMCS) data to develop classification schemes [for example, Schneider 1979, Schneeweiss 1983]. Although later found to have some relevance in this regard, these schemes were not specifically designed to group patients on the basis of resource use. The Ambulatory Care Classification Systems (ACCS) study presents several methods of classifying patient data into iso-resource groups [Stimson 1986]. It, however, is episode- rather than visit-based, that is, generating groups based on patient-years (incorporating a number of patient visits) rather than focusing on a single patient visit. An attempt was also made to develop an ambulatory scheme that could be linked with DRGs [Schneider 1991]. The definition of resource use adopted therein was, however, too narrow to capture the total resource demands of an ambulatory visit, and, in addition, certain ambulatory procedures were excluded altogether.

Table 2.1: Sample of Patient Resource Classification Systems/Studies

Patient Scheme	Setting	Purpose	Clustering & Validation Methods	Sample Size	Classes Obtained	Nature of Scheme	Reference
Professional Activity Study - PAS	In-Patient	Length of Stay benchmarks	Expert intuition	n/a	7 000	Post-classification	CPHA 1976
Patient Classification by Type of Care - PCTC	In-Patient	Case mix management	Discriminant analysis, expert intuition, Bayesian procedures	585	5	Pre-classification	Bay et al 1982
Diagnosis Related Groups (DRGs)	In-Patient	Case mix management & PPS	Expert intuition & AUTOGRP	702000	475	Post-classification	Fetter et al 1980 Freeman et al 1995
Function Related Groups - FRGs	In-Patient	Rehabilitation PPS & Case mix management	CART Regression	8000	33	Post-classification	Harada et al 1993
MEDISGRPs	In-Patient	Generate predictive iso-resource groups	Expert intuition & summary statistics	19477	5	Pre-classification	Brewster et al 1985
Predicting Inpatient Costs	In-Patient	Cost Prediction	Regression, Error rates	2355	-	Pre-classification	Tierney 1995
Diagnosis Clusters	Ambulatory	Code diagnoses	Expert intuition	96332	92	Post-classification	Scheneeweiss et al 1983
Reason for Visit Classification (RVC)	Ambulatory	Code patient's reason for visit	Expert intuition & summary statistics	n/a	7 modules	Post-classification	Schneider et al 1979
Ambulatory Visit Groups (AVGs)	Ambulatory	Possible PPS & link with DRGs	Expert intuition & AUTOGRP	10145	570	Post-classification	Fetter et al 1991
Ambulatory Care Classification System	Ambulatory	Generate iso-resource groups, Possible PPS	Summary statistics	871	17	Post-classification	Stimson et al 1986
Products of Ambulatory Care - PACs	Ambulatory	Possible PPS & Case mix management	Expert intuition, SAS & AUTOGRP	10000	24	Post-classification	Tenan et al 1988
Ambulatory Patient Groups - APGs	Ambulatory	Reimbursement, case management	Classification	-	297	Post-classification	Orion 1997
Ambulatory Care Groups (ACGs)	Ambulatory	Generate iso-resource groups	Expert intuition, summary statistics & AUTOGRP	106551	51	Pre-classification	Starfield et al 1991; Weiner et al 1991
Low Vision Patient Resource Groups-LVPRGs	Ambulatory	Generate iso-resource groups	Expert intuition, Block-clustering & replication	99 by 2	5	Post-classification	Dilts et al 1994

The Ambulatory Care Group system [Starfield 1991; Wiener 1991] was developed for predicting both concurrent and subsequent ambulatory care. It is, however, primarily based on categorization of diagnoses according to their likelihood of persistence, thus yielding an aggregated system (akin to ACCS) rather than a visit-based system.

The Products of Ambulatory Care (PACs) scheme set out to avoid these shortcomings [Tenan 1988]. Its wide scope, nonetheless, is such that some of the groups therein appear to be too general. For instance, all patients with eye complaints were classified into one group giving the inaccurate impression that their resource demands were similar. Like all the other schemes, PACs appear to be limited to primary entry level health facilities - to the near total exclusion of specialty or secondary/tertiary level health facilities. This explains the general nature of some of the patient groups of PAC. The second aspect that detracts from the versatility of this system is its use of one aggregate measure (price) in the classification. Price differentials between regions and between health care facilities (e.g. hospital emergency as opposed to office physician services, teaching versus non-teaching institution, and so forth) limit the general applicability of PACs. The use of a single price figure loses certain details that are necessary in such planning activities as scheduling especially in an environment with constrained resources. For instance a planner may want to know more than just how much a patient visit will cost - s/he may also want to know whether the patient used (or will require the use of) certain specific services within the health care facility. Similar drawbacks can be said of AVGs [Schneider 1991] and APGs [Orion 1997].

Schemes with more concentrated scopes have been attempted in the recent past. Cameroun [1990] developed one for an emergency department. The patient/provider parameters of the emergency department are, however, so unique that they can not easily be transferred to other ambulatory settings. A scheme in the specialty/secondary area of low vision has yielded a parsimonious set of patient groups [Dilts, 1994]. Although it relied on abstracted discharge data, this research suggests that it is possible to use patient admission data to develop patient groupings. Such an undertaking, however, is yet to be attempted in the ambulatory setting.

In sum, existing ambulatory resource-based schemes address the issue of resource utilisation with varying degrees of success. To a large extent, the search for a convenient, single proxy for LOS has meant that these schemes have certain features or limitations that detract from their application in the determination of health care resource requirements for patients in ambulatory health care in general, and in specialised areas of ambulatory care (for instance low vision) in particular. Table 2.1 summarizes the main features of a sample of resource classification schemes in in-patient and ambulatory health care settings.

Of more immediate concern to this study is the fact that ambulatory schemes in general do not attempt, at admission, a prediction of the expected sets and levels of resources that patients will utilize per visit. This implies that, useful as these ambulatory schemes may be in such activities as health care expense reimbursement, they do not have strong utility in planning activities like workload, patient and resource scheduling, and by extension, budgeting and cost forecasts at the clinic level. On the other hand, the in-patient setting documents the use of classification schemes for resource (or cost) prediction purposes. Examples include PCTC [Bay 1982], MEDISGRPS [Brewster 1985] and [Tierney 1995].

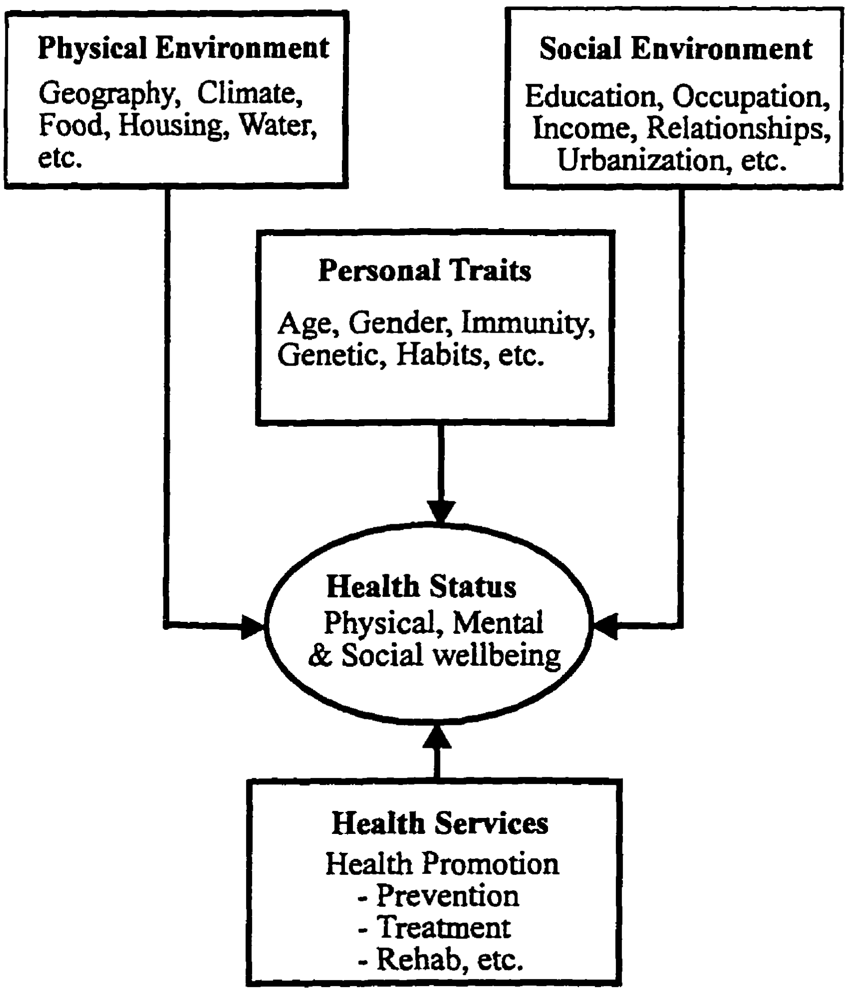
2.4 Overall Pre-Classification Architecture

The PCTC scheme commences with a set of predetermined patient resource groupings and uses a combination of subjective and statistical procedures to assess, classify, and place patients in appropriate groupings according to the types of care the patients will need. Its overall aim was to provide a prototype of a system to supply information useful in long-term patient care planning and resource allocation to such bodies as the provincial governments of Canada [Bay 1982]. MEDISGRPS, another method, uses admitting information, such as reason for admission, to place a patient in one of five severity groups, subsequently review these severity placements during the hospital stay, and demonstrate that severity groups are an important predictor of patient resource use [Brewster 1985]. The study by Tierney and others [1995] uses clinical data available within 24 hours of admission to develop statistical models for predicting a patient's hospital costs. The model underestimates in-patient costs by 10% to 13%.

The foregoing three studies/schemes were predicated on the assumption that the health care needs of patients can be determined beforehand. This is supported in Roemer [1991] where it is shown that health care resources 'consumed' by an individual in large part depend on that individual's health status and the health care system. The individual's health status is in turn determined by her/his personal traits, physical environment, and social environment as depicted in Figure 2.1. This position has been repeatedly confirmed in the literature [for instance Belloc 1972, Lalonde 1974, Townsend 1982, Lindheim 1983, Epp 1986, Syme 1986, Rachlis 1989, Gold 1991, Weiner 1996].

Based on Roemer's model, patient resource-based classification systems in general have hitherto proceeded in a manner similar to that depicted in Figure 2.2a. They work on the premise that although each individual patient is unique with regard to the resources they consume (much like each tangible product in manufacturing is unique), broad but distinct patterns of similarities can indeed be discerned in the overall resource usage by these patients [Fetter 1991a].

Figure 2. 1: Determinants of Resource Utilization



(Adapted from Roemer 1991, pp. 21)

Hence the schemes apply some objective or subjective clustering techniques to patient discharge data to generate well-defined iso-resource groups on the basis of the resources the patients used, that is, after the treatment and outcome have already been determined (Figure 2.2b). The resulting groupings are then used for a variety of purposes, most of which have to do with billing (or reimbursement) purposes (as in DRGs).

Figure 2.2a: The Traditional Classification Approach

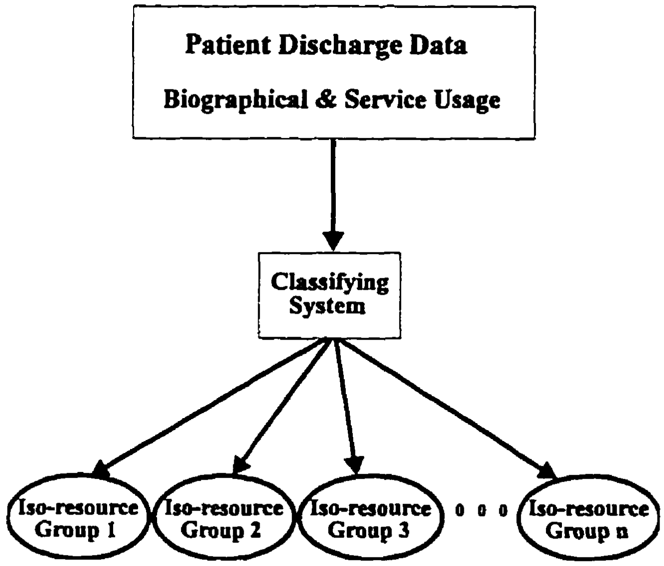
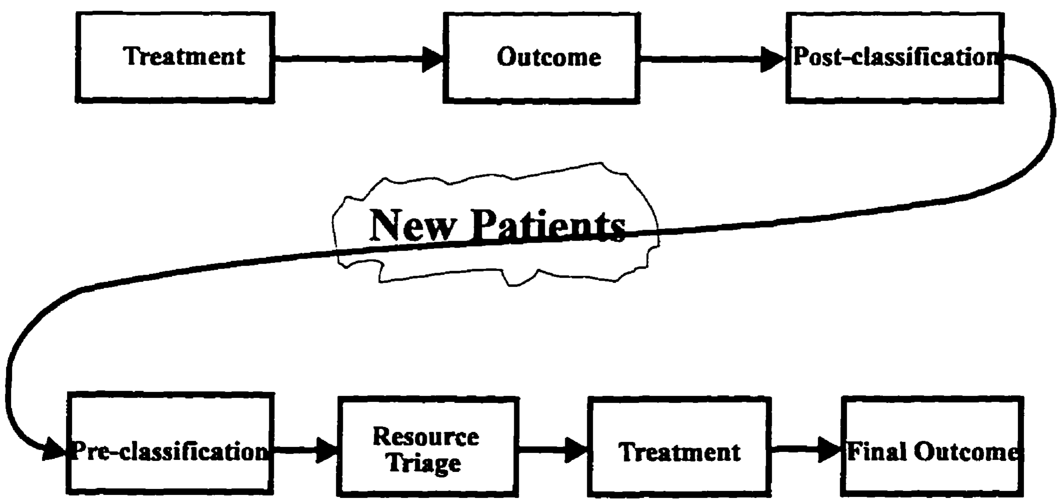


Figure 2.2b: The stage at which Classification is done in the Traditional Model

The PCTC system, although apparently adhering to what would later be referred to as Roemer's model (Figure 2.1), used an approach radically different from the one in Figures 2.2. It attempted a resource-based classification of patients before the service utilization data were captured. Like other in-patient schemes, however, PCTC relied on LOS as a measure of resource utilization - a measure that has no ready equivalent in ambulatory care. A duplication of the PCTC approach in ambulatory care in general and specialty/secondary ambulatory care in particular does not, therefore, seem to be feasible at the moment. The MEDISGRPS model is not totally pre-classification, hence its duplication in ambulatory care would be equally infeasible.

The current study incorporates Roemer's model and suggests a confirmatory approach akin to Tierney [1995], but one which does not rely on a single overall measure of resource use. It opts, instead, to use several measures of resource utilization [Dilts 1994]. It suggests the extension of the traditional model by applying the accomplished classification on incoming (new) patients on whom no service data is available. Figure 2.3 presents the sequence of these activities in the proposed approach.

Figure 2.3: Sequence of Activities in the Proposed Approach



It is, in essence, a dual-task (grouping/placement) methodology that first develops iso-resource groups from discharge patient data (consisting of the patients' biographical characteristics - physical environment, social environment, and personal traits - and the characteristics of the health services received). It then proceeds to encapsulate the profiles of the generated groupings in a learning system that is subsequently employed in the identification of the iso-resource group to which an incoming patient belongs (using only the available biographical data).

The first of the two tasks is basically that of categorization. This mirrors the primary aims of the cited schemes - grouping and distinguishing comparable units, and separating them from differing units. As can be noted from Table 2.1, the principal statistical tool employed for this task in patient resource classification systems has been AUTOGRP or CART. In both methods, the algorithm that generates the initial groups is based on Sonquist and Morgan's Automatic Interaction Detector (A.I.D.) [Breiman 1984; Fetter 1991]. Although not frequently recognized as such, A.I.D. (and the various algorithms it has engendered) is basically a cluster analysis algorithm that falls under the genus of hierarchical divisive monothetic methods [Everitt 1993; Dilts 1995]. A.I.D. determines those variables, and the categories within them, which combine in defining groups which are maximally different with respect to some dependent variable - for instance LOS in in-patient systems or total charges in ambulatory systems. It then proceeds by dividing the data set through a series of binary splits into mutually exclusive monothetic classes [Everitt 1993]. At each split, the method seeks optimal reduction in the unexplained sum of squares of the dependent variable.

Recall from Section 2.3 that the purposes of this study preclude the reduction of expected patient resource use into a single index or measure such as total charges. Such a single dependent variable would not supply the clinic decision makers with the appropriate information on how to determine which set of patient groups uses which set of resources. Unlike the cited systems, therefore, successive splits of the data or regressing upon a single dependent variable would be unsuitable [Dilts 1995]. In the light of the foregoing, it is more appropriate to consider the data as consisting only of dependent variables. The basic goal then becomes one of determining interrelations among this set of variables with respect to the utilization of a variety of clinical resources. Thus, the choice to be made is one of finding an appropriate cluster analysis algorithm for use given the largely categorical nature of the available data. Hartigan's Block Clustering algorithm lends itself to this task [Dixon 1992].

Although the literature indicates that cluster analysis can be applied to a variety of tasks [Aldenderfer 1984, Jain 1988, Wilson 1990, Everitt 1993], in this study, as in the cited systems, it is employed only towards grouping similar entities into homogeneous resource classes. This grouping will be realised at the post-classification stage in Figures 1.1 and 2.3.

The second task in the model involves assigning new patients to the appropriate groups. Except for PCTC (for which this was the basic task) and, to some extent DRGs and MEDISGRPS, the majority of the cited schemes do not directly address this task. PCTC used discriminant analysis (in addition to subjective methods) to assign patients into predetermined groups. Likewise, this study employs discriminant analysis in addition to other techniques (statistical, machine learning and neural networks) for these assignments.

The assignment task is performed prior to the actual treatment in the model (i.e. at the pre-classification stage in Figure 2.3) using biographical data only. How well these pre-classification (placements) approximate the actual resource utilization (the final Outcome in the model) provides a measure of the learning system's performance.

The scope of the methodology is also implicit in Figure 2.3. In general, it is intended to be less global in scope and application than the cited in-patient and ambulatory schemes, hence its focus on the clinic as the unit of analysis. It is envisaged that it will be applied in front-office use in individual health care facilities in scheduled secondary/specialty ambulatory settings. By identifying expected resource (input) requirements for incoming patients, it will provide worthwhile short- and medium-term information to service providers for use in such areas as workload, resource and patient scheduling - wherein other planning systems can be invoked to yield desired schedules. If monetary values are attached to these inputs, the model can be extended beyond front-office use into financial planning and budgeting functions.

2.5 Review of Classification Methods

The pre-classification architecture presented in Figure 2.3 relies on cluster analysis to perform the initial categorization (post-classification) of patients. As can be noted from Table 2.1, cluster analysis algorithms have indeed been the only objective tools used extensively in patient resource classification schemes to achieve this categorization. This is not to say, however, that categorization is the only end-product of cluster analysis. The literature is replete with indications that cluster analysis can be applied to such varied objectives as finding a true typology, model fitting, prediction based on groups, hypothesis generation, hypothesis testing, data exploration, and data reduction [Aldenderfer 1984, Jain 1988, Wilson 1990, Everitt 1993]. In this study, as in other research cited, cluster analysis is employed only towards grouping and distinguishing comparable units (patients), and separating them from differing units.

A review of the methods used to build existing medical resource classification schemes shows that there is a standard set of decisions which must be made when doing patient clustering. These decisions include sampling, choice of variables and data scales, dimensional analysis, choice of similarity measure, treatment of missing values, choice of clustering algorithm, number of clusters, and interpretation and validation of the clusters. For the foregoing decision points in the cluster analysis phase, this study utilizes the set of choices that are, in large part, similar to the approach in Dilts [1995].

Although it is commonly recognized that the objects of cluster analysis are typically drawn from a much larger population (hence the necessity of ensuring that a representative sample is obtained), it is known that strict adherence to the principles of random and independent selection may result in the loss of small or rare groups in the data. Selective sampling, therefore, need not be avoided [Anderberg 1973]. Once the sample has been selected, it should be consistently described in terms of the attributes that comprehensively measure the domain of interest [Anderberg 1973, Kaufman 1990], for instance resource utilization in the case of this study. The absence of a pre-theory on the area may entail collecting a large number of variables which can thereafter be reduced using dimensional analysis [Dilts, 1995].

The type of data scale used is an important determinant of what choices are available in subsequent steps in the clustering process (for instance it influences the choice of clustering algorithm). The presence of transformation techniques that can be used to convert one scale into another (subject to the 'costs' entailed), however, mitigates some of the constraints imposed by this step on the classification process [Anderberg 1973]. Similarly, the availability of dimensional analysis explains why certain disciplines (like zoology) use the so-called 'hypothesis of non-specificity' - where they set off with a large number of variables which are subsequently reduced to get a more parsimonious set [Sokal 1963]. Closely dependent on the choice of data scale is the choice of similarity/distance measure. There are a myriad of clustering algorithms, each one of which is dependent on one or the other of the similarity/distance measures to determine how similar or disparate the objects in the analysis are [Anderberg, 1973; Kaufman, 1990; Everitt, 1993].

A common difficulty encountered in clustering, is the aspect of missing values. 'Holes' in the data may result from any number of causes [Kaufman 1990]. Regardless of their origin, these missing values have to be appropriately dealt with (for instance replacing them with suitable estimates) because most clustering algorithms will either 'choke' on them or simply delete all data on objects with missing values [Norusis 1988].

Another common problem in clustering is the difficulty associated with determining the optimal number of clusters in a data set [Everitt 1993]. How this is resolved will depend on a number of factors, not least of which is the type of algorithm used. Some algorithms give a configuration of clusters from one to the number of variables used. Others find the best fitting structure for a given number of clusters. Yet others begin with a user-supplied number of clusters and then alter these as per the dictates of some given criteria [Aldenderfer 1984]. A completely satisfactory solution to this difficulty is yet to be discovered.

Clusters may not only be summary descriptive statistics about the data, but also, they can serve as an aid to reasoning from the data [Anderberg 1973]. Viewed as a proposition about the organization of the data, the clusters may give rise to novel interpretation of what is already known, and shed light on previously unnoticed regularities and relations in the data. Clusters thus have to be interpreted. In this study, they are expected to bring to light similarities in patient resource use. Finally, clusters have to be evaluated against a background of validating criteria. The literature is replete with examples of these validating criteria [Aldenderfer 1984, Romesburg 1984, Jain 1988, Wilson 1990, Dilts 1995].

2.6 Choice of Classification System

Figures 1.1 and 2.3 highlight the distinctive features of the proposed methodology with respect to the tasks it performs, namely classifying and assigning. So far, clustering and classification have been used interchangeably in this study (as in some of the cited schemes). Traditionally, however, the two terms address different, albeit related, tasks. The former is associated with the concept of forming classes or groups, whereas the latter has been used in identifying or assigning individual objects to predetermined classes based on some specified criteria [Bock 1988]. Henceforth, this distinction is adopted in this thesis.

The prediction task addressed in this study after patient clusters have been generated is basically that of assignment, and one that is typical of many areas of human life - where one is called upon to make some decision. Frequently, the decision involves choosing between a given number of alternatives. In such situations, there is a notable reliance on past experience - accumulated experience that may be contained in the knowledge held by a human expert, or alternatively in samples of solved cases contained in some data set [Weiss, 1991]. It is the latter scenario, and the available practical classification techniques that can examine a sample of solved cases and propose some generalized decision rules in terms of an underlying model, that are considered in this study. Recall from Section 1.3 that it was not possible to use new patients for this phase of the study. Hence, the prediction portion of the study will in effect be a 'simulation' of phases IV and V (Figure 1.1) using surrogates for new patients in a manner similar to that in [Tierney 1995]. The specific task at hand therefore, is one of using only patient data available at the 'admission' stage, to determine which iso-resource group the particular 'new' patient belongs to. The actual group membership of the patient is used to assess the predictive accuracy of the classification system used.

The central question regarding which classification system to be used for this task has no easy answer. There are numerous classification systems in existence today. They generally fall under the categories of machine learning, statistical, and "intelligent" systems [Weiss, 1991; Michie, 1994]. The study restricts itself to those classification methods which make no assumptions about the underlying distribution, and for which successful experiences have been reported in the literature [Michalski and Chilausky, 1980; Shapiro and Michie, 1986; Bratko, 1989; Weiss, 1992; Tam and Kiang, 1992; Michie, 1994]. The foregoing narrows the choice from the myriad of existing systems to four, namely: decision trees (machine learning), non-parametric discriminant analysis and K-nearest neighbour methods (statistical), and back-propagation neural networks ('intelligent' systems). In the overview of each of these classification systems that is considered next, a general perspective that discusses their underlying concepts, rather than their mathematical derivation, is given.

2.6.1 Decision Trees

It is believed that of all classifiers, the format of decision trees (a machine learning technique) is, by far, the most easily understood by, and compatible with human reasoning

[Weiss, 1991]. In general, a decision tree consists of a starting point (usually referred to as the root node), nodes, branches and leaves. Each node represents a single test or decision. Following the result at a node (typically either a YES or a NO), the tree branches to another node (where another test is performed). A terminal node (sometimes called a leaf) identifies the class to which the case under consideration belongs.

The decision tree is induced through a non-backtracking recursive partitioning of the sample space into nodes [Michie, 1994]. At each stage in the process, a node is scrutinized to see if it may be split into two nodes (or more, in non-binary situations), the split usually running parallel to the coordinate axes. By repeatedly splitting the data along a selected variable, the classifier finally produces a tree whose every leaf contains members of only one class (or a majority of one class - in those situations where some duplication of the same pattern for multiple classes exists) [Quinlan 1990; Weiss, 1991].

In essence, the classifier's goal is to split the sample of cases in a manner that reduces 'impurity' and randomness of the classes within the current node and future nodes. This is commonly achieved by minimizing the following entropy and gini functions:

$$-\sum_j p_j \log p_j \qquad \textit{entropy}$$

$$1-\sum_j p_j^2 \qquad \textit{gini}$$

where p_j is the probability of class j.

Since entropy and gini represent impurity, the smaller they are, the better [Weiss, 1991]. The classifier's next candidate for splitting is that variable which reduces this impurity the greatest. At any given split, this reduction in impurity can be expressed as:

$\Delta i(n) = i(n) - p_l i(n_l) - p_r i(n_r)$ for a binary tree, and

$\Delta i(n) = i(n) - \sum_k p_k i(n_k)$ for a non-binary tree

where n is the node being split, $i(n)$ is the impurity of the current node, p_r and p_l are the probabilities of branching right and left, $i(n_r)$ and $i(n_l)$ are the impurities of the resultant right and left branch nodes, and k is the number of branches at the current non-binary node. The probability of branching left or right (or in any one of k ways for a non-binary node) is given by the percentage of cases in the current node that will branch left or right (or k-wise) respectively. Some stopping criterion (for instance statistical significance, information gain error reduction, etc) is used to terminate these recursive splits [Breiman, 1984].

There are a variety of decision tree algorithms reported in the literature. They include, among others, AQ11 [Michalski and Chilausky, 1980], CHAID [Kass 1980], CART [Breiman, 1984], ID3 [Quinlan 1986], C4 [Quinlan 1987], PVM [Weiss, 1990], and C4.5 [Quinlan 1992]. In a study that evaluated the performance of a variety of classification algorithms, it was found that in general, there are no significant differences in their predictive performance when the major decision tree algorithms were used on the same data sets [Michie, 1994].

2.6.2 K-Nearest Neighbor

This statistical method is, by far, the simplest learning system in existence [Weiss, 1991]. It has been likened to a direct table look-up and it possesses no explanatory power, i.e. it 'delivers' no explanations or reasoning to the user as to why it classified a given case to a given group [Mitchell 1994]. It is completely nonparametric - making no assumptions about the underlying population in the data. Weiss [1991] avers that geometrically, there is no general form for the nearest neighbor method to draw a boundary between classes since it can produce any arbitrarily complex surface to separate the classes based only on the configuration of the cases and their metric or distance relations to one another.

Unlike the foregoing method, the nearest neighbor does not attempt any generalization or learning from the data. Instead, it simply evaluates each 'new' case, finds the closest patterns from the set of solved cases, picks the class/group to which such patterns belong and assigns the said class/group to the case being evaluated [Weiss 1991; Feng 1994]. It requires that the distance between a new case and every case in the 'training' set be compared variable by variable and then summed. With absolute distance, the absolute difference between the values for each variable is summed, whereas the difference between the values for each variable is squared and summed in situations where Euclidean distance is used. Various other normalized distances can be used in determining proximity between cases, but these distance measures usually yield the same results [Weiss 1991].

Since variables may be scaled differently (for instance gender and age), it is recommended that the data be normalized or standardized for use with this method. Some of the commonly used normalizations in the literature include measuring distance in terms of standard deviations from the sample mean of each feature and standardizing by the range on each feature [Weiss 1991; Mitchell 1994]. We use the latter standardization method on non-categorical variables in this research.

A final consideration under this method is the determination of k (the number of nearest neighbors to use). An odd number of neighbors is used to avoid ties (especially for situations where neighbors from different classes are tied). While using large values for k may be desirable, the literature avers that this entails an increase in the computation time especially in moderate to large sample sizes, hence a lower value for k may be preferable [Mitchell 1994].

2.6.3 Non-parametric Discriminant Analysis

Among the statistical classifiers, linear discriminants are not only the oldest but also the most commonly implemented form of classifiers in existence [Gordon, 1981; Bock, 1988; Hair, 1995]. Some of the patient classification schemes presented in Table 2.1 (for instance PCTC) used discriminant analysis to assign objects to classes initially generated by cluster analysis [Bay, 1982]. The literature indicates that discriminant analysis has traditionally been the technique "to beat" in empirical comparisons with other classification systems in assignment tasks [Weiss, 1991; Tam and Kiang, 1992; Zahedi, 1993; Michie, 1994].

Architecturally, the technique divides the sample space into classes by a series of lines or planes in d-1 dimensional hyperplanes (where d is the number of features present in the data) [Michie, 1994]. Graphically, the line separating one class from another is drawn to bisect the line joining the centers of those classes. The general form of the linear classifier is given by the equation:

$$w_1 e_1 + w_2 e_2 \ldots + w_d e_d - w_0$$

where $e_1, e_2, \ldots e_d$ are the list of features (variables), d is the number of variables and w_i are constants that must be estimated [Weiss, 1991]. In essence, it is a score, or weighted sum of the values of the observations. When testing a case, the class selected will be that one in which the case results in the highest score. Like other parametric techniques, linear discriminant classifiers make normality assumptions about the underlying population in the data.

Previous work suggests that the data in this study may lend itself to the use of a variant of the linear discriminant classifier that makes no assumptions about the underlying population in the data. Such a variant is based on a non-parametric estimate of group-specific probability densities and uses similar distance measures as the previous classification method [SAS, 1990; Weiss, 1991].

2.6.4 Back-Propagation Neural Networks

Available literature presents extensive evidence showing that neural networks (NNs) perform very well in many general classification situations [Li 1994, Sharda 1994]. The same is true in medical classifications. For instance, it has been found that NNs outperform the expert judgement of physicians in predicting pulmonary embolism shown in lung scans and chest radiographs [Tourassi 1993]. Similar conclusions were reached with respect to classifying ST-T abnormalities of ECGs [Devine 1993], predicting in-patient survival rates from CPR [Ebell

1993], predicting relapse in patients with breast cancer [Radvin 1993], and in cell classification [Molnar 1993], among others.

In general, NNs are mathematical constructs modeled along the lines of a human brain [Michie, 1994]. They are variations of the linear classifier, and, unlike the latter, they are completely nonparametric [Weiss, 1991].

In a comparative study of several classification approaches, Tam and Kiang [1992] show that NN approaches offer better predictive accuracy than other widely used alternatives. It has been averred that any task that can be performed by traditional discriminant analysis can be done at least as well (and almost always much better) by a NN [Masters 1993]. Further, it is held that NNs are likely to be superior to other methods in situations where:

1. the data on which conclusions are to be based are "fuzzy", for instance, human opinions, ill-defined categories, or situations subject to possibly large errors;
2. the required decision involves seeking subtle or deeply-hidden patterns that are obscure to human minds, for instance, predicting the credit-worthiness of loan applicants based on their spending and payment history, salary, debt level, etc;
3. the data exhibit significant unpredictable non-linearity;
4. the data are chaotic (in the mathematical sense), for instance in telephone line noise, stock-market prices, and many other physical processes. Although this may be devastating to other techniques, NNs are generally robust with such inputs.

In sum, any problem that can be solved with traditional modelling or statistical methods can most likely be solved more effectively with an NN [Masters 1993]. The success of this variant of learning systems is largely based on the fact that it tackles decision problems that are semistructured or unstructured (with significant qualitative components) that can not effectively be handled by quantitative tools (linear classifiers and regression) [Kroenke 1990; Tam 1992; Zahedi 1993; Li 1994].

This research concentrates on multi-layered (as opposed to two-layer) NNs. It has been shown that a two-layer NN is synonymous to a linear classifier [Hornik 1991; Blum 1991; Masters 1993]. Whereas two-layer NNs have their uses, they are inappropriate for the non-linear situations encountered in classification problems such as the one considered in this research. The preferred method in classification problems is the multi-layer (three-layer) feedforward NN that has been shown to possess powerful function-approximation capabilities that can approach any arbitrary accuracy given sufficient hidden neurons [Masters 1993].

The configuration of the multi-layered back-propagation NNs used in this research consists of nodes representing neurons and links representing connections. Each neuron is a processing unit capable of simple computations. The neurons, arranged in layers, are of three kinds. Neurons in the input layer (residing in the lowest layer of the network) receive signals from the environment and they in turn send signals to neurons in the hidden layer (with no direct interaction with the external environment). The latter send signals to neurons in the output layer (the highest layer in the network) which then transmit their signals to the external environment. Each link has an associated weight and (sometimes) a bias. Thus a neuron i receives input signals (from the environment or other units), uses an input function I_i to aggregate these signals, generates an output signal based on a transfer function O_i, and sends this ouput to other neurons (or the external environment) as directed by the topology of the network. This is captured in the following suggested functions [Rumelhart, 1986]:

$$I_i = \sum w_{ij} O_j + 2_i \qquad \text{and} \qquad O_i = (1/(1 + e^{I_i})$$

where I_i is the input of neuron i, O_i is the output of neuron i, w_i is the connection weight between neurons i and j, and 2_i is the bias of neuron i.

An NN's pattern of connectivity is described by its weight vector *W* (weights associated with the connections in the network). *W*, which in essence defines the knowledge 'stored' in the network, determines how the network responds to any input from the environment. The causal relationship between a set of variables can be modeled by an appropriate *W*. Modifying the weights associated with each connection changes the model.

A distinctive characteristic not evident in other classification methods is the NN's ability to learn by example. In general, NNs can be trained by repeatedly being presented with input patterns. The desired result may (in supervised learning) or may not be (in unsupervised learning) be made available to the network. The network learns by adapting its weights as a function of its inputs, the computed output, and the desired output (if one is made available). The literature abounds with examples of NN applications, the most commonly cited being classification problems (see, for examples, Sharda [1994]). Several learning algorithms exist, but the algorithm whose performance has been evaluated alongside other learning systems and not found wanting in supervised learning is back-propagation [Michie, 1994].

Typically, the back-propagation learning algorithm consists of two phases: forward-propagation and backward-propagation [Masters, 1993; Zahedi, 1993; Rao, 1995]. In the first phase, an input vector is fed into the input layer, and an output vector is generated on the basis of the current *W*. The output vector is then compared to the desired output by calculating the squared error at each output neuron. The differences are summed to generate an error function.

The network's objective is to minimize this error function by changing *W* so that all input vectors are correctly mapped to their corresponding output vectors. In the second phase, a gradient descent in the weight space is performed to locate an optimal solution. Thus the total squared error computed in the preceding phase is propagated back, layer by layer from the output neurons to the input neurons. At each level, weight adjustments are determined and *W* is updated accordingly.

2.7 Evaluation Framework

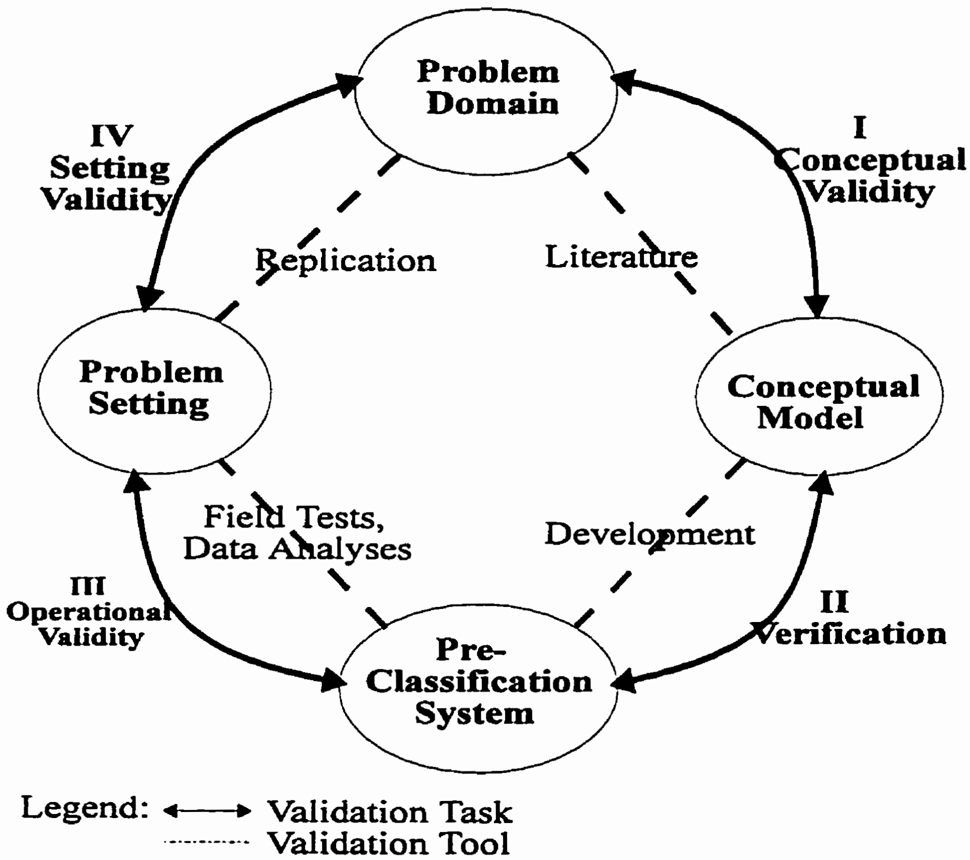
The term "methodology", as used in this study, is interchangeable with approach, system, or process whereas "validation" is taken to mean 'the formal demonstration that a system does what it is supposed to do and continues to do so' [Tranter 1990]. Typically, validation goes hand in hand with verification, and they both constitute evaluation - a broader concept that seeks to assess a system's overall value. Clear evaluation guidelines and methodologies exist for cluster analysis and learning systems - the twin building blocks of the proposed APRCM methodology. These will be incorporated in this study.

To begin with, the cluster validation criteria suggested in the literature include agreement with existing classifications, replication, cophonetic correlation, agreement with expert intuition, agreement of different multivariate methods, agreement of classification with one derived using a different data matrix, demonstration of stability and robustness, significance tests, Monte Carlo procedures, and internal consistency, among others [Aldenderfer 1984, Romesburg 1984, Jain 1988, Wilson 1990]. Table 2.1 shows that the patient resource utilization classification schemes cited earlier invariably relied on expert (physicians') intuition to validate the patient groupings generated by the chosen clustering algorithm.

Evaluation (validation and verification) of a classification system borrows heavily from simulation - an area with a relatively long history as regards these two concepts [Fishman 1968]. To some extent, the definitions and processes of validation and verification in simulation are (with suitable adaptations) applicable here [Zahedi 1993]. This position is affirmed by other authors who maintain that the terminology is general in nature and can therefore be applied to other subject matters or methodologies [Banks 1987]. In line with this, suggested validation methods include informal validation, testing against expert judgement, field tests, and sensitivity analysis, among others [O'Keefe 1991; Gonzalez and Danzel, 1993]. The non-existence of expert judgement leaves informal methods as the primary validation tools for use at the prediction phase. The foregoing considerations suggest that validation is integrally tied to the successful performance of each aspect of the APRCM methodology. This implies a circular development/evaluation exercise along the lines of Figure 2.4. For a model to be useful, it must have conceptual validity, verification, operational validity and setting validity.

The model delineates specific evaluation stages and validation tools called for at each point in the research process. The tools used at each stage are represented by the dashed lines in the model. The APRCM methodology, validated by literature, is incorporated in the Conceptual bubble. The model's Development stage, leading to the Pre-classification System, is confined to activities involved in determining the appropriate *a priori* profiles. Verification is used to determine that the system is build according to the specifications. The system's application to the data by way of various learning methods and the results therefrom constitute the data analyses stage which determines the system's operational validity in the problem setting. The iterative application of the system at various sites or problem domains, is the concentration of the Replication stage.

Figure 2.4: The APRCM Evaluation Model



(Adapted from Sargent 1984, Banks 1987)

It should be pointed out, however, that the evaluation model in Figure 2.4 is more suited to this study when each (clustering and learning) method is considered singly. Further work is needed for the model to be applied to the APRCM process in total.

2.8 Propositions

From the foregoing evaluation considerations, the following propositions and answers thereof are of interest to this study:

Proposition I: A valid generalizeable method for use in developing an *a priori* classification system can be build.

Given the absence of an existing system (addressing the same problem), or an expert against whose judgement the APRCM model can be compared and contrasted, its efficacy is evaluated on the basis of the performance of the learning systems used relative to chance assignments. How well the iso-resource groupings for patients are predicted provides an indication of the overall utility of the APRCM approach.

Proposition II: Generalizeable patient characteristics which lend themselves to the determination of *a priori* potential resource needs across all clinics can be identified.

This helps in the identification of the learning system(s), patient grouping features, and provider characteristics across the different clinic settings that significantly impact patient resource prediction tasks.

2.9 Recapitulation

This chapter attempted to cover the wide-ranging background material underlying both the motivation and the individual components entailed in this research undertaking. It sets the stage, and provides the basis and rationale, for the specific activities and decisions discussed in Chapter 3.

CHAPTER 3

RESEARCH METHODS

3.1 Overview

This chapter describes the research methods followed in the study. Issues covered include the population of interest, sampling considerations, instrument and procedures used in data collection, data clean-up and pre-processing issues, and the analyses completed. A field-based research design [JOM 1991] which relies on the analysis of secondary data was adopted in the study. These predominant secondary data were supplemented by primary data obtained from open-ended interviews of low vision expert(s) at the study sites.

3.2 Population and Sampling Methods

The study was predicated on two premises, namely; that biographical data about patients can be obtained prior to the actual appointment date, and that there is a 'reasonable' lead-time between first contact with the patient and actual appointment date. The former enables a before-the-fact categorization to be done whereas the latter ensures that there is sufficient time so that categorization can be achieved prior to the commencement of actual treatment.

3.2.1 Population

Recall from Chapters 1 and 2 that previous work done was conducted in a clinic providing several low vision services[1] to a diverse patient population[2] receiving varied financial

[1] Besides low vision sight assessment, a clinic can also provide high technology sight enhancement assessment, and rehabilitation.

support from a broad base of funding agencies[3]. In extending this work to other clinical low vision settings, this study sought to determine the robustness of the methodology not only in a heterogeneous patient environment (as the foregoing), but also in more homogeneous settings (i.e. clinics catering to a specific category of patients). Further, the study also seeks to determine whether the proposed methodology is applicable in settings outside the North American environment.

Against this backdrop, the population of interest for the study consisted of specialty/secondary, scheduled, health care clinics in low vision ambulatory care in North America and Sub-Saharan Africa. A sampling frame was compiled from the International Low Vision Directory [Yeadon 1988] and the Directory of Services for Blind and Visually Impaired Persons [AFB 1993]. These directories provide a listing of about 190 accredited agencies offering low vision services in North America and Sub-Saharan Africa. Of these, 48 (47 in the U.S. and 1 in Eastern Africa) met the definitions of speciality/secondary (i.e. offered services only on scheduled and referral basis [Newcomb 1980; Roemer 1991]. These constituted the sampling frame.

3.2.2 Sampling

The findings of the previous work indicated that the most notable patient characteristics that distinguished between the profiles of the resultant patient iso-resource groupings (i.e. age,

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[2] The patient population was diverse not only in terms of the presenting eye-conditions, but also in impairment, age (infants and school-aged, adults, and elderly patients), and visit category (new, follow-up and repeats), among others.

[3] For example, the clinic is housed in the School of Optometry, University of Waterloo. It also receives funding support from the Ontario Ministry of Health, the Ontario Ministry of Community and Social Services, professional service fees, and service contracts.

impairment, gender, goal, glare, category, etc.) could be translated into three higher-level dimensions that, in turn, served to distinguish between clinics, namely; 1) type of patient base, 2) services provided, and 3) funding support.

Other dimensions that would help to distinguish between low vision clinics emerged in discussions held with two low vision experts[4]. They included the clinic's size (indicated by, among others, the number of staff, size of annual budget, and number of new patients seen per year), level of patient needs (i.e. multiply-impaired versus non-multiply-impaired patients), and whether or not the clinic provides training facilities for patients. Regrettably, these dimensions were not included in the information provided by the sources of the sampling frame.

The Patient-base splits clinics on the basis of the ages of the patients seen (Paediatric, Adult, Geriatric, All Ages). Funding-Base dichotomises clinics on whether or not they received government funding (Federal and/or State/Provincial). Finally, Services-Provided divides clinics into High-Tech, Rehabilitation, Orientation & Mobility, and Multiple-discipline environments. This stratification suggested that for all characteristics of the clinics to be 'captured' a full factorial design of 48 (4 x 4 x 3) samples, as depicted in Figure 3.1, was needed. These dimensions were used in stratifying and selecting study sites from the sampling frame.

Three aspects namely, the absence of 'willing' participants in certain quadrants (for instance Patient-Base: Geriatric - notably V.A. clinics), the non-existence of clinics in others (for example Paediatric: Client-Fees, High-Tech only), and the multifaceted nature of most clinics in terms of funding base and services offered, permitted a far smaller sample (n = 7) to 'capture' all

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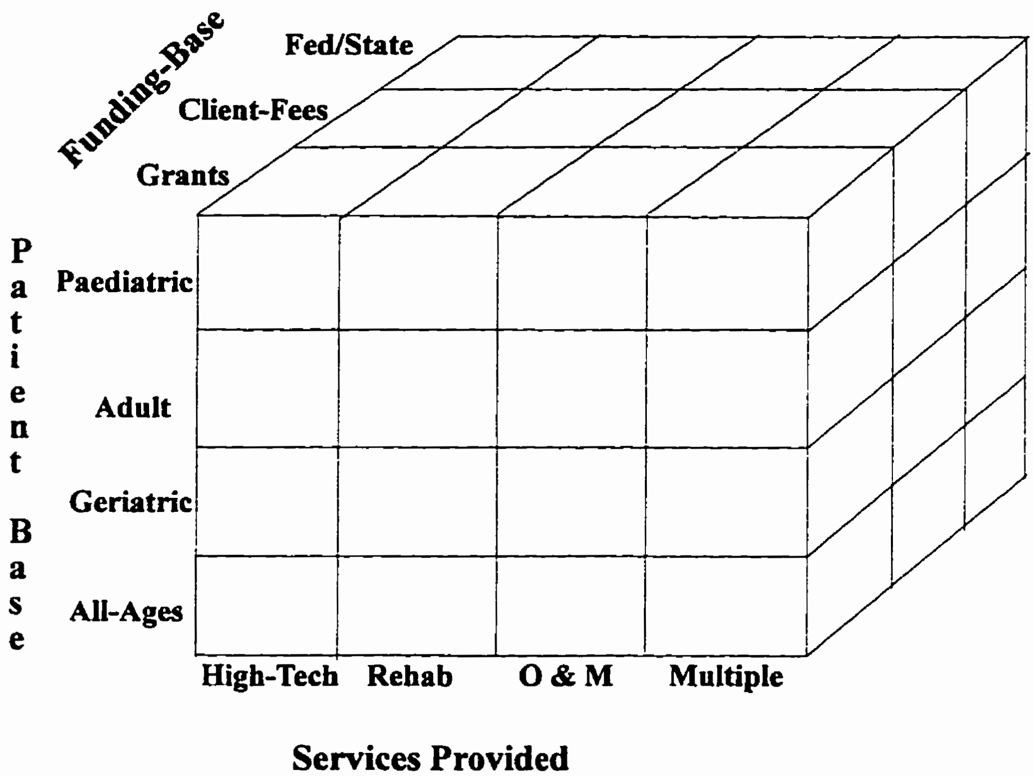
[4] The Director of the Centre for Sight Enhancement (CSE) at the School of Optometry, and a Clinician at the Low Vision Clinic (LVC) within the CSE, University of Waterloo.

the dimensions of interest, i.e. to ensure that the 'possible' quadrants contained at least one clinic/center. This, however, does not allow for in-depth discussion of interaction effects. Further, due to time and other resource constraints, the study focused on the Eastern, North-Eastern, and Mid-Western regions of the U.S. and Kenya.

Figure 3.1: Dimensions of Interest in Study Sample



Of the 28 clinics/centers contacted (either by phone or e-mail, and fax) in North America, 22 could not participate due to one or more of the following reasons:

a) the clinic/center was not a stand-alone clinic (i.e. it provided other non-low vision services and maintained mixed patient records) hence would present operational difficulties in the data collection process;

b) the clinic/center was principally a residential facility;

c) the clinic/center either did not have in place a system that addressed existing legal guidelines on confidentiality/privacy of patient information, or the necessary approvals for these could not be obtained in sufficient time.

The clinic contacted in Sub-Saharan Africa was the only specialty/secondary low vision service provider in the Eastern and Central regions of Africa.

The same set-up procedure was followed at each clinic contacted. An initial telephone call by the researcher initiated each contact. This was followed by the faxing of a one page description of the study (see Appendix A). Where the clinic's contact person (Coordinator or Director) so desired, an eight-page summary of the study plus the Office of Human Research's approval (see Appendix B) was also faxed. Whenever a clinic (hereafter referred to as 'site') agreed to participate in the study, the corresponding quadrant(s) in the dimensions checklist (Figure 3.1) was checked. The next clinic contacted would then have characteristics in an unchecked quadrant. After the necessary consent form had been obtained, a mutually convenient data collection period of at least one week was set. This set-up procedure resulted in all the major quadrants of interest being covered in the study.

3.3 Data

Data for this study are of two basic types, namely primary data obtained by way of the open-ended interview method, and secondary data retrieved from the sites' patient records. The former consisted of background information on the site, the patient-flow process, and a description of the resources required/utilized in the process. The latter consisted of patient biographical information (age, gender, goals, etc.) and resource usage data (units of staff time, facilities used, devices prescribed, etc.) found in patient record files.

3.3.1 Data Collection

The open-ended interviews were conducted at the site on the first morning in the data collection phase. The interviewees for this part of the study were the contact persons at the sites (Clinic Director/Coordinator) and, where necessary, other low vision specialists at the site. Sample patient record forms, patient statistics, and available literature describing the site were also collected during this time as the interviews 'walked' the researcher through a typical patient visit.

The previous work indicated that the diversity of the clinics would rule out the use of a single standard data collection instrument at all the sites. A custom data collection instrument was therefore developed, with the assistance of the contact person, for each site using information obtained from the interviews and the sample patient record forms. This instrument was basically a flat file (in hard copy or electronic form) with the columns representing the variables of interest and the rows representing cases (patients) in the sample (see individual site appendices for examples of these). The first afternoon and subsequent days of this phase was spent using this instrument to collect data from available patient record files.

Sample size of subjects at sites does not seem to have been an issue that was confronted directly in the schemes cited in Chapter 2. The common approach appears to have been an inclusion of all units available in the patient data set at the researcher's disposal. In this study, we elected to take at least 25% of subjects at each site (for the targeted period) as a sufficiently large sample to provide the information needed.

Site 1 (in a large non-teaching hospital), Site 3 (in a specialty ophthalmological hospital), Site 4 (in a medium sized non-teaching hospital), Site 5 (in a rehabilitation facility) and Site 7 (in a small non-teaching hospital) had all their data in hard copy (physical files). The data collection process therefore involved retrieval and encoding of the required items of interest from patient files in the targeted sample. Site 2 (in a large teaching hospital) and Site 6 (in a residential school for the blind) had part of their patient records in electronic form. A copy of these computerized data (with appropriate variables to serve as primary/connecting keys) was obtained and merged with the data from the physical patient files.

'In-house' university students were used as paid research assistants at Sites 2, 3, and 7. A training session was conducted prior to the commencement of the actual data collection exercise at these sites to familiarize the research assistants with the data collection instrument, contents of the patient records, agreement with the interpretation and coding of the contents, and a common approach in the handling of unique cases. Periodic reviews were conducted each day to ensure that there was consistency between their work and that of the primary researcher.

3.3.2 Data Clean-up and Pre-processing

One of the issues addressed at the pre-processing stage, was the question of how to handle missing values. Both the clustering and classification algorithms used in this study delete cases that contain missing values on any of the variables in the data. We had two options: either filling in the missing values with estimates from, or mean values of, the non-missing cases over the same variables, or establish some surrogates for features when their values were missing [Weiss 1991]. Previous work indicated that replacing missing values with estimates introduces some measure of 'artificiality' and noise in the data that penalized the clarity of the groupings which eventually emerged. For clustering purposes, we avoided this by including a category 'n/i' (not indicated) in the respective variable(s) in the place of missing values. For classification purposes, however, some degree of noise in the data is not totally undesirable or avoidable [Feng 1994; Rao 1995]. In addition to retaining the 'n/i' category in the categorical variables, missing values in non-categorical variables (for instance Onset of Eye Condition, Visual Acuity, etc.) were replaced by the means of their respective non-missing values.

The variables were coded following the respective coding scheme (see individual site appendices for this). Those variables relating to dates were transformed into time lengths (expressed in weeks, months or years) using the appointment date (visit date) as the base point. The resulting data set was then preliminarily analyzed for descriptive statistics. Some variables were deleted from the data set due to either redundancy (the variable contained information that was provided, or could be inferred from another variable), lack of variability (the variable could not discriminate between patients since all patients had identical values on the variable), or had insufficient responses (the size of the 'n/i' category exceeded a stipulated minimum - 50%).

3.4 Generation of Patient Groupings

For clustering purposes, the study followed the procedures outlined in Dilts [1995]. As observed earlier, data collected at each site emanated from a variety of forms and records in a site's patient database. These were captured in variables using a variety of continuous and categorical (ordinal and nominal) scales. To avoid the difficulties encountered when clustering a mixed data set, it has been recommended that the data be transformed into the dominant scale present therein [Anderberg 1973; Kaufmann 1990]. In line with this, the data were transformed into a homogeneous categorical scale by grouping each of the interval variables and treating these, together with those of the other variables, as simply different groups. For instance, age was divided into categories of 10 years (see Site Appendices for site-specific details).

Since the intention was to cluster patients on the basis of the resources they consumed, each of the variables was scrutinized to determine its nature, that is, whether it was one giving biographical information about the patient, or had a bearing on the resources the patient utilized at the site. A variable was defined as biographical if it could be known before the appointment date (for instance age), whereas a resource variable was defined as such if it measured a service, facility, or time expended by the clinic or its staff on the patient on or after the appointment date (for instance usage of High-Tech assessment). In the generation of patient groups, all biographical and resource variables were used, whereas the latter were discarded (and only the former used) in the classification task.

The categorical scale of the data dramatically reduced the options in terms of the clustering algorithms that could be used. Hartigan's Block Cluster Analysis in Release 7 of the BMDP statistical software package was the only clustering algorithm identified that was designed to handle categorical rather than continuous data [Dixon 1992]. This algorithm uses modal values to group cases. It was first applied in an experimental manner on the data to determine the row and column minima, and the desired number of clusters that would yield the best results.

As pointed out by its designers, a good clustering from the algorithm is one where block counts are substantial fractions of the total data values [Dixon 1992]. The study, therefore, sought configurations that would yield block counts accounting for the highest percentage of the total data values. The best results were generally obtained when the row and column minima were set at five. The algorithm was then used iteratively on a data set to generate patient groupings using these row and column minima but with different desired numbers of clusters. Five and (at one site) four clusters were found to yield the best results from the data. Finally, for validation of groups, the data set was split into two halves and the most distinctive cluster configuration that replicated itself in both halves was adopted [Anderberg 1973].

3.5 Classification Systems Used

The refined clusters generated by the foregoing process served as the "gold-standard" at the prediction phase. Once the clusters had been generated, an extra variable, identifying the group to which a patient belonged, was added to the data set. Thereafter, resource variables (and all other variables providing information that is not available at admission) were stripped from the data.

Recall from Chapter 2 that several considerations narrowed the choice of the classification techniques to four, namely: decision trees, k-nearest neighbor, non-parametric discriminant analysis, and back-propagation neural networks. A general description of each was given in Chapter 2. They are all implemented on a computer, albeit under two different operating systems - Microsoft Windows and UNIX.

3.5.1 Decision Tree - C4.5

Due to its ability to handle both continuous and categorical data, the C4.5[5] decision tree algorithm was implemented on an IBM RISC 6000 workstation under the UNIX operating system. The algorithm is fairly easy to run since it requires very few parameters. It needs a declaration for the types and range of variables used, and such information has to be placed in a file separate from the data file [Quinlan 1993]. For ease of reading the algorithm's output, we modified the data to have all the values in the categorical variables expressed in their original qualitative (text) form. Windowing was used to develop 10 decision trees from the data. The 'best' tree from these was adopted in a 10-fold cross-validation invoked through the **xval.sh** option of the classifier. The average error on the training cases constituted the apparent error, whereas the estimate of true error was obtained from the average errors on the testing cases [Quinlan 1993; Weiss 1991; Michie 1994].

Default values for most of the settings (confidence level, amount of output, trees generated, window size, etc.) work reasonably well for most tasks (as was borne out by experimentation with the algorithm), hence the user may not need to specify these [Quinlan 1993]. Once the data and declarations have been set up in suitable formats, the algorithm's developmental time requirements are negligible (less than three minutes to train and test the tree and generate the attendant decision rules at the sites given the moderate sizes of the data

[5] Release 5.1 - Documentation and source code for this is found in [Quinlan, 1993].

sets - 200 to 850 cases). Generating a graphical format of the tree is, however, more demanding timewise since it has to be done manually. Further, since the application of this learning method in the study was for the purposes of determining its prediction performance for comparisons with other learning systems, most of its modules were not used, and the decisions called for were limited to formatting the data, invoking the cross-validation module, and specifying the number of splits in the data for cross-validation (10).

3.5.2 K-Nearest Neighbor - SAS's DISCRIM

We implemented the 3-nearest neighbor module in the DISCRIM procedure of SAS[6] (the only commonly available statistical package containing this algorithm). For this quantitative tool, data formatting decisions involved standardizing the quantitative variables using their ranges and transforming all categorical variables (with the exception of the group variable) into binary form. This invariably meant an increase in the number of variables present in the data set. We used 'hold-back-one' (the only available form of) cross-validation to get estimates of true error. In effect, this meant that all cases but one are used to determine the classification criterion (as training data), and the remaining case is tested on this criterion. This process is repeated until each case has been tested (assigned) [SAS 1990].

For the purposes of this study, this is an easy learning system to use. The required decisions include specifying the desired number of nearest neighbors to use for each case tested, the grouping variable, the distance measure (we used the commonly-used Euclidean distance), whether or not cross-validation is to be used, and the format of the output. The

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[6] Version 6.11 - Documentation can be found in [SAS 1990].

learning system's time requirements are minor (less than 20 seconds for each site). Another feature in this classifier's favor is its accommodation of user-specified output preferences. In addition to the standard classification matrices, a listing of the correctly and incorrectly classified cases can be generated for further scrutiny and analysis. Group (class)-specific apparent- and true error rates were also computed and generated in the output.

3.5.3 Non-parametric Discriminant Analysis - SAS's DISCRIM

Like the foregoing, we implemented this classifier in the DISCRIM procedure of SAS[7] (again, the only major statistical package with this learning system) on an IBM RISC 6000 workstation under the UNIX operating system. The classifier employs the estimated class specific probability densities from the training set to evaluate the posterior probability of class membership for each case tested and assigns the case into the class with the largest probability value. Whenever there is a tie for the largest probability, or whenever this largest probability is less than a specified threshold (0.5 in this study due to rounding reasons), the case is assigned to the default class 'OTHER' [SAS 1990].

This classifier is also easy to use and runs in either batch or interactive mode. Similar decisions as in the foregoing learning system have to be made except for the number of nearest neighbors. Once the data are in the appropriate format, the classifier's computation time requirements are also minor (less than 20 seconds real time on average). Performance degrades somewhat with an increase in the number of variables or cases. Like the foregoing learning system, this method accommodates user-specified output preferences and generates a

[7] Version 6.11

listing of the correctly and incorrectly classified cases and group (class)-specific apparent- and true error rates in addition to the standard classification matrices in its output.

3.5.4 Back-Propagation Neural Networks - WinNN

We implemented WinNN[8], a Microsoft Windows-based back-propagation NN, on a Pentium PC running at 166 MHz. For this method, even the group variable in the data set was transformed into binary variables. The input data carried the necessary flags enabling WinNN to identify them as input pattern and test files. Like the decision tree, a 10-fold cross-validation was used to estimate the true error.

Experiments were completed to determine the appropriate architecture and parameters to yield the best converging speed in the training sessions. The prevalent three-layer (with one hidden layer) design was adopted. The common 'pyrammidal shape' rule of thumb regarding determination of number of neurons in the hidden layer was used [Masters 1993].

This learning system turned out to be quite costly in terms of time. The training phase took several (2 to 7) days per data set. Likewise, it requires more parameters than the foregoing learning systems from the user, and extensive tweaking (in terms of commencing at different starting points, learning and momentum parameters) to get apparent performance that exceeds chance assignments. Again, no group specific estimates were drawn from this learning system's predictions, hence no inter-group and inter-system comparisons could be made regarding its performance on the individual patient groups.

[8] Version 1.1 - Developed by Y. Danon.

3.6 Predictive Performance Measures

The basic objective of the analysis at this point is to determine the performance of each learning system, i.e. how well each learning system predicts the group membership for the cases at each site using only that information about the patient that is available before the appointment date. This performance can be evaluated using several measures or rates [SAS 1990; Weiss 1991]. These measures include apparent error rate, estimated true error rate, and usage of some misclassification cost.

3.6.1 Apparent Error Rate

A sample of data (training data) is presented to the classification system to enable a classification criterion (rule) to be set up. This criterion is then tested on a second independent sample of cases (test data) whose true classification (group) are known but are 'hidden' from the learning system. A simple counting of the mis-classified cases (%) in the testing set yields the apparent error rate. This method of determining the apparent error rate is sometimes referred to as the 'one-shot' train and test [Henery 1994]. Where group-specific error count estimates are desired, they represent the proportion of mis-classified cases in a particular group. Although apparent error rates are unbiased if the test cases are independent of the training cases, they tend to have large variances [SAS, 1990].

3.6.2 Estimate of True Error Rate

The second evaluation criterion is the posterior probability error-rate (estimate of true error) which is a sum of the mis-classified independent test cases. However, instead of obtaining this in a 'one-shot' manner, it is determined through a cross-validation procedure [Henery 1994; Weiss 1991]. Cross-validation involves dividing the data into *m* sub-samples. Each sub-sample is used as the test-data for a classification criterion developed from *m*-1 sub-samples (training data). The estimated error rate is the average error rate from all *m* sub-samples. The 'hold-back-one' (leave-one-out) method is an *m*-fold cross-validation with *m* equal to the number of cases in the data [Lachenbrach 1968]. It is reported that the resulting error rate estimate has a smaller variance than the apparent error rate [SAS 1990; Glick 1978; Weiss 1991]. It is also pointed out in the literature that in practice, the estimate of true error rate, be it for the whole sample or for a specific group therein, is usually larger than the apparent error rate, especially in modest ($n < 1000$) and small ($n < 100$) samples [SAS 1990].

3.6.3 Misclassification Costs

A misclassification cost is basically a value that is attached as a penalty for incorrect class assignments. Using such values biases decisions in different directions. Raising or lowering the misclassification cost has the same effect as having more or less cases in a given class. This, however, is user-supplied and inconsistent with the objective of this phase of the study - that of determining the performance of the classification method and comparing it with the performance of other methods. We, therefore, elected not to use this measure, and instead, present the classifiers' performance as is, without biasing them with arbitrary indications of misclassification costs. Thus the only indicators of a classifier's performances in the study are the apparent error rate and estimated true error rate.

3.6.4 Evaluation of Classifier Performance

Finally, a determination of how well each method performs is a fitting issue with which to close this section. Going only with the predictive performance of each classification method, the lower the error (apparent and true), the 'better' the classifier. The question of how good this performance is, is difficult to answer in the absence of a readily available benchmark against which the performance can be judged. Hair [1984] suggest the usage of the chance criterion, i.e. determining the percentage of the cases in the data set that could be classified correctly by chance (without the aid of the learning system). The maximum chance criterion (frequently given by the proportion of the largest group in the data set) or the proportional chance criterion are suggested. The latter is given by:

$$C_p = \sum_{i=1} p_i^2$$

where C_p is the proportional chance, P_i is the proportion of group i in the data sets.

In our research, for the classifier to have utility, it must, at the minimum, deliver a predictive performance that surpasses this value.

3.7 Conclusions

A standard set of procedures in the APRCM methodology as outlined in sections 3.3 through 3.6 was followed at each site. Distinctive patient groupings validated through replications were obtained. Resource and other after-the-fact data were stripped from the data sets and the remainder (biographical data) presented to the learning systems for classification (prediction). Empirical data with respect to the overall performance of the different learning systems in predicting a case's iso-resource group membership (i.e. pre-classifying patients) using these biographical data only were obtained. The predictive accuracy of each learning system, and hence overall efficacy of APRCM, can be determined from these performances relative to chance assignments. Disparate performance from learning systems across sites were noted and these are presented and discussed in Chapter 4.

CHAPTER 4

SITE-SPECIFIC RESULTS

4.1 Overview

The APRCM methodology was applied on data from seven field sites. The various activities undertaken in site-selection, collection and pre-processing of the data, generation of the patient groups, and the performance of the individual classification methods in assigning cases to their respective groups at each site were presented and discussed in Chapter 3. These, together with a description of the patient groups, are covered more specifically in the individual site appendices (D.1 through D.7). Presented in this chapter are the summary findings from the classification analyses and prediction phases of the study.

4.2 Setting

As pointed out in Section 3.2.2, the clinics/centers that make up the study sites are drawn from the Eastern, North-Eastern and Mid-Western parts of the US and the whole of Eastern Africa. All seven sites are the principal referral specialty/secondary low vision facilities for the category of patients served for the state/country they are located in (and in some cases, for the neighboring states/countries). Brief descriptions of these study sites is given below.

Site 1 is located in the vision center of a medium-sized (> 500 bed), non-teaching hospital in a large Mid-Western metropolis (4 million inhabitants). The hospital fully funds the operations of the clinic. The clinic's staff of seven is a multidisciplinary complement of ophthalmologists, optometric low vision specialists, rehabilitation and occupational therapists and a receptionist/secretary who handle related duties in the host vision center and periodically at the local Children's Hospital. The clinic accepts patient referrals from the host hospital, self-referrals, and referrals from community eye and rehabilitation practitioners in the surrounding metropolis. Its patient base is largely geriatric, racially mixed, and predominantly female. Other distinguishing features of this site include its relatively short waiting period before patients are seen in the clinic (frequently a fortnight or less) and a very active follow-up program.

Site 2 is located in a vision research and rehabilitation center at a large (> 1000 bed), university hospital in an East Coast metropolis of about 2 million inhabitants. In addition to funding from the host hospital and client fees, it receives grants from a major philanthropic organization. Its multidisciplinary staff consists of ophthalmologists, optometric low vision specialists, rehabilitation and occupational therapists, a receptionist/secretary and two co-op medical students routinely assigned duties within the clinic. The clinic accepts patient referrals from within the host center and hospital and from community eye and rehabilitation practitioners in the surrounding metropolis and adjoining states. A small proportion of its patients are from international referral sources. Its patient base is largely geriatric and racially mixed.

Site 3 is located in a medium-sized (> 500 bed) specialty ophthalmological hospital in a large East Coast metropolis (4 million inhabitants). The host hospital is affiliated with three major medical schools. The clinic is funded by the hospital and client fees. Its staff consists of an ophthalmologist, four optometrists, occupational therapists, ophthalmology residents, and social workers. The staff also includes two secretaries, an ophthalmic assistant, and trained volunteers. It accepts patient referrals from the host hospital, self-referrals, and eye and rehabilitation practitioners from the surrounding metropolis. A significant proportion of its predominantly geriatric and largely female patient base is drawn from adjoining states and a number of foreign countries. One of the distinguishing features of the clinic is its integration of eye, ear, nose, and throat rehabilitative services for its clients.

Site 4 is located at one of the two campuses of a 500-bed non-teaching hospital system serving a midwestern metropolitan region of about 0.35 million inhabitants. It is an accredited regional referral center for a predominantly geriatric and largely female patient base drawn from the host- and the adjoining states. Its free public screenings is aimed at determining the appropriateness of a complete low vision consultation and it generates most of the self-referrals. In addition to these, it accepts referrals from the host hospital and from eye and rehabilitation practitioners. It is staffed by an optometrist/director, educationist/social workers, secretary and other support staff.

Site 5 is situated in a small suburb of a metropolis (2 million inhabitants) in an Eastern state. It is located in, and funded by, a non-hospital institution that provides both out-patient and in-resident visual rehabilitation services (personal adjustment to blindness training). It accepts patient referrals from the host institution, self-referrals, physician-referrals, and state agency referrals. The center's patient base is geographically drawn from three states - the state it is located in and the two adjoining ones. This patient base is exclusively adult (18 years and above) and predominantly geriatric. It is headed by a Low Vision Coordinator who reports to the host institution's Director of Rehabilitation. Its staff also includes an optometrist, a rehabilitation evaluator and a secretary.

Site 6 is the outreach services department (OSD) of a school for visually impaired children located in a small mid-western town (< 10 000 inhabitants). The school is the state's primary repository of expertise in the education of blind and visually impaired children. It conducts field based low vision clinics in different education agencies throughout the state in an effort aimed at reaching its geographically dispersed and exclusively young (< 21 years) patient base. These clinics are funded by a grant from the state's Department of Education and the Lions Club, hence, they are provided free of charge to the clients. It offers special eye examinations and follow-up services to determine if assistive devices will help a partially-sighted child to read print and better see other visual materials. In support of this, it runs a loaner program covering a variety of these devices. Also offered are orientation and mobility instruction and itinerant teaching (direct instruction of students to meet their educational needs). Its staff includes a Director who reports to the school's superintendent, specialized faculty members in charge of infant and preschool consultancy, clinics coordination, instructional materials, itinerant teaching, orientation and mobility instruction, a low vision specialist (optometrist), a secretary and two copy typists. Referrals to the OSD clinic emanates from several different sources namely; parents/guardians, early intervention service providers, health or social services agency, physician, and teachers.

Site 7 is housed in the eye unit of a small (< 250 bed) hospital located on the outskirts of a large metropolis (about 2.5 million inhabitants) in Kenya. The clinic is funded by a non-governmental European philanthropic organization. Its patient base is predominantly young (pre-school and school-aged patients below 25 years) who are geographically dispersed over the Eastern African region. It, by default, also serves adult and geriatric clients. It conducts field based low vision clinics in different schools for the blind and organizes training sessions throughout the region. The clinics and the prescribed assistive devices, are provided free of charge to pre-school and school-going clients. It offers visual evaluations and follow-up services to determine a) if the client is indeed low-visioned, and b) if assistive devices will help improve the client's visual functioning. Towards this end, it has instituted a loaner program covering a variety of optical and non-optical devices. Also offered are training and counseling services. The center is staffed by a low vision therapist, a low vision advisor/educator, and two trainee therapists, a secretary and a typist. It liaises closely with the host eye unit for clinical/ophthalmologic support/input. Referrals to the clinic emanate from the host hospital, physicians from other medical facilities in the region, parents, and teachers.

Tables 4-1 (a-c) summarize some of the characteristics of the sites.

Table 4.1a: Patient Categories Served by Site

	Primarily Children	Primarily Adults	All Ages
Site 1	-	-	Yes
Site 2	-	-	Yes
Site 3	-	-	Yes
Site 4	-	Yes	-
Site 5	-	Yes	-
Site 6	Yes	-	-
Site 7	Yes	-	-

Table 4.1b: Services Provided by Site

	High-Tech	Rehabilitation	O & M	Multiple
Site 1	-	Yes	Yes	Yes
Site 2	-	Yes	Yes	Yes
Site 3	Yes	Yes	Yes	Yes
Site 4	Yes	Yes	Yes	Yes
Site 5	Yes	Yes	Yes	Yes
Site 6	Yes	Yes	Yes	Yes
Site 7	-	Yes	Yes	Yes

Table 4.1c: Funding Base by Site

	Federal	State	Patient Fees	Grants
Site 1	-	-	Yes	Yes
Site 2	-	-	Yes	Yes
Site 3	-	-	Yes	Yes
Site 4	-	-	Yes	Yes
Site 5	-	-	Yes	Yes
Site 6	Yes	Yes	-	Yes
Site 7	-	-	-	Yes

4.3 Data

Table 4-2 shows the number of cases covered at each site and the proportion of these to the number of total patient visits handled by the site over the year of interest.

Table 4.2: Cases collected from each site

	Period Covered (Year)	Total Patient Visits	Sample size	Sample/Pt Visits
Site 1	1994	750	270	36.0 %
Site 2	1994	1242	310	25.0%
Site 3	1995	1515	388	25.6%
Site 4	1994	700	204	29.1%
Site 5	1995	261	204	78.2%
Site 6	1994/5	282	203	72.0%
Site 7	1995/6	2530	848	33.5%
Total/Average		7280	2427	33.3%

Appendices D.1 through D.7 discuss the foregoing in greater detail. These appendices have a similar structure and address the same issues for each site. In addition to describing the setting and giving descriptive statistics for patients in the data, they also cover data pre-processing decisions. Further, they describe the characteristics of the iso-resource groupings generated from the data and the predictive performance of each learning system on these groupings.

4.4 Cluster Analysis

As pointed out in Section 3.4, Block Clustering was used to generate patient groupings. It is assumed that the groupings identified constitute the latent patient groups at each site (see individual site appendices for the characteristics of the specific groups). From the data set, the clustering algorithm groups (blocks) subsets of cases into clusters that are alike for subsets of variables [Dixon 1992]. Each block contains a group of cases defined by variables that are constant (i.e. have the same modal value) over the cases in the block. In its output, the algorithm reorders the rows (cases) and columns (variables) to make the blocks contiguous and succinct. Overlaps in the groupings generated may exist, and these are evident in cases carrying modal values in variables for one block and modal values for a different block on another set of variables. In the output, a block is identified by block symbols (digits or letters) that represent the case-variable pair that is placed in a particular block.

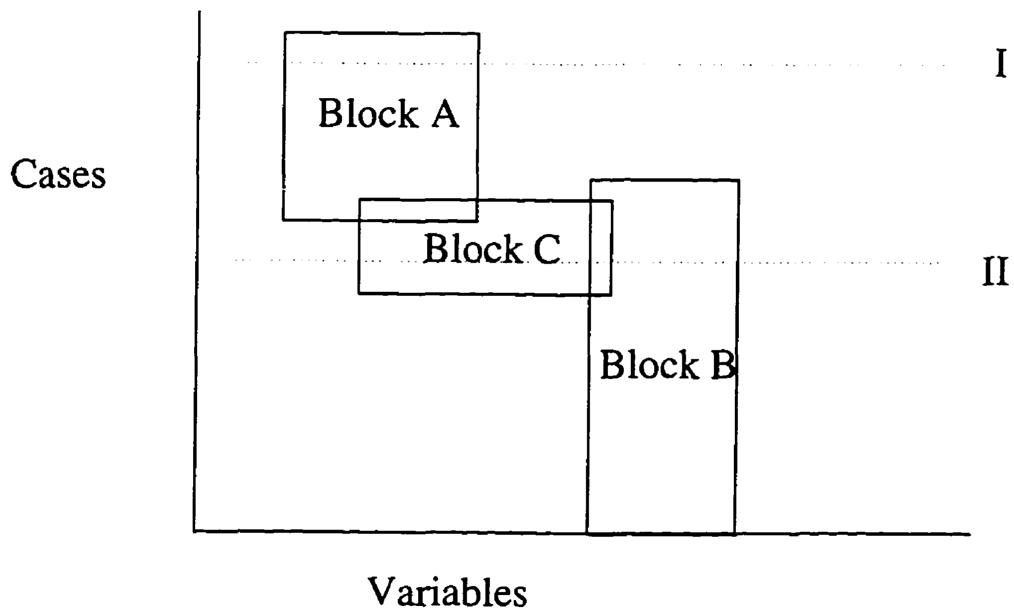
Another important result of block counts is the identification of singletons. A singleton describes an instance where a case's value deviates from all modal values in identified blocks on that variable. Singletons are outside the blocks and they represent the unique case-variable pair that could not be placed in a block. The algorithm also highlights these singletons in its output. Table 4.3 summarizes the number of patient groupings obtained at each site. It also shows the proportion of the data set contained in the sum of the block counts. A block count is the count (number) of symbols in a block and the number of singletons is one minus the block count. Block count is used to determine the crispness of the resulting blocks. Note: blocks represent clusters of case-variable data.

Table 4.3: Patient Groups Generated at Sites

	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7
# of Patient Groupings	4	5	5	5	5	5	5
% Block Counts in Data Set	60.38%	59.01%	59.72%	63.01%	66.14%	70.41%	64.77%

Every patient case is placed in a group based upon the dominant block, that is, the block having the highest number of features (variables) in the case (for example, see Figure 4.0).

Figure 4.0: Illustration of Patient Groupings



In this example, there are 3 blocks representing patient groups. Patient I is placed in Group A because it is the only block with modal values in the variables describing Patient I; the other variables for Patient I are singletons. Patient II's variables have modal values for two groups, B and C. Patient II would be placed in group C because it is the dominant block.

Dixon avers that a good clustering is obtained when block counts are substantial fractions of the total data values. Feature-selection is a prevalent technique for increasing the proportion of block counts in the data set. It involves eliminating insignificant distinguishers (variables) from the data set. This technique is not used in this research for two reasons. First, the research is exploratory, not confirmatory, in nature, and it is unknown if the use of such a technique would have removed critical variability in the data sets. Second, such a technique would reduce the number of variables available to the learning systems and, as such, may remove critical variables from the data set. Future research should investigate how the use of such techniques affect the performance of the various learning systems.

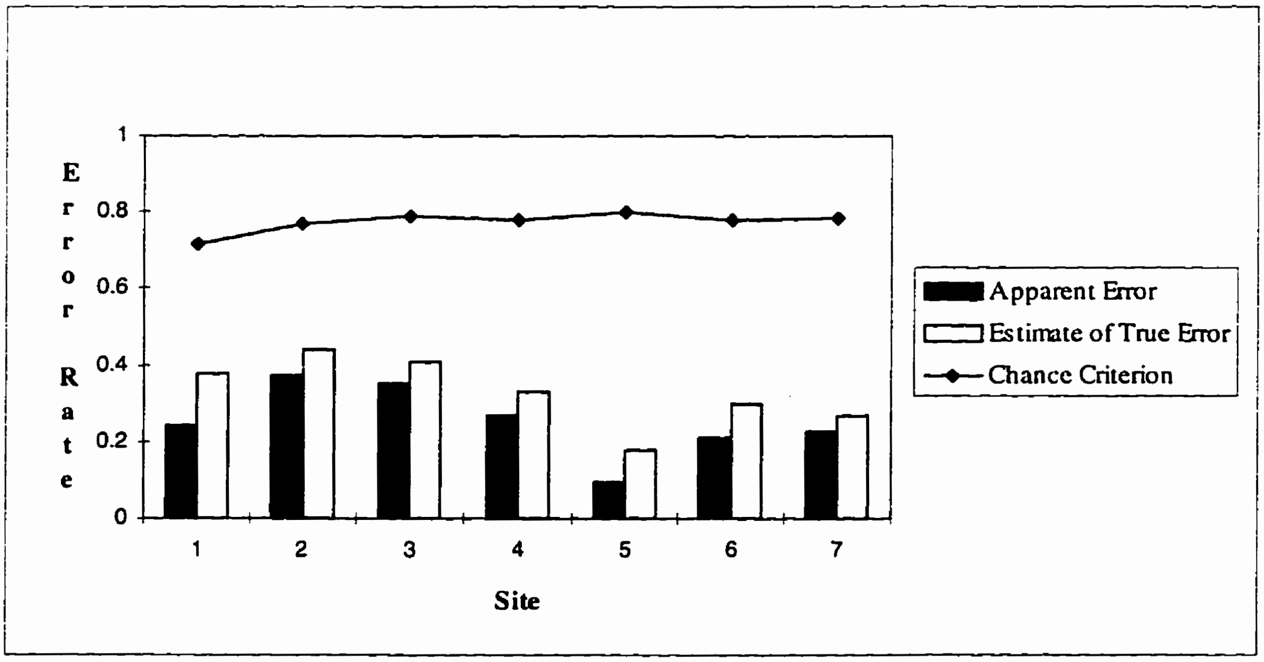
4.5 Classification/Assignment

At each site, the cases were presented to each of the four learning systems (decision tree, nearest-neighbor, discriminant analysis, and neural networks described in Chapter 3). The objective at this point was to determine how well each method predicted the group membership for the cases using only patient information available before the appointment date. The apparent and estimate of true error rates were taken as the indicators of each method's performance.

4.5.1 Decision Tree

As discussed in Chapter 3, a 10-fold cross-validation was used to estimate the true error using this learning system [Henery, 1994]. The performance of this classification method at all the sites is presented in Figure 4.1 (see individual site's appendices for the classification matrices and composite rule-sets generated). As the table demonstrates, this method consistently posts better prediction of each case's group membership (hence resource utilization) than the chance criterion benchmark. At Site 5 (where the best predictions were achieved) it more than triples this predictive accuracy.

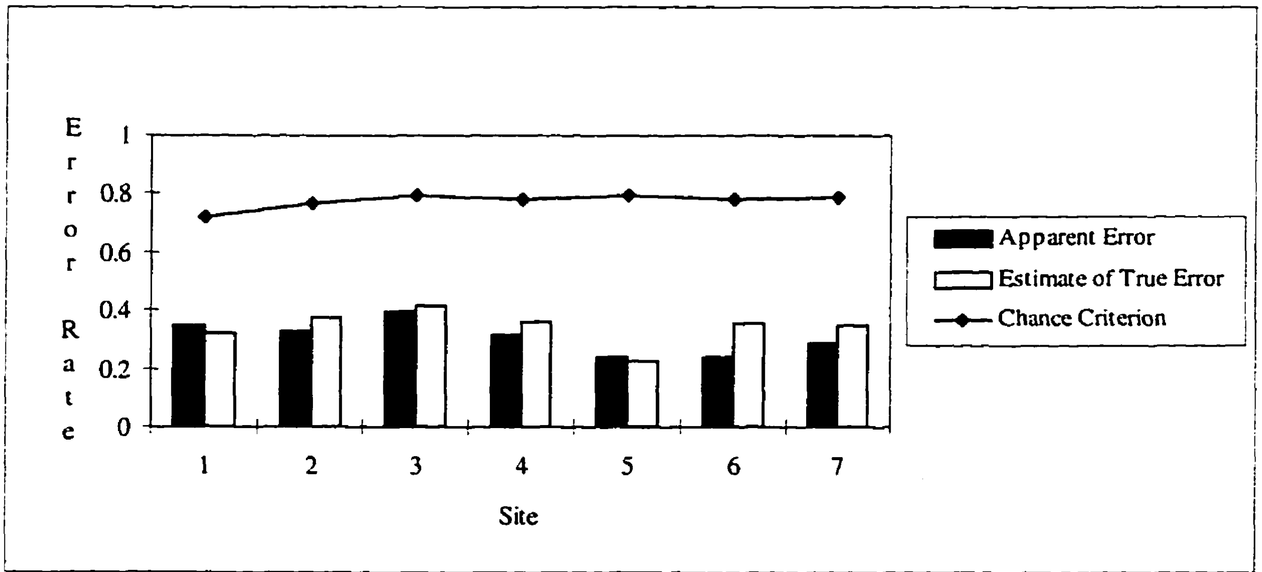
Figure 4.1: Decision Tree's Prediction of Cases



4.5.2 K-Nearest-Neighbor

In order to present this learning system with non-categorical data, all categorical variables were transformed into binary variables (0's and 1's). This invariably resulted in an increase in the number of variables. The 'hold-back one' (the software's only available) cross-validation option was used. A summary of the results obtained using this method is presented in Figure 4.2.

Figure 4.2: 3-Nearest Neighbor Prediction of Cases

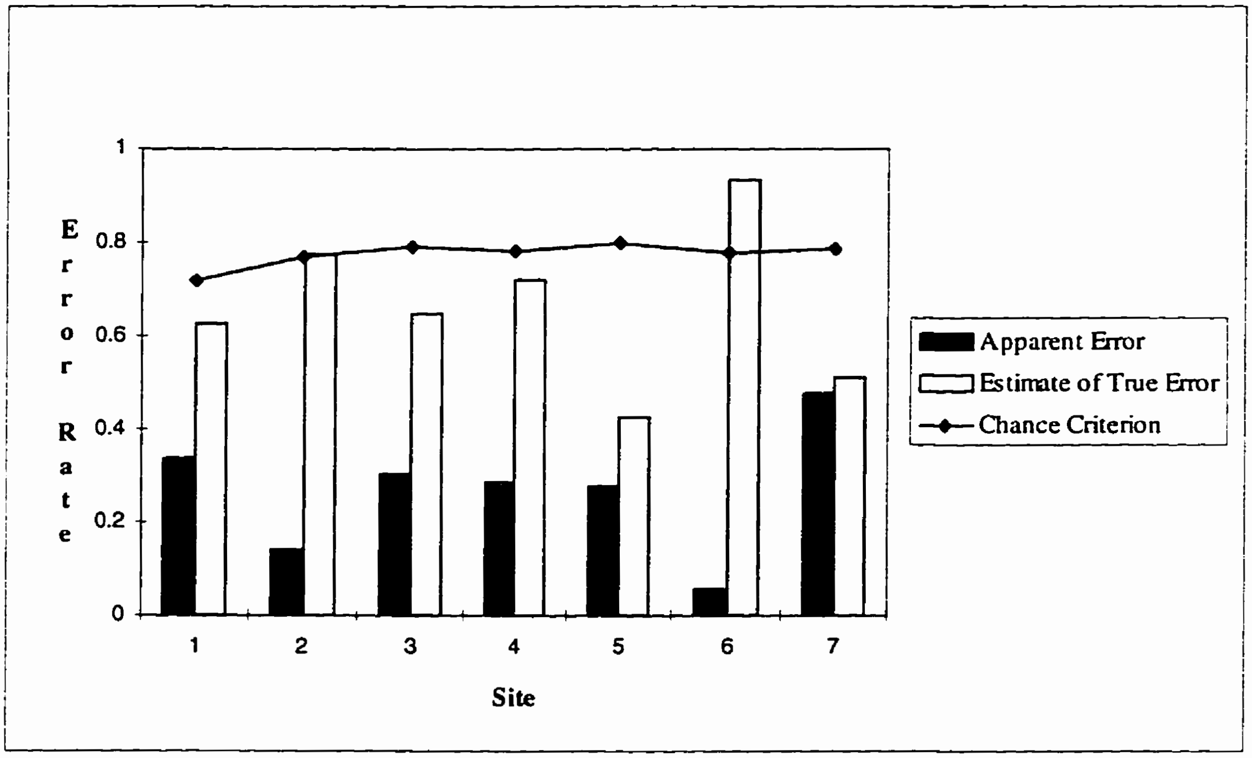


The performance of this learning system varied across sites (with the best predictions being seen at Site 5 and the worst at Site 3), but overall, it compares favorably with the decision tree (outperforming the latter at Sites 1 and 2, and coming closely after it at the remaining sites).

4.5.3 Non-parametric Discriminant Analysis

As with the foregoing method, binary forms of the data sets and 'hold-back one' cross validation were used. A summary of the results obtained with this method is presented in Figure 4.3.

Figure 4.3: Nonparametric Discriminant Analysis Prediction of Cases



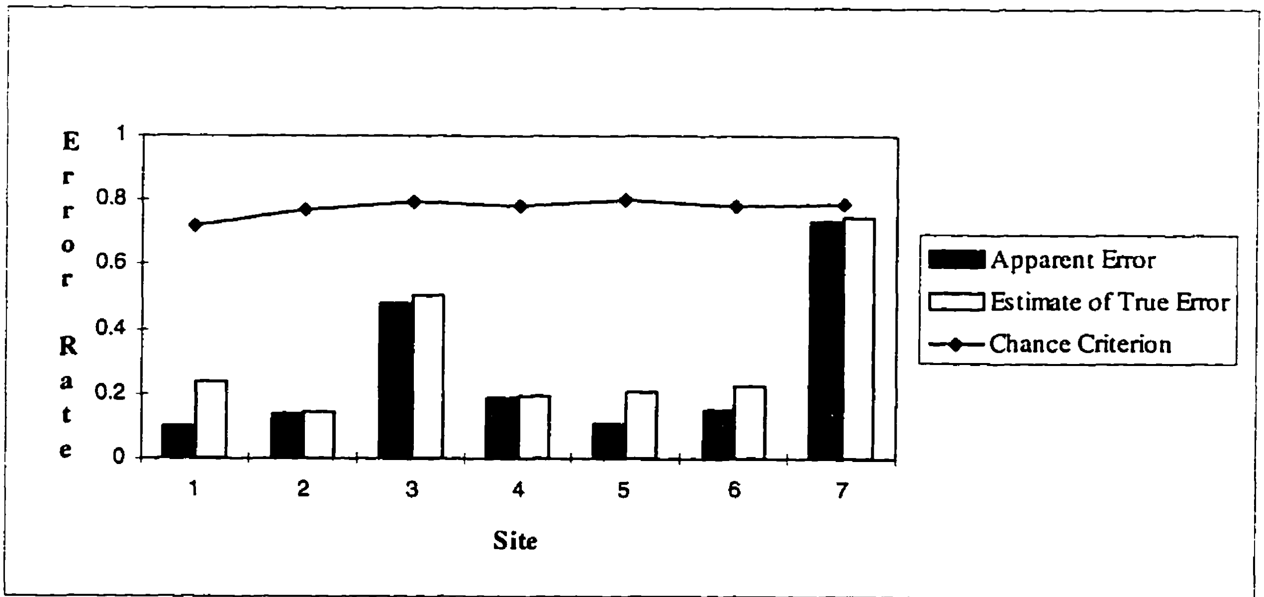
Although it posted apparent error rates at each of the sites that compared favorably with those of the outgoing two methods, its estimates of true error indicate that the method predicts group membership of the cases presented very poorly. This overall poor performance could in large part be due to the fact that the method is drawn from a category of statistical classifiers that lend themselves to continuous rather than the largely categorical data used in this study.

Except at Site 5 (exclusively adult and predominantly female patients) and Site 7 (predominantly young and male patients), this performance was close to, or worse than, the chance criterion benchmark. The dimensions of interest in Figure 3.1 do not reveal characteristics unique only to Sites 5 and 7 - making the task of finding explanations for the method's relatively better performance at these two sites quite difficult.

4.5.4 Neural Network

Like the previous learning systems, binary forms of the data (including the grouping variable) were used, but 10-fold cross-validation (rather than hold-back one) was employed in generating the true error. Figure 4.4 summarizes the neural network's predictive performance.

Figure 4.4: Neural Network's Prediction of Cases



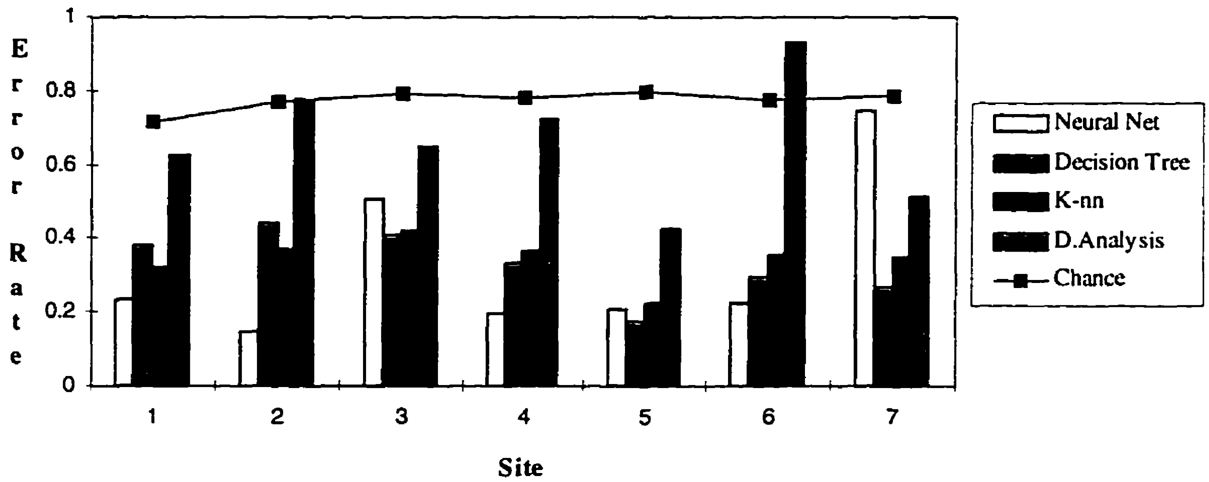
This method posted the most disparate predictions across the sites. Its performance at Sites 1, 2, 4, 5 and 6 more than doubled (at times tripled) the predictive accuracy of the chance criterion. It, however, did not do as well at Site 3 (predominantly adult and female patients) and Site 7 (predominantly young and male patients). Its' performance at the latter almost equals that of the chance criterion.

The foregoing results are indicative of the 'black-box' nature of this learning system - an inherent weakness which makes it difficult for a user to 'see', let alone understand, the reasoning behind its predictions. It is difficult to determine why the neural network performs extremely well on data sets from five sites, rather poorly on another, and terribly on data from the last site. The method requires its performance to be taken on faith, a characteristic that does not commend it especially in situations where other methods offer some insights into the prediction process.

4.5.5 Overall Performance

A summary of the performance of all the four classification methods is presented in Figure 4.5. The results give an indication of the comparative predictive ability of group membership (hence expected resource utilization) of the techniques used at the various sites. Except for Sites 2 and 6, all the four methods post assignments that are better than the chance criterion. A comparison of their performance indicates, however, that no learning system emerges as being consistently superior to the others across all sites.

Figure 4.5: Overall Prediction of Cases



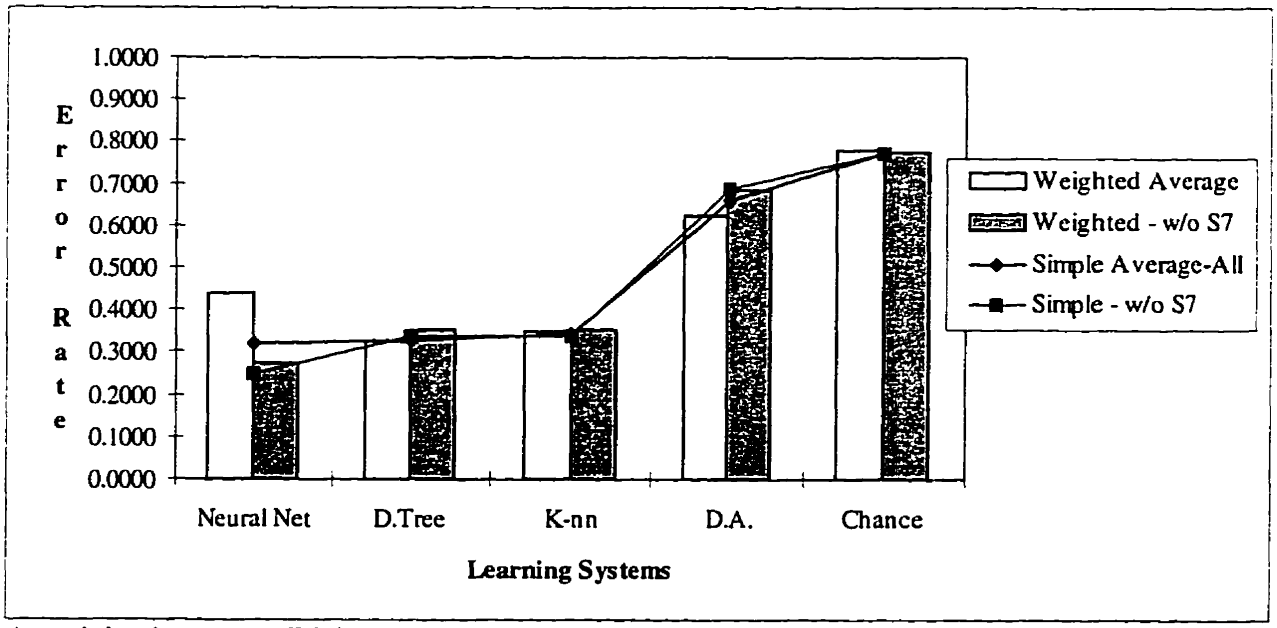
The neural network out-performs the other methods at Sites 1, 2, 4 and 6, and ranks second at Site 5. It is, however, second to last at Site 3 and the worst at Site 7. The decision tree method ranks first at Sites 3, 5 and 7, second at Sites 4 and 6, and second to last at Sites 1 and 2. The 3-nearest-neighbor method did not rank first at any site. Its' best comparative performance is seen at Sites 1,2, 3 and 7 where it ranked second best. It ranked third at the remaining sites (4, 5 and 6). Nonparametric discriminant analysis' performance was the worst at all sites except Site 7 where it ranked second to last. From the foregoing, the last two methods (nearest neighbor and nonparametric discriminant analysis) should be dropped from contention as viable *a priori* learning systems. These rankings are presented in Table 4.4.

Table 4.4: Ranking of Learning Systems' Prediction Performance

	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7
Neural Network	1	1	3	1	2	1	4
Decision Tree	3	3	1	2	1	2	1
Nearest-Neighbor	2	2	2	3	3	3	2
Discriminant Analysis	4	4	4	4	4	4	3

This general ranking is confirmed when the learning systems' performance is simply averaged across the sites as shown in Figure 4.6.

Figure 4.6: Averages (Weighted & Simple) of Learning Systems' Performance



A weighted average [Fleiss 1974] ranks neural networks behind decision trees and nearest-neighbor. When Site 7 is excluded, the weighted average confirms the earlier rankings suggested by Table 4.4. This weighted average is obtained by the formula:

$$\sum_{i=1}^{7} W_i e_i$$

where w_i is the proportion of cases classified at site i; and e_i is the true error rate.

4.6 Conclusions

Figures 4.5 and 4.6 in essence tell us that the APRCM methodology proposed in this study does work, albeit with varying degrees of performance depending on the learning system used. As seen from Figure 4.5, learning systems in general post predictive performance that is much better than the benchmark at all the sites, implying, therefore, that in general, group membership (resource utilization) prediction is enhanced when these methods are used.

The question of which learning system should be used at which site has no easy answer. It first requires a determination of an acceptable level of predictive accuracy. The 25% rule of thumb that requires the classifier to yield a performance that is at least 25% greater than chance for it to be acceptable has been suggested in the literature [Hair 1984]. Going by this, discriminant analysis is eliminated from consideration. Similarly, since nearest neighbor never "wins" (i.e. as the best method) at any site, it is also dropped from contention. No clear 'winner', however, emerges from the remaining two methods regardless of whether we use the posted error performances, rankings of performance or averages of posted errors. This suggests that getting an answer to the problem may be more protracted than initially suspected.

Other considerations that may help in determining the technique of choice include training times and ease of understanding. Time-wise, neural networks are very expensive to train (requiring days for this), however, their testing time requirements are minor. On the other hand, decision trees' 'training' and testing time requirements are minor. Ease of understanding both the process and the output generated favors decision trees. They generate easy to understand and apply decision rules which show the reasoning behind the classifications. The operation of neural networks, on the other hand, is basically a 'black box' - requiring a non-technical user to take the results on faith.

The foregoing considerations would tend to favor decision trees over neural networks. Before such a conclusive determination can be made, however, it is necessary to investigate the performance of the four learning systems on amalgamated data from all sites. This is considered in Chapter 5.

CHAPTER 5

COMBINED RESULTS

5.1 Overview

The focus of this chapter is on the second research study question, i.e. Are there any generalizeable iso-resource variables or groupings which are systematic across all low vision clinics? The chapter's basic goal is to determine common patient characteristics that can be seen across the study sites, and whether they are useful in forming a basis for a standardized resource measure(s) in low vision settings. The chapter also discusses the various activities in the harmonization, pre-processing, and amalgamation of the data from all sites, generation of patient groups from these data, and the performance of the learning systems on predicting the iso-resource group membership of patients. In sum, it covers the implementation of APRCM to aggregated data from all the study sites.

5.2 Subjects

Subjects for this phase of the research were obtained from the amalgamation of the data sets from all seven study sites (n = 2427). Initial statistics of interest about these patients are summarized in Table 5.1. For instance, the majority (> 81%) of the patients were aged either below 20 years or above 59 years. They were almost equally split on the dimension of gender, however, the majority of female subjects (60.8%) fall in the geriatric category. This is the exact opposite of the male subjects (among whom the majority, 61.1%, fall in the school-aged categories). Excluding cases with missing (not indicated) values, the subjects were equally split on Disability (47.8% without disability and 47.7% with additional disability), and almost as equally distributed on Patient-Type (with slightly more New patients - 51.1% - than Repeats - 48.9%).

Table 5.1: Composition of Patients on Age, Gender, Pt-Type, Marital Status & Disability

Characteristic	Category	n	%
Age	< 10	438	18.0%
	10 - 19	544	22.5%
	20 - 29	86	3.5%
	30 - 39	107	4.4%
	40 - 49	117	4.8%
	50 - 59	132	5.5%
	60 - 69	146	6.0%
	70 - 79	396	16.3%
	80 - 89	407	16.8%
	>= 90	54	2.2%
Gender	Female	1244	51.3%
	Male	1183	48.7%
Patient-type	New	1241	51.1%
	Repeat	1183	48.9%
Marital Status	Not indicated	309	12.7%
	Single	1157	47.7%
	Married	567	23.4%
	Divorced	51	2.1%
	Widowed	343	14.1%
Disability	Not indicated	104	4.3%
	No Additional Disability	1161	47.8%
	Additional Disability	1162	47.9%
TOTALS		2427	100%

5.3 Data

Each of the 2427 patients was described by more than 165 unique variables. In order to create a parsimonious set, these variables were categorized into those present at: a) all sites, b) some of the sites, and c) a single site. All category (a) variables were retained, category (b) were retained only if the variable in question was present at a majority of the sites (at least 4 in this study), whereas category (c) variables were discarded. In sum, a total of 31 variables were retained in the combined data set. Appendix E gives a listing of all variables, describes their coding scheme, highlights those retained, and explains the harmonization decisions made.

5.4 Common Patient Characteristics

The same general approach with respect to data formatting and cluster analysis decision choices outlined in Chapter 3 was followed in the generation of patient groups from the combined data set. Five general groups were generated. Table 5.2 summarizes the dominant features in the characteristics of these groups. It should be noted that the value indicated for a given variable denotes the predominant value on that variable for patients in the group. It is possible to find a patient categorized in a group with a modal value that differs from the patient's 'score' on the given variable. Such a patient would, however, have values equal to the modal values of the group on the rest of the group's characteristics. The final block count of the configuration in Table 5.2 (68.72% of total data points) compared favorably with the corresponding block counts of the iso-resource groups in the individual sites' data sets (which, as indicated in Chapter 4, ranged from 59.01% to 70.41%).

These general groupings are relatively well-defined with respect to biographical variables. Distinguishing characteristics between these larger groupings, such as Patient-type, Age, Gender, Marital status, and Additional disabilities also featured prominently in the profiles of the site-specific groupings. The clustering algorithm also uses Current-Visual-Devices, Medications, Visual-Acuity, and Patient-Goals to distinguish between groups from the combined data set.

Table 5.2: Age, Gender, Pt-Type, Marital Status & Disability Features of General Groups

VARIABLE	Group 1	Group 2	Group 3	Group 4	Group 5
PtType	New	Repeat	New	Repeat	Repeat
Age	<= 10	<= 10	70-79	60-69	Varied (all ages)
Gender	Female	Male	Female	Female	Female
Diagnosis	Macular deg.	Other	Macular deg.	Macular deg.	Macular deg.
Other Disability	Disabled	Not Disabled	Disabled	Disabled	Disabled
Marital Status	Single	Single	Married/Widowed	Varied	Varied
Pre V.A. (best)	81-200	201-400	26-80	81-200	Varied
Current Ivaid	Spectacles	Magnifiers	Spectacles	Magnifiers	Varied
Medications	n/i	n/i	Yes	n/i	n/i
Goals	Read/Write	n/i	Read/Write Mobility	Read/Write n/i	Read/Write Other
Letters/reports	0	0	1	0	1
Recall Time	0	0	0	0	1 month
Main Site	Site 7	Sites 6 & 7	Mixed (Site 2)	Site 5	Mixed (Site 3)

The clarity seen in the biographical characteristics of the larger groupings is, however, totally absent with respect to the latter's resource characteristics. To begin with, not many resource variables were retained at the data amalgamation stage. Only four resource variables, namely Loans, Total-time, Letters/reports, and Revisit-time, were available at the majority of the sites. Of these, the clustering algorithm includes Revisit-time and Letters/Reports in the critical variables used to distinguish between groups. Total-time and Loans do not feature among these. Hence, in spite of being quite succinct on the biographical aspects, the groups are at best very weak in the resource description of patients. Table 5.3 shows the values on the two variables (Letters/reports and Time) that characterized the groupings obtained at the individual sites. It is evident that areas of similarity, if any, are minimal. This picture is indeed confirmed by the resource portion of the larger groupings as shown in Table 5.2.

Table 5.3: Partial Resource Profiles of Patient Groups at Study Sites

	Group 1	Group 2	Group 3	Group 4	Group 5
Letters: Site 1	0	1	0	0	n/a
Site 2	0	0	1	0	0
Site 3	n/a	n/a	n/a	n/a	n/a
Site 4	1	2	1	2	1
Site 5	1	Varied (0 or 1)	0	1	1
Site 6	n/a	n/a	n/a	n/a	n/a
Site 7	n/a	n/a	n/a	n/a	n/a
Time: Site 1	n/i	60 min	60 min	60 min	n/a
Site 2	76-120	106-120	91-120	136-180	106-120
Site 3	n/a	n/a	n/a	n/a	n/a
Site 4	< 40	15-90	< 30	30-60	20-50
Site 5	4.5-7.5	3.0-6.0	6.0-7.5	1.5-6.0	7.5-10.0
Site 6	n/a	n/a	n/a	n/a	n/a
Site 7	n/a	n/a	n/a	n/a	n/a

Note: n/a = not applicable; n/i = not indicated

It is evident that the data amalgamation process was 'costly' in that numerous variables which distinguish between groups (in terms of the resources unique to each group) were discarded due to their site-specificity, i.e. they were not available at a majority of the sites. Given this, although the study can attest to the robustness of the biographical aspects of the groups spanning the study sites, few, if any, categorical statements can be made with respect to how distinct the general groups are resource-wise.

5.5 Prediction on Combined Data

It will be recalled from Chapter 4 that no single learning system was universally superior on the prediction task. Notwithstanding the resource-deficiency of the groupings obtained from the combined data, the research sought to determine whether the choice of a learning system can be more easily tackled on the combined data than on the individual data sets. Towards this end, the larger groupings obtained were subjected to the various classification methods in the same manner as discussed in Chapter 3. The problem of medium and small sample sizes was, however, not of concern here since n = 2427. For prediction purposes, therefore, the data were split into two halves (a training set of n = 1214 and a testing set of n = 1213). These were then uploaded to the respective learning systems for group-membership prediction.

5.5.1 Decision Tree

Table 5.4 presents the decision tree's classification matrix for these predictions. The cells in the matrix contain two entries each. The top entry is the number of cases and the bottom entry gives the proportion of these cases to the total number of cases in the given group. Cells on the left-to-right downward sloping diagonal represent the correct classifications. The decision tree yields a very good overall predictive performance (testing error of 0.1640). This is about half its average error on the individual sites' data sets.

Table 5.4: Decision Tree's Classification of Patients in Groups from the Combined Data

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**367**	13	17	37	27	461
	0.7961	0.0282	0.0369	0.0803	0.0586	1.0000
Group 2	44	**749**	0	3	8	804
	0.0547	**0.9316**	0.0	0.0037	0.0095	1.0000
Group 3	27	6	**353**	19	19	424
	0.0637	0.0142	**0.8325**	0.0448	0.0448	1.0000
Group 4	43	14	47	**299**	5	408
	0.1054	0.0343	0.1108	**0.7052**	0.0118	1.0000
Group 5	13	1	5	11	**300**	330
	0.0394	0.0030	0.0152	0.0333	**0.9091**	1.0000
Total	494	783	422	369	359	2427
	0.2035	0.3226	0.1739	0.1520	0.1479	1.0000
		Apparent Error				**0.1480**
		Estimated Error				**0.1640**

The method posts extremely good predictions in Groups 2 and 5 (above 90% accuracy) and reasonably well on the rest (above 70% accuracy). It assigns all 'new' cases into the predefined groups. Its predictions, however, show some overlaps between Groups 1, 3 and 4, suggesting that the boundaries between the groups can be better defined.

5.5.2 3-Nearest Neighbor

The classification matrix of the 3-nearest neighbor method is presented in Table 5.5.

Table 5.5: 3-Nearest-Neighbor's classification of cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**304**	87	15	34	19	2	461
	0.6594	0.1887	0.0325	0.0738	0.0412	0.0043	1.0000
Group 2	49	**728**	9	11	6	2	804
	0.0609	**0.9055**	0.0112	0.0137	0.0075	0.0012	1.0000
Group 3	18	15	**285**	71	33	2	424
	0.0425	0.0354	**0.6722**	0.1675	0.0778	0.0047	1.0000
Group 4	28	14	55	**302**	6	3	408
	0.0686	0.0343	0.1348	**0.7402**	0.0147	0.0074	1.0000
Group 5	20	2	11	10	**285**	2	330
	0.0606	0.0061	0.0333	0.0303	**0.8636**	0.0061	1.0000
Total	419	846	375	428	349	**10**	2427
	0.1726	0.3486	0.1545	0.1763	0.1438	**0.0041**	1.0000
Apparent Error							**0.1582**
Estimated Error							**0.2155**

Like the previous method, 3-nearest neighbor's performance is better on this combined data set than on the individual sites' groupings. A possible explanation for the 'improved' performance (for this and other methods) may lie in the fact that the number of samples has increased remarkably whereas there has been a reduction in the variables. The method's overall rate of 0.2155 surpasses its best performance on the individual sites' data sets (0.2353 at Site 5). It is unable to place only 0.4% of the cases in any of the predetermined groups. It predicts Group 2 extremely well (above 90% accuracy), does reasonably well on Groups 4 and 5 (above 70%), and rather poorly on Groups 1 and 3 (below 67.5% accuracy). This, and a review of the classification matrix in Table 5.5, suggest that there are overlaps (between Groups 1 and 2, and between Groups 3 and 4) which a refinement of the groupings can target for reduction.

5.5.3 Non-parametric Discriminant Analysis

Results obtained using this classifier are presented in Table 5.6.

Table 5.6: Non-parametric Discriminant Analysis' classification of cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**162**	207	10	32	13	37	461
	0.3514	0.4490	0.0217	0.0694	0.0282	0.0803	1.0000
Group 2	13	**749**	2	5	5	30	804
	0.0162	**0.9316**	0.0025	0.0062	0.0062	0.0373	1.0000
Group 3	18	8	**199**	79	30	90	424
	0.0425	0.0189	**0.4693**	0.1863	0.0708	0.2123	1.0000
Group 4	39	13	37	**292**	3	24	408
	0.0956	0.0319	0.0907	**0.7157**	0.0074	0.0588	1.0000
Group 5	11	3	9	15	**246**	46	330
	0.0333	0.0091	0.0273	0.0455	**0.7455**	0.1394	1.0000
Total	243	980	257	423	297	**227**	2427
	0.1001	0.4038	0.1059	0.1743	0.1224	**0.0935**	1.0000
Apparent Error							**0.2324**
Estimated Error							**0.3210**

Like the previous methods, its performance exceeds that of the individual sites' groupings. The overall error rate of 0.3210 is almost one half of its average performance on the individual sites' data. This performance is, however, quite disparate across the five groups. First, it is unable to place 9.4% of the cases in any predetermined group. It then predicts Group 2 extremely well (above 90% accuracy), does reasonably well on Groups 4 and 5 (above 70%), but very poorly on Groups 1 and 3 (below 50%). Despite this relatively poor performance, its overall prediction accuracy surpasses the chance criterion benchmark.

5.5.4 Neural Network

The neural network's predictive performance was reminiscent of its corresponding performance on Site 7's data. The neural network was trained over 10 000 iterations with significant adjustments in the parameters and starting points. The best training results, however, did not exceed 15% accuracy, and its testing accuracy did not exceed 13.5%, i.e. an error rate of 0.8650, results that were far below its average performance on individual sites' data sets. Possible explanations for this include the fact that the larger groups were not as well-defined (especially with regard to resource features) as the corresponding groups at most of the sites.

5.6 Overall Performance

A summary of the performance of all the four classification methods is presented in Table 5.7.

Table 5.7: Overall Classifier Performance on the Prediction Task

Classifier	**Apparent Error**	**Estimate of True Error**
Decision Tree - C4.5	0.1480	0.1640
K-Nearest Neighbor - SAS	0.1582	0.2155
Discriminant Analysis - SAS	0.2324	0.3210
Neural Networks - WinNN	0.8500	0.8650
Chance Criterion	***0.7769***	***0.7769***

In addition to the apparent and estimate of the true error, the proportional chance criterion (computed as 0.2231, that is, an expected error rate of 0.7769) was used to evaluate the performance of these techniques in the overall prediction task. This, together with the classifiers' performance, is shown in the table.

The best overall estimate of true error in the prediction task is posted by the decision tree. Nearest neighbor and discriminant analysis are second and third in rank, whereas the neural network comes a distant fourth. The performance of the neural network is far poorer than its average on the individual sites' data sets, and is the only method that does not outperform the chance criterion benchmark. In general, these results confirm the overall results seen at the sites, i.e. that predictive performance is better with than without these techniques, and that decision tree tends to dominate performance. The resource-deficiency of the groupings on which the predictions are made in the first place calls for the results to be taken cautiously.

5.7 Conclusions

A comparison of the individual sites' groupings discussed in Chapters 3 and 4 raises the possibility that, despite their heterogeneity and that of the populations from which they are drawn, appearances of some similarities can be discerned in sections of their profiles especially with regard to biographical characteristics. This is confirmed when the data are combined and the APRCM approach employed. Features such as age, gender, patient-type, disability and marital status distinguish unique patient groupings. Regrettably, the resource component of these groupings is not as definitive.

Given the foregoing findings, it may be tempting to abandon the implementation of APRCM on amalgamated data from multiple clinics. These 'poor' resource predictions and 'unsuccessful' identification of general resource characteristics confirm part of the argument calling for the application of APRCM to clinic-specific settings in the first place. It will be recalled from Chapters 1 and 2 that rather than the more general macro approach followed in the cited resource classification studies, APRCM calls for a clinic-specific focus. The heterogeneity of resource variables from the sites is indicative of the variation in data kept (and/or practice). For robust general low vision iso-resource groupings to be achieved, it is necessary to have standardized characteristics describing the services rendered across low vision clinics. This calls for uniform data maintenance procedures across low vision clinics.

CHAPTER 6

CONCLUSIONS

6.1 Overview

This chapter presents the conclusions emanating from the research. It commences with a synopsis of previous chapters and proceeds to present a summary of the major findings, contributions and implications of the study. It then addresses the limitations of the study and closes with recommendations for further research.

Recall that Chapter 1 commenced with the problem of escalating costs of health care and misallocation of health resources generally faced by health care systems. It was suggested that a better understanding of the resources required by a clinic prior to the rendering of services might help address part of the problem. The APRCM, a generalised methodology employing cluster analysis and learning systems, was proposed to provide a framework for predicting expected health care resource requirements for specialty ambulatory patients at the clinic level on the basis of information available prior to a patient receiving the health care service.

6.2 Summary of Study Findings

The findings of this study are summarized and discussed here in line with the study's general propositions as outlined in Chapter 2, i.e. whether it is possible to build a generalizable model for use in the development of an *a priori* resource-based classification and prediction for low vision patients, and whether there are identifiable characteristics of low vision patients that lend themselves to the *a priori* identification of expected patient resource needs across clinics.

6.2.1 Generalizable Model for Pre-classification and Prediction

Results from site-specific analyses show that it is possible to pre-classify low vision patients. Towards this end, retrospective discharge data from the sites are cluster-analyzed to produce groupings based on patient characteristics and descriptions of services rendered at the site. These groupings are clinically coherent and resource-distinct, i.e. a patient in a given group utilizes a set of clinic resources that are distinct and different from those utilized by a patient in another group. In essence, 'patient-group' in itself incorporates a composite measure of resource use and, therefore, can serve (and was indeed used in this study as) the dependent variable in expected patient resource prediction tasks.

Variations in patient records across clinics (and, by extension, data used in this research) meant that the resultant patient groupings, and the *a priori* portions of their profiles utilized in the prediction task are normally clinic-specific. Hence, although the same general APRCM approach can be used across clinics, the particular prediction results obtained are clinic-specific.

The different learning systems performed at varying degrees of predictive accuracy as measured by their prediction error rates. No single learning system is universally superior at all sites. In general, however, neural networks and decision trees outperform other learning systems since they deliver better predictive power. Whenever the 'better' of the two methods is used, the predictive accuracy obtained is more than 300% that of the benchmark used. In other words, less than one third of the patients will be mis-classified in terms of resource use. In a scenario where clinics schedule patients for similar sets of resources, this would be a significant contribution.

Several considerations from the study findings, however, favor the decision tree over neural networks as the learning method of choice for the prediction task. To begin with, the neural network method posts very disparate predictions in the site-specific analyses. Small sample sizes (for training and testing) and the presence of missing data at the sites may be responsible for this. The nature of the neural network, however, makes it extremely difficult for a user to understand precisely why it performs extremely well at some sites and extremely poorly at others, thus making its implementation a 'risky' venture. Its' set-up requirements ("tweaking" and prolonged training) are added features that detract from its attractiveness. On the other hand, the decision tree not only performs relatively well at all sites, but also, its output provides the user with explanations for it predictions and a 'tool' to refine (if necessary) the initial groupings that served as the gold standard.

6.2.2 Generalizable Characteristics of Low Vision Patients

As mentioned earlier, variations in patient records and the data lead to resultant pre-classification patient group profiles that are clinic-specific. Certain common features, however, are evident in these profiles, raising the prospect that it may be possible to identify patient groupings or characteristics that cut across low vision clinics. This is borne out when data from all sites are combined - distinct patient groupings emerge from the large data set. Further, the distinguishing biographical variables characterizing these groupings are consistent with the corresponding biographical characteristics of the patient groups generated from the site-specific analyses. The groupings obtained from the combined data portray notable differences with regard to patient category, age, gender, marital status, and additional disabilities, among others.

The foregoing correspond to the distinguishing biographical variables in the site-specific analyses, raising the possibility that these underlying variables, may be indicative of the biographical profiles of 'universal' low vision patient resource groupings.

A similar effort with respect to resource variables was not as definitive as the foregoing due to the disparities in the patient resource usage information that is maintained at different sites. A harmonization and combination of data across sites does not yield a sufficient number of distinguishing resource variables. This makes it difficult to make substantive statements with regard to composite resource measures across the sites covered. For instance, not all clinics tracked the length of time (directly or indirectly) expended by the various low vision specialists, items loaned, or ancillary services used by the patient on the appointment date. Similarly, most clinics did not track the different categories of low vision staff who attend to the patient on the appointment date. Despite this, the identification of distinguishing biographical characteristics suggests that there appears to be critical resource variables which can also be identified if a uniform set of patient information is tracked and maintained at each clinic, i.e. usage of uniform data maintenance procedures across all low vision clinics.

6.3 Contributions and Implications of the Research

The APRCM demonstrates a formal, practical approach of determining *a priori* patient characteristics in a manner that links in with a patient's level of resource use. The methodology's application to several low vision clinical settings yields results that are significantly 'better' than the case would be in the absence of the methodology. The application shows that unique clinic characteristics make the choices at various stages in the APRCM model to be clinic-specific, for instance, some learning systems are preferred over others but this does not occur universally.

This research has far-reaching implications for the management of low vision clinics. APRCM provides management with information that is useful in patient- and resource scheduling in the short-term. For instance, an appropriate adjustment in the duration of a patient's appointment can be made once it is determined that s/he is in a grouping with such 'additional impairments' as language difficulties. Provision for, say, an interpreter, would be made and scheduled accordingly. The incorporation of patient resource requirements in scheduling operations would optimize not only the usage of a clinic's facilities (staff and equipment), but also the number of patients being treated over a given period (say, a day). This would contribute in reducing current patient waiting periods (between first contact and actual appointment date) that range anywhere from a few weeks to several months at the clinics.

Continuous application of APRCM, coupled with appropriate forecasting tools would help to determine the effects that tracked changes in the demographics of a clinic's patient base would have on the resources of a clinic. For instance, it has been noticed that geriatric patients constitute unique iso-resource groups at some of the clinics covered in this research. Population trends (ageing population - baby-boomers in North America and an increasing life expectancy in Sub-Saharan Africa) suggest that geriatric patient groups will be a significantly larger proportion of patients seeking care at the clinics in the future. Similarly, the increasing levelling of differences in educational opportunities between the genders in Sub-Saharan Africa implies that iso-resource groups in which young female patients predominate will be seen at the clinics in the future in larger proportions than is currently the case. The specific resources demanded by these categories of patients, therefore, have to be factored into the clinic's long-term capacity (staff and equipment) planning.

Also, the study identifies generalizable *a priori* biographical characteristics that are systemic across the sites. As mentioned earlier, these may form the basis of a set of biographical features that would find useful application in the iso-resource grouping of low vision patients in general. In connection with this, the study identifies a need for a standard protocol for patient records at clinics. Such a development would be an invaluable source of data useful not only for research in studies such as the current one, but also in other health services, epidemiological, and administrative undertakings.

In this research, APRCM has been applied to a specialty/secondary ambulatory patient care setting providing a time-perishable, non-transferable 'service-product' of an individualized nature to a diverse set of clients. The challenge for management is to equate the capacity to provide such a 'service-product' to the demand for the same. Like all service organizations, an hour without a patient in the clinic can never be recovered, and since the clinic's service can not be stored, it is lost forever when not used. On the flip side, periods of consumer waiting result when capacity is outstripped by demand. Whereas a clinic's capacity to provide service is 'fixed' (over the short term), patient demand for this service typically fluctuates as in most high customer contact services.

Time-perishability, idle servers and facilities when capacity outstrips demand, consumer waiting when the opposite holds true, a 'fixed' capacity, and fluctuating demand due to a variety of reasons/conditions, are typical of many areas in the service sector. Attempting to maintain full utilization of capacity in these conditions is an extremely challenging management problem

[Murdick 1990; Fitzsimmons 1994]. The problem addressed in this research is, therefore, one that is frequently confronted in the service sector.

The conventional approach is to commence with long-range forecasts that are subsequently broken down into aggregate plans from whence detailed schedules can be drawn. APRCM suggests an alternate approach that commences with a prediction of the specific 'product' components which when summed, yield demand forecasts that can be factored into capacity management decisions. From this general perspective, it lends itself to resource-intensive settings in the service sector where reservations/referral systems are used, where there can be a long delay between booking and service delivery, and where the utilization of specific resources varies widely across classes or categories of clients served.

By estimating the various specific resource components that are expected for a given patient visit, the proposed APRCM in essence provides information useful in scheduling (patients and resources), hence equating a variable patient demand to a 'fixed' service capacity over a given time period. A Component-to-Aggregate forecast can also be achieved from the foregoing by summing the specific resource components for each patient visit over a given period to yield a demand forecast [Murdick 1990]. The latter can then form a basis for aggregate management decisions with regard to capacity management. For instance informed decisions can be made with respect to the acquisition of equipment, expansion of the physical facility, or the recruitment of additional personnel in line with the forecasted demand for the same.

In sum, the APRCM is a tool that, with further development, may find useful application in equating the resource capacity of ambulatory health care (and other high customer contact service) providers to the expected demand for the same in a manner that is apparent to the user.

It demonstrates that a classification system can be applied to a patient to determine his/her expected resource requirements. The logical attendant to this is the usage of the APRCM's results as input information for such planning functions as patient- and resource-scheduling in the short-term, and capacity planning in the long-term.

6.4 Limitations of the Study

The foregoing contributions are, however, tempered by a number of limitations which although alluded to in earlier chapters, are now formally recognized and discussed. These limitations do not necessarily negate the benefits of this research, however, they provide a useful backdrop against which the findings of this research should be interpreted.

To begin with, it should be pointed out that the configuration of patient groupings (taken as the gold standard in this research) is not perfect. A large number of data points were not covered in the groupings (both in the site-specific and combined analyses), and this suggests that the patient groupings generated contain significant overlaps. Coupled with this is the presence of missing values in data at the sites. These factors may partly explain why the learning methods do not yield perfect or near perfect prediction results. The fact that some of the learning systems posted impressive results shows that the objectives of the research at the prediction phase were not unduly compromised by these shortcomings. Likewise, more rigorous post-cluster validation should be completed with local experts.

Secondly, the diversity in the recording procedures across sites resulted in an insufficient number of common resource (as opposed to biographical) variables available in the combined data set. This precluded an in-depth multiple-clinic analysis, therefore, hampering efforts to determine systemic patient resource characteristics.

Thirdly, this study used a small clinic sample size (n = 7). It may be difficult to generalize its findings to the 48 specialty/secondary clinics in the sampling frame (or 190+ accredited agencies) providing ambulatory low vision services in North America and Sub-Saharan Africa.

Finally, time and other resource constraints dictated that surrogates, rather than actual 'new' patients be used at the prediction stage. The same considerations, in large part, meant that modest (rather than large) patient sample sizes were obtained at the clinics covered in the study. To obtain realistic estimates of prediction performance from the learning systems, it was necessary to 'simulate' large data sets through such means as cross-validation.

6.5 Suggestions for Further Research

The foregoing limitations, do not, as pointed out earlier, invalidate the findings of this research. They, however, call for extensions incorporating measures designed to surmount these limitations. The following suggestions for further research are made from this perspective.

An immediate extension to this research would involve drawing from the available features of some of the learning systems (for instance, decision trees and discriminant analysis), coupled with a panel of low vision experts from the study sites to iteratively weed out (using sensitivity analysis) those variables in the data that account for insignificant variation in the data while not contributing significantly to the medical meaningfulness of the resultant groupings. Such a scenario would have the added advantage of validating the groupings obtained from the combined data set using the Delphi method.

The APRCM attempts to foster a focus on predicted patient resource needs. For its full potential to be realized, accurate, practical, reproducible conditions across clinics are required. This calls for the development of a standard patient record protocol, i.e. uniform data collection and maintenance procedures at low vision clinics. It is envisaged that where such procedures incorporate the tracking of all aspects of the patient care delivery process, all relevant resource and biographical variables would be captured across clinics, thus facilitating research projects in this area and the making of appropriate management decisions.

It is also recommended that when sufficient research resources are available, extensions of APRCM should be done using actual new patients in larger clinic samples coupled with the collection of data on large numbers of patients at each clinic. This would not only eliminate both the usage of surrogates for new patients and the problems attendant to small sample sizes mentioned earlier, but also ensure that APRCM is applied in practical conditions. Such undertakings would have the added advantage of enhancing the external validity of the findings. Current efforts at some of the clinics to computerize their patient data bases are developments that will help immensely in future research of this kind.

With advances in both types and features of various learning systems, such systems should be explored in the future. For example, as more knowledge is gained with neural networks, the resulting techniques should become a more viable alternative for application in iso-resource groupings. One case in point is if neural networks can become more computationally efficient.

For purposes of replicating or extending this research, it is recommended that an evaluation/testing "assistant" akin to those in Michie [1994] be incorporated and used at the prediction phase. It is envisaged that such an "assistant" would be a computer program running in one operating system (rather than in a multiplicity of systems - MS Windows, UNIX, etc.) to select a learning system, apply it to data from a given study site, get results, and record or output the results. The "assistant" should be capable of iterating such a process until all study sites are covered.

Another immediate avenue for further research is the extension of the APRCM methodology into other resource-intensive ambulatory clinical settings such as specialty diagnosis (MRI), sports medicine, etc.

6.6 Conclusions

In closing, this research has shown that APRCM can be a viable tool in predicting the expected patient resource demands in the specialty setting of low vision. Although potential for refinements exist, the methodology is an improvement over current practices at most clinics where patients are block-booked and scheduled for similar sets of clinic resources. APRCM is grounded in the recognition that different categories of patients impose different demands on the clinic's facilities/staff. The method is presented in this thesis in a manner that permits easy implementation at the clinic level. Its application delivers to the clinic management a useful tool in the utilization of scarce resources. It fosters an intimate knowledge of not only the characteristics of patients served by the clinic, but also the population base from which these patients are drawn. Using it in conjunction with other management planning techniques should help in the optimal usage of constrained clinic resource facilities and aid in dealing with the world-wide need for better resource decisions.

APPENDIX A

COVER LETTER TO CLINICS CONTACTED

Dear Dr. ....,

In our telephone discussion of ...., 199.., I mentioned that I am a Ph.D. student in the Department of Management Sciences at the University of Waterloo. I am conducting research under the supervision of Dr. David Dilts on the *a priori* prediction of health care resource utilization of low vision patients in scheduled secondary/tertiary settings. This research study has been undertaken as part of a University of Waterloo Centre for Sight Enhancement initiative - the preliminary part of which was published in *Optometry & Vision Science* **Vol. 71(7)**:422-436, and the methodology in *Medical Decision Making* **Vol. 15(4)**, Oct-Dec 1995.

As you are aware, the health care sector has over the recent past been called upon to operate in an environment of increasingly constrained resources - escalating costs on the one hand and government cutbacks on the other. One of the main policy recommendations of the World Bank in 1993 was a call for most countries to scale down public spending for speciality/tertiary care facilities. Planning for and delivering quality care under such conditions is indeed a far more challenging task than ever before. A tool that facilitates the advance determination of potential resources to be demanded by patients would assist in the making of informed decisions at the planning stage. This study, which involves analysis of secondary data from a number of low vision clinics/centres in North America and Africa, is aimed at developing a methodology for generating such a tool.

We would appreciate the participation of your Clinic/Centre in this study. Your participation will entail:
a. about an hour's set-up time to familiarize the investigator with your service delivery process;
b. provide the investigator with a working table/desk (for about five working days); and
c. 'supply' the patient records, or point the investigator to where the records can be accessed. It would be ideal if such information were computerized, but it is not necessary.

We understand the private and confidential nature of the data involved, hence all information provided by your clinic will be treated in the strictest of confidence. We are interested in the resource utilization patterns of patients in the entire group of clinics surveyed, thus, such unique identifiers as individual patient's name, health-card/file number, etc, are not necessary for the purposes of this study. Further, your clinic/centre will not be identified by name in the report except as an acknowledgement. Upon completion of the study, a copy of the findings shall be made available to you.

This study has been reviewed and approved for ethics through the office of Human Research at the University of Waterloo. However, if you have any ethical/confidentiality questions or concerns vis-à-vis your Centre's participation in the study, please contact that office at (519)885-1211 Ext 6005. For other questions concerning this study, please contact Professor D. Dilts at (519)888-4838.

Please let us know when we can contact you to set up a time to participate in this study.

Thank you,

Joseph N. Khamalah
Ph.D. Student
Dept of Management Sciences

David Dilts, Ph.D.
Associate Professor
Dept of Management Sciences

APPENDIX B

COPY OF RESEARCH APPROVAL LETTER

Office of Human Research and Animal Care

November 29, 1995

Professor David Dilts
Department of Management Sciences
University of Waterloo

Dear Professor Dilts,

Subject: Confirmation of Ethics Approval to Conduct Research with Humans

Recently you submitted an application entitled *"An A Prior Resource-based Classification Methodology for Specialty/Tertiary Ambulatory Patients" (OHR 7218)* to the Office of Human Research for ethics review, in accordance with the University of Waterloo's requirement that all research involving humans must be conducted in compliance with the Office of Human Research Guidelines for Research Involving Human Participants. This project will be conducted by Mr. Joseph Khamalah, a Ph.D. student in Management Sciences who is working under your supervision.

Ethics review of your application through the Office of Human Research and Animal Care is now complete and I am pleased to advise that the project has been judged to comply with the University of Waterloo Guidelines for Research with Human Participants and the Medical Research Council of Canada Guidelines on Research Involving Human Subjects. It is understood from your November 16, 1995 letter that only hospitals/health care settings which have a practice of requesting prior written consent from patients for use of their medical data for research purposes will be included in this study.

As we have discussed, there are always ethical issues to be addressed whenever patient data will be accessed for purposes of secondary data analyses. Thus, it is recommended that Mr. Khamalah take every precaution to ensure that patient identities and the identities of individual health care settings/hospitals are protected both during the conduct of this project and in any report or publication arising from this project. Specifically, all identifying or potentially identifying information must be removed from the data at the earliest opportunity. Further, Mr. Khamalah should be aware that he may be requested by individual hospitals to sign a statement of confidentiality.

I trust that this letter meets your request for confirmation of ethics approval of Mr. Khamalah's project. Please do not hesitate to contact me if you require further documentation from my office.

Yours sincerely,

Susan E. Sykes

Susan E. Sykes, Ph.D., C.Psych.
Associate Director
Office of Human Research and Animal Care

c.c. Joseph Khamalah, Department of Management Sciences

University of Waterloo
Needles Hall, Room 3015
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APPENDIX C

COPY OF PRIVACY AND CONFIDENTIALITY LETTER

I, Joseph Nalukulu Khamalah, agree that:

1. data collected from the ________ clinic/center will not be used for any other reason or purpose except statistical analysis for research, and
2. individuals served by the _______ clinic/center will not be identified in my research reports, and
3. no material copied or otherwise obtained from the ___________ clinic/center will be shared unless authorized by the ___________ clinic/center in advance.

Signed, ___________.

APPENDIX D

SITE-SPECIFIC RESULTS & WRITE-UP

Overview

This appendix describes the application of the APRCM methodology to data from Site 1. The various activities undertaken in the process of data collection, generation of patient groups, and the performance of several methods in assigning/classifying cases to their respective groups are presented. Technical descriptions of the clustering and classification features are not included, as they are presented and discussed in Chapters 2 and 3 of the thesis. Covered here are: a description of the setting, data collection exercise, descriptive statistics of the data, various transformations of the data, clustering results, and the performance of each of the four classification tools in predicting each case's iso-resource group membership.

Setting

The host clinic for this part of the study is located in the Center For Clear Vision at a medium-sized (> 500 bed), urban, private, non-teaching hospital. The clinic is fully funded by the hospital. Ophthalmologists, optometric low vision specialists, rehabilitation and occupational therapists (also referred to as 'technicians') and a receptionist/secretary make up its staff of seven. The staff handles related duties in the Center and periodically at the local Children's Hospital.

It is a secondary/tertiary facility that accepts patient referrals from multiple sources - the host hospital, self-referrals, and referrals from community eye and rehabilitation practitioners in the surrounding metropolis of more than four million inhabitants. It is open eight hours a day, Monday through Friday, and on the average serves about fifteen patients per week. The site's patient base is largely geriatric, racially mixed, and predominantly female (see Table D1.1). Distinguishing features of this site include its relatively short waiting period before patients are seen in the clinic (frequently a fortnight or less) and an active follow-up program. To facilitate the visual evaluation on the appointment date, the patient is typically asked to fill out a low vision questionnaire before the appointment date. This questionnaire provides information on the patient's current visual aids, age of prescription, current medications, allergies, and an indication of her/his medical and ocular history.

An initial patient visit is scheduled to last from 1 to 1.5 hours and includes a visual assessment, and orientation and mobility training using a variety of visual devices including CCTVs, magnifiers (hand-held, pocket and stand), clear image glasses, telescopes, binoculars, lamps, etc. These devices are routinely loaned out for short periods (usually two weeks) for the patient's trial and are returned to the clinic in the follow-up visit. Follow-up visits in general last from 15 to 30 minutes.

Subjects

A systematic sample (n = 270) was drawn from the 750 patients seen in the clinic in 1994 (a period over which there was relative stability in the standard forms used at the site). Every third file in the patient records arranged alphabetically (and tagged by year) was pulled for inclusion in the sample.

Table D1.1 presents a summary of some descriptive statistics of interest about the patients included in the sample. For example, although the ages of patients in the sample ranged from 7 to 102 years, almost 60% were aged between 70 - 89 years. About 85% were aged 50 or above whereas the below 20 years category made up 2.6% of the sample. This spread is typical of the general low vision patient population in North America and is confirmed by the visual diagnoses - with the majority presenting with conditions that are of adult onset in nature. The subjects are predominantly female (66%) and white (67.8%) - reflective of local demographics that are atypical of the nation's distribution across those two dimensions. Finally, the majority of the subjects (60.7%) were established (repeat) patients - a reflection of the follow-up program mentioned earlier.

Table D1.1a: Composition of Sample across Age, Gender, Race, Patient Type & Diagnosis.

Feature	Category	n	%
	< 10	4	1.5
	10 - 19	3	1.1
	20 - 29	7	2.6

	30 - 39	9	3.3
Age	40 -49	18	6.7
	50 - 59	34	12.6
	60 -69	27	10.0
	70 -79	79	29.3
	80 -89	82	30.4
	>=90	7	2.6
Totals		270	100.0

Table D1.1b: Composition of Sample across Gender, Race, Patient Type, and Diagnosis.

Feature	Category	n	%
Gender	Male	92	34.1
	Female	178	65.9
	Hispanic	3	1.1
Race	Black	60	22.2
	White	183	67.8
	Not indicated	24	8.9
Patient Type	New	106	39.3
	Established	164	60.7
	Not indicated	6	2.2
	Nystagmus	2	0.7
	Progressive Myopia	4	1.5
	Ocular Albinism	5	1.9
	Cataracts	6	2.2
Primary Diagnosis	Diabetic retinopathy	21	7.8
	Glaucoma	26	9.6
	Macular degeneration.	76	28.1
	Aphakia	81	30.0

Other	43	15.9
Totals	270	100.0

Data

Initial discussions with the acting clinic director and a perusal of a few of the patient files determined that 44 biographical and resource pieces of information (14 discrete and 30 qualitative) were to be targeted for each case in the sample (see Addendum D1.A for a description of these). The data collection instrument was developed from this description. This instrument was a flat file with the columns representing the 44 variables and each row representing one case (patient) in the sample. The data were entered directly from the patient records to a spreadsheet on a lap-top computer. In total, data obtained from this site covered 36% of the patients seen at the site over the year of interest.

The data collection activity was conducted during the week of December 3, 1995. Data collected each day were perused in the evening for initial clean-up which entailed making sure that all the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were identified for verification or explanation by the acting clinic director on the following day.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D1.A. The resulting data file was preliminarily analyzed for descriptive statistics. Variables (n = 9) containing insufficient responses were deleted (see Chapter 3 for a discussion of this). These deleted variables included Oconsult, Consults, and all the visual acuity variables except (for each case in the data set, the better of the acuity variables). Again, a discussion of how missing values in the remaining variables were handled is covered in Chapter 3.

In line with the study objectives, after the generation of patient groups from the data using cluster analysis, subsequent study tasks transform the data into suitable formats for analysis under each classification/assignment tool (decision trees, nearest neighbor, discriminant analysis, and neural networks - in that order).

Cluster Analysis

Block Clustering in the BMDP statistical package (see Chapter 3 for a discussion of the decision points with regard to cluster considerations) was used to generate four distinct clusters (groups) from the data (see Addendum D1.B for the block output from BMDP). Table D1.2 presents the characteristics (from the modal values) of the four groups.

Table D1.2: Site 1's Grouping Characteristics

VARIABLE/GROUP	1	2	3	4
Demographics: Pt Type	Established	New	Established	Established
Pt's Age	70-89	70-89	70-89	80-89
Gender	Female	Female	Female	Male
Marital	Married	Married	Widowed	Married
Religion	Catholic	Catholic	Catholic	Protestant
Current Visual Aids	Reading Glasses	None	Stand Magnifiers	Reading Glasses
Patient's Main Goals	Read/Write, Glare	Read/Write	Read/Write, followup	Read/Write
Services Used: V-fields	No Visual fields	Visual fields	No Visual fields	No Visual fields
# of Letters	0	1	0	0
Service type	Moderate	Comprehensive	Moderate	Comprehensive
Dr's time	n/i	60 mins	60 mins	60 mins
Vaid tried	None	CI, Stand.Mag	Training, Lamp	None
Follow-up	2 weeks	2 weeks	6-12 weeks	2 weeks
Medical History	HBP, Cataract	HBP, Mac. Deg	HBP, Stroke	HBP, Stroke, Cataract
Primary Diagnosis	Aphakia	Macular Deg	Aphakia	Aphakia

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = 0V + 0L + 2S + zC + 0T + 0D$$

$$RU_2 = 1V + 1L + 3S + 60C + 0T + 2D$$

$$RU_3 = 0V + 0L + 2S + 60C + 1T + 1D$$

$$RU_4 = 0V + 0L + 3S + 60C + 0T + 0D$$

where RU_i is the expected set of resources demanded by patient group i;

V is visual fields (0 = not done, 1 = done)

L is number of reports/letters (either 0, 1, 2, 3)

S is service type (1 = Brief, 2 = moderate, 3 = comprehensive)

C is clinician's time (in minutes, with z signifying 'not indicated')

T is training (0 = not done, 1 = done)

D is devices used (0, 1, 2, 3, etc).

Further pre-processing of the data after the groups were obtained was called for to:

a) add in the group variable,

b) strip from the data all the resource variables (see Addendum D1.A) and the variables (Revisit and RevisitT) that could not be known prior to the appointment date,

c) use of the qualitative form of the reduced variables in step (b) for the decision tree analysis phase of the assignment task, and

d) transform all the qualitative variables in step (c) into binary variables for the rest of the assignment tools.

Steps (a) and (b) left the data set with a total of 22 variables. Step (d) expanded these to 90, however, 14 of them lacked variability (i.e. had a standard deviation of 0) and had to be deleted (see Addendum D1.C for a list of these).

These data were analyzed under each of the four classification methods. As discussed in Chapters 2 through 4, the basic objective of the analysis at this point was to determine how well each method predicts the group membership for the 270 cases using only that information about the case that is available before the appointment date (after step b). The performance of the different classifiers is presented in subsequent sections below. Each section identifies the classifier, gives some explanatory comments on its general philosophy, what splitting of the data was made, and closes with a presentation of the results obtained from that classifier. Apparent error and estimate of the true error rate are the indicators of each classifier's performance used.

Decision Tree - C4.5

The classification matrix in Table D1.3 presents the results obtained from C4.5 (see Addendum D1.D for the classification rules obtained from this classifier). The decision tree's assignments are presented in the cell. Each cell contains two figures (the number of cases, and the proportion of this to the cases that belong in that group). The totals on the right are the numbers (cases) originally placed in that group at the cluster analysis stage. The diagonal cells contain the correct assignments. The apparent error rate is drawn from these. The decision tree's overall estimate of the true error rate is shown in the last row. Its predictions on cases in Group 4 (26.9%) is relatively poorer than that in Groups 1 through 3.

Table D1.3: Decision Tree (C4.5) Classification Matrix of Site 1's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Total
Group 1	**60**	10	16	0	86
	0.6977	0.1163	0.1860	0.0	1.0000
Group 2	9	**69**	0	1	79
	0.1139	**0.8734**	0.0	0.0127	1.0000
Group 3	10	1	**67**	1	79
	0.1266	0.0127	**0.8481**	0.0127	1.0000
Group 4	12	6	1	**7**	26
	0.4615	0.2308	0.0385	**0.2692**	1.0000
Total	91	86	84	9	270
	0.3370	0.3185	0.3111	0.0333	1.0000
Apparent Error					0.2480
Estimated Error					0.3780

Non-parametric Discriminant Analysis

We implemented this classifier in the DISCRIM procedure of SAS. The size of the data set at this site precluded a simple splitting of the data into two - training and testing sets. Instead, 'hold-back one' cross-validation was used. In effect, this meant that 269 cases were used to determine the classification criterion (as training data) and the remaining case was tested on this criterion. This process was repeated until each case had been tested (assigned). Before submitting the data for analysis, it was necessary to transform qualitative variables into binary variables and replace the text (qualitative) values used under the decision tree with numeric values (0's and 1's). This meant that a total of 77 variables were included in the data set at this point. The results obtained are presented in the table below. The interpretation of the table is similar to the one above, in addition, the classifier computes apparent and true error rates that are group specific. The priors row simply indicates the initial proportion of that group membership vis-à-vis the whole sample set. Like the foregoing technique, prediction on Group 4 is relatively poorer than that on the other groups, however, the tool's overall estimated error is more than 62%.

Table D1.4: Non-parametric D. A. Classification Matrix of Site 1's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Other	Total
Group 1	**32**	8	6	1	39	86
	0.3721	0.0930	0.0698	0.0116	0.4535	1.0000
Group 2	9	**24**	20	1	25	79
	0.1139	**0.3038**	0.2532	0.0127	0.3165	1.0000
Group 3	3	19	**44**	2	11	79
	0.0380	0.2405	**0.5570**	0.0253	0.1392	1.0000
Group 4	1	5	4	**1**	15	26
	0.0385	0.1923	0.1538	**0.0385**	0.5769	1.0000
Total	45	56	74	5	**90**	270
	0.1667	0.2074	0.2741	0.0185	**0.3333**	1.0000
Apparent Error						0.3370
Estimated Error						0.6259

K-Nearest-Neighbor:

The 3-nearest neighbor routine in SAS's DISCRIM procedure using the cross-validation option was applied to the same data that were used under non-parametric discriminant analysis. Here too, the data set was not split into a training and testing set (for the same reasons as under the previous section) instead, the 'hold-back-one' approach was used. The table below presents a summary of the results obtained. Mis-classified cases are handled in a manner similar to that under the foregoing classifier, and the column 'OTHER' carries the same meaning here. Like the foregoing two techniques, performance on Group 4 is by far the most lackluster, whereas that on Group 3 compares favorably with performance under other techniques.

Table D1.5: K-NN Classification Matrix of Site 1's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Other	Total
Group 1	**46**	18	16	4	2	86
	0.5349	0.2093	0.1860	0.0465	0.0233	1.0000
Group 2	4	**60**	8	5	2	79
	0.0506	**0.7595**	0.1013	0.0633	0.0253	1.0000
Group 3	3	6	**68**	0	2	79
	0.0380	0.0759	**0.8608**	0.0	0.0253	1.0000
Group 4	1	10	3	**10**	2	26
	0.0385	0.3846	0.1154	**0.3846**	0.0769	1.0000
Total	54	94	95	19	**8**	270
	0.2000	0.3481	0.3519	0.0704	**0.0296**	1.0000
Apparent Error						0.3444
Estimated Error						0.3185

Neural Network

We implemented WinNN, a Microsoft Windows-based back-propagation neural network (see Chapter 3 for a description). Before submitting the data for classification under WinNN, the binary data set used in the previous two classifiers was modified to:

a) have the group variable represented in binary form (by four variables rather than one), thus bringing the total number of variables to 80. Due to the small number of cases, experimentation was also done with the same number of variables as used under the decision tree - with only the group variable represented in binary form and equal distance scaling used in the rest of the variables, for instance the third category on a variable represented by 0.3 and the sixth by 0.6 ;

b) use cross-validation by splitting the data set into ten equal sets of 27 cases each. 10 input and 10 test files were drawn from these. Each input pattern file contained 9 of these sets (243 cases) and the remaining 1 was used as a test file (27 cases). Care was taken to ensure that each of these 10 sets of 27 cases was used only once as a test file, and that no single set was used both as an input and a test file simultaneously; and

c) have the foregoing datafiles carry the necessary flags that enabled WinNN to identify them as input pattern and test files.

From experimentation, the learning parameter was set at 0.5, momentum at 0.005, and the noise factor at 0.0005.

As can be noted from the results below, this classifier turned out to be quite costly in terms of time. The first two runs took thousands of iterations (at 16 seconds per iteration on a Pentium 166 machine) without the performance going beyond 90% prediction accuracy on the training cases. In order to speed up the process, in subsequent runs, we:

a) commenced the network from the saved weights of the foregoing run;

b) stopped the training when the prediction performance on training cases reached 90 % or better. It was noticed that even in the case where more than 90% was reached after the first few iterations, performance did not improve significantly when the net was allowed to run for more than 1000 iterations.

The average of the errors obtained from testing the 10 trained networks on their corresponding testing sets is taken here to be an estimate of the true error. The apparent error rate is drawn from an average of the misclassification of the trained networks on the training cases. No group specific estimates were drawn from the network's predictions, hence no inter-group and inter-technique comparisons can be made.

Table D1.6: Summary of Neural Network Predictions of Site 1's Cases

Run #	Epochs	Training Good patterns %	Testing Good patterns %	Testing Error
1	12500	90	44.4	0.556
2	5670	90	70.4	0.296
3	565	90	59.3	0.407
4	47	87	63.0	0.370
5	10	90	96.3	0.037
6	16	90	88.9	0.111
7	21	90	81.5	0.185
8	22	90	85.2	0.148
9	23	90	81.5	0.185
10	3	91	96.3	0.037
Apparent Error				**0.1020**
Estimated Error				**0.2332**

Overall Performance

A summary of the performance of all the four classification methods is presented in the table below. It is evident, however, that the neural network outperforms the other classification techniques in predicting group membership (hence expected resource utilization) of the cases at this site.

Table D1.7: Summary of classifier performance in the prediction task

Classifier	Apparent Error	Estimate of True Error
Neural Networks - WinNN	0.1020	0.2332
K-Nearest Neighbor - SAS	0.3444	0.3185
Decision Tree - C4.5	0.2480	0.3780
Discriminant Analysis - SAS	0.3370	0.6259
Chance Criterion	0.7181	0.7181

Addendum D1.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 7 to 102 years)			
Lastexam	Last eye examination	Discrete (in weeks)			
Medhis1	Patient's Medical history	0 = n/a, n/i	1 = None (healthy)	2 = Diabetic	3 = Arthritis
		4 = HBP	5 = Stroke	6 = Paraplegic	7 = Respiratory
		8 = Accident/Injury	9 = Other		
Medhis2	Patient's Medical history	0 = n/a, n/i	1 = None (healthy)	2 = Diabetic	3 = Arthritis
		4 = HBP	5 = Stroke	6 = Paraplegic	7 = Respiratory
		8 = Accident/Injury	9 = Other		
OcularH1	Patient's ocular history	0 = n/a, n/i	1 = Aphakia	2 = CME	3 = Cataract
		4 = Diabetic Ret.	5 = Diplopia	6 = Glaucoma	7= Prog. Myopia
		8 = CVA	9 = Mac. Deg.	10 = CRVO	11=Mult. Scleros
		12 = Albinism	13 = Nystagmus	14 = Optic Atrophy	
		15=Optic Neuritis	16 = Ret. Pigmentosa	17 = Retinopathy	18 = Other
OcularH2	Patient's ocular history	0 = n/a, n/i	1 = Aphakia	2 = CME	3 = Cataract
		4 = Diabetic Ret.	5 = Diplopia	6 = Glaucoma	7= Prog. Myopia
		8 = CVA	9 = Mac. Deg.	10 = CRVO	11=Mult. Scleros
		12 = Albinism	13 = Nystagmus	14 = Optic Atrophy	
		15=Optic Neuritis	16 = Ret. Pigmentosa	17 = Retinopathy	18 = Other
OcularH3	Patient's ocular history	0 = n/a, n/i	1 = Aphakia	2 = CME	3 = Cataract
		4 = Diabetic Ret.	5 = Diplopia	6 = Glaucoma	7= Prog. Myopia
		8 = CVA	9 = Mac. Deg.	10 = CRVO	11=Mult. Scleros
		12 = Albinism	13 = Nystagmus	14 = Optic Atrophy	
		15=Optic Neuritis	16 = Ret. Pigmentosa	17 = Retinopathy	18 = Other
Gender	Patient's gender	0 = n/i	1 = Female	2 = Male	
Religion	Patient's religion	0 = n/i	1 = None	2 = Catholic	3 = Protestant
		4 = Methodist	5 = Baptist	6 = Episcopelian	7 = Presbyterian
		8 = Jewish	9 = Other		
Race	Patient's race	0 = n/i	1 = Black	2 = White	3 =
		Hispanic			
MaritalS	Patient's marital status	0 = n/i	1 = Single	2 = Married	3 = Divorced
		4 = Widowed			
Ptcateg	Patient category	0 = n/i	1 = Inpatient	2 = Outpatient	
Pttype	Patient type	0 = n/i	1 = New	2 = Established	
DiagnosP	Primary Diagnosis	0 = n/a, n/i	1 = Aphakia	2 = CME	3 = Cataract
		4 = Diabetic Ret.	5 = Diplopia	6 = Glaucoma	7= Prog. Myopia
		8 = CVA	9 = Mac. Deg.	10 = CRVO	11=Mult. Scleros
		12 = Albinism	13 = Nystagmus	14 = Optic Atrophy	
		15=Optic Neuritis	16 = Ret. Pigmentosa	17 = Retinopathy	18 = Other
DiagnosS	Secondary Diagnosis	0 = n/a, n/i	1 = Aphakia	2 = CME	3 = Cataract
		4 = Diabetic Ret.	5 = Diplopia	6 = Glaucoma	7= Prog. Myopia
		8 = CVA	9 = Mac. Deg.	10 = CRVO	11=Mult. Scleros
		12 = Albinism	13 = Nystagmus	14 = Optic Atrophy	
		15=Optic Neuritis	16 = Ret. Pigmentosa	17 = Retinopathy	18 = Other
Goal, Visual acuity and Visual aid Data					
Goal1	Patient's first complain / objective	0 = n/i	1 = Read/write	2 =Glare	3 = Watch TV
		4 = follow-up	5 = General Vision	6 = Color test	7 = ADL
		8 = Driving	9 = Other		
Goal2	Patient's second complain / objective	0 = n/i	1 = Read/write	2 =Glare	3 = Watch TV
		4 = follow-up	5 = General Vision	6 = Color test	7 = ADL
		8 = Driving	9 = Other		
Goal3	Patient's third complain /	0 = n/i	1 = Read/write	2 =Glare	3 = Watch TV

	objective	4 = follow-up	5 = General Vision	6 = Color test	7 = ADL
		8 = Driving	9 = Other		
Vaid1	Patient's first current visual aid	0 = n/i	1 = Hhmags	2 =Pkt Mags	3 = Stand mags
		4 = Bifocals	5 = Glasses	6 = Bi/Monocs	7 = Contacts
		8 = Filters	9 = Other		
Vaid2	Patient's second current visual aid	0 = n/i	1 = Hhmags	2 =Pkt Mags	3 = Stand mags
		4 = Bifocals	5 = Glasses	6 = Bi/Monocs	7 = Contacts
		8 = Filters	9 = Other		
RxOD	Present Rx OD	Discrete			
RxOS	Present Rx OS	Discrete			
OD-C	Acuities - C	Discrete			
OS-C	Acuities - C	Discrete			
OD-S	Acuities - S	Discrete			
OS-S	Acuities - S	Discrete			
ReadRxOD	Reading Rx OD	Discrete			
ReadRxOS	Reading Rx OS	Discrete			
Resource Data					
TriedVA1	First visual aid tried	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Training	9 = Other		
TriedVA2	Second visual aid tried	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Training	9 = Other		
Loan1	First device loaned to patient	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Lamp	9 = Other		
Loan2	Second device loaned to patient	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Lamp	9 = Other		
Servtype	Description of service rendered	0 = n/i	1 = Comprehensive	2 = Intermediate	3 = Moderate
		4 = Technician only			
Vservice	Vision services rendered	0 = n/I 1 = Visual field	2 = Color test	3 = EOG	4= ERG
Device1	First device prescribed / dispensed	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Lamp	9 = Other		
Device2	Second device prescribed / dispensed	0 = None, n/i	1 = ½ Eyes	2 = CI glasses	3 = Filters
		4 = Hhmags	5 = Pkt Mags	6 = Illum SMags	7 = Read glasses
		8 = Lamp	9 = Other		
Letters	Number of letters written	Discrete			
Source	Source of letters	0 = n/a (for none)	1 = Doctor	2 = Other	
Dr-time	Doctor's time on patient	Discrete (in minutes)			
Dr-conuns	Dr &Tech's time on patient	Discrete (in minutes)			
Consults	Consultations	0 = n/i			
Oconsult	Office consultations	0 = n/i	1 = Eye appliance		
Other Data					
Revisit	Reason for revisit	0 = n/i, none	1 = Review status	2 =Review device	3 = Visual Field
		4 = Training	5 = Other		
RevisitT	Time for the revisit	Discrete (in weeks)			

Addendum D1.B: Block (Cluster) Output from BMDP

```
               Revisit   Triedva2  Lastexam  Vaid1
                Pttype    Loan1     Ocularh3  Goal2
                 Vservice  Loan2     Goal1     Servtype
                  Diagnosp  Ptcateg   Revisitt  Drtime
                   Letters   Oconsult  Maritals  Cvacuity
                    Source1   Consults  Age       Gender
                     Drcouns   Diagnoss  Ocularh2  Religion
                      Ocularh1  Device1   Triedva1
                       Goal3     Device2   Medhis1
                        Vaid2     Race      Medhis2
BLK COUNT+....+....+....+....+....+....+....+...
 A   4840 12010002000002000002001228204051301 12
 B    596 2116112..................762..0011...
 C    373 ....................24454718543......
 D    180 ............................545011223
         +....+....+....+....+....+....+....+...

NO. OF SINGLETONS   3930
```

Notes: Tracking a variable downwards to the block values will show the modal value for the block on the given variable. Such values can be deciphered from the coding scheme in Addendum D1.A.

Addendum D1.C: Variables Discarded due to lack of variability after Transformation into binary variables

1. Oculah2	2. Oculah8	3. Oculah10	4. Oculah11	5. Oculah14	6. Oculah15
7. Oculah17	8. Oculah18	9. Vaid8	10. Diagno2	11. Diagno14	12. Diagno15
13. Religio6	14. Religio7				

Addendum D1.D: Classification Rules from C4.5

Rule 1
Goal1 = genvision
Cvacuity > 80
Pttype = repeat
=> class Group 4 [70.7%]

Rule 2
OcularH2 = other
MaritalS = single
=> class Group 4 [35.2%]

Rule 3
Goal1 = fup
MaritalS = single
=> class Group 3 [88.2%]

Rule 4
MedHis1 = stroke
Lastexam <= 24
Goal1 = fup
=> class Group 3 [84.5%]

Rule 5
MedHis1 = other
Goal1 = fup
=> class Group 3 [77.7%]

Rule 6
MaritalS = single
Lastexam <= 24
Goal1 = fup
=> class Group 3 [70.0%]

Rule 7
OcularH2 = other
Pttype = repeat
=> class Group 3 [56.8%]

Rule 8
Goal1 = colort
=> class Group 1 [85.7%]

Rule 9
MedHis1 = hbp
Pttype = repeat
MaritalS = married
Lastexam <= 24
=> class Group 1 [75.9%]

Rule 10
Goal1 = tv
Pttype = repeat
=> class Group 1 [70.7%]

Rule 11
MedHis1 = none
Goal1 = fup
=> class Group1 [63.0%]

Rule 12
MedHis1 = arthritis
MaritalS = single
=> class Group 1 [63.0%]

Rule 13
Goal1 = readw
Pttype = repeat
=> class Group 1 [51.2%]

Rule 14
OcularH2 = cataract
Goal2 = glare
=> class Group 1 [50.0%]

Rule 15
Goal1 = glare
=> class Group 1 [50.0%]

Rule 16
Goal1 = driving
Pttype = new
=> class Group 2 [79.4%]

Rule 17
Pttype = new
Religion = catholic
=> class Group 2 [78.6%]

Rule 18
Goal1 = genvision
Pttype = new
=> class Group 2 [72.2%]

Rule 19
Goal1 = readw
Pttype = new
=> class Group 2 [71.9%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 2. It follows Appendix D.1's outline, and covers similar issues with respect to Site 2 but with more brevity since explanatory notes have been given in Appendix D.1.

Setting

The host clinic is located in the Vision Research and Rehabilitation Center at a large (>1000 bed), urban, university hospital. In addition to funding from the hospital and client fees, the clinic receives grants from a major philanthropic organization. Its staff (n > 9) is a multidisciplinary complement of ophthalmologists, optometric low vision specialists, rehabilitation and occupational therapists (clinical social workers). It also includes a receptionist/secretary and two undergraduate medical students who are routinely assigned duties within the clinic.

It is a secondary/tertiary facility that accepts patient referrals from within the host center and hospital and from community eye and rehabilitation practitioners in the surrounding metropolis and adjoining East coast states. A small proportion of its patients are from international referral sources. It is open eight hours a day, Monday through Thursday. Its patient base is largely geriatric and racially mixed (see Table D2.1). To facilitate the visual evaluation on the appointment date, the clinic receives a detailed letter from the referring doctor providing information on the patient's condition, her/his medical and ocular history, current visual aids, age of prescription, medications, etc.

The clinical social worker will typically be the patient's first contact with the clinic's professional staff. In addition to eliciting the patient's medical, ocular, family and health history, the social worker also performs an assessment of the patient's functional problems, goals and objectives. This initial contact takes about 40 to 50 minutes. The patient then proceeds for a 90 to 120 minutes visual evaluation by an optometrist/ophthalmologist. Various optical, electronic and mechanical devices or techniques are used and their impact on the patient's visual performance is determined. Based on this, some selection, recommendation, and prescription of devices, techniques, or other service is made. About 50% of the patients meet with the clinical social worker again for follow-up work that lasts between 10 and 15 minutes. Thus, an initial patient visit typically takes from 2 to 3 hours.

Subjects

A systematic sample (n = 310) was drawn from the 1250 patients seen in the clinic in 1994 (a period over which there was relative stability in the standard forms used at the site). Every fourth file in the patient records arranged alphabetically and tagged by year was pulled for inclusion in the sample.

Table D2.1 presents a summary of some descriptive statistics of interest about the patients included in the sample. For example, although the ages of patients in the sample ranged from 2 to 94 years, about 45% were aged 70 years or above. In fact, more than 75% were aged 50 or above whereas the below 20 years category made up about 4% of the sample. This spread is typical of the general low vision patient population in North America. The subjects are split almost equally on the gender dimension (49% female and 51% male). The spread on race was reflective of local demographics that are typical of the nation's distribution (white 73.5%, black 14.5%, other 0.6%, and not indicated 11.3%). Finally, the majority of the subjects (68.7%) were new patients (with repeats comprising 31.3%).

Table D2.1: Composition of Sample across Age, Gender, Race, Patient Type & Diagnosis.

Feature		Group 1	Group 2	Group 3	Group 4	Group 5	Total
Age	< 10	1	0	1	1	5	8 (2.6%)
	10 - 19	1	1	1	0	1	4 (1.3%)
	20 - 29	2	0	2	1	2	7 (2.3%)
	30 - 39	10	3	2	6	3	24 (7.7%)
	40 -49	5	2	14	3	5	29 (9.4%)
	50 - 59	14	3	11	5	5	38 (12.3%)
	60 -69	12	17	9	14	7	59 (19.0%)
	70 -79	42	16	4	5	8	75 (24.2%)
	80 -89	20	6	9	6	20	61 (19.7%)
	>=90	2	1	2	0	0	5 (1.6%)

Gender	Female	32	38	27	28	27	152 (49.0%)
	Male	77	11	28	13	29	158 (51%)
	Not indicated	17	5	6	4	3	35 (11.3%)
Race	White	78	33	41	35	41	228 (73.5%)
	Black	13	11	8	2	11	45 (14.5%)
	Other	1	0	0	0	1	2 (0.6%)
Patient	New	79	31	46	18	39	213 (68.7%)
Type	Established	30	18	9	23	17	97 (31.3%)
	Albinism	0	0	1	0	3	4 (1.3%)
	Glaucoma	2	0	2	1	1	6 (1.9%)
Primary	Visual cortex	2	0	2	1	2	7 (2.3%)
	Visual field disorder	2	0	2	0	4	8 (2.6%)
Diagnosis							
	Glaucoma	6	1	3	0	1	11 (3.5%)
	Diabetic retinopathy	7	1	1	0	3	12 (3.9%)
	Retinitis pigmentosa	6	6	4	0	5	21 (6.8%)
	Choroidal disorder	18	17	14	9	4	62 (20.0%)
	Macular degeneration	54	20	20	22	25	141 (45.5%)
	Other	12	4	6	8	8	38 (12.3%)
Group Totals		109	49	55	41	56	310

Data

45 biographical and resource pieces of information (8 discrete and 37 qualitative) were targeted for each case in the sample (see Addendum D2.A for a description of these). The data were entered directly from the patient records to a spreadsheet on a lap-top computer. In total, data obtained from this site covered about 25% of the patients seen at the site over the year of interest.

The data collection activity was conducted during the week of February 4, 1996. Data was collected by the investigator and two research assistants (medical students attached to the clinic). A training session was conducted to familiarize the research assistants with the modalities of the data collection exercise. Data collected each day were perused in the evening to ensure that there was consistency across the three data collectors, all the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were tagged for verification or explanation by the clinic director on the following day.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D2.A. The resulting data file was preliminarily analyzed for descriptive statistics. The variable Preva (presenting visual acuity of better eye) was created from Preod and Preos (the lower of the two for each case was picked). The difference between Time-in and Time-out was used to create the variable Time which replaced the former two. The discrete variables were categorized and the resulting data set uploaded for categorical cluster analysis.

Cluster Analysis

Table D2.2 presents the characteristics of the five groups generated from the data. Addendum D2.B gives the block count portion of the output from the clustering algorithm.

Table D2.2: Site 2's Grouping Characteristics

VARIABLE/GROUP	1	2	3	4	5
Demographics: Pt Type	New	New	New	Established	New
Pt's Age	70-89	60-79	40-59	50-69	80-89
Gender	Male	Female	Female/Male	Female	Female/Male
Living	Not alone	Alone	Not alone	Not alone	Not alone
Pre-visual acuity	25-80	80-400	25-80	25-200	25-1330
Current Visual Aids	Bifocs, mags	Bifocs, mags	Bifocs, mags, r/glasses	Mags, r/glasses	Bifocs, r/glasses
Patient's Main complaint	Declining vision	Declining vision	Declining vision	amd	Declining vision
Services Used: Consult	Level 3, 4 & Other	Level 4	Level 4	Level 4	Level 3, 4 & Other
# of Letters	0	0	1	0	0
Msw	No	No	No	Yes	No
Time	76-120 mins	106-120 mins	91-120 mins	136-180 mins	106-120 mins
Disposition	Npr	Npr	f/up	f/up	Npr
Oldevs	No	No	Yes	No	No
Bestva	25-80	80-200	25-80	25-200	25-1330

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = (3 <= C <= 5) + 0L + 0M + (75 < T < 121) + 1P + 0D$$

$$RU_2 = 4C + 0L + 0M + (105 < T < 121) + 1P + 0D$$

$$RU_3 = 4C + 1L + 0M + (90 < T < 121) + 2P + 1D$$

$$RU_4 = 4C + 0L + 1M + (135 < T < 181) + 2P + 0D$$

$$RU_5 = (3 <= C <= 5) + 0L + 0M + (105 < T < 121) + 1P + 0D$$

where RU_i is the expected set of resources demanded by patient group i;

C is consultation level (1, 2, 3, 4, or 5 (other))

M is social worker consultation (0 = No, 1 = Yes)

T is clinician time (in minutes)

P is disposition (1 = npr, 2 = f/up)

D is optical low vision devices dispensed (0 = No, 1 = Yes).

Further pre-processing of the data after the groups were obtained was called for to:

a) add in the group variable,
b) strip from the data all the resource and other variables that can not be known prior to the appointment date (Addendum D2.A),
c) use of the qualitative form of the reduced variables in step b) for the decision tree analysis phase of the assignment task, and
d) transform the qualitative variables in step c) into binary variables for the rest of the assignment tools.

Steps (a) and(b) left the data set with a total of 26 variables. Step (d) expanded these to 113 (for DA and K-NN) and 117 (for WinNN).

These data were analyzed under each of the four classification methods. As discussed in the thesis report, the basic objective of the analysis at this point was to determine how well each method predicted the group membership for the 310 cases using only that information about the case that is available before the appointment date (after step b). The performance of the different classifiers is presented in subsequent sections below. Each section identifies the classifier, gives explanatory comments on its general philosophy (technical descriptions of the classifier are presented in the report), what splitting of the data was made, and closes with a presentation of the results obtained from that classifier.

As discussed in Chapters 3, the performance of each classifier can be evaluated using a number of measures namely; apparent error rate, estimate of true error, and a misclassification cost. We elected to present the classifiers' performance as is, without biasing them with any arbitrary indication of misclassification costs. Thus, the apparent error rate and an estimate of the true error rate are used here as the indicators of each classifier's performances.

Decision Tree

C4.5's assignments are presented in Table D2.3. The decision tree's correct predictions on cases in Group 4 (48.8%) is relatively poorer than those in the other groups (all above 60.0%).

Table D2.3: Decision Tree (C4.5) Classification Matrix of Site 2's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**74**	2	17	5	11	109
	0.6789	0.0183	0.1559	0.0459	0.1009	1.0000
Group 2	2	**31**	12	3	1	49
	0.0408	**0.6327**	0.2449	0.0612	0.0204	1.0000
Group 3	10	2	**34**	2	7	55
	0.1818	0.0364	**0.6182**	0.0364	0.1273	1.0000
Group 4	4	2	14	**20**	1	41
	0.0976	0.0488	0.3415	**0.4878**	0.0244	1.0000
Group 5	4	3	12	2	**35**	56
	0.0714	0.0536	0.2143	0.0357	**0.6250**	1.0000
Total	94	40	89	32	55	310
	0.3032	0.1290	0.2871	0.1032	0.1774	1.0000
Apparent Error						**0.3740**
Estimated Error						**0.4420**

Non-parametric Discriminant Analysis

Table D2.4 summarizes the predictions of this learning system. Unlike the previous technique, prediction on Group 4 is remarkably better than predictions on other groups. The method's overall estimated error of 77.5%, however, implies that it does not perform well as a predictor.

Table D2.4: Non-parametric D. A. Classification Matrix of Site 2's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**29**	0	6	1	1	72	109
	0.2661	0.0	0.0550	0.0092	0.0092	0.6606	1.0000
Group 2	0	**16**	6	1	1	25	49
	0.0	**0.3265**	0.1224	0.0204	0.0204	0.5102	1.0000
Group 3	6	6	**2**	3	1	37	55
	0.1091	0.1091	**0.0364**	0.0545	0.0182	0.6727	1.0000
Group 4	1	1	3	**17**	2	17	41
	0.0244	0.0244	0.0732	**0.4146**	0.0488	0.4146	1.0000
Group 5	1	1	1	2	**6**	45	56
	0.0179	0.0179	0.0179	0.0357	**0.1071**	0.8036	1.0000
Total	37	24	18	24	11	**196**	310
	0.1194	0.0774	0.0581	0.0774	0.0355	**0.6323**	1.0000
Apparent Error							**0.1419**
Estimated Error							**0.7749**

K-Nearest-Neighbor:

Table D.5 gives a summary of this method's performance. The method predicted membership in Groups 3 and 5 poorly (below 40.0%), about average on Group 4 (58.5%) and very well on Groups 1 and 2 (86.2% and 73.5% respectively). Its overall estimated error of 0.3710 implies that it will more than double the predictive accuracy of the discriminant analysis classifier.

Table D.5: K-NN Classification Matrix of Site 2's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**94**	3	6	2	3	1	109
	0.8624	0.0275	0.0550	0.0183	0.0275	0.0092	1.0000
Group 2	6	**36**	1	4	0	2	49
	0.1224	**0.7347**	0.0204	0.0816	0.0	0.0408	1.0000
Group 3	23	7	**19**	1	1	4	55
	0.4182	0.1273	**0.3455**	0.0182	0.0182	0.0727	1.0000
Group 4	4	5	2	**24**	1	5	41

	0.0976	0.1220	0.0488	**0.5854**	0.0244	0.1220	1.0000
Group 5	23	4	2	0	**22**	5	56
	0.4107	0.0714	0.0357	0.0	**0.3929**	0.0893	1.0000
Total	150	55	30	19	31	**27**	310
	0.4839	0.1774	0.0968	0.0704	0.1000	**0.0871**	1.0000
Apparent Error							**0.3258**
Estimated Error							**0.3710**

Neural Network

Similar experimentation as those at Site 1 with the same parameters were used. As can be noted from the results in Table D.6, this classifier turned out to be quite costly in terms of time. The first run took thousands of iterations (at 26 seconds per iteration on a Pentium 166 machine, this worked out to be more than 26 hours) for the performance to reach about 95% prediction accuracy on the training cases. In order to speed up the process, in subsequent runs, we:

a) commenced the network from the saved weights of the foregoing run;

b) stopped the training when the network indicated that it had achieved 80% (or more) good patterns on training set. It was noticed that even in the case where more than 80% was reached after the first few iterations (run # 2), performance did not improve significantly when the net was allowed to run for more than 1000 iterations.

The average of the errors obtained from testing the 10 trained networks on their corresponding testing sets is taken here to be an estimate of the true error. The apparent error rate is drawn from an average of the misclassification of the trained networks on the training cases. No group specific estimates were drawn from the network's predictions, hence no inter-group and inter-technique comparisons can be made. The first and ninth runs are intriguing. Although the network performed relatively well on the training cases (with about 95% accuracy), it did so poorly on the testing cases (about 26% accuracy). Contrary to this, the network posted perfect prediction on the testing cases in the ninth run even though its performance on the training cases had not been outstanding.

Table D2.6: Summary of Neural Network Predictions of Site 2's Cases

Run #	Iterations	Training Good patterns %	Testing Good patterns %	Testing Error
1	3611	94.6	25.8	0.742
2	1847	85.7	87.1	0.129
3	12	83.5	90.3	0.097
4	56	87.5	96.8	0.032
5	5	83.2	83.9	0.161
6	9	87.5	93.5	0.065
7	42	87.1	93.5	0.065
8	28	83.5	87.1	0.129
9	3	85.7	100.0	0.0
10	35	87.1	96.8	0.032
Apparent Error				**0.1346**
Estimated Error				**0.1452**

Overall Performance

A summary of the performance of all the four classification methods is presented in the table below.

Table D2.7: Summary of classifier performance in the prediction task

Classifier	Apparent Error	Estimate of True Error
Neural Networks - WinNN	0.1346	0.1452
K-Nearest Neighbor - SAS	0.3258	0.3710
Decision Tree - C4.5	0.3740	0.4420
Discriminant Analysis - SAS	0.1419	0.7749
Chance Criterion	0.7698	0.7698

Addendum D2.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 2 to 94 years)			
Race	Patient's race	1 = Black	2 = White	3 = Hispanic	4 = n/i
MaritalS	Patient's marital status	1 = Single	2 = Married	3 = Divorced	4 = Widowed
		5 = n/i			
Gender	Patient's gender	1 = Female	2 = Male		
Pttype	Patient type	1 = New	2 = Repeat (established)		
Network	Pt's support network	1 = Family	2 = Friends	3 = Church/Com	4 = n/i
Distance	Distance traveled	1 = Local	2 = In-state	3 = Out-state	4 = n/i
Living	Patient living alone?	1 = No	2 = Yes		
Educ-Voc	Patient's	0 = n/i	1 = Attorney	2 = On disability	3 = Eng/mech
	Education/vocation	4 = Nursing	5 = Office-work	6 = Student	7 = Teaching/mgt
		8 = Other	9 = Retired		
Systemic	Systemic condition	0 = n/i	1 = Good/healthy	2 = Heart cond'n	3 = Arthritic
		4 = Diabetic	5 = Asthma	6 = Cancer	7 = Other
Medicats	Medications	0 = No	1 = Yes	2 = n/i	
ChiefC	Patient's chief complaint	0 = n/i	1 = Reading difs	2 = Fuzzy vision	3 = Declining vis
		4 = Dis/Nr vision	5 = General Vision	6 = Glare control	7 = AMD
		8 = Diab ret	9 = Other		
Onset	Onset of eye condition	Discrete (in years)			
Prefeye	Preferred eye	1 = OD	2 = OS	3 = Same	4 = n/i
Ocdiag1	Primary ocular diagnosis	0 = Albinism	1 = Amd	2 = Diabetic ret.	3 = Optic atrophy
		4 = Retinal defect	5 = Cataracts	6 = Glaucoma	7= Retinitis Pig.
		8 = High Myopia	9 = Other		
Ocdiag2	Secondary ocular diagnosis	0 = Albinism	1 = Amd	2 = Diabetic ret.	3 = Optic atrophy
		4 = Retinal defect	5 = Cataracts	6 = Glaucoma	7= Retinitis Pig.
		8 = High Myopia	9 = Other		
Goal, Visual acuity and Visual aid Data					
Ptgoal1	Patient's first objective	0 = n/i	1 = Reading	2 = Writing	3 = Driving
		4 = TV/Spec sports	5 = Signs	6 = Mobility	7 = ADLs
		8 = Glare	9 = Other (Educational, vocational, etc)		
Ptgoal2	Patient's second objective	0 = n/i	1 = Reading	2 = Writing	3 = Driving
		4 = TV/Spec sports	5 = Signs	6 = Mobility	7 = ADLs
		8 = Glare	9 = Other (Educational, vocational, etc)		
Ptgoal3	Patient's third objective	0 = n/i	1 = Reading	2 = Writing	3 = Driving
		4 = TV/Spec sports	5 = Signs	6 = Mobility	7 = ADLs
		8 = Glare	9 = Other (Educational, vocational, etc)		
Ptgoal4	Patient's fourth objective	0 = n/i	1 = Reading	2 = Writing	3 = Driving
		4 = TV/Spec sports	5 = Signs	6 = Mobility	7 = ADLs
		8 = Glare	9 = Other (Educational, vocational, etc)		
Ptgoal5	Patient's fifth objective	0 = n/i	1 = Reading	2 = Writing	3 = Driving
		4 = TV/Spec sports	5 = Signs	6 = Mobility	7 = ADLs
		8 = Glare	9 = Other (Educational, vocational, etc)		
PreVaOd	Presenting vis. acuity OD	Discrete			
PreVaOs	Presenting vis. acuity OS	Discrete			
BestVaOd	Best visual acuity OD	Discrete (with n/t = not tested)			
BestVaOs	Best visual acuity OS	Discrete (with n/t = not tested)			
Rehab1	Current rehab device 1	0 = n/i	1 = half eyes	2 = Bifocs/trifocs	3 = Telescopes
		4 = Magnifiers	5 = Dist/Nr Rx	6 = Filters	7 = Lp/Talk bks
		8 = CCTV	9 = Other		
Rehab2	Current rehab device 2	0 = n/i	1 = half eyes	2 = Bifocs/trifocs	3 = Telescopes

		4 = Magnifiers	5 = Dist/Nr Rx	6 = Filters	7 = Lp/Talk bks
		8 = CCTV	9 = Other		
Rehab3	Current rehab device 3	0 = n/i	1 = half eyes	2 = Bifocs/trifocs	3 = Telescopes
		4 = Magnifiers	5 = Dist/Nr Rx	6 = Filters	7 = Lp/Talk bks
		8 = CCTV	9 = Other		
Resource Data					
Time	Time patient took in clinic	Discrete (in minutes)			
Individ	Service code	1 = n/i	2 = Ind. Thrpy 30 (mc)	3 = Ind. Thrpy 50 (mc)	
Consult	Office Consultations	0 = n/i	1 = Level 5	2 = Level 4	3 = Level 3
		4 = Purchase only	5 = Other		
Examin	Office Examinations	0 = n/i	1 = Level 4	2 = Level 3 (100)	3 = Level 3 (75)
		4 = Level 2			
OLvdevs	Optical low vision devices	0 = No	1 = Yes		
SLvdevs	Spectacle low vision devs	0 = No	1 = Yes		
Nonops	Non-optical low vis. devs	0 = No	1 = Yes		
Letters	Number of letters/reports	Discrete			
Source	Source of letters/reports	0 = n/a	1 = Doctor	2 = Social worker	
Msw	Seen by social worker	0 = No	1 = Yes	2 = n/i	
Other Data					
Disposit	Patient's disposition	1 = Follow-up	2 = Return PRN	3 = n/i	
Return	Patient's return date	Discrete (in weeks)			

Addendum D2.B: Block (Cluster) Output from BMDP

```
            Race      Individ   Living    Pttype
             Distance  Examin    Prefered  Msw
              Medics    Slvdevs   Pgoal3    Preod
               Chiefc    Nonops    Age       Preos
                Onset     Ocdiag1   Ptgoal2   Gender
                 Rehab3    Ocdiag2   Disposit  Systemic
                  Ptgoal1   Time      Network   Bestvaod
                   Ptgoal4   Olvdevs   Eduvoc    Bestvaos
                    Ptgoal5   Letters   Rehab1    Marital
                     Return    Source    Consult   Rehab2
BLK COUNT+....+....+....+....+....+....+....+....+.
 A   6142 101390100900000190000107220922101112221O
 B    374 ....................104.........32044344
 C    375 ...............5111008431.............
 D    250 .......................611305022230055..
         +....+....+....+....+....+....+....+....+.

NO. OF SINGLETONS   5183
```

Addendum D2.C: Classification Rules from C4.5

Rule 1:
Eduvoc = Office-w
Medics = Yes
Pttype = Repeat
=> class Group 4 [46.2%]

Rule 2:
Chiefc = Amd
=> class Group 4 [39.8%]

Rule 3:
Systemic = arthritis
Rehab3 = halfeyes
=> class Group 4 [31.6%]

Rule 4:
Systemic = Diabetes
Chiefc = declivis
Ptgoal2 = write
=> class Group 2 [72.6%]

Rule 5:
Living = alone
Systemic = Diabetes
=> class Group 2 [58.4%]

Rule 6:
Age = 70 - 79
Living = alone
=> class Group 2 [43.3%]

Rule 7:
Systemic = heart
Ptgoal5= mobility
=> class Group 2 [31.6%]

Rule 8:
Systemic = healthy
=> class Group 5 [48%]

Rule 9:
Preva = 400-1329
=> class Group 5 [43.5%]

Rule 10:
Age = 80 - 89
Chiefc = readdifs
Prefered = OS
=> class Group 5 [41.8%]

Rule 11:
Systemic = asthma
=> class Group 3 [41.8%]

Rule 12:
Age = 40 - 49
=> class Group 3 [35.2%]

Rule 13:
Systemic = heart
Prefered = OD
Pttype = new
=> class Group 3 [31.6%]

Rule 14:
Gender = Male
Systemic = heart
Prefered = OS
=> class Group 1 [77.2%]

Rule 15:
Age = 70 - 79
Living = not alone
=> class Group 1 [69.2%]

Rule 16:
Preva = 25 - 80
Gender = male
Medics = Yes
=> class Group 1 [63.8%]

Rule 17
Distance = local
Systemic = arthritis
Prefered = OS
=> class Group 1 [54.5%]

Rule 18:
Systemic = heart
Ocdiag = other
=> class Group 1 [50.9%]

Rule 19:
Systemic = cancer
Ptgoal1 = read
=> class Group 1 [46.2%]

Rule 20:
Medics = yes
Chiefc = other
=> class Group 1 [41.0%]

Rule 21:
Rehab3 = lptkbks
=> class Group 1 [40.2%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 3. It follows Appendix D.2's outline and structure.

Setting

The host center for this part of the study (hereafter referred to as Site 3) is located in an urban, specialty ophthalmological hospital within an academic environment. The hospital is affiliated to a major medical school and has close links with two other nearby schools. The center was established with the help of funds from a philanthropic organization and is currently funded by the hospital. Its staff is a multidisciplinary complement of an ophthalmologist, four optometrists, occupational therapists, ophthalmology residents, and social workers. The staff also includes two secretaries, an ophthalmic assistant, and trained volunteers.

It is a specialty/tertiary facility that accepts patient referrals from multiple sources. About fifty percent of its referrals are from nongeographic ophthalmologists, 41% from the host hospital, and 9% from practitioners not affiliated with the host hospital. Some (8%) of its patients are from adjoining states on the East Coast and foreign (about 2%). This patient base is predominantly geriatric, and largely female (see Table D3.1). Among the services offered at this center are evaluation testing (to measure functional vision and assess visual needs), instruction and training, assistive devices, counselling services, and library services (with a wide collection of alternatives to regular printed materials). One of the distinguishing features of the center (largely due to its very location) is its integration of eye, ear, nose, and throat rehabilitative services for persons of all ages.

Prior to the appointment date, the patient is contacted by the staff (volunteer) who elicits information with regard to the patient's condition, current visual aids, age of prescription, medical and ocular history, visual problems, and objectives. In initial visits, all patients are booked to see all members of the center's evaluation team in sequence for a total of two hours. In cases where the patient becomes fatigued before the whole examination is done, the remaining portion is rescheduled for a later date. The patient first undergoes a visual assessment to determine her/his visual acuities using a variety of optical and non-optical devices. S/he is then trained by an occupational therapist to use adaptive techniques, devices and non-visual skills to perform self-care, work and recreational activities. Therafter the patient is seen by a social worker who assesses the social and emotional issues facing the patient. Counselling and/or referrals to appropriate resources/agencies are offered at this point depending on the patient's needs. Arrangement for follow-up visits are made depending on the specific needs of the patient. The follow-up visit is not as lengthy as the initial visit.

Subjects

A systematic sample (n = 388) was drawn from the more than 1500 patient visits that the center handled over the fiscal year 1995. Every fourth file in the patient records arranged alphabetically (and tagged by year) was pulled for inclusion in the sample. Table D3.1 presents a summary of some descriptive statistics of interest about the patients included in the sample. For example, although the ages of patients in the sample ranged from 6 to 97 years, more than 61% were aged between from 70 - 89 years. Almost 80% were aged 50 or above whereas the below 20 years category made up a little over 6% of the sample. This spread is typical of the general low vision patient population in North America and is confirmed by the visual diagnoses - with the majority presenting with conditions that are of adult onset in nature. The subjects are predominantly female (63.4%). Finally, the majority of the subjects (59.3%) were established (repeat) patients.

Table D3.1: Composition of Sample across Age, Gender & Patient Type.

Feature	Category	n	%
	< 10	2	0.5
	10 - 19	23	5.9
	20 - 29	10	2.6
	30 - 39	20	5.2
Age	40 -49	25	6.4
	50 - 59	25	6.4
	60 -69	27	7.0
	70 -79	112	28.9

	80 -89	125	32.2
	>=90	19	4.9
Gender	Male	246	63.4
	Female	142	36.6
Patient Type	New	158	40.7
	Repeat	230	59.3
Totals		388	100.0

Data

109 biographical and resource pieces of information were to be targeted for each case in the sample. Only 77 (7 discrete, 70 qualitative) of these, however, contained sufficient responses for the purposes of this study (see Addendum D3.A for a description). In total, data obtained from this site covered 25.6% of the patient visits handled by the center over the year of interest.

The data collection activity was conducted by a team consisting of the investigator and two research assistants over the week of March 10, 1996 and (by the research assistants) over the week of March 17, 1996. Data collected each day over the first week were perused in the evening for initial clean-up which entailed making sure that consistency across the data collectors was achieved, the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were identified for subsequent verification or explanation by the director.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D3.A. The resulting data file was preliminarily analyzed for descriptive statistics. Variables (n=32) containing insufficient responses were deleted (see thesis report for discussion of this). In line with the study objectives, after the generation of patient groups from the data using cluster analysis, subsequent study tasks required the transformation of the data into suitable formats for analysis under each classification/assignment tool (decision trees, nearest neighbor, discriminant analysis, and neural networks respectively).

Cluster Analysis

Block Clustering in the BMDP statistical package (see thesis report for a discussion of the decision points with regard to cluster configuration and blocking parameters) was used to generate four distinct clusters (groups) from tha data (see Addendum D3.B for the block output from BMDP). In the absence of expert opinion, it is assumed here that these five constitute the latent patient groups at this site. Table D3.2 presents the characteristics of these five groups.

Table D3.2: Site 3's Grouping Characteristics

VARIABLE/GROUP	1	2	3	4	5
Demographics: Pt Type Pt's Age Gender Marital	Repeat 80-89 Female Married, Widow	Repeat 70-79 Female Widow, Married	Repeat 80-89 Female Married, Widow	New 70-79 Female Married, Widow	Repeat 80-89 Male Single, Married
Current Visual Aids	Readers, Bfl, Hhms	Readers, Bfl, Hhms	Readers, Bfl,Hhms	Readers, Bfl	Readers, Bfl
Patient's Main Goals	Mobility, Reading	Mobility, St-Ssgns	Mobility, Reading	Mobility, Reading	Mobil, St-sign, Leisur
Family support	Yes	Yes	Not avail/approp	Yes	No
Services Used: Drvistyp Otvistyp Swvistyp Recdev	Cons Lv, Fup Lv No OT None None	Cons Lv No OT None None	Cons Lv, Ext Fup Lv No OT None None	Cons Lv, Ext Cons Lv 1/2 Hr OT Eval Brf Initial Gnl, Lap Desk	Fup Lv, Ext Fup Lv No OT None None

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = (C \in \{1,2\}) + 0M + 0T + 0D$$

$$RU_2 = 1C + 0M + 0T + 0D$$

$$RU_3 = (C \in \{1,4\}) + 0M + 0T + 0D$$

$$RU_4 = (C \in \{1,2\} + 1M + 1T + 1D$$

$$RU_5 = (C \in \{3,4\} + 0M + 0T + 0D$$

where RU_i is the expected set of resources demanded by patient group i;

C is Doctor's Visit Type (1 = Cons Lv, 2 = Ext Cons Lv, 3 = Fup Lv, 4 = Ext Fup Lv)

M is OT Visit Type (0 = None, 1 = 1/2 Hr OT eval)

T is Social Worker Visit Type (0 = None, 1 = Brief initial)

D is optical low vision devices dispensed (0 = No, 1 = Yes).

Further pre-processing of the data after the groups were obtained was called for to:

a) add in the group variable,
b) strip from the data all the resource and other variables that could not be known prior to the appointment date,
c) use of the qualitative form of the reduced variables in step b for the decision tree analysis phase of the assignment task, and
d) binarize all the qualitative variables in step c for the rest of the assignment tools (non-parametric discriminant and nearest neighbor analysis in SAS and neural network assignment in WinNN).

Steps a) and b) left the dataset with a total of 40 variables. Step d) expanded these to 73. One lacked variability and had to be deleted.

Decision Tree

Table D3.3 presents C4.5's classification matrix (see Addendum D3.C for the attendant decision rules). The decision tree's overall estimate of the true error rate is shown in the last row. It predicts cases in Groups 2 and 4 (89% and 85% respectively) relatively better than those in the other three groups (all below 60.0% accuracy).

Table D3.3: Decision Tree (C4.5) Classification Matrix of Site 3's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**53**	0	10	19	9	91
	0.5824	0.0	0.1099	0.2088	0.0989	1.0000
Group 2	1	**50**	0	5	0	56
	0.0179	**0.8928**	0.0	0.0893	0.0	1.0000
Group 3	17	2	**25**	24	6	74
	0.2297	0.0270	**0.3378**	0.3243	0.0811	1.0000
Group 4	8	0	1	**79**	5	93
	0.0860	0.0	0.0108	**0.8495**	0.0538	1.0000
Group 5	15	2	7	6	**44**	74
	0.2027	0.0270	0.0946	0.0811	**0.5946**	1.0000
Total	94	54	43	133	64	388
	0.2423	0.1392	0.1108	0.3428	0.1649	1.0000
Apparent Error						**0.3530**
Estimated Error						**0.4080**

Non-parametric Discriminant Analysis

Table D3.4 gives a the classification matrix from this learning system. The best predictions are seen on cases in Group 2 (55%) and the worst on Group 4 (14%). Predictions on cases in Groups 1, 3 and 5 are all below 50%. The tool's overall estimated error of about 65% implies that it does not perform well as a predictor on these data.

Table D3.4: Non-parametric D. A. Classification Matrix of Site 3's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**29**	3	5	11	9	34	91
	0.3187	0.0330	0.0549	0.1209	0.0989	0.3436	1.0000
Group 2	1	**31**	0	5	1	18	56
	0.0179	**0.5536**	0.0	0.0893	0.0179	0.3214	1.0000
Group 3	3	3	**28**	6	4	30	56
	0.0405	0.0405	**0.3784**	0.0811	0.0541	0.4054	1.0000
Group 4	17	6	7	**13**	5	45	93
	0.1828	0.0645	0.0753	**0.1398**	0.0538	0.4839	1.0000
Group 5	9	2	2	4	**36**	21	74
	0.1216	0.0270	0.0270	0.0541	**0.4865**	0.2838	1.0000
Total	59	45	42	39	55	**148**	388
	0.1521	0.1160	0.1082	0.1005	0.1418	**0.3814**	1.0000
Apparent Error							**0.3015**
Estimated Error							**0.6469**

K-Nearest-Neighbor:

This technique predicted membership in Groups 2 very well (80%), Group 4 rather poorly (42.0%), above average on Groups 1 and 3 (53.9% and 56.8 respectively), and surprisingly well for Group 5 (68.9%). Its overall estimated error of about 42% implies that it is a relatively good predictive tool. These results are summarised in the classification matrix in Table D3.5.

Table D3.5: K-NN Classification Matrix of Site 3's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**49**	6	13	7	13	3	91
	0.5385	0.0659	0.1429	0.0769	0.1429	0.0330	1.0000

Group 2	2	**45**	2	4	0	3	56
	0.0357	**0.8036**	0.0357	0.0714	0.0	0.0536	1.0000
Group 3	5	8	**42**	4	8	7	74
	0.0676	0.1081	**0.5676**	0.0541	0.1081	0.0946	1.0000
Group 4	16	9	16	**39**	7	6	93
	0.1720	0.068	0.1720	**0.4194**	0.0753	0.0645	1.0000
Group 5	11	4	4	2	**51**	2	74
	0.1486	0.0541	0.0541	0.0270	**0.6892**	0.0270	1.0000
Total	83	72	77	56	79	**21**	310
	0.2139	0.1856	0.1985	0.1443	0.2036	**0.0541**	1.0000
Apparent Error							**0.3943**
Estimated Error							**0.4175**

Neural Network

For WinNN, we:

a) had the group variable represented in binary form (by five variables rather than one), thus bringing the total number of variables to 76. Similar experimentation with equal distance scaling as in Site 2 were done;

b) used cross-validation by splitting the dataset into ten sets. The first through eigth sets 39 cases each, whereas the nineth and tenth had 38 cases each. From these, 10 training (input pattern) and 10 testing files were drawn. Each input pattern file contained nine of these sets (of either 350 or 349 cases) and the remaining 1 set was used as a test file (either 39 or 38 cases). Care was taken to ensure that each of these 10 sets was used only once as a test file, and that no single set was used both as an input and a test file simultaneously.

As can be noted from the results below, this classifier turned out to be very costly in terms of time. The first run took 12601 iterations (at 29 seconds per iteration on a Pentium 166 machine). In this run alone, it took more than 100 hours for prediction accuracy on the training cases to pass the 50% mark. To speed up the process, we followed the same procedures used at the earlier sites. Results from this technique's performance are shown in Table D3.6.

Table D3.6: Summary of Neural Network Predictions of Site 3's Cases

Run #	Iterations	Training Good patterns %	Testing Good patterns %	Testing Error
1	12601	52	28.2	71.8

2	176	53	10.3	89.7
3	14	51	59.0	41.0
4	21	55	51.3	48.7
5	31	53	61.5	38.5
6	17	51	56.4	43.6
7	23	52	59.0	41.0
8	12	53	48.7	51.3
9	19	51	63.2	36.8
10	33	52	57.9	42.1
Apparent Error				**0.4770**
Estimated Error				**0.5045**

Overall Performance

A summary of the performance of all the four classification methods is presented in Table D3.7.

Table D3.7: Summary of classifier performance in the prediction task

Classifier	Apparent Error	Estimated Error	Chance Criterion
Decision Tree - C4.5	0.3530	0.4080	0.7931
K-Nearest Neighbor - SAS	0.3943	0.4175	0.7931
Neural Networks - WinNN	0.4770	0.5045	0.7931
Discriminant Analysis - SAS	0.3015	0.6469	0.7931

As shown in the table, the lowest overall estimate of true error in the prediction task are posted by the decision tree and nearest neighbour techniques. Neural networks come in third and discriminant analysis is a distant fourth. With the proportional chance as a benchmark, it can be seen that using either of the decision tree or nearest neighbour almost doubles the probability of assigning a case to the correct iso-resource group. Even the non-parametric discriminant analysis' lack-lusture performance yields better predictions than this bechmark. This implies that predictive performance is better with than without using these techniques.

Addendum D3.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 6 to 97 years)			
Gender	Patient's gender	1 = Female	2 = Male		
MaritalS	Patient's marital status	0 = Single	1 = Married	2 = Divorced	3 = Widowed
		4 = n/i			
Occupation	Patient's occupation	0 = Student/child	1 = Retired	2 = On disability	3 = Unemployed
		4 = Janitor/orderly	5 = At home	6 = Self-employed	7 = Sec'ry/teacher
		8 = Other	9 = n/i		
Insurance	Patient's insurance carrier	0 = Medicare	1 = Self-pay	2 = Medicaid	3 = Baystate
		4 = Blind Comm'n	5 = Other		
Distance	Distance travelled	1 = Local	2 = In-state	3 = Out-state	4 = n/i
Diagnosp	Primary ocular diagnosis	0 = Albinism	1 = Amd	2 = Diabetic ret.	3 = Optic atrophy
		4 = Retinal defect	5 = Cataracts	6 = Glaucoma	7= Retinitis Pig.
		8 = High Myopia	9 = Other		
Diagnoss	Secondary ocular diagnosis	0 = Albinism	1 = Amd	2 = Diabetic ret.	3 = Optic atrophy
		4 = Retinal defect	5 = Cataracts	6 = Glaucoma	7= Retinitis Pig.
		8 = High Myopia	9 = Other		
Onset	Onset of eye condition	Discrete (in years)			
Pttype	Patient type	1 = New	2 = Repeat (established)		
Disabil	Observed limitations?	1 = No	2 = Yes		
Lastexam	Patient's last eye exam	Discrete (in weeks)			
Understand	Does patient understand why s/he is visiting clinic?	1 = No	2 = Yes	3 = n/i	
Living	Patient living alone?	1 = No (not alone)	2 = Yes (alone)		
Working	Patient currently working?	1 = No	2 = Yes	3 = n/i	
School	Patient currently in school?	1 = No	2 = Yes	3 = n/i	
Diffics	Vocational/Sch difficulties?	1 = No	2 = Yes	3 = n/i	
Namecond	Can pt name eye condition?	0 = No	1 = Yes		
Eyemedic	Eye medications?	0 = No	1 = Yes		
Eyesurg	Eye surgery?	0 = No	1 = Yes		
HBP	Does pt have HBP?	0 = No	1 = Yes		
Diabetes	Does pt have diabetes?	0 = No	1 = Yes		
Stroke	Has pt ever had stroke?	0 = No	1 = Yes		
Heartdis	Does pt have heart disease?	0 = No	1 = Yes		
Orthoped	Does pt have arthritis?	0 = No	1 = Yes		
Anxiety	Does pt have depression?	0 = No	1 = Yes		
Otherdis	Does pt have other cond's?	0 = No	1 = Yes		
Medicats	Medications	0 = No	1 = Yes		
Surghosp	Surgery/hospital in past yr?	0 = No	1 = Yes		
Prefeye	Preferred eye	1 = OD	2 = OS	3 = Same	4 = n/i
Goal, Visual acuity and Visual aid Data					
Assess1	Assessment of skills 1	0 = n/i	1 = Mobility	2 = Tv/movie/Spec	3 = Street signs
		4 = Writing	5 = Reading newsp	6 = Read lp	7 =Readmenu/lab
		8 = ADLs	9 = Driving (hobbies, etc)		
Assess2	Assessment of skills 1	0 = n/i	1 = Mobility	2 = Tv/movie/Spec	3 = Street signs
		4 = Writing	5 = Reading newsp	6 = Read lp	7 =Readmenu/lab
		8 = ADLs	9 = Driving (hobbies, etc)		
Assess3	Assessment of skills 1	0 = n/i	1 = Mobility	2 = Tv/movie/Spec	3 = Street signs
		4 = Writing	5 = Reading newsp	6 = Read lp	7 =Readmenu/lab
		8 = ADLs	9 = Driving (hobbies, etc)		
Assess4	Assessment of skills 1	0 = n/i	1 = Mobility	2 = Tv/movie/Spec	3 = Street signs
		4 = Writing	5 = Reading newsp	6 = Read lp	7 =Readmenu/lab

		8 = ADLs	9 = Driving (hobbies, etc)		
PreVaOd	Presenting vis. acuity OD	Discrete			
PreVaOs	Presenting vis. acuity OS	Discrete			
Evaldev1	Evaluation device 1	0 = None	1 = Hhmags	2 = Illum h/pkt mgs	3 = Half eyes
		4 = Illum Smags	5 = Stand mags	6 = Telescopes	7 = Non-opticals
		8 = Deferred	9 = Filters		
Evaldev2	Evaluation device 2	0 = None	1 = Hhmags	2 = Illum h/pkt mgs	3 = Half eyes
		4 = Illum Smags	5 = Stand mags	6 = Telescopes	7 = Non-opticals
		8 = Deferred	9 = Filters		
Vacuity1	Best visual acuity OD	Discrete (with n/t = not tested)			
Vacuity2	Best visual acuity OS	Discrete (with n/t = not tested)			
Device1	Current LV device 1	0 = None	1 = Hhmags	2 = Stand mags	3 = CI
		4 = Telescopes	5 = Bifocals	6 = Filters	7 = Half eyes
		8 = Dist/Nr Rx	9 = Other (lamp, cctv, talking bks, etc)		
Device2	Current LV device 2	0 = None	1 = Hhmags	2 = Stand mags	3 = CI
		4 = Telescopes	5 = Bifocals	6 = Filters	7 = Half eyes
		8 = Dist/Nr Rx	9 = Other (lamp, cctv, talking bks, etc)		
Device3	Current LV device 3	0 = None	1 = Hhmags	2 = Stand mags	3 = CI
		4 = Telescopes	5 = Bifocals	6 = Filters	7 = Half eyes
		8 = Dist/Nr Rx	9 = Other (lamp, cctv, talking bks, etc)		
Resource Data					
Drvistyp	Doctor visit type	0 = Cons LV	1 = Ext Cons LV	2 = Comp LV	3 = Ext Comp LV
		4 = F-up LV	5 = Ext F-up LV	6 = Int F-up LV	7 = Visual fields
		8 = n/i			
Otvistyp	O.T. visit type	0 = No OT	1 = 1/4hr OT Eval	2 = 1/2hr OT Eval	3 = 3/4hr OTEval
		4 = 1hr OT Eval	5 = 1/4hr OT Tx	6 = 1/2hr OT Tx	7 = 3/4hr OT Tx
		8 = 1hr OT Tx	9 = Other (1.25 hr OT Eval or Tx)		
Ssctype	Soc.service consult'n type	0 = None	1 = Brief Initial	2 = Std Initial	3 = Brief F-up
Letters	Number of letters/reports	Discrete			
Other Data					
Nextvis	Patient's return date	Discrete (in weeks)			
Prognost	Short term prognosis	0 =n/i	1 = Good	2 = Fair	3 = Poor
Prognolt	Long term prognosis	0 =n/i	1 = Good	2 = Improving	3 = Guarded
Planref	Pla refraction	0 = No	1 = Yes		
Planlvd	Plan low vision devices	0 = No	1 = Yes		
Recomot	Recommend'ns - OT	0 = No	1 = Yes		
Recomtr	Recommend'ns - Training	0 = No	1 = Yes		
Recomss	Recommend'ns-Soc.service	0 = No	1 = Yes		
Recomvr	Recommend's-Vis. Rehab	0 = No	1 = Yes		
Mcb	MCB support?	0 = No	1 = Yes		
Othercs	Other community support?	0 = No	1 = Yes		
MOW	Meals on Wheels support?	0 = No	1 = Yes		
Hmaker	Homemaker comm'ty – ?	0 = No	1 = Yes		
Transp	Transport comm'ty support	0 = No	1 = Yes		
Familys	Family support	0 =No	1 = Yes	2 = Not available/appropriate	
Objsp	Spot functional objective	0 = No	1 = Yes		
Objtx	Text functional objective	0 = No	1 = Yes		
Objadl	ADL functional objective	0 = No	1 = Yes		
Objcom	Com'n functional objective	0 = No	1 = Yes		
Objhom	Homemaking funct'l obj.	0 = No	1 = Yes		
Objlei	Leisure funct'l objective	0 = No	1 = Yes		
Objdrv	Driving funct'l objective	0 = No	1 = Yes		
Objmob	Mobility funct'l objective	0 = No	1 = Yes		

Objsed	Sedentary view funct'l obj.	0 = No	1 = Yes		
Dispdev1	Device 1 dispensed	0 = None	1 = Hhmags	2 = Illum H/Pkt mgs	3 = Half eyes
		4 = Illum Smags	5 = Stand mags	6 = Telescopes	7 = Non-opticals
		8 = Filters	9 = CCTV		
Dispdev1	Device 2 dispensed	0 = None	1 = Hhmags	2 = Illum H/Pkt mgs	3 = Half eyes
		4 = Illum Smags	5 = Stand mags	6 = Telescopes	7 = Non-opticals
		8 = Filters	9 = CCTV		
Dispdev1	Device 3 dispensed	0 = None	1 = Hhmags	2 = Illum H/Pkt mgs	3 = Half eyes
		4 = Illum Smags	5 = Stand mags	6 = Telescopes	7 = Non-opticals
		8 = Filters	9 = CCTV		
Recdev1	Recommended device 1	0 = None	1 = Blk felt pen	2 = Bold l paper	3 = Bookstand
		4 = Clipboard	5 = GNL	6 = lap desk	7 = Typoscope
		8 = Write-guide	9 = Other		
Recdev2	Recommended device 2	0 = None	1 = Blk felt pen	2 = Bold l paper	3 = Bookstand
		4 = Clipboard	5 = GNL	6 = lap desk	7 = Typoscope
		8 = Write-guide	9 = Other		
Recdev3	Recommended device 3	0 = None	1 = Blk felt pen	2 = Bold l paper	3 = Bookstand
		4 = Clipboard	5 = GNL	6 = lap desk	7 = Typoscope
		8 = Write-guide	9 = Other		

Addendum D3.B: Block (Cluster) Output from BMDP

```
Distance   RecDev2    Assess4    Prevaod
 Diagnosp   Letters    Hbp        Prevaos
  Diagnoss   Otvistyp   Orthoped   Recomss
   Diabetes   Pttype     Maritals   Familys
    Stroke     Recomtr    Assess2    Recomot
     Anxiety    Ssctype    Devices2   Heartdis
      Planlvd    Dispdev1   Gender     Devices1
       Recomos    RecDev1    Drvistyp   Prognost
        Recomvr    Age        Assess1    Prognolt
         Dispdev2   Assess3    Eyesurg    Planrefr

BLK COUNT+....+....+....+....+....+....+....+....+.
 A   7614 1090000010010100008000015000112211108111
 B    459 ..................75511331.........1....
 C    552 ................................02005000
 D    566 ............2011357...............1.....
 E    433 ........................0081400770......
         +....+....+....+....+....+....+....+....+.

NO. OF SINGLETONS   5820
```

Addendum D3.C: Classification Rules from C4.5

Rule 1:
Hmaker = No
Pttype = New
HBP = Yes
Insuranc in {Medicare, Medicaid}
PrDiagno in {Macular, Cataract, Retpigm}
Assess2 in {Tvmovie, Stsigns, Writing, Readlp,Adl}
Assess4 in {Writing, Reading, Readlp, Adl, Driving}
=> class Group2 [90.6%]

Rule 2:
Pttype = Repeat
Stroke = No
Assess1 in {Mobility, Stsigns}
Assess3 in {Writing, Reading}
Orthoped = Yes
Devices1 in {Bifocal, Halfeye, Distnrrx}
=> class Group2 [89.1%]

Rule 3:
Pttype = Repeat
Assess1 in {Mobility, Reading}
Heartdis = Yes
Orthoped = Yes
=> class Group2 [84.3%]

Rule 4:
Pttype = Repeat
HBP = Yes
Heartdis = Yes
Devices2in {Hhmag, Telescop, Filter, Halfeye, Distnrrx}
=-> class Group2 [73.0%]

Rule 5:
Distance = Outstate
Devices3 = Distnrrx
=> class Group2 [63.0%]

Rule 6:
Maritals in {Married, Widowed}
Pttype = Repeat
Eyesurg = Yes
Diabetes = No
Heartdis = No
Medicats = Yes
Devices2 in {None, Standmag, Telescop, Filters,
Halfeye, Distnrrx}
=> class Group1 [60.3%]

Rule 7:
Occupati = Student
=> class Group1 [52.4%]

Rule 8:
Pttype = Repeat
HBP = No
Heartdis = Yes
=> class Group1 [40.5%]

Rule 9:
HBP = Yes
Medicats = No
=-> class Group3 [61.2%]

Rule 10:
Pttype = Repeat
Diabetes = Yes
=> class Group3 [34.8%]

Rule 11:
Gender = Female
Pttype = Repeat
Occupati in {Retired, Disabled, Unemploy, Athome,
Other}
Eyesurg = Yes
Heartdis = No
=> class Group3 [34.6%]

Rule 12:
Pttype = Repeat
HBP = No
Diabetes = No
Heartdis = No
Hmaker = No
Devices2 in {None, Standmag, Telescop, Bifocal,
Filters, Halfeye, Distnrrx}
=> class Group5 [44.2%]

Rule 13:
Pttype = New
=> class Group4 [50.1%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 4. It follows Appendix D.3's outline and structure.

Setting

The host clinic is located at one of the two campuses of a 500-bed non-teaching hospital system serving a midwestern metropolitan region of 350 000 inhabitants. The clinic is an accredited regional referral center for the visual rehabilitation of individuals who have suffered from a permanent reduction in their vision. It is funded by the host hospital.

The clinic is a specialty/tertiary facility that accepts patient referrals from multiple sources. About 60 % of its referrals are from ophthalmologists and optometrists within the region, 20% are self-referrals (including those referred by family or friends), 15% from physicians and other agencies, and about 5% from screenings. The bulk of its patient base is from the states adjoining this metropolis. This patient base is predominantly geriatric, and largely female (see Table D4.1). The clinic offers diagnostic, consultative, rehabilitative, educational and referral services for visually impaired persons of all ages. It also offers free public screenings to determine the appropriateness of a complete low vision consultation. This generates most of the self-referrals mentioned earlier. The clinic is staffed by an optometrist/director, educationist/social workers, secretary and other support staff.

Prior to the appointment date, the patient is sent an information package from the clinic. This is typically followed by an interview to elicit information with regard to the patient's condition, current visual aids, age of prescription, medical and visual history, visual problems and objectives, and biographical information. The patient is booked to see the optometrist/director and educationist. The time spent by the patient (in the clinic), the devices prescribed, tests done and referrals made are tracked by way of a number of forms used in the clinic. A variety of optical and non-optical devices are used in the consultation/examination to determine the patient's visual acuities. Counselling and/or referrals to appropriate resources/agencies are made depending on the patient's needs. Follow-up visits are arranged depending on the specific needs of the patient. The follow-up visit takes the same format as the initial visit but is not as lengthy.

Subjects

A systematic sample (n = 204) was drawn from the 700 patient visits that the clinic handled over the fiscal year 1994. Every third file in the patient records arranged alphabetically (and tagged by year) was pulled for inclusion in the sample. Table D4.1 presents a summary of some descriptive statistics of interest about the patients included in the sample. For example, although the ages of patients in the sample ranged from 4 to 99 years, more than 67.5% were aged between 70 - 89 years. More than 80% were aged 50 years or above whereas the below 20 years categories made up 3% of the sample. The predominance of geriatic patients is typical of the general low vision patient population in North America. The subjects are predominantly female (63.7%), the majority (59.8%) are new patients, and not living alone (60.3%).

Table D4.1: Composition of Sample across Age, Gender, Pt Type, Living Situation.

Feature	Category	n	%
	< 10	2	1.0
	10 - 19	4	2.0
	20 - 29	3	1.5
	30 - 39	10	4.9
Age	40 -49	6	2.9
	50 - 59	5	2.5
	60 -69	26	12.7
	70 -79	71	34.8
	80 -89	67	32.8
	>=90	10	4.9
Gender	Female	130	63.7
	Male	74	36.3
Patient Type	Repeat	82	40.2
	New	122	59.8
	Unknown	11	5.4
	w/parents	8	3.9
Living Situation	w/children	16	7.8
	w/sibling	4	2.0
	w/spouse	95	46.6
	Alone	70	34.3
Totals		204	100.0

Data

89 biographical and resource pieces of information were targeted for each case in the sample (see Addendum D4.A for a description of all the variables). Data obtained from this site covered a little over 29% of the patient visits handled by the clinic over the year of interest.

The data collection activity was completed over the week of April 21, 1996. Data collected each day were perused in the evening for initial clean-up which entailed making sure that the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were identified for subsequent verification or explanation by the clinic director.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D4.A. The resulting data file was preliminarily analyzed for descriptive statistics. Variables (n = 9) containing insufficient responses were deleted (see Addendum D4.B). In line with the study objectives, after the generation of patient groups from the data using cluster analysis, subsequent study tasks required the transformation of the data into suitable formats for analysis under each classification/assignment tool (decision trees, nearest neighbor, discriminant analysis, and neural networks respectively).

Cluster Analysis

Block Clustering generated five distinct clusters (groups) from tha data (see Addendum D4.B for the block output). Table D4.2 presents the characteristics of these five groups.

Table D4.2: Site 4's Grouping Characteristics

VARIABLE/GROUP	1	2	3	4	5
Demographics: PtType	New/Repeat	New	Repeat	New	New/Repeat
Pt's Age	Varied (4 - 94)	80-89	70-89	70-89	70-99
Gender	Female	Female	Male	Female	Male
Marital	Married	Widow	Married	Married	Widowed
Presenting Visual Acuity	26 - 80	81 - 200	26 - 400	81 - 400	26 - NLP
Gen. Health	Good	Good/ Diabetic	HBP/ Diabetic/ Other	Good/ Diabetic	Varied (n/i)
Medications	None	None/Yes	Yes	None/Yes	Varied (n/i)
Patient's Main Goal	Evaluation/ Screening	Reading	Follow-up	Evaluation/ Screening	Folloup/ Evalualion/

					Screening
Living Environment	W/spouse	Alone	W/spouse	W/spouse	Alone
Services Used: Dr-Time	Varied (<15-40)	25-60 min	< 25 min	Varied (40-60)	Varied
Edu-Time	None	Varied	None	Varied (0-30)	None
Tot-Time	< 40 mins	Varied (<15-90)	< 30 min	30-60 min	20 - 50 min
Letters/Reports	1	2	1	2	1

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = (15 <= C <= 40) + 0M + (15 <= T <= 40) + 1D$$

$$RU_2 = (25 <= C <= 60) + (0 <= M <= 30) + (15 <= T <= 90) + 2D$$

$$RU_3 = (25 <= C) + 0M + (30 <= T) + 1D$$

$$RU_4 = (40 <= C <= 60) + (0 <= M <= 30) + (30 <= T <= 60) + 2D$$

$$RU_5 = (15 <= C <= 40) + 0M + (20 <= T <= 50) + 1D$$

where RU_i is the expected set of resources demanded by patient group i;

C is Doctor's Time (in minutes)

M is Educationist's Time (in minutes)

T is Total Time (in minutes)

D is Letters/reports (0,1,2, etc).

Decision Tree

C4.5's classification matrix is presented in Table D4.3 (see Addendum D4.C for decision rules from this classifier).

Table D4.3: Decision Tree (C4.5) Classification Matrix of Site 4's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**23**	1	2	14	0	40
	0.5750	0.0250	0.0500	0.3500	0.0	1.0000
Group 2	0	**32**	1	16	0	49
	0.0	**0.6531**	0.0204	0.3265	0.0	1.0000
Group 3	1	0	**41**	5	0	47

	0.0213	0.0	**0.8723**	0.1064	0.0	1.0000
Group 4	0 0.0	1 0.0196	2 0.0392	**48** **0.9412**	0 0.0	51 1.0000
Group 5	0 0.0	3 0.1765	1 0.0588	7 0.4118	**6** **0.3529**	17 1.0000
Total	24 0.1176	37 0.1814	47 0.2304	90 0.4412	6 0.0294	204 1.0000
Apparent Error						**0.2647**
Estimated Error						**0.3310**

This classifier predicts cases in Groups 3 and 4 (87% and 94% respectively) relatively better than those in Groups 1, 2 and 5 (57.5%, 65.3% and 35.3% respectively).

Non-parametric Discriminant Analysis

None of the predictions are above 39% in accuracy with this technique. As indicated by the sum of the cells under the column 'OTHER', this technique will not be able to place more than 46 of every 100 cases it tests into any of the five groups initially identified in the data. The tool has an overall estimated error of slightly over 72% - implying that it does not perform well as a predictor.

Table D4.4: Non-parametric D. A. Classification Matrix of Site 4's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**11**	5	3	2	0	19	40
	0.2750	0.1250	0.0750	0.0500	0.0	0.4750	1.0000
Group 2	9	**19**	4	0	0	17	49
	0.1837	**0.3878**	0.0851	0.0	0.0	0.3469	1.0000
Group 3	8	4	**14**	1	0	20	47
	0.1702	0.0851	**0.2979**	0.0213	0.0	0.4255	1.0000
Group 4	3	7	3	**8**	0	30	51
	0.0588	0.1373	0.0588	**0.1569**	0.0	0.5882	1.0000
Group 5	1	1	1	0	**5**	9	17
	0.0588	0.0588	0.0588	0.0	**0.2941**	0.5294	1.0000
Total	32	36	25	11	5	**95**	204
	0.1569	0.1765	0.1225	0.0539	0.0245	**0.4657**	1.0000
Apparent Error							**0.2843**
Estimated Error							**0.7206**

K-Nearest-Neighbor:

The 3-nearest neighbor routine in SAS's DISCRIM procedure generated the results presented in Table D4.5. 3-nn predicted membership in Groups 1 and 2 very well (80% and 81.6% respectively), Group 3 above average (61.7%), and poorly on the Groups 4 and 5 (below 44%). Its overall estimated error of about 36.3% implies that it is a relatively good predictive tool.

Table D4.5: K-NN Classification Matrix of Site 4's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**32** **0.8000**	2 0.0500	5 0.1250	0 0.0	0 0.0	1 0.0250	40 1.0000
Group 2	5 0.1020	**40** **0.8163**	1 0.0204	1 0.0204	1 0.0204	1 0.0204	49 1.0000
Group 3	14 0.2979	1 0.0213	**29** **0.6170**	1 0.0213	1 0.0213	1 0.0213	47 1.0000
Group 4	8 0.1569	16 0.3137	2 0.0392	**22** **0.4314**	0 0.0	3 0.0588	51 1.0000
Group 5	0 0.0	2 0.1176	4 0.2353	3 0.1765	**7** **0.4118**	1 0.0588	17 1.0000
Total	59 0.2892	61 0.2990	41 0.2010	27 0.1324	9 0.0441	**7** **0.0343**	204 1.0000
Apparent Error							**0.3137**
Estimated Error							**0.3627**

Neural Network

Similar data formatting and experimentation with the same parameters as in Site 3 were done. WinNN performance is summarised in Table D4.6

Table D4.6: Summary of Neural Network Predictions of Site 4's Cases

Run #	Iterations	Training Good patterns %	Testing Good patterns %	Testing Error
1	6746	83	61.9	38.1
2	5855	81	57.1	42.7
3	34	82	90.5	9.5
4	3	81	95.2	4.8

5	5	83	80.0	20.0
6	32	80	95.0	5.0
7	23	80	90.0	10.0
8	9	80	85.0	15.0
9	11	80	60.0	40.0
10	10	84	90.0	10.0
Apparent Error				**0.1860**
Estimated Error				**0.1951**

Overall Performance

A summary of the performance of all the four classification methods is presented in Table D4.7. The proportional chance criterion for groups at this site was calculated to be 0.2187, that is, an expected error rate of 0.7813. This, together with the classifiers' performance, is shown in the table.

Table D4.7: Summary of classifier performance in the prediction task

Classifier	**Apparent Error**	**Estimate of True Error**
Neural Networks - WinNN	0.1860	0.1951
Decision Tree - C4.5	0.2647	0.3310
K-Nearest Neighbor - SAS	0.3137	0.3627
Discriminant Analysis - SAS	0.2843	0.7206
Chance Criterion	0.7813	0.7813

As shown in the table, the best (lowest) overall estimate of true error in the prediction task is posted by the neural network followed by the decision tree and nearest neighbour. With the proportional chance as a benchmark, it can be seen that using either of these three more than doubles the probability of assigning a case to the correct iso-resource group. The non-parametric discriminant analysis' performance is rather lack-lusture - although it yields slightly better predictions than the benchmark. In general, this implies that predictive performance is better with than without these techniques.

Addendum D4.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 4 to 99 years)			
Gender	Patient's gender	1 = Female	2 = Male		
MaritalS	Patient's marital status	0 = n/i	1 = Single	2 = Married	3 = Divorced
		4 = Widowed			
Pttype	Patient type	1 = Repeat	2 = New		
Living	Pt's living situation	0 = n/i	1 = Parents	2 = Children	3 = Sibling
		4 = Spouse	5 = Alone		
Insurance	Patient's insurance carrier	0 = n/i	1 = DOCS-IL	2 = BCBS	3 = Medicare
		4 = Medicare/BCBS		5 = Other	
Ref-by	Referred By	0 = n/i	1 = Recall/F-up	2 = Self/Family/Fr	3 = MD/OD
		4 = Department of Rehabilitation Services (DORS)			
ChiefC	Patient's Chief complaint	1 = Evaluation/Screening		2 = Driving/Eval	3 = F-up
		4 = Reading	5 = Other		
Disability	Patient's general health (or other non-visual disabilities)	0 = n/i	1 = Arthritic	2 = HBP/heart ail	3 = Diabetic
		4 = Hearing imp't	5 = Respiratory	6 = Good	7 = Other
Rec-surg	Recent surgery?	0 = n/i	1 = No	2 = Yes	
Medicats	Medications	0 = n/i	1 = No	2 = Yes	
Emp-ret	Employed/retired	0 = n/i	1 = No	2 = Employed	3 = Retired
Occupatn	Patient's occupation	0 = n/i	1 = Student/child	2 = At home	3 = Sec'ry/office
		4 = Farmer	5 = Technical worker		6 = Sup'dent/mgr
		7 = Other			
DiagnosP	Primary Visual diagnosis	0 = n/i	1 = Histoplasmosis	2 = Diabetic ret.	3 = Amd
		4 = Ret. dystrophy	5 = Glaucoma	6 = Cataracts	7 = Optic atrophy
		8 = Aphakia	9 = Other		
DiagnosS	Secondary Visual diagnosis	0 = n/i	1 = Histoplasmosis	2 = Diabetic ret.	3 = Amd
		4 = Ret. dystrophy	5 = Glaucoma	6 = Cataracts	7 = Optic atrophy
		8 = Aphakia	9 = Other		
Onset	Onset of eye condition	Discrete (in years)			
Lastexam	Patient's last eye exam	Discrete (in months)			
Eyesurg	When was eye surgery done?	Discrete (in years, w/ 0 = No)			
Lasertx	When was laser Tx done?	Discrete (in years, w/ 0 = No)			
Eye-med	Eye medications?	0 = No	1 = Yes		
Eye-pain	Eye pain/discomfort?	0 = No	1 = Yes		
Fluctuat	Fluctuations in vision?	0 = No	1 = Yes		
Prev-lve	Previous low vision exam?	0 = No	1 = Yes		
Pref-eye	Preferred eye	0 = n/i	1 = OD	2 = OS	3 = Ou (same)
Glasses	Does Patient wear glasses?	0 = n/i	1 = No	2 = Yes	
Gla-help	Do the glasses help?	0 = n/i	1 = No	2 = Yes	
Sunlight	Sunlight bothersome - Glare?	0 = n/i	1 = No	2 = Yes	
Pref-lig	Preferred lighting	0 = n/i	1 = No specific one	3 = Bright	3 = Direct-task sp
		4 = Tinted			
Prob-nig	Problems with night vision?	0 = n/i	1 = No	2 = Yes	
Read-pt	Does patient read print?	0 = n/i	1 = No	2 = Yes	
Print-sz	What print size?	0 = None	1 = Regular	3 = Large	
What-rd1	What materials does patient want to read better?	0 = n/i	1 = Books/bible	2 = Newsprint	3 = Vocational
		4 = Checks/bills	5 = Menu/mail	6 = Writing, etc	7 = Dials/recipes
		8 = Phonebk/phone	9 = Other (music, hobbies, etc)		
What-rd2	What materials does patient want to read better?	0 = n/i	1 = Books/bible	2 = Newsprint	3 = Vocational
		4 = Checks/bills	5 = Menu/mail	6 = Writing, etc	7 = Dials/recipes
		8 = Phonebk/phone	9 = Other (music, hobbies, etc)		
What-rd3	What materials does patient want to read better?	0 = n/i	1 = Books/bible	2 = Newsprint	3 = Vocational
		4 = Checks/bills	5 = Menu/mail	6 = Writing, etc	7 = Dials/recipes
		8 = Phonebk/phone	9 = Other (music, hobbies, etc)		
Othdif1	Other dificult visual tasks?	0 = n/i	1 = Depth percep'n	2 = TV viewing	3 = Driving

		4 = Street signs	5 = Recog. faces	6 = Hobbies	7 = Vocational
		8 = ADLs	9 = Other		
Othdif2	Other dificult visual tasks?	0 = n/i	1 = Depth percep'n	2 = TV viewing	3 = Driving
		4 = Street signs	5 = Recog. faces	6 = Hobbies	7 = Vocational
		8 = ADLs	9 = Other		
Othdif3	Other dificult visual tasks?	0 = n/i	1 = Depth percep'n	2 = TV viewing	3 = Driving
		4 = Street signs	5 = Recog. faces	6 = Hobbies	7 = Vocational
		8 = ADLs	9 = Other		
Diff-sid	Difficulties seeing side objs?	0 = n/i	1 = No	2 = Yes	
Turn-hd	Turn head to see better?	0 = n/i	1 = No	2 = Yes	
Drive	Does patint drive?	0 = n/i	1 = No	2 = Yes	
Public-t	Does pt use public transport?	0 = n/i	1 = No	2 = Yes	
In-outdr	Does pt walk in- out-doors?	0 = n/i	1 = No	2 = Yes	
Cane	Does patient use white cane?	0 = n/i	1 = No	2 = Yes	
Goals, Visual acuity and visual aid data					
Goals1	Patient's first goal	0 = n/i	1 = ADL/ind.living	2 = Driving	3 = Gen Eval'n
		4 = Glare control	5 = Nearpoint vis.	6 = Distance vis.	7 = Read/write
		8 = Hobbies	9 = Other		
Goals2	Patient's second goal	0 = n/i	1 = ADL/ind.living	2 = Driving	3 = Gen Eval'n
		4 = Glare control	5 = Nearpoint vis.	6 = Distance vis.	7 = Read/write
		8 = Hobbies	9 = Other		
Goals3	Patient's third goal	0 = n/i	1 = ADL/ind.living	2 = Driving	3 = Gen Eval'n
		4 = Glare control	5 = Nearpoint vis.	6 = Distance vis.	7 = Read/write
		8 = Hobbies	9 = Other		
Pre-va-Od	Presenting visual acuity OD	Discrete			
Pre-va-Os	Presenting visual acuity OS	Discrete			
C-va-Od	Corrected visual acuity OD	Discrete			
C-va-Os	Corrected visual acuity OS	Discrete			
Dev-used	Used lv devices?	0 = No	1 = Yes		
What-dev1	Current LV device 1	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
What-dev2	Current LV device 2	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
What-dev3	Current LV device 3	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
Resource Data					
Dev-loan1	First device loaned	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = CCTV	5 = Non-opticals	6 = Other	
Dev-loan2	Second device loaned	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = CCTV	5 = Non-opticals	6 = Other	
Dev-loan3	Third device loaned	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = CCTV	5 = Non-opticals	6 = Other	
Letters	Number of letters/reports	Discrete			
Dirtime	Time seen by physician	Discrete (in minutes)			
Edutime	Time seen by social worker	Discrete (in minutes)			
Tottime	Total time taken by pt	Discrete (in minutes)			
Letters	Number of letters/reports	Discrete			
Other Data					
Revisitt	Patient's return appointment	Discrete (in weeks)			
Dev1-rec	Recommended device 1	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects

		4 = CCTV	5 = Non-opticals	6 = Other	
Dev2-rec	Recommended device 2	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = CCTV	5 = Non-opticals	6 = Other	
Dev3-rec	Recommended device 3	0 = n/i	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = CCTV	5 = Non-opticals	6 = Other	
Newpresc	New prescription?	0 = n/i	1 = No	2 = Yes	
Devices	Devices?	0 = n/i	1 = No	2 = Yes	
Read1	First reading device	0 = None	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = Telemiscrope	5 = CCTV	6 = Other	
Read2	Second reading device	0 = None	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = Telemiscrope	5 = CCTV	6 = Other	
Read3	Third reading device	0 = None	1 = Hhmags	2 = Stand mags	3 = Read/spects
		4 = Telemiscrope	5 = CCTV	6 = Other	
Distance1	First distance device	0 = None	1 = Monoculars	2 = Binoculars	3 = Hand held
		4 = Spectacle mounted		5 = Driving bioptics	6 = Other
Distance2	Second distance device	0 = None	1 = Monoculars	2 = Binoculars	3 = Hand held
		4 = Spectacle mounted		5 = Driving bioptics	6 = Other
Distance3	Third distance device	0 = None	1 = Monoculars	2 = Binoculars	3 = Hand held
		4 = Spectacle mounted		5 = Driving bioptics	6 = Other
Filters	Absorbptive Filters	0 = No	2 = NoIRS		
Lightng1	Lighting 1	0 = n/i	1 = Positioning	2 = Bulbsize	3 = Other
Lightng2	Lighting 2	0 = n/i	1 = Positioning	2 = Bulbsize	3 = Other
Writing1	Writing device 1	0 = n/i	1 = Bold l paper	2 = Felt tip markers	3 = Check-guide
		4 = Signature guide	5 = Other		
Writing2	Writing device 2	0 = n/i	1 = Bold l paper	2 = Felt tip markers	3 = Check-guide
		4 = Signature guide	5 = Other		
Activit1	Activity 1 pt is involved in	0 = n/i	1 = ADLs	2 = Walking	3 = Boardgames
		4 = Outdoor acts	5 = Church/com'y	6 = Garden/farm	7 = Social acts
		8 = Hobbies (sew,etc)		9 = None	
Activit2	Activity 2 pt is involved in	0 = n/i	1 = ADLs	2 = Walking	3 = Boardgames
		4 = Outdoor acts	5 = Church/com'y	6 = Garden/farm	7 = Social acts
		8 = Hobbies (sew,etc)		9 = None	
Act1Miss	Activity 1 pt misses most	0 = n/i	1 = Driving	2 = ADLs	3 = Hobbies
		4 = Vocational	5 = Sports	6 = Read/writing	7 = Social acts
		8 = Other			
Act2Miss	Activity 2 pt misses most	0 = n/i	1 = Driving	2 = ADLs	3 = Hobbies
		4 = Vocational	5 = Sports	6 = Read/writing	7 = Social acts
		8 = Other			
Accessor1	Accessory 1	0 = n/i	1 = Hi-marks	2 = Phone dial	3 = LP books
		4 = Lap board	5 = Able table	6 = Talking clocks/watches	
		7 = Jumbo cards	8 = Ind. living tips	9 = Other	
Accessor2	Accessorry 2	0 = n/i	1 = Hi-marks	2 = Phone dial	3 = LP books
		4 = Lap board	5 = Able table	6 = Talking clocks/watches	
		7 = Jumbo cards	8 = Ind. living tips	9 = Other	
Refferr1	First referral	0 = n/i	1 = Talking bks	2 = Directory ass't	3 = DORS/ICB
		4 = Ind. living Eval	5 = Drivers licence	6 = Legally Blind Statements	
		7 = Other			
Refferr2	Second referral	0 = n/i	1 = Talking bks	2 = Directory ass't	3 = DORS/ICB
		4 = Ind. living Eval	5 = Drivers licence	6 = Legally Blind Statements	
		7 = Other			
Pt-respo	Patient's response	0 = n/i	1 = Motivated	2 = Indifferent	3 = Other
Followup	Follow-up	0 = n/i	1 = Office	2 = Phone	

Addendum D4.B: Variables discarded due to insufficient responses

Date	Present Grade	Distance1
Distance2	Distance3	Filters
Lighting1	Lighting2	Pt-response

Addendum D4.C: Block (Cluster) Output from BMDP

```
                Eyesurg   Followup  Lastexa   Dev2rec
                 What1dev  Icd91     GHealth   Ptrespo
                  What2dev  Icd92     Medicatn  Insuranc
                   What3dev  Eyemed    Recsurg   TotTime
                    Glare     Pvaos     Printsz   DirTime
                     Readprt   Chiefcom  Age       Goals2
                      Goals1    Cvaos     Cvaod     Firstvis
                       Goals3    Letters   EduTime   Gender
                        Devloan2  Marital   Devloan1  Refby
                         Devloan3  Living    Dev1rec   Pvaod
BLK   COUNT+....+....+....+....+....+....+....+....+.
  A    3976 0411027000030133212426112720000042501034
  B     374 ...............432451....839112136......
  C     286 ...................622..........31270113
  D     293 .............2414224.............477....
  E     159 ..................453000184.............
           +....+....+....+....+....+....+....+....+.
NO. OF SINGLETONS   2987
```

Addendum D4.D: C4.5 Classification Rules

Rule 1:
Pt-type = New
Living in {Parents, Sibling, Spouse, Alone}
PrevaOS > 200
DiagnosS in {Histoplas, Diab Ret, Amd, Cataract, Other}
==> Group 2 [91.2%]

Rule 2:
Pt-type = New
Lasertx =< 2 yrs
PrevaOS > 200
MaritalS in {Single, Married}
ChiefC = Reading
What1dev in {None, Hhmags, Smags}
==> Group 4 [88.2%]

Rule 3:
Lasertx > 8 yrs
MaritalS in {Single, Married}
ChiefC in {Eval/Screen, Driving}
==> Group 4 [87.1%]

Rule 4:
Lastexa > 0.75 months
PrevaOS > 600
Living in {Children, Alone}
==> Group 5 [70.7%]

Rule 5:
Pt-type = Repeat
Gender = Male
PrevaOS > 200
Lastexa > 24 months
==> Group 5 [50.0%]

Rule 6:
Eyesurg <= 0.21 yrs
DiagnosP in {RetDystrophy, Aphakia, Other}
==> Group 1 [89.1%]

Rule 7:
Pt-type = Repeat
Lastexa <= 1.5 months
G-Health = Good
==> Group 1 [73.1%]

Rule 8:
Lasertx > 1 yr
PrevaOS <= 100
What1dev = None
==> Group 1 [70.7%]

Rule 9:
Pt-type = New
PrevaOD > 50
PrevaOS > 200
Living in {Chldren, Alone}
What2dev in {None, Readers, Hhmags, Smags, Nonoptics}
DiagnosP in {Histoplas, Diab Ret, Amd, Glaucoma, Cataract, Optic atrophy}
==> Group 2 [73.9%]

Rule 10:
ChiefC in {Driving, F-up}
Ghealth in {HBP, Diabetic, Respirator, Other}
What2dev = None
==> Group 3 [86.1%]

Rule 11:
Pttype = Repeat
What2devin Readers, CCTV, Hhmss, Bimonoc
==> Group 3 [84.1%]

Rule 12:
Pt-type = Repeat
Gender = Male
==> Group 3 [69.5%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 5. It follows Appendix D.4's outline and structure.

Setting

The host center is situated in a small surburb of a large metropolis (>2 million inhabitants) in an Eastern state. It is located in, and funded by, a non-hospital institution that provides both out-patient and in-resident visual rehabilitation services (personal adjustment to blindness training). It is a specialty/tertiary facility that accepts patient referrals from several sources namely; referrals from the host institution, self-referrals, physician-referrals, and state agency referrals. The center's patient base is geographically drawn from three states - the state it is located in and the two adjoining ones. This patient base is exclusively adult (18 years and above - predominantly geriatric) and largely composed of female (see Table D5.1). The center offers clinical evaluations, functional assessments and training services using a variety of optical and non-optical devices. It is headed by a Low Vision Coordinator who reports to the host institution's Director of Rehabilitation. Its staff also includes an optometrist, a rehabilitation evaluator and a secretary.

Prior to the appointment date, the patient or referring person/agency is contacted by the center's staff to elicit required basic information about the patient. Typically, such contacts will either be an on-phone interview by the Coordinator or an information packet from the center is sent to the patient for filling and subsequent return. The required information is with respect to the patient's condition, current visual aids, age of prescription, medical and visual history and medications, visual problems and objectives, and general biographical information. Upon receipt of the requisite information, the patient is booked and scheduled for an initial visit which consists of a functional assessment by the rehabilitation evaluator, an initial clinical session with the optometrist and a training session. Invariably, such initial visits are all scheduled for a 2.5 hour block of time. The time spent by the patient (at the center), the devices prescribed, tests done and services rendered are tracked by way of a number of forms used in the clinic. A follow-up visit (depending on the patient's needs) is made a week or two after the initial visit.

Such follow-up visits take the general form of the initial visit but are much shorter (1 hour of scheduled time). Depending on the patient's needs, a third and even fourth visit may be required.

Subjects

All the non-residential patient visits (n = 204) that the clinic handled over the fiscal year 1995 were included in the data set. Table D5.1 presents a summary of some descriptive statistics of interest about the patients covered at this site. Although their ages ranged from 18 to 97 years, only 14.7% were aged below 40 years. About 65% were aged 50 years or above. Such a large proportion of geriatric patients is typical of the general low vision patient population in North America. The subjects are predominantly females (62.3%), almost equally split on type of visit (49.0% new and 51% repeats), and an atypical proportion (8.3%) lives alone. The majority (75.5%) is drawn from within the state and the rest from the two neighboring states.

Table D5.1: Composition of Sample across Age, Gender, Pt-Type, Distance & Living Situation.

Feature		n	%
Age	< 20	16	7.8
	20 - 29	6	2.9
	30 - 39	8	3.9
	40 - 49	22	10.8
	50 - 59	14	6.9
	60 - 69	20	9.8
	70 -79	60	29.4
	80 - 89	50	24.5
	>= 90	8	3.9
Gender	Female	127	62.3
	Male	77	37.7
Patient Type	Repeat	104	51.0
	New	100	49.0
Distance	Instate	154	75.5
	Outstate	50	24.5
Living Situation	Unknown	88	43.1
	w/parents	17	8.3
	w/spouse	59	28.9
	w/children	11	5.4
	w/sibling	1	0.5

w/companion	2	1.0
Alone	17	8.3
w/friend	9	4.4
Totals	204	100.0

Data

48 biographical and resource pieces of information were targeted for each case covered (see Addendum D5.A for a description of all the variables). Although data obtained from this site covers 78.2% of total patient visits (n = 261) handled by the center over the year of interest, these data are actually a census of all the out-patient cases dealt by the center.

The data collection activity was completed over the week of March 18, 1996. Data collected each day were perused in the evening for initial clean-up which entailed making sure that the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were identified for subsequent verification or explanation by the center's coordinator.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D5.A. The resulting data file was preliminarily analyzed for descriptive statistics. For clustering purposes, 8 variables (Training, Came-w, Eye-Surg, Eval1, Eval2, Eval3, Eval4 and Eval5) were deleted due to one or more of the following: lack of sufficient responses, lack of variability, or the information contained in the variable was covered in another variable.

Cluster Analysis

Five patient groups were generated from the data (see Addendum D5.C for the block output). Table D5.2 highlights the distinguishing features of these groups.

Table D5.2: Site 5's Grouping Characteristics.

VARIABLE/GROUP	1	2	3	4	5
PtType	Repeat	New	Mixed	Mixed	Mixed
Pt's Age	70-79	70-89	70-89	Mixed	Below 50
Gender	Females	Females	Females	Mixed (more males)	Mixed (more females)
Marital-S	Married	Married	Widowed	Married	Singles
Better eye Vis-acuity	81-400	26-200	26-1330	26-400	26-80

Other Disabilities Medications Current visual aids	Yes Yes Hhm/Glasses	Yes Yes Hhm/Glasses	Yes Mixed Hhm/Glasses	No No Hhm/Glasses	Yes Yes Glasses
Patient's main goals	Mobility, Read/write, Recog faces	Mobility, Read/write, Recog faces	Mobility, Read/write, Recog faces	Mobility, Read/write, Recog faces	Adl, Mobility, Read/write
Living Environment	W/spouse	Alone	W/spouse	W/spouse	Alone
ResourceUse: Direct	1.0 - 1.49	2.5 - 2.99	2.5 - 2.99	2.0 - 2.49	2.5 - 2.99
Indirect1	< 0.5	0.5 - 0.99	0.01 - 0.99	0.01 - 0.99	0.01 - 0.99
Indirect2	< 0.5	< 0.5	0.5 - 0.99	0.5 - 0.99	0.5 - 0.99
Total-Time	4.5 - 7.49	3.0 - 5.99	6.0 - 7.49	1.5 - 5.99	7.7 - 10.0
Special Diag Service	None	Comp-Refrac	Mixed	Comp-Refrac	Mixed
Letters/Reports	1	Mixed (0 or 1)	0	1	1
Devices dispensed	Spects, Mags, Nonopts	Spects, Mags, Nonopts	Nonopts	Mags	Mixed

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = (1 <= C < 1.5) + (M < 0.5) + (T < 0.5) + (4.5 <= P < 7.5) + 0S + 1L + 1D$$

$$RU_2 = (2.5 <= C < 3) + (0.5 <= M < 1) + (T < 0.5) + (3 <= P < 6) + 2S + (L \in \{0,1\} + 1D$$

$$RU_3 = (2.5 <= C < 3) + (M < 1) + (0.5 <= T < 1) + (6 <= P < 7.5) + 2S + 0L + 1D$$

$$RU_4 = (2 <= C < 2.5) + (M < 1) + (0.5 <= T < 1) + (1.5 <= P < 6) + 1S + 1L + 1D$$

$$RU_5 = (2.5 <= C < 3) + (M < 1) + (0.5 <= T < 1) + (7 <= P <= 10) + 2S + 1L + 1D$$

where RU_i is the expected set of resources demanded by patient group i;

C is Direct Time (Ranging from 0 to 2.99)

M is Indirect Clinical Time (Ranging from 0 to 0.99)

T is Indirect Non-clinical Time (Ranging from 0 to 0.99)

P is Total Time (Ranging from 0 to 10.0)

S is Special diagnostic Services (0 = None, 1 = Comp-Refraction, 3 = Mixed)

L is Letters/Reports (0, 1, 2, 3, etc)

D is Devices dispensed (0 = No, 1 = Yes).

Stripping resource and other after-the-fact variables left the data set with a total of 23 variables. Transforming categorical variables into binary variables increased these to 53.

Decision Tree

The decision tree's classification matrix is shown in Table D5.3 (see Addendum D5.C for the decision). The classifier predicts cases in Groups 1, 2 and 5 extremely well (with an error of 5% or less). It performs relatively worse on Groups 3 and 4, but, in both cases, its predictive accuracy is above 79%. All these combine to give it an overall apparent error of less than 10% and an estimated true error of less than double this figure.

Table D5.3: Decision Tree (C4.5) Classification Matrix of Site 5's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**36**	0	1	0	0	37
	0.9730	0.0	0.0270	0.0	0.0	1.0000
Group 2	2	**43**	0	0	0	45
	0.0444	**0.9556**	0.0	0.0	0.0	1.0000
Group 3	1	7	**31**	0	0	39
	0.0256	0.1795	**0.7949**	0.0	0.0	1.0000
Group 4	6	0	0	**38**	0	44
	0.1364	0.0	0.0	**0.8636**	0.0	1.0000
Group 5	2	0	0	0	**37**	39
	0.0513	0.0	0.0	0.0	**0.9487**	1.0000
Total	47	50	32	38	37	204
	0.2304	0.2450	0.1569	0.1863	0.1814	1.0000
Apparent Error						**0.0930**
Estimated Error						**0.1760**

Non-parametric Discriminant Analysis

The results obtained with this technique are presented in the Table D5.4. This technique's performance was quite disparate across the five groups. The best predictive accuracy was obtained in Groups 3 and 5 (89.7% and 84.6% respectively). Group 1 was above average (at 67.6%) whereas Groups 2 and 4 posted mediocre predictions (both below 32%). For every 100 cases tested, the technique will not be able to assign about 16 of them to any one of the five groups identified in the data. All these combine to give it an overall estimated true error rate of over 42%.

Table D5.4: Non-parametric D. A. Classification Matrix of Site 5's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**25**	7	4	0	0	1	37
	0.6757	0.1892	0.1081	0.0	0.0	0.0270	1.0000
Group 2	12	**10**	9	3	1	10	45
	0.2667	**0.2222**	0.2000	0.0667	0.0222	0.2222	1.0000
Group 3	1	1	**35**	1	0	1	39
	0.0256	0.0256	**0.8974**	0.0256	0.0	0.0256	1.0000
Group 4	4	2	8	**14**	0	16	39
	0.0909	0.0255	0.1818	**0.3182**	0.0	0.3636	1.0000
Group 5	1	1	0	0	**33**	4	39
	0.0256	0.0256	0.0	0.0	**0.8462**	0.1026	1.0000
Total	43	21	56	18	34	**32**	204
	0.2108	0.1029	0.2745	0.0882	0.1667	**0.1569**	1.0000
Apparent Error							**0.2745**
Estimated Error							**0.4265**

K-Nearest-Neighbor:

This technique predicted membership in Group 5 extremely well (with a little less than 95% accuracy), very well on Group 3 (about 85% accuracy), and above average on the other groups (all 60% or above) - see classification matrix in Table D5.5. These combine to give it an overall estimated true error rate of 22.55%. For every 100 cases it tests, the technique will not be able to assign 1.5 cases to any of the existing 5 groups.

Table D5.5: K-NN Classification Matrix of Site 5's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**27**	1	5	2	0	2	37
	0.7297	0.0270	0.1351	0.0541	0.0	0.0541	1.0000
Group 2	8	**27**	6	4	0	0	45
	0.1778	**0.6000**	0.1333	0.0889	0.0	0.0	1.0000
Group 3	0	4	**33**	2	0	0	39
	0.0	0.1026	**0.8462**	0.0513	0.0	0.0	1.0000
Group 4	1	3	5	**34**	0	1	44
	0.0227	0.0682	0.1136	**0.7727**	0.0	0.0227	1.0000
Group 5	1	0	0	1	**37**	0	39
	0.0256	0.0	0.0	0.0256	**0.9487**	0.0	1.0000
Total	37	35	49	43	37	**3**	204
	0.1814	0.1716	0.2402	0.2108	0.1814	**0.0147**	1.0000
Apparent Error							**0.2353**

Estimated Error	0.2255

Neural Network

10 training (input pattern) and 10 testing files were drawn drawn from the data using the same procedures and parameters as in the earlier sites. Each input pattern file contained nine of these sets (of either 183 or 184 cases) and the remaining 1 set was used as a test file (either 21 or 20 cases). Table D5.6 shows that this classifier was quite costly in terms of time. The first run alone took 9726 iterations without performance going beyond the low 80's. Combined, the 10 runs took 24984 iterations (at 3 seconds per iteration on a Pentium 166 machine, this works out to at least 20.82 hours - exluding the set-up time between runs). Similar procedures as in earlier sites were used to speed up the training phase.

Table D5.6: Summary of Neural Network Predictions of Site 5's Cases

Run #	Iterations	Training Good patterns %	Testing Good patterns %	Testing Error
1	9726	80	61.9	38.1
2	8038	90	42.9	57.1
3	6919	92	66.7	33.3
4	106	90	85.7	14.3
5	30	90	90.0	10.0
6	8	90	95.0	5.0
7	53	91	75.0	25.0
8	12	90	95.0	5.0
9	40	90	100.0	0.0
10	52	90	80.0	20.0
Apparent Error				**0.1070**
Estimated Error				**0.2078**

Overall Performance

A summary of the performance of all the four classification methods is presented in Table D5.7.

Table D5.7: Summary of classifier performance in the prediction task at Site 5

Classifier	Apparent Error	Estimated Error	Chance Criterion
Decision Tree - C4.5	0.0930	0.1760	0.7988
Neural Networks - WinNN	0.1070	0.2078	0.7988
K-Nearest Neighbor - SAS	0.2353	0.2255	0.7988
Discriminant Analysis - SAS	0.2745	0.4265	0.7988

As shown in the table, the best (lowest) overall estimate of true error in the prediction task is posted by the the decision tree closely followed by the neural network and then nearest neighbor. With the proportional chance as a benchmark, it can be seen that using either of these three will more than triple the probability of assigning a case to the correct iso-resource group. Specifically, the decision tree will correctly place all but 18 out of every 100 cases handled at this site. On the other hand, going only by a knowledge of the sizes of the groups, one would correctly place 20 out of every 100 cases handled. Even the non-parametric discriminant analysis whose performance is rather lack-lusture, yields better predictions than such a benchmark. In general, this implies that predictive performance is enhanced with than without these techniques.

Addendum D5.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 18 to 97 years)			
Gender	Patient's gender	0 = Female	1 = Male		
MaritalS	Patient's marital status	0 = n/i	1 = Single	2 = Married	3 = Divorced
		4 = Widowed			
Pttype	Patient type	0 = New	1 = Repeat		
Ref-by	Patient Referred By	0 = Self/Family/Fr	1 = OBVSI	2 = EBVS	3 = PaBSVI
		4 = In-house			
Distance-T	Distance travelled	1 = In-state	2 = Out-state		
DiagnosP	Primary Visual diagnosis	0 = Amd	1 = Diab. Ret.	2 = Cataracts	3 = Acc/Injury
		4 = Glaucoma	5 = Nystagmus	6 = Optic atrophy	7 = Deg. Myopia
		8 = Ret. Pigment'n	9 = Other		
DiagnosS	Secondary Visual diagnosis	0 = Amd	1 = Diab. Ret.	2 = Cataracts	3 = Acc/Injury
		4 = Glaucoma	5 = Nystagmus	6 = Optic atrophy	7 = Deg. Myopia
		8 = Ret. Pigment'n	9 = Other		
Eyesurg	When was eye surgery done?	Discrete (in months)			
Eye-med	Eye medications?	0 = No	1 = Yes		
Disability	Other medical condition (or disability)?	0 = No	1 = Yes		
Medicats	General medications?	0 = No	1 = Yes		
Came-w	Came with (accompanied by)	0 = n/i	1 = Parent(s)	3 = Spouse	3 = Child(ren)
		4 = Sibling	5 = Companion	6 = Self/alone	7 = Friend
Living	Present living situation	0 = n/i	1 = w/parents	2 = w/spouse	3 = w/child(ren)
		4 = w/sibling	5 = w/companion	6 = Alone	7 = w/friend
Goals, Visual acuity and visual aid data					
Chiefc1	Patient's first complaint/ objective	0 = n/i	1 = Read/write	2 = Mobility	3 = Educ'l/vocatl
		4 = Glare control	5 = ADLs	6 = Driving	7 = Hobbies
		8 = Recog faces	9 = Other		
Chiefc2	Patient's second complaint/ objective	0 = n/i	1 = Read/write	2 = Mobility	3 = Educ'l/vocatl
		4 = Glare control	5 = ADLs	6 = Driving	7 = Hobbies
		8 = Recog faces	9 = Other		
Chiefc3	Patient's third complaint/ objective	0 = n/i	1 = Read/write	2 = Mobility	3 = Educ'l/vocatl
		4 = Glare control	5 = ADLs	6 = Driving	7 = Hobbies
		8 = Recog faces	9 = Other		
Chiefc4	Patient's fourth complaint/ objective	0 = n/i	1 = Read/write	2 = Mobility	3 = Educ'l/vocatl
		4 = Glare control	5 = ADLs	6 = Driving	7 = Hobbies
		8 = Recog faces	9 = Other		
Dva-Od	Presenting visual acuity OD	Discrete (converted w/ numerator = 20)			
D-va-Os	Presenting visual acuity OS	Discrete (converted w/ numerator = 20)			
Lvaid1	Current LV device 1	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
Lvaid2	Current LV device 2	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
Lvaid3	Current LV device 3	0 = n/i	1 = None	2 = Readers	3 = CCTV
		4 = Hhmags	5 = Stand mags	6 = Binocs/monocs	7 = Non-opticals
		8 = Other			
Resource Data					
Office-s	Office service type	0 = None	1 = Expanded focus	2 = Low complex	3 = Mod complex
		4 = Complex cons	5 = Intermed cons	6 = Comprehensive	

Spec-ds	Special diagnostic services	0 = No	1 = Complex Refraction		
Assessts	Assessments	0 = No	1 = Functional	2 = CCTV	
Training	Training in	0 = No	1 = Vision		
Ophthal	Ophthalmic services rendered	0 = No	1 = Hhmag	2 = Spectacle-mounted magnifier	
		3 = Telescope	4 = Other		
Feetype	Fee Type	0 = Clinical/diagnostic		1 = Functional/Training	
		2 = Materials	3 = C/D,F/T	4 = C/D,M	5 = C/D,F/T,M
		6 = F/T,M	7 = None		
F-type	Functional visit type	0 = None, n/a	1 = Brief	2 = Comprehensive	3 = CCTV Assess
Loan1	First device loaned	0 = None	1 = Spectacles	2 = HHm/Smags	3 = Telescopes
		4 = Non-opticals			
Loan2	Second device loaned	0 = None	1 = Spectacles	2 = HHm/Smags	3 = Telescopes
		4 = Non-opticals			
Loan3	Third device loaned	0 = None	1 = Spectacles	2 = HHm/Smags	3 = Telescopes
		4 = Non-opticals			
Letters	Number of letters/reports	Discrete			
Direct	Direct time by physician and/or Coordinator	Discrete (in minutes)			
Indir1	Indirect time by physician and/or Coordinator	Discrete (in minutes)			
Indir2	Indirect time by secretary and/or support staff	Discrete (in minutes)			
Tottime	Total time taken on patientt	Discrete (in minutes)			
Letters	Number of letters/reports	Discrete			
Other Data					
Eval1	Evaluation/Assessment areas	0 = None	1 = ADLs	2 = CCTV	3 = Reading
		4 = Lighting	5 = Handwriting	6 = Filters	7 = Mobility
		8 = Other			
Eval2	Evaluation/Assessment areas	0 = None	1 = ADLs	2 = CCTV	3 = Reading
		4 = Lighting	5 = Handwriting	6 = Filters	7 = Mobility
		8 = Other			
Eval3	Evaluation/Assessment areas	0 = None	1 = ADLs	2 = CCTV	3 = Reading
		4 = Lighting	5 = Handwriting	6 = Filters	7 = Mobility
		8 = Other			
Eval4	Evaluation/Assessment areas	0 = None	1 = ADLs	2 = CCTV	3 = Reading
		4 = Lighting	5 = Handwriting	6 = Filters	7 = Mobility
		8 = Other			
Eval5	Evaluation/Assessment areas	0 = None	1 = ADLs	2 = CCTV	3 = Reading
		4 = Lighting	5 = Handwriting	6 = Filters	7 = Mobility
		8 = Other			
Rec-spec	Received spectacles?	0 = No	1 = Yes		
Rec-smag	Received magnifier?	0 = No	1 = Yes		
Rec-dist	Received telescope?	0 = No	1 = Yes		
Rec-nonop	Received non-optical device?	0 = No	1 = Yes		
Dispens	Dispensed devices/aid?	0 = No	1 = Yes		

Addendum D5.B: Block Cluster Output from BMDP

```
                  Indir2    lvaid2    Diagnop   OthMc
                   Loan1     lvaid3    Recdist   Medicats
                    Loan2     Visit     Age       Recnonop
                     Loan3     Indirl    Marital   TotalT
                      Diagnos   SpecDs    Chiefc2   lvaidl
                       Ophthal   Assessm   FeeType   Dvaos
                        EyeMed    FType     Gender    Recspec
                         Chiefcl   Living    Direct    Dvaod
                          Chiefc3   Distanc   Dispens   Rechsmag
                           Chiefc4   Refer     OfficS    Reports
BLK COUNT +....+....+....+....+....+....+....+....+.
 A   4205 1000900100001100000000727306041114321411
 B    378 ............021112......................
 C    236 .....................841........5250500
 D    308 .......................0115100003230...
 E    218 ................2111611130..............
          +....+....+....+....+....+....+....+....+.

NO. OF SINGLETONS   2736
```

Addendum D5.C: C4.5 Classification Rules

Rule 1:
Medicats = No
Refer in {Private, Pbsvi}
Disabil = No
Chiefc2 in {No, Readwrit, Schvoc, Adl, Recogf}
Lvaid1 in {Hhmag, Glasses}
Lvaid3 in {None, Hhmag, Ismag}
=> class Group4 [91.7%]

Rule 2:
Visit = New
Refer in {Private, Ebvs, Pbsvi, Guild}
Chiefc1 = Other
=> class Group4 [89.9%]

Rule 3:
Visit = Repeat
Eyesurg > 4
Refer in {Private, Ebvs, Pbsvi, Guild}
Diagnos in {Cataract, Glaucoma, Opticatr}
Lvaid2 in {None, Hhmag, Glasses, Ihpmag, Smag, Ismag, Nonopts}
=-> class Group4 [79.4%]

Rule 4:
Visit = Repeat
Lvaid1 in {Smag, Ismag}
=> class Group4 [70.7%]

Rule 5:
Dvaod <= 1200
Refer = Obvsi
Chiefc1 in {Readwrit, Mobility, Schvoc, Other}
=> class Group5 [96.3%]

Rule 6:
Age > 79
Diagnop in {Macdeg, Diabret}
Chiefc1 in {Readwrit, Glare, Other}
Chiefc2 = Readwrit
Lvaid1 in {Hhmag, Glasses}
=> class Group3 [93.0%]

Rule 7:
Dvaos > 300
Marital = Widowed
Diagnop in {Macdeg, Opticatr, Retpigm}
Disabil = Yes
=> class Group3 [82.2%]

Rule 8:
Visit = Repeat
Refer in {Private, Ebvs, Pbsvi, Guild}
Lvaid2 in {Filters, Telescop}
=> class Group3 [75.8%]

Rule 9:
Eyesurg > 2
Eyesurg <= 3
=> class Group3 [50.0%]

Rule 10:
Visit = Repeat
Refer = Obvsi
Dvaod > 1200
=> class Group1 [70.7%]

Rule 11:
Visit = Repeat
Medicats = Yes
Refer in {Private, Ebvs, Pbsvi, Guild}
Diagnos = Other
Lvaid2 in {None, Hhmag, Glasses, Ihpmag, Smag, Ismag, Nonopts}
=> class Group1 [67.4%]

Rule 12:
Visit = New
Refer in {Private, Ebvs, Pbsvi, Guild}
Chiefc1 in {Readwrit, Mobility, Glare, Hobby, Recogf}
=> class Group2 [58.4%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 6. It follows Appendix D5's outline and structure.

Setting

This site is the outreach services department (OSD) of a school for visually impaired children located in a small mid-western town (< 10000 inhabitants). The school is the state's primary repository of expertise in education of blind or visually impaired children. However, the target children who need such specialized services receive their education in local education agencies. In an effort to bring the services to the target children, the school conducts field based low vision clinics in different education agencies throughout the state in the spring and fall terms of the school year. These clinics are funded by a grant from the state's Department of Education and the Lions Clubs, hence, they are provided free of charge to the clients. In essence therefore, the site's patient base is geographically dispersed all over the state. It is exclusively young (from birth to age 21 years).

Services offered under these low vision clinics include special eye examinations and follow-up services to determine if assistive devices will help a partially sighted child to read print and see other visual materials better. In support of this, a loaner program covering a variety of these devices has been instituted. Also offered are orientation and mobility instruction and itinerant teaching (direct instruction of students to meet their educational needs). The OSD is headed by a Director who reports to the school's superintendent. It has specialized faculty members in charge of infant and preschool consultancy, clinics coordination, instructional materials, itinerant teaching, orientation and mobility instruction, and a low vision specialist (optometrist). Support staff include a secretary and two copy typists.

Referrals to an OSD clinic emanates from several different sources namely; parents/guardians, early intervention service providers, health or social services agency, physician, and teachers. Prior to the appointment date, the parent/guardian (and where applicable, teacher) is required to complete a pre-examination report form which provides background information about the child's visual history, current visual functioning, general medical and physical condition/history, and evaluation goals. Upon receipt of this information, the child is booked and scheduled to be seen at one of the clinics. Depending on the needs of the child, the appointment may last from one half hour to two hours. Follow-up visits are invariably much shorter than initial visits.

Subjects

The sample at this site contained all the patient visits covered over the year 1995 (n = 124) and 50% of the patient visits covered in the year 1994 (every second patient file from a total of 158 patient visits in 1994 was taken for inclusion in the sample). Table D6.1 presents a summary of descriptive statistics of interest about the patients covered at this site. Their ages ranged from 0.2 to 19.8 years. About 13.3% were aged 3 years and below and 16.7% aged above 15 years with the rest almost uniformly spread over the categories in-between. They are predominantly males (61.1%), almost equally split on type of visit (50.2% new, 49.8% repeats), and a slight majority (58.6%) have an additional (non-visual) disability. The majority (70.0%) sought information with respect to the determination of their current visual abilities (i.e. reevaluation, current visual acuity, or general assessment).

Table D6.1: Composition of Sample across Age, Gender, Pt-Type, Disability & Info-Sought.

Feature	Category	n	%
	=< 3.01	27	13.3
	3.01 - 6.00	38	18.7
Age	6.01 - 9.00	44	21.7
	9.01 - 12.00	32	15.8
	12.01 - 15.00	28	13.8
	> 15.00	34	16.7
Gender	Female	127	62.3
	Male	77	37.7
Patient Type	Repeat	79	38.9
	New	124	61.1
Additional Disability	No	84	41.4
	Yes	119	58.6
	n/i	25	12.3
	Reevaluation	38	18.7
Information Sought	Current VA	74	36.5

	Gen. Assess't	30	14.8
	Available devs	18	8.9
	Drivers license	6	3.0
	Any & all info	12	5.9
Totals		203	100.0

Data

Initial discussions with the site's Director and a perusal of some of the patient files identified 109 biographical and resource pieces of information that were to be targeted for each case covered. A data collection instrument (a flat file with the columns representing the variables and each row representing one case) was developed and used to capture these data. Some of the data (64 variables) was available in electronic form and the rest in the physical student files. After all the data had been collected, it was determined that only 54 variables contained sufficient responses to meet the requirements of this study (see Addendum D6.A for a description of these variables). The data obtained from this site covers 72% (n = 203) of the client visits handled by the site in their outreach program over the years 1994 and 1995.

The data collection activity was completed over the week of June 24, 1996. Data collected each day were perused in the evening for initial clean-up which entailed making sure that the fields of interest had been covered for the cases dealt with on that day, missing values were noted for subsequent verification that they were indeed unavailable, and new or unfamiliar values were identified for subsequent verification or explanation by the center's coordinator.

At the end of the collection phase, the data were numerically coded as per the coding scheme in Addendum D6.A. The resulting data file was preliminarily analyzed for descriptive statistics. For clustering purposes, only 54 of the original 109 variables had sufficient responses. These were retained and the rest discarded.

Cluster Analysis

Table D6.2 presents the distinguishing features of the groups generated at this site, whereas Addendum D6.C contains the block output.

Table D6.2: Site 6's Grouping Characteristics.

VARIABLE	Group 1	Group 2	Group 3	Group 4	Group 5
PtType	New	New	Mixed	Repeat	Repeat
Pt's Age	3 - 12	Below 9	Above 3	Varied (most> 9)	Varied (Above 3)
Gender	Males	Males	Males	Females	Mixed
Achieve't-Level	< Gr-level	< Gr-level	At Gr level	Mixed (< & At)	Varied
Visual Acuity	81-200	n/i	26-80	81-400	>1330
Disabilities	Yes	Yes	Yes	No	Yes
Medications	No	Yes	No	No	No
Pt's main goals	Assess-FV, Recommend devs	Assess-FV, Recommend devs, Parental info	Assess-FV, Recommend devs	Assess-FV, Recommend devs	Assess-FV, Recommend devs
ResourceUse:					
ServiceMode	n/i	n/i	n/i	Educ-Cons	n/i
Rec-O&M	No	No	No	No	Yes
Recall	1.5 yr	1-1.5 yr	1-2 yr	1-2 yr	1.5 yr

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = 1C + 0M + 1.5T$$

$$RU_2 = 1C + 0M + (1 <= T <= 1.5)$$

$$RU_3 = 1C + 0M + (1 <= T <= 2)$$

$$RU_4 = 2C + 0M + (1 <= T <= 2)$$

$$RU_5 = 1C + 1M + 1.5T$$

where RU_i is the expected set of resources demanded by patient group i;

C is Service Mode (1 = n/i, 2 = Education-Consultation)

M is Recommended Orientation & Mobility (0 = No, 1 = Yes)

T is Recall Time (in years)

43 variables were left in the data set after non-biographical variables were stripped. These expanded to 70 when categorical variables were transformed into binary variables. The same approach for cross-validation as in previous sites was used.

Decision Tree

The classification matrix in Table D6.3 presents C4.5's results (see Addendum D6.C contains the decision rules developed from this classifier). This classifier predicts cases in Groups 1, 2 and 3 quite well (with an error of 20% or less). It performs relatively worse on

Groups 4 (error of 36.2%) and 5 (error of 23.8%) but, in both cases, its predictive accuracy is above 60%. It treats Group 1 as the default group (lumping here all cases that it can not assign to the other groups) - hence half of all cases it assigns to this group are misclassified ones. All these combine to give this method an overall apparent error of less than 21.2% and an estimated true error rate of 29.6%.

Table D6.3: Decision Tree (C4.5) Classification Matrix of Site 6's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**24**	0	0	6	0	30
	0.8000	0.0	0.0	0.2000	0.0	1.0000
Group 2	6	**44**	0	0	0	50
	0.1200	**0.8800**	0.0	0.0	0.0	1.0000
Group 3	5	0	**46**	4	0	55
	0.0909	0.0	**0.8364**	0.0727	0.0	1.0000
Group 4	11	1	0	**30**	5	47
	0.2340	0.0213	0.0	**0.6383**	0.1064	1.0000
Group 5	2	2	0	1	**16**	21
	0.0952	0.0952	0.0	0.0477	**0.7619**	1.0000
Total	48	47	46	41	21	203
	0.2365	0.2315	0.2266	0.2020	0.1034	1.0000
Apparent Error						**0.2120**
Estimated Error						**0.2960**

Non-parametric Discriminant Analysis

This technique's performance across the groups was, in general, quite poor. The best predictive accuracy was obtained in Group 3 (16.4%). It could correctly predict 3.3% in Group 1, 6.0% in Group 2, 2.1% in Group 3 and 0% in Group 5. For every 100 cases it tests at this site, this technique will be unable to assign upwards of 87 cases in any of the five predetermined groups. All these combine to give it an estimated error rate of 93.1%.

Table D6.4: Non-parametric D. A. Classification Matrix of Site 6's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**1**	0	2	2	0	25	30
	0.0333	0.0	0.667	0.667	0.0	0.8333	1.0000
Group 2	0	**3**	0	0	0	47	50
	0.0	**0.0600**	0.0	0.0	0.0	0.9400	1.0000
Group 3	4	0	**9**	1	0	41	55
	0.0727	0.0	**0.1636**	0.0182	0.0	0.7455	1.0000

Group 4	1 0.0213	0 0.0	1 0.0213	**1** **0.0213**	0 0.0	44 0.9362	47 1.0000
Group 5	0 0.0	0 0.0	0 0.0	0 0.0	**0** **0.0**	21 1.0000	21 1.0000
Total	6 0.0296	3 0.0148	12 0.0591	4 0.0197	0 0.0	**178** **0.8768**	203 1.0000
Apparent Error							**0.0542**
Estimated Error							**0.9310**

K-Nearest-Neighbor:

This technique predicted membership in Group 2 extremely well (with 94% accuracy) and rather poorly in Group 5 (33.3%). Performance on the other three groups was in-between these extremes - 50%, 61.8% and 59.6% for Groups 1, 3 and 4 respectively. The method is unable to place about 1.5% of the cases it tests into any of the five existing groups. These combine to give it an overall estimated true error rate of 35.5%.

Table D6.5: K-NN Classification Matrix of Site 6's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**15** **0.5000**	0 0.0	13 0.4333	2 0.0667	0 0.0	0 0.0	30 1.0000
Group 2	1 0.0200	**47** **0.9400**	2 0.0400	0 0.0	0 0.0	0 0.0	50 1.0000
Group 3	17 0.3091	0 0.0	**34** **0.6182**	4 0.0727	0 0.0	0 0.0	55 1.0000
Group 4	5 0.1064	0 0.0	12 0.2553	**28** **0.5957**	0 0.0	2 0.0426	47 1.0000
Group 5	3 0.1429	0 0.0	3 0.1429	7 0.3333	**7** **0.3333**	1 0.0476	21 1.0000
Total	41 0.2020	47 0.2315	64 0.3153	41 0.2020	7 0.0345	**3** **0.0148**	203 1.0000
Apparent Error							**0.2365**
Estimated Error							**0.3547**

Neural Network

Similar procedures, data formatting and parameters as in the earlier sites were used. Table D6.6 presents a summary results from the neural network.

Table D6.6: Summary of Neural Network Predictions of Site 6's Cases

Run #	Iterations	Training Good patterns %	Testing Good patterns %	Testing Error
1	9812	86	57.1	42.9
2	5579	86	42.9	57.1
3	195	85	85.7	14.3
4	91	85	85.0	15.0
5	74	85	75.0	25.0
6	14	85	80.0	20.0
7	10	85	90.0	10.0
8	12	86	90.0	10.0
9	37	85	80.0	20.0
10	18	85	90.0	10.0
Apparent Error				**0.1470**
Estimated Error				**0.2243**

Overall Performance

A summary of the performance of all the four classification methods is presented in Table D6.7.

Table D6.7: Summary of classifier performance in the prediction task at Site 6

Classifier	Apparent Error	Estimate of True Error
Neural Networks - WinNN	0.1470	0.2243
Decision Tree - C4.5	0.2120	0.2960
K-Nearest Neighbor - SAS	0.2365	0.3547
Discriminant Analysis - SAS	0.0542	0.9310
Chance Criterion	***0.7798***	***0.7798***

As shown in the table, the best (lowest) overall estimate of true error in the prediction task is posted by the the neural network, followed by the decision tree and then the nearest neighbor classifier. With the proportional chance as a benchmark, it can be seen that using either of these three will more than double the probability of assigning a case to the correct iso-resource group. Specifically, the neural network will correctly assign 77.6%, the decision tree 70.4% and the nearest neighbor 64.5% of all cases tested at this site. On the other hand, going only by a knowledge of the sizes of the groups, one would correctly classify only 22 out of every 100 cases handled. The non-parametric discriminant analysis (which would correctly assign only 7% of the cases), would not be a technique of choice at this site since it would yield a performance that is worse than the chance criterion benchmark. In sum, these results demonstrate that predictive performance is enhanced by the usage of the first three techniques.

Addendum D6.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 0.2 to 19.8 years)			
Gender	Patient's gender	0 = Female	1 = Male		
Pttype	Patient type	0 = New	1 = Repeat		
DiagnosP	Primary Visual diagnosis	0 = n/i	1 = Nystagmus	2 = Optic atrophy	3 = R.o.P
		4 = Cataracts	5 = Detached retina	6 = Celebral palsy	7 = cortical imp't
		8 = Albinism	9 = Other		
DiagnosS	Secondary Visual diagnosis	0 = n/i	1 = Nystagmus	2 = Optic atrophy	3 = R.o.P
		4 = Cataracts	5 = Detached retina	6 = Celebral palsy	7 = cortical imp't
		8 = Albinism	9 = Other		
Onset	Onset of eye condition?	Discrete (in years)			
Med-treat	Medical treatment at onset?	0 = No	1 = Yes		
Betterey	Preferred (better) eye	0 = Same (OU)	1 = OD	2 = OS	3 = n/i
Changevs	Has vision changed recently?	0 = None	1 = Worse	2 = Better	
Guardian	Patient's guardian	1 = Mother	2 = Father	3 = Both	
Medicats	General medications?	0 = No	1 = Yes		
Physical	Physical condition	1 = Good	2 = Poor	3 = Unstable	
Hearloss	Hearing loss?	0 = No	1 = Yes		
Leardis	Learning disability?	0 = No	1 = Yes		
Balpmove	Balance, posture, mobility probs?	0 = No	1 = Yes		
Disabil	Additional disabilities?	0 = No	1 = Yes		
Travsch	Independently travel in school building?	0 = No	1 = Yes		
Schplayg	Independently travel on school playground?	0 = No	1 = Yes		
Crossstr	Independently cross streets?	0 = No	1 = Yes		
Usepubtr	Use public transport	0 = No	1 = Yes		
Omserv	Received O & M services?	0 = No	1 = Yes		
Prefvis	Preference in use of vision?	0 = No	1 = Yes		
Achielev	Achievement level	0 = n/i	1 = Below aver/age	2 = Average	3 = At grade levl
		4 = Preschool/ECSE			
Grade	Grade of patient	0 = n/i	1 = Pre-sch/ECSE	2 = Home interv'n	3 = Special class
		4 = Grade 1 - 4	5 = Grade 5 - 8	6 = Grade 9 - 12	
Goals, Visual acuity and visual aid data					
Infoseek	Information sought	0 = n/i	1 = Re-eval'n	2 = Current VA	3 = Gen. assess't
		4 = Avail'ale devs	5 = Drivers licence	6 = Any and all information possible	
Addlreps	Additional reports requested?	0 = No	1 = Yes		
Evalgl1	Patient's first evaluation objective	0 = n/i	1 = Update info	2 = Assess f'l vis	3 = Recom'd dev
		4 = Learn'g adpt'n	5 = Parental info	6 = New Rx	7 = Other
Evalgl2	Patient's second evaluation objective	0 = n/i	1 = Update info	2 = Assess f'l vis	3 = Recom'd dev
		4 = Learn'g adpt'n	5 = Parental info	6 = New Rx	7 = Other
Evalgl3	Patient's third evaluation objective	0 = n/i	1 = Update info	2 = Assess f'l vis	3 = Recom'd dev
		4 = Learn'g adpt'n	5 = Parental info	6 = New Rx	7 = Other
Pva-Od	Presenting visual acuity OD	Discrete (converted w/ numerator = 20)			
P-va-Os	Presenting visual acuity OS	Discrete (converted w/ numerator = 20)			
Pva-OU	Presenting visual acuity OU	Discrete (converted w/ numerator = 20)			
Cva-OD	Corrected visual acuity OD	Discrete (converted w/ numerator = 20)			
Cva-OS	Corrected visual acuity OS	Discrete (converted w/ numerator = 20)			
Usedevs	Currently use visul devices?	0 = No	1 = Yes		
Device1	Current LV device 1	0 = None	1 = Glasses	2 = Magnifiers	3 = CCTV
		4 = Binoc/monocs	5 = Bifocals	6 = Other	
Device2	Current LV device 2	0 = None	1 = Glasses	2 = Magnifiers	3 = CCTV

		4 = Binoc/monocs	5 = Bifocals	6 = Other	
TV	Watch TV?	0 = No	1 = Yes		
Seebett	Lighting conditions preferred	0 = Unsure	1 = Bright	2 = Overcast	3 = No difference
Glare	Glare problems?	0 = No	1 = Yes		
Readprt	Read printed material	0 = No	1 = Yes	2 = Unsure, n/i	
Readlprt	Read large printed material?	0 = No	1 = Yes	2 = Unsure, n/i	
Braille	Use braille?	0 = No	1 = Yes	2 = Unsure, n/i	
Talkbks	Use talk books?	0 = No	1 = Yes	2 = Unsure, n/i	
Resource Data					
Service-m	Service mode	0 = n/i	1 = Educ'l consult	2 = O & M evaluation	
Omeval	O & M evaluation	0 = No	1 = Yes		
Loan1	First device loaned	0 = None	1 = Half eyes	2 = Magnifiers	3 = Telescopes
		4 = Filters			
Loan2	Second device loaned	0 = None	1 = Half eyes	2 = Magnifiers	3 = Telescopes
		4 = Filters			
Other Data					
Recall	Patient to be recalled (revisit)	Discrete (in years)			
Reclvdev	Recommended low vision dev	0 = None	1 = Telescope	2 = Half eyes	3 = Magnifiers
		4 = Little Room	5 = O & M	6 = Other	
Descrdev	Description of dev. purchased	0 = None	1 = Half eyes	2 = Magnifiers	3 = Other
RecOM	Recommended for O & M?	0 = No	1 = Yes		
Recdirs	Recom'd for direct service	0 = No	1 = Yes		
Largeprt	large print (other services)	0 = No	1 = Yes		
Aphregis	APH registered?	0 = No	1 = Yes		
Regdeafb	Registered Deaf/Blind?	0 = No	1 = Yes		

Addendum D6.B: Block Cluster Output from BMDP

```
          Diagnos1   Talkbks    Regdeafb  Pvaod      Aphregis  SchPlayg
           Diagnos2   Usepubtr   Loan1     Pvaos      Age        Seebeter
            Physical   OMservs    Loan2     Cvaos      Learndis  Readlprt
             Hearloss   PrefVis    RecOM     Balpmove  Disabil   Usedevs
              Besteye    EvalGl2    Omeval    Gender     Device1
               Changevs   EvalGl3    Medicatn  Pttype     Crossstr
                TV         Reclvdev   Medtreat  Guardian  AchieLev
                 Glare      DescrDev   ReadPrnt  Infoseek  Grade
                  Device2    RecDirS    Cvaod      Addreps   EvalGl1
                   Braille    LargePrt   Pvaou      ServiceM  TravSch
BLK COUNT+....+....+....+....+....+....+....+....+....+....+.
 A   5826 90100011000001000000000000001123333010121005110001211211
 B    585 .........................1008.8881...............00000
 C    622 .............................2222........9001135311...
 D    447 ............................33333101310117............
 E    164 .......................1100055555.....................
NO. OF SINGLETONS   3213
```

Addendum D6.C: C4.5 Classification Rules

Rule 1:
Age <= 11.6
Pttype = New
Medtreat = Yes
Pvaod > 80
Pvaos <= 320
=> class Group1 [88.2%]

Rule 2:
SchPlyg = Yes
ReadPrnt = Yes
Pvaod <= 90
=> class Group3 [95.6%]

Rule 3:
Usedevs = Yes
Crossst = Yes
Pvaos <= 80
=> class Group3 [93.6%]

Rule 4:
Gender = Male
Disabil = No
Guardian = Mother
Readlprt = Yes
=> class Group3 [83.3%]

Rule 5:
Pttype = New
Medtreat = No
TravSch = Yes
Readlprt = Yes
=> class Group3 [82.0%]

Rule 6:
Age <= 2.6
Diagnos1 in {Nystagmu, Opticatr, Rop, Cataract, Cortical, Other}
Infoseek in {Reeval, CurrAids, GenAsses, Availdev}
=> class Group2 [93.9%]

Rule 7:
Physical in {Poor, Unstable}
Readlprt = No
=> class Group2 [88.2%]

Rule 8:
Diagnos1 in {Nystagmu, Opticatr, Detachr, Celebral, Cortical, Other}
TravSch = No
Readlprt = No
Device1 = No
=> class Group2 [86.7%]

Rule 9:
Age > 2.6
Pvaou > 400
=> class Group5 [61.7%]

Rule 10:
Device1 = Cctv
=> class Group5 [37.3%]

Rule 11:
Pttype = Repeat
TravSch = Yes
Pvaod > 90
=> class Group4 [51.4%]

Overview

This appendix describes the application of the APRCM methodology to data from Site 7. It follows Appendix D.6's outline and structure.

Setting

The host center is housed in the Eye Unit of a small (< 250 bed) hospital located on the outskirts of a large (> 2.5 million) metropolis in Sub-Saharan Africa. The clinic is funded by a European, non-governmental philanthropic organization. It was set up in 1994 to address the educational needs of pre-school and school-going patients, but being the only secondary/tertiary low vision facility in Eastern and Central Africa, it, by default, also serves adult and geriatric clients. In essence therefore, its patient base is geographically dispersed all over the region, but predominantly young (between 1 and 25 years). Since the target children who need the center's specialized services are either located, or receive their education in diverse schools all over the country, the center conducts field based low vision clinics in different schools for the blind throughout the country. In addition, it runs such clinics and organizes training sessions in the neighbouring countries. The clinics and the prescribed assistive devices, are provided free of charge to pre-school and school-going clients.

Services offered by the center include visual evaluations and follow-up services to determine a) if the client is indeed low-visioned, and b) if assistive devices will help improve the client's visual functioning. Towards this end, the center has instituted a loaner program covering a variety of optical and non-optical devices. Also offered are training and counselling services. The center is headed by a low vision therapist who reports to the Eye Unit's director. In addition, its staff includes a low vision advisor/educator, and two trainee therapists. Support staff include a secretary and a typist/cleaner. It liases closesly with the rest of the Eye Unit especially for clinical/ophthalmologic support/input.

Referrals to the center emanate from several different sources namely; in-house referrals from the Eye Unit/host hospital, physicians from other medical facilities in the region, parents, and teachers. The center uses a variety of forms to collect background and service information about the child's visual history, current visual functioning, general medical and physical condition/history. The client is booked and scheduled to be seen (in-clinic or outreach) after the requisite background information has been received. The initial appointment lasts for about 2.5 hours, but this may vary depending on the needs of the client. The client is scheduled to be seen first by the trainee therapist, then the low vision therapist and finally by the low vision advisor. Follow-up visits may not involve all three categories of the staff and are generally shorter in duration.

Subjects

The sample at this site contained all the patient visits covered over the years 1994 to 1996 within the center and in field based clinics at three of the eight schools for the blind covered in the center's outreach program (n = 848). Table D7.1 presents a summary of descriptive statistics of interest about the patients covered at this site. Their ages ranged from 1 to 78 years, with the majority (85.3%) falling between ages 3 and 25. Only 1.2% were aged 55 years and above. They are predominantly male (60.8%), almost equally split on type of visit (51.9% new, 48.1% repeats), and a small proportion (7.1%) have an additional (non-visual) disability. Similarly, 9.1% are not low-visioned at all (Category 5).

Table S6-1: Composition of Sample on Age, Gender, Pt-Type, Disability & Category.

Feature	Category	n	%
	=< 3	29	3.4
	3.01 - 6.00	111	13.1
	6.01 - 9.00	167	19.7
Age	9.01 - 12.00	147	17.3
	12.01 - 15.00	153	18.0
	15.01 - 18.00	87	10.3
	18.01 - 25.00	59	7.0
	25.01 - 35.00	41	4.8
	35.01 - 45.00	28	3.3
	45.01 - 55.00	16	1.9
	> 55.00	11	1.3
Gender	Female	332	39.2
	Male	516	60.8
Patient	Repeat	408	48.1

Type	New	440	51.9
Additional impairment	No	788	92.9
	Yes	60	7.1
	n/i	131	15.4
	1	1	0.1
Category	2	156	18.4
	3	204	24.1
	4	279	32.9
	5	77	9.1
Totals		848	100.0

Data

52 biographical and resource variables were collected on each case covered. A data collection instrument (a flat file with the columns representing the variables and each row representing one case) was developed from these and 24 hard-copies of it printed. None of the information of interest was available in electronic form, hence all the data were obtained manually from the clinic's patient files. Three research assistants were involved in the collection of the data. Before the data collection activity commenced, a training session was conducted to familiarise the assistants with the usage of the collection instrument, where to get the required information, its interpretation, and what to do when unfamiliar fields of information were encountered.

After all the data had been collected, it was determined that only 32 variables contained sufficient responses to meet the requirements of this study (see Addendum D7.A for a description of these variables). The data collection activity was completed over November and part of December, 1996. Daily quality control activities were done to ensure consistency across the data collectors. In addition, data collected each day were perused in the evening for initial clean-up which entailed making sure that the fields of interest had been covered for the cases dealt with on that day, missing values were noted for verification on the subsequent day that they were indeed unavailable, and new or unfamiliar values were identified for follow-up with the clinic's coordinator.

At the end of the data collection exercise, the data were converted into electronic form and numerically coded as per the coding scheme in Addendum D7.A. The resulting data file was preliminarily analyzed for descriptive statistics. For clustering purposes, 20 of the original 52 variables had to be discarded due to insufficient responses.

Cluster Analysis

Block Clustering generated five distinctive clusters (groups) from the data (see Addendum D7.B for the block output). In the absence of expert opinion, it is assumed here that these five constitute the latent patient groups at this site. Table D7.2 presents the distinguishing features of these groups.

Table D7.2: Site 7's Grouping Characteristics.

VARIABLE	Group 1	Group 2	Group 3	Group 4	Group 5
PtType	New	Repeat	Repeat	Mixed	New
Pt's Age	3 - 25	9 - 15	3 - 12	3 - 15	Varied (all ages)
Gender	Males	Females	Males	Females	Males
Class	Lower primary	Upper primary	Lower primary	Mixed	Not in school, n/i
School	Mixed	Schs f.t. Blind	Regular, Niep	Niep, St. Oda	St. Oda, Not in Sch
Visual Category	3, 4	2, 3, 4	3, 4	4, 5	2, 3
Wear Glasses	No	No	Yes	Yes	No
Reading ability	Good	Not yet, Good	Good	Not yet, Good, At Grade	Braille
ResourceUse:					
Seen-By	Th, Th-Tr, Th-Tr-Ad	Th, Th-Tr	Th, Th-Tr, Th-Ad, Th-Tr-Ad	Th, Th-Tr, Th-Ad	Th, Th-Tr
Event	Lva	Fup, Getdev	Lva,Fup,Getdev	Lva	Lva,Fup,Getdev
Clinic/Outreach	Mixed	Outreach	Mixed	In-clinic	In-clinic

The resource portion of these characteristics can be expressed by the resource demand formulae:

$$RU_1 = (C \in \{1,4,6\}) + 1M + 3T$$

$$RU_2 = (C \in \{1,4\}) + 4M + 2T$$

$$RU_3 = (C \in \{1,4,5,6\}) + 4M + 3T$$

$$RU_4 = (C \in \{1,4,5\}) + 1M + 1T$$

$$RU_5 = (C \in \{1,4\}) + 4M + 1T$$

where RU_i is the expected set of resources demanded by patient group i;

C is Seen-by (1 = Th, 2 = Tr, 3 = Ad, 4 = Th&Tr, 5 = Th&Ad, 6 =Th,Tr&AD)

M is Event (1 = Lva, 2 = Fup, 3 = Get Device, 4 = Mixed)

T is Type of service (1 = clinic, 2 = Outreach, 3 = Mixed)

When resource and other after-the-fact variables were stripped from the data set, 21 biographical variables were left. Transforming categorical variables into binary variables increased the number to 53 (for the nearest neighbor and non-parametric discriminant classifiers) and 57 (for the neural network).

Decision Tree

The classification matrix in Table D7.3 presents the results obtained from C4.5 (see Addendum D7.C for the attendant decision rules). The classifier predicts cases in Groups 1, 2, 3 and 5 quite well (with an error between 14% and 21%). It performs relatively worse on Groups 4 (error of 49.3%). It treats Group 1 as the default group (lumping here all cases that it can not assign to the other groups) - hence more than one quarter of all cases it assigns to this group are misclassified ones. In spite of this, it predicts cases in Group 1 better than those in any other group. Overall, this method's apparent error of 22.6% and estimated true error rate of 26.5% make it the technique of choice at this site.

Table D7.3: Decision Tree (C4.5) Classification Matrix of Site 7's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Group 1	**196**	16	1	5	11	229
	0.8559	0.0699	0.0044	0.0218	0.0480	1.0000
Group 2	22	**132**	0	3	10	167
	0.1317	**0.7904**	0.0	0.0180	0.0599	1.0000
Group 3	5	3	**95**	5	4	112
	0.0446	0.0268	**0.8482**	0.0446	0.0358	1.0000
Group 4	21	25	1	**70**	21	138
	0.1522	0.1812	0.0072	**0.5072**	0.1522	1.0000
Group 5	22	5	3	9	**163**	202
	0.1089	0.0248	0.0149	0.0446	**0.8069**	1.0000
Total	266	181	100	92	209	848
	0.3137	0.2134	0.1179	0.1085	0.2465	1.0000
Apparent Error						**0.2260**
Estimated Error						**0.2650**

Non-parametric Discriminant Analysis

Results obtained with this technique are presented in Table D7.4. The technique has quite a disparate performance across the five groups. It predicts cases in Group 5 very well (87.1%), relatively worse in Group 1 (50.2%), and rather poorly in Groups 2, 3 and 4 (all with less than 35%). Surprisingly, only in less than 5% of the cases tested at this site was the technique unable to place them in any of the pre-existing schemes. This suggests some overlap in the initial groupings - with some cases falling into more than one group. Overall, this technique had an estimated error rate of 50.9%.

Table D7.4: Non-parametric D. A. Classification Matrix of Site 7's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**115** **0.5022**	7 0.0306	5 0.0218	0 0.0	87 0.3799	15 0.0655	229 1.0000
Group 2	38 0.2275	**50** **0.2994**	2 0.0120	9 0.0539	59 0.3533	9 0.0539	167 1.0000
Group 3	35 0.3125	3 0.0268	**39** **0.3482**	4 0.0357	24 0.2143	7 0.0625	112 1.0000
Group 4	16 0.1159	10 0.0725	5 0.0362	**36** **0.2609**	64 0.4638	7 0.0507	138 1.0000
Group 5	14 0.0693	1 0.0050	6 0.0297	1 0.0050	**176** **0.8713**	4 0.0198	202 1.0000
Total	218 0.2571	71 0.0837	57 0.0672	50 0.0590	410 0.4835	**42** **0.0495**	848 1.0000
Apparent Error							**0.4764**
Estimated Error							**0.5094**

K-Nearest-Neighbor:

The 3-nearest neighbor results are presented in Table D7.5. The technique predicted membership in Groups 1, 2, 3, and 5 fairly well (with 60.0% or better accuracy). Predictive accuracy in Group 4 was relatively worse (at 53.6%). This method is unable to place about 1.7% of the cases it tests into any of the five existing groups. All these combine to give it an overall estimated true error rate of 35%.

Table D7.5: K-NN Classification Matrix of Site 7's Cases

From\To	Group 1	Group 2	Group 3	Group 4	Group 5	Other	Total
Group 1	**158** **0.6900**	25 0.1092	7 0.0306	12 0.0524	25 0.1092	2 0.0087	229 1.0000
Group 2	35 0.2096	**101** **0.6048**	2 0.0120	15 0.0898	12 0.0719	2 0.0120	167 1.0000
Group 3	21 0.1875	7 0.0625	**74** **0.6607**	3 0.0268	6 0.0536	1 0.0089	112 1.0000
Group 4	15 0.1087	22 0.1594	7 0.0507	**74** **0.5362**	16 0.1159	4 0.0290	138 1.0000
Group 5	22 0.1089	12 0.0594	8 0.0396	11 0.0545	**144** **0.7129**	5 0.0248	202 1.0000
Total	251 0.2960	167 0.1969	98 0.1156	115 0.1356	203 0.2394	**14** **0.0165**	203 1.0000
Apparent Error							**0.2866**
Estimated Error							**0.3502**

Neural Network

Similar procedures with regard to data formatting, experimentation and parameters as in earlier sites were followed. As can be noted from the results below, this classifier is costly in terms of time. Each iteration took 80.13 seconds (real time) on a Pentium 166 machine. Regardless of the number of iterations, it was noticed that performance (good patterns) never went beyond 27% in any run. In keeping with the approach used at previous sites:

a) except for the first run, the training of the network was commenced from the saved weights of the foregoing run;

b) training was stopped when the network indicated that no improvement in performance was forthcoming. It was noticed that even in the case where 26% or 27% was reached after the first few iterations (for instance runs # 1, 2 and 3), performance did not improve when the network was trained with extra iterations.

The average of the errors obtained from testing the 10 trained networks on their corresponding testing sets is taken here to be an estimate of the true error. The apparent error rate is drawn from an average of the misclassification of the trained networks on the training cases. No group specific estimates were drawn from the network's predictions, hence no inter-group comparisons can be made. Results from this technique's performance are shown in Table D7.6. The relatively poor overall performance is puzzling.

Table D7.6: Summary of Neural Network Predictions of Site 7's Cases

Run#	Iterations	Training % Good Patterns	Testing % Good Patterns	Testing Error
1	177	27	24.7	75.3
2	75	27	25.9	74.1
3	42	27	25.9	74.1
4	4	26	30.6	69.4
5	4	27	25.9	74.1
6	5	27	22.4	77.6
7	4	26	34.1	65.9
8	8	26	28.2	71.8
9	4	27	9.7	90.3
10	12	27	26.2	73.8
Apparent Error				**0.7330**
Estimated Error				**0.7464**

Overall Performance

A summary of the performance of all the four classification methods is presented in Table D7.7.

Table D7.7: Summary of classifier performance in the prediction task at Site 7

Classifier	Apparent Error	Estimate of True Error
Decision Tree - C4.5	0.2260	0.2650
K-Nearest Neighbor - SAS	0.2866	0.3502
Discriminant Analysis - SAS	0.4764	0.5094
Neural Networks - WinNN	0.7330	0.7464
Chance Criterion	***0.7876***	***0.7876***

As shown in the table, the best (lowest) overall estimate of true error in the prediction task is posted by the decision tree, followed by the nearest neighbor and then the non-parametric discriminant analysis classifiers. The neural network was ranked a distant fourth. With the proportional chance as a benchmark, it can be seen that using the first two will more than double the probability of assigning a case to the correct iso-resource group (the decision tree will almost triple it). Specifically, the decision tree will correctly assign 73.5% and the nearest-neighbor 65.9% of all cases tested at this site. On the other hand, going only by a knowledge of the sizes of the groups, one would correctly classify 21.2 of all cases tested. Both the non-parametric discriminant analysis and the neural network, despite posting poorer performances than the first two, will nonetheless perform better than the chance criterion benchmark. In sum, going only by these results, it can be demonstrated that predictive performance is enhanced by the usage of either of these four techniques - with the decision tree being the tool of choice at this site.

Addendum D7.A: Description of Study Variables

Variable	Description	Range			
Background Data					
Age	Patient's age	Discrete (from 1 to 78 years)			
Gender	Patient's gender	0 = Female	1 = Male		
Pttype	Patient type	0 = New	1 = Repeat		
Pt-categ	Patient category	0 = In (Kikuyu)	1 = Outreach (schools for the blind)		
Class	Patient's grade at school	0 = None, n/a	1 = Presch/nursery	2 = Grade 1 - 4	3 = Grade 5 - 8
		4 = Form 1 - 4	5 = College/university		
School	Patient's school	0 = None, n/a	1 = NIEP	2 = Regular	3 = St. Oda
		4 = St. Francis	5 = Kibos		
DiagnosP	Primary Visual diagnosis	0 = n/i	1 = Albinism	2 = Retinitis Pig'sa	3 = Macular deg.
		4 = Optic atrophy	5 = Cataracts	6 = Nystagmus	7 = Aphakia
		8 = High Myopia	9 = Other		
DiagnosS	Secondary Visual diagnosis	0 = n/i	1 = Albinism	2 = Retinitis Pig'sa	3 = Macular deg.
		4 = Optic atrophy	5 = Cataracts	6 = Nystagmus	7 = Aphakia
		8 = High Myopia	9 = Other		
Onset	Onset of eye condition?	Discrete (in years)			
Treated	Medical treatment at onset?	0 = No	1 = Yes		
Disabil	Additional disabilities?	0 = No	1 = Yes		
Condfam	Similar condition in family?	0 = No	1 = Yes		
Birthod	Patient's birthorder	Discrete			
Siblings	Patient's siblings	Discrete			
Goals, Visual acuity and visual aid data					
Interest1	Patient's primary interest	0 = n/i	1 = Music/singing	2 = Reading	3 = Writing
		4 = ADL-cooking	5 = Driving	6 = Sports	7 = Socializing
		8 = Farmwork	9 = Other		
Interest2	Patient's primary interest	0 = n/i	1 = Music/singing	2 = Reading	3 = Writing
		4 = ADL-cooking	5 = Driving	6 = Sports	7 = Socializing
		8 = Farmwork	9 = Other		
Interest3	Patient's primary interest	0 = n/i	1 = Music/singing	2 = Reading	3 = Writing
		4 = ADL-cooking	5 = Driving	6 = Sports	7 = Socializing
		8 = Farmwork	9 = Other		
Category	Patient's visual category	1 = Category 1	2 = Category 2	3 = Category 3	4 = Category 4
		5 = Category 5			
Wearglas	Patient wears glasses?	0 = No	1 = Yes		
Readabil	Patient's reading ability	0 = No, none	1 = Can't read yet	2 = Prob's w/ it	3 = Good/at grade
		4 = Fluently	5 = Braille		
Writeabl	Patient's writing ability	0 = No, none	1 = Can't write yet	2 = Prob's w/ it	3 = Good/at grade
		4 = Fluently	5 = Braille		
Needs	Patient needs	0 = n/i	1 = LV device	2 = Training	3 = Vis. stimul'n
		4 = NIEP	5 = Read/writing	6 = Educ adapt'ns	7 = New Rx
		8 = Other			
Prefeye	Patient's preferred eye	0 = None	2 = RE (OD)	3 = LE (OS)	4 = BE (OU)
Vaf-re	Presenting visual acuity OD	Discrete (converted w/ numerator = 20)			
Vaf-le	Presenting visual acuity OS	Discrete (converted w/ numerator = 20)			
Vfa-bin	Presenting visual acuity binoc	Discrete (converted w/ numerator = 20)			
Resource Data					
Event	Visit description	0 = n/i	1 = LV assess't	2 = Follow-up	3 = Get device
		4 = Vis. stimul'n	5 = Refract'n/V.fld	6 = letter/report	7 = intro to prt
		8 = Training	9 = Other		
Loandev	Loned device	0 = No	1 = Yes		

Seenby	Patient seen by	0 = n/i 1 = Therapist 4 = Th/Tr5 = Th/Ad	2 = Advisor 6 = Tr/Ad	3 = Trainee 7 = Th/Ad/Tr
Other Data				
Revisitt	Patient to be recalled (return)	Discrete (in months)		
Devprescr	Device prescribed	0 = No	1 = Yes	
Lvdn	Received low vision device?	0 = No	1 = Yes	

Addendum D7.B: Block Cluster Output from BMDP

```
               Diagnos    Letters    Gender     Birthord
                NextVis    Diagnop    Seenby     Siblings
                 Lvdn       VAfre      WearGl
                  Needs      VAfle      School
                   Loandev    ReadAbil   VAfbin
                    Devpresc   WriteAbl   Inout
                     Disabil    Age        Event
                      Condfam    Class      Pttype
                       Interes1   Category   Onset
                        Interes2   Prefeye    Treated
BLK COUNT +....+....+....+....+....+....+...
 A  14284 01000000000933332240110080101000
 B   1041 ................333204.33131....
 C    694 ......................1230216113
 D    719 ...........54200....05112.......
 E    792 ............8800102.............
         +....+....+....+....+....+....+....

NO. OF SINGLETONS   9536
```

Addendum D7.C: C4.5 Classification Rules

Rule 1:
Pttype = Repeat
Treated = Yes
WearGl = Yes
School in {None, Regular}
Diagnop in {Albinism, Retpigme, Stargart, Opticatr, Nystagmu, Highmyop,Other}
=> class Group3 [95.2%]

Rule 2:
School = Regular
Onset > 3
WearGl = Yes
Class in {Pre-schl, Class1-4}
=> class Group3 [93.0%]

Rule 3:
Birthord <= 3
Diagnop in {Albinism, Opticatr, Nystagmu, Aphakia, Other}
Class in {Pre-schl, Class1-4, Class5-8, Form1-4}
WearGl = Yes
Treated = Yes
=> class Group3 [92.2%]

Rule 4:
Pttype = Repeat
Treated = Yes
WearGl = No
Class = Form1-4
=> class Group3 [89.1%]

Rule 5:
Gender = Male
WearGl = Yes
Pttype = Repeat
Readabil in {Problems, Good, Fluently, Braille}
Treated = Yes
=> class Group3 [87.9%]

Rule 6:
Birthord <= 2
Diagnop in {Stargart, Opticatr, Nystagmu}
WriteAbl in {Problems, Good}
Pttype = Repeat
=> class Group3 [85.7%]

Rule 7:
Gender = Male
Treated = Yes
Age <= 10
School in {Regular, St-oda, St-franc, Kibos}
Pttype = Repeat
Diagnop in {Albinism, Stargart, Opticatr, Other}
=> class Group3 [84.3%]

Rule 8:
Class in {None, Form1-4}
School = Regular
Prefeye in {Re, Le}
=> class Group3 [79.7%]

Rule 9:
WearGl = Yes
Interst1 = Writing
=> class Group3 [63.0%]

Rule 10:
Inout = In
WearGl = No
WriteAbl in {Cannot, Problems, Good}
Pttype = New
=> class Group1 [77.8%]

Rule 11:
Class = Class1-4
WearGl = No

Readabil in {Cannot, Problems, Good, Fluently, Braille}
Pttype = New
=> class Group1 [73.1%]

Rule 12:
Gender = Male
School in {None, Niep, St-oda, St-franc, Kibos}
Readabil = Good
WriteAbl in {Cannot, Problems, Good, Braille}
=> class Group1 [69.8%]

Rule 13:
Age > 13
Gender = Male
Readabil = No
=> class Group5 [83.0%]

Rule 14:
School in {Niep, St-oda}
Diagnop in {Cataract, Other}
WearGl = No
WriteAbl = Braille
Pttype = New
=> class Group5 [72.0%]

Rule 15:
Class in {None, Varsity}
WriteAbl in {No, Cannot, Problems, Fluently}
=> class Group5 [71.3%]

Rule 16:
Age > 48
Pttype = Repeat
Treated = No
=> class Group5 [61.0%]

Rule 17:
Class = Pre-schl
School in {Niep, Regular, St-franc}
Readabil = No
Pttype = New
=> class Group5 [59.4%]

Rule 18:
Inout = Out
Gender = Female
Readabil = Braille
Pttype = Repeat
=> class Group2 [85.7%]

Rule 19:
Inout = Out
Age > 10
WearGl = No
Class in {Pre-schl, Class1-4, Class5-8}
Pttype = Repeat
=> class Group2 [83.6%]

Rule 20:
Treated = No
School in {Regular, St-oda, St-franc, Kibos}
Readabil in {Cannot, Problems, Good, Fluently, Braille}
Class in {Pre-schl, Class1-4, Class5-8}
Pttype = Repeat
WriteAbl in {Cannot, Problems, Good, Braille}
=> class Group2 [69.4%]

Rule 21:
Gender = Female
Onset <= 1
Disabil = Yes
=> class Group2 [63.0%]

Rule 22:
Gender = Female
Class = Class5-8
=> class Group2 [57.0%]

Rule 23:
Age <= 4.5
Gender = Female
School in {Niep, Kibos}
Pttype = Repeat
=> class Group2 [56.6%]

Rule 24:
    Diagnop = Aphakia
    WearGl = No
=> class Group2 [44.5%]

Rule 25:
    Inout = Out
    Age <= 11
    Readabil = Fluently
=> class Group4 [70.7%]

Rule 26:
    Class = Class1-4
    WearGl = Yes
    Readabil = No
=> class Group4 [64.8%]

Rule 27:
    Diagnop = Cataract
    WriteAbl = No
    Treated = No
=> class Group4 [62.6%]

Rule 28:
    Gender = Female
    School in {Niep, St-oda, St-franc,
      Kibos}
    WearGl = Yes
    Readabil in {Cannot, Problems, Good,
      Fluently, Braille}
=> class Group4 [55.6%]

Rule 29:
    School = Niep
    Readabil = No
=> class Group4 [47.2%]

APPENDIX E

VARIABLES FOR THE COMBINED DATA SET

To combine data from the seven sites, a listing of the variables used for clustering at each site was made. This list was sorted into three categories: Biographical (i.e. background, goals, visual acuity, visual aid), Resource, and Other (see subsequent pages of this appendix).

1. An administrative decision was made to retain only those variables present at the majority of the sites (i.e. >= 4). These are highlighted in bold.
2. The variables Goals (Goals 1 - 5) and Current Visual Aids (CurVde1 - 3) different 'scaling' was used at sites. For uniformity, the scale used at the University of Waterloo's LVC was adopted.
3. For Occupation, every patient aged 18 or less and unmarried was categorized under Student/child.
4. For Marital-Status, every Student/child was categorized under Single.
5. With expert assistance from an Epidemiologist, the 140+ different diagnoses were reduced to 17 and represented in two variables.

VARIABLES AT SITES 1-7

SITE	Site 1										Site 2								
Variables	Values										Values								
BACKGROUND																			
Age	Discrete (in years)		•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•	•	•
Gender	Female	Male	•	•	•	•	•	•	•	•	Female	Male	•	•	•	•	•	•	•
Marital-St	n/i	Single	Married	Divorced	Widowed	•	•	•	•	•	n/i	Single	Married	Divorced	Widowed	•	•	•	•
Pt-type	n/i	New	Repeat	•	•	•	•	•	•	•	n/i	New	Repeat	•	•	•	•	•	•
Diagnos-P	n/i	Aphakia	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Nystagmu	Other	Ret. Pigm	Optic atro	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Retinal de
Diagnos-S	n/i	Aphakia	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Nystagmu	Other	Ret. Pigm	Optic atro	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Retinal de
Distance-T	•	•	•	•	•	•	•	•	•	•	n/i	Local	In-state	Out-state	•	•	•	•	•
Onset	•	•	•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•	•	•
Treated?	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Disability	(can be inferred from medical history)				•	•	•	•	•	•	n/i	Good/heal	Heart con	Arthritic	Diabetic	Asthma	Cancer	Other	•
Medication	•	•	•	•	•	•	•	•	•	•	n/i	No	Yes	•	•	•	•	•	•
Eye-surgery	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Race	n/i	Black	White	Hispanic	•	•	•	•	•	•	n/i	Black	White	Hispanic	•	•	•	•	•
Pt-categ	n/i	In-patient	Outpatient	•	•	•	•	•	•	•	n/i	In-patient	Outpatient	•	•	•	•	•	•
Lastexam	Discrete (in weeks)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Religion	n/i	None	Catholic	Protestant	Methodist	Baptist	Episcope'n	Presbyte'n	Jewish	Other	n/i	None	Catholic	Protestant	Methodist	Baptist	Episcope'n	Presbyte'n	Jewish
MedHist1-2	n/i	Healthy	Diabetic	Arthritic	HBP	Stroke	Paraplegic	Respiraton	Acc/Injury	Other	n/i	Healthy	Diabetic	Arthritic	HBP	Stroke	Paraplegic	Respiraton	Acc/Injury
OcularHis1-2	(captured in diagnosis?)			•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Network	•	•	•	•	•	•	•	•	•	•	n/i	Family	Friends	Church/community		•	•	•	•
Came-with	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Living(alone)	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•	•
Occupation	•	•	•	•	•	•	•	•	•	•	n/i	Arttorney	On disabil	Eng/mech	Nursing	Officewor	Student/c	Teach/mgr	Retired
Employ/Retirec	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Insurance	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Understand	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Working	•	•	•	•	•	•	•	•	•	•	(can be inferred from occupation)				•	•	•	•	•
School	•	•	•	•	•	•	•	•	•	•	(can be inferred from occupation - as Yes/No)					•	•	•	•
Diffs(Voc/edu)	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
NameCond'n	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye Medicats	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
HBP	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diabetes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Stroke	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Heart disease	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Orthopeadic	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Anxiety	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Surghospital	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Referred-By	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
LaserTX	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye pain	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
FluctuationVis	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Previous LVE	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Sunlight/Glare	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
PreferredLight	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ProbNightVis	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Guardian	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Physical cond'r	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Hearing loss	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Learning disab	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Balpmove	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
WatchTV	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Seebett	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Glareprobs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Braille	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Talkbooks	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE	Site 1										Site 2								
Variables	Values										Values								
Travsch	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Schplayg	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Crossstr	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Usepublr	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Omserv	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Achieve'tlevel	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Grade	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
School	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CondinFamily	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Birthorder	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Siblings	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
GOALS, VA, VAID																			
Chiefcomplaint	•	•	•	•	•	•	•	•	•	•	n/i	Read/difs	Fuzzy Vis	Decl'g Vis	Dis/Nr vis	Gen Vision	Glare cont	AMD	Diab ret
Goals(1-5)	n/i	Read/Writ	Glare Con	TV-watchi	Follow-up	Gen Visio	Color test	ADL	Driving	Other	n/i	Reading	Writing	Driving	TV/Spec a	Signs	Mobility	ADLs	Glare
UseLVaid	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CurVde1-3	n/i	Hhmags	Pkt Mags	Stand Ma	Bifocals	Glasses	Bi/monoc	Contacts	Filters	Other	n/i	Half eyes	Bifoca/trif	Telescope	Magnifiers	Dist/Nr Rx	Filters	LP/Talk bk	CCTV
Pres-VA-Od	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•
Pres-VA-Os	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•
Pres-VA-OU	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Via-bin	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Corr-VA-Od	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20, w/ n/t = Not Tested)						•	•	•
Corr-VA-Os	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20, w/ n/t = Not Tested)						•	•	•
Preferred eye	•	•	•	•	•	•	•	•	•	•	n/i	OD	OS	OU - same		•	•	•	•
WearGlasses	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
GlassesHelp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadPrint	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadLprt	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Printsize read	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
What-read	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherDifVisTas	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ActivityMissed	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Prefervision	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Infosought	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Add'lreports	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadAbil	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
WriteAbil	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Needs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CategoryVisual	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RESOURCE DATA																			
Dr-time	Discrete-minutes		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Edu-time	Discrete-minutes		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect1	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
TotalTime	(can be obtained from the above two)				•	•	•	•	•	•	Discrete-minutes		•	•	•	•	•	•	•
Letters/report	Discrete	•	•	•	•	•	•	•	•	•	Discrete	•	•	•	•	•	•	•	•
Source	n/a, n/i	Doctor	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Loaned 1-3	n/i	Half eyes	Cl glasses	Filters	Hhmags	Pkt mags	IllumSmag	Read glas	Lamp	Other	•	•	•	•	•	•	•	•	•
ServType	n/i	Comprehe	Intermedia	Moderate	Tech only	•	•	•	•	•	n/i	Level 5	Level 4	Level 3	Purchase c	Other	•	•	•
DevsPrescribe	n/i	Half eyes	Cl glasses	Filters	Hhmags	Pkt mags	IllumSmag	Read glass	Lamp	Other	•	•	•	•	•	•	•	•	•
RecomDEVS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Dispdevice1-3	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Vservice	n/i	Color test	EOG	ERG	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
VAidTried	n/i	Half eyes	Cl glasses	Filters	Hhmags	Pkt mags	IllumSmag	Read glass	Training	Other	•	•	•	•	•	•	•	•	•
Individ-code	•	•	•	•	•	•	•	•	•	•	n/i	IndThrpy3(	IndThrpy5(	•	•	•	•	•	•
Exam-office	•	•	•	•	•	•	•	•	•	•	n/i	Level 4	Level 3-10	Level 3-75	Level 2	•	•	•	•
OLVdevs	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE	Site 1										Site 2								
Variables	**Values**										**Values**								
SLVdevs	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•	•
Source-letter	•		•	•	•	•	•	•	•	•	n/a	Doctor	Social worker	•	•	•	•	•	•
Oconsult	n/l	Eye appliance		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Social worker	•	•		•	•	•	•	•	•	•	n/l	No	Yes	•	•	•	•	•	•
OTvisittype	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Spec-diagnosti	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Assessments	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Training in	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Ophthalmic ser	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Feetype	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Func-type	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Service-m	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
O&MEval'n	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Event/VisDesc	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Seen By	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OTHER DATA																			
Revisit-why	n/l	Review sta	Review de	Visual field	Training	Other	•	•	•	•	n/l	Follow-up	Return Prn	n/l	•	•	•	•	•
Revisit-Time	**Discrete-wks**		•	•	•	•	•	•	•	•	**Discrete-wks**				•	•	•	•	•
Follow-uptype	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
PtResponse											•	•	•	•	•	•	•	•	•
Prognos-ST	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Prognos-LT	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Planref	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Planlvd	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomOT	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomTR	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomSS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomVR	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MCB	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherCS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MOW	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Hmaker	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Transp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
FamilyS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSP	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjTX	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjADL	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjCOM	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjLEI	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjDRV	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjMOB	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSEDVIEW	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diff-side	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Turn-head	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Drive	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
PublicTransp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
In-Outdoor	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Cane	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadingDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
DistanceDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Filters	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Lighting	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Writing1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Accessor1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Referral1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eval areas	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE	Site 1									Site 2									
Variables	Values									Values									
Received-Devs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomO&M	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomDirServ	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Largeprt	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
AphRegistered	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RegdeafBlind	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE		Site 3										Site 4							
Variables		Values										Values							
BACKGROUNI																			
Age	•	Discrete (in years)		•	•	•	•	•	•	•	•	Discrete (in years)	•	•	•	•	•	•	•
Gender	•	Female	Male	•	•	•	•	•	•	•	•	Female	Male	•	•	•	•	•	•
Marital-St	•	n/l	Single	Married	Divorced	Widowed	•	•	•	•	•	n/l	Single	Married	Divorced	Widowed	•	•	•
Pt-type	•	New	Repeat	•	•	•	•	•	•	•	•	New	Repeat	•	•	•	•	•	•
Diagnos-P	Other	Ret. Pigm	Optic atro	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Retinal de	Other	n/l	Histoplasr	Diab. Ret	Amd	Ret. Dystr	Glaucoma	Cataracts	Optic atro
Diagnos-S	Other	Ret. Pigm	Optic atro	Cataracts	Diab. Ret.	Glaucoma	Pr.Myopia	Mac.Deg.	Albinism	Retinal de	Other	n/l	Histoplasr	Diab. Ret	Amd	Ret. Dystr	Glaucoma	Cataracts	Optic atro
Distance-T	•	n/i	Local	In-state	Out-state	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Onset	•	Discrete (i	•	•	•	•	•	•	•	•	•	Discrete (in years)	•	•	•	•	•	•	•
Treated?	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Disability	•	No	Yes	•	•	•	•	•	•	•	•	n/l	Good	HBP/Heart	Diabetic	Hearing In	Respirator	Arthritic	Other
Medication	•	No	Yes	•	•	•	•	•	•	•	•	n/l	No	Yes	•	•	•	•	•
Eye-surgery	•	No	Yes	•	•	•	•	•	•	•	•	Discrete (in years)	•	•	•	•	•	•	•
Race	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Pt-categ	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Lastexam	•	Discrete (in weeks)		•	•	•	•	•	•	•	•	Discrete (in months)	•	•	•	•	•	•	•
Religion	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MedHist1-2	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OcularHis1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Network	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Came-with	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Living(alone)	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Occupation	Other	n/l	Student/cl	Retired	On disabil	Unemploy	Janitor/or	At home	Self-emp'c	Sec/teach	Other	n/l	Student/cl	At home	Sec/office	Farmer	Techwork	Sup'd/mgr	Other
Employ/Retirec	•	•	•	•	•	•	•	•	•	•	•	n/l	No	Employed	Retired	•	•	•	•
Insurance	•	Medicare	Self-pay	Medicaid	Baystate	Blind Com	Other	•	•	•	•	n/l	DOCS-IL	BCBS	Medicare	BCBS/Med	Other	•	•
Understand	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Working	•	n/i	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
School	•	n/i	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diffs(Voc/edu)	•	n/i	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
NameCond'n	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye Medicals	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
HBP	•	No	Yes	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•
Diabetes	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Stroke	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Heart disease	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Orthopeadic	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Anxiety	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Surghospital	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Referred-By	•	•	•	•	•	•	•	•	•	•	•	n/l	No	Yes	•	•	•	•	•
LaserTX	•	•	•	•	•	•	•	•	•	•	•	n/l	Recall/Fup	Self/Fam/F	MD/OD	DORS	•	•	•
Eye pain	•	•	•	•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•	•
FluctuationVis	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•
Previous LVE	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•
Sunlight/Glare	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•
PreferredLight	•	•	•	•	•	•	•	•	•	•	•	n/l	No	Yes	•	•	•	•	•
ProbNightVis	•	•	•	•	•	•	•	•	•	•	•	n/l	No specific	Bright	Direct-task	Tinted	•	•	•
Guardian	•		•	•	•	•	•	•	•	•	•	n/l	No	Yes	•	•	•	•	•
Physical cond'r	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Hearing loss	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Learning disab	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Balpmove	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
WatchTV	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Seebelt	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Glareprobs	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Braille	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Talkbooks	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE		Site 3										Site 4							
Variables		Values										Values							
Travsch	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Schplayg	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Crossstr	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Usepubtr	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Omserv	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Achieve'tlevel	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Grade	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
School	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CondinFamily	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Birthorder	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Siblings	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
GOALS, VA, V.																			
Chiefcomplaint	Other	•	•	•	•	•	•	•	•	•	•	Eval/Scrne	Drive/Eval	F-up	Reading	Other	•	•	•
Goals(1-5)	Other	n/i	Mobility	Tv/movie/	Street sign	Writing	Read news	Read LP	Readmenu	ADLs	Driving	n/i	ADL/Ind,Li	Driving	Gen Eval	Glare cont	Nr Vis	Dist Vis	Read/write
UseLVaid	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•	•
CurVde1-3	Other	None	Hhmags	Smags	CI	Telescope	Bifocals	Filters	Half eyes	Dis/NrRX	Other	n/i	None	Readers	CCTV	Hhmags	Smags	Bi/monoc	Non-optic
Pres-VA-Od	•	Discrete (converted to a numerator of 20)					•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•
Pres-VA-Os	•	Discrete (converted to a numerator of 20)					•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•
Pres-VA-OU	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Via-bin	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Corr-VA-Od	•	Discrete (converted to a numerator of 20)					•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•
Corr-VA-Os	•	Discrete (converted to a numerator of 20)					•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•
Preferred eye	•	n/i	OD	OS	OU-Same	•	•	•	•	•	•	n/i	OD	OS	OU-Same	•	•	•	•
WearGlasses	•	•	•	•	•	•	•	•	•	•	•	n/i	No	Yes	•	•	•	•	•
GlassesHelp	•	•	•	•	•	•	•	•	•	•	•	n/i	No	Yes	•	•	•	•	•
ReadPrint	•	•	•	•	•	•	•	•	•	•	•	n/i	No	Yes	•	•	•	•	•
ReadLprt	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Printsize read	•	•	•	•	•	•	•	•	•	•	•	None	Regular	Large	•	•	•	•	•
What-read	•	•	•	•	•	•	•	•	•	•	•	n/i	Books/Bibl	Newsprint	Vocational	Checks/bill	Menu/mail	Writing	Dials/recip
OtherDifVisTas	•	•	•	•	•	•	•	•	•	•	•	n/i	Depth perc	TVviewing	Driving	Street sign	Recog face	Hobbies	Vocational
ActivityMissed	•	•	•	•	•	•	•	•	•	•	•	n/i	ADLs	Walking	Boardgam	Outdoor ac	Church/cor	Garden/lan	Social act
Prelervision	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Infosought	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Add'lreports	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadAbil	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
WriteAbil	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Needs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CategoryVisual	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RESOURCE D.																			
Dr-time	•	Cons Lv	Ext Cons N	Comp Lv	Ext Comp	F-up Lv	Ext F-up lv	Int F-up Lv	Visual field	n/i	•	Discrete (in minutes)		•	•	•	•	•	•
Edu-time	•	None	Brief Initial	Std Initial	Brief F-up	•	•	•	•	•	•	Discrete (in minutes)		•	•	•	•	•	•
Indirect1	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
TotalTime	•	•	•	•	•	•	•	•	•	•	•	Discrete (in minutes)		•	•	•	•	•	•
Letters/reports	•	Discrete	•	•	•	•	•	•	•	•	•	Discrete	•	•	•	•	•	•	•
Source	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Loaned 1-3	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ServType	•	•	•	•	•	•	•	•	•	•	•	n/i	Hhmags	Smags	Read/spec	CCTV	Non-optic	Other	•
DevsPrescribed	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomDEVS	•	None	Blk felt pen	Bold L pap	Bookstand	Clipboard	GNL	Lap desk	Typoscope	WriteGuide	Other	n/i	Hhmags	Smags	Read/spec	CCTV	Non-optics	Other	•
Dispdevice1-3	•	None	Hhmags	IllumH/Pm	Half eyes	IllumSmag	Smags	Telescope	Non-optics	CCTV	Filters	No	Yes	•	•	•	•	•	•
Vservice	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
VAidTried	•	None	Hhmags	IllumH/Pm	Half eyes	IllumSmag	Smags	Telescope	Non-optics	Deferred	Filters	•	•	•	•	•	•	•	•
Individ-code	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Exam-office	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OLVdevs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE	Site 3										Site 4							
Variables	Values										Values							
SLVdevs																		
Source-letter																		
Oconsult																		
Social worker																		
OTvisittype	No OT	1/4hrEval	1/2hrEval	3/4hrEval	1hrEval	1/4hrTx	1/2hrTx	3/4hrTx	1hrTx	Other								
Spec-diagnosti																		
Assessments																		
Training in																		
Ophthalmic ser																		
Feetype																		
Func-type																		
Service-m																		
O&MEval'n																		
Event/VisDesc																		
Seen By																		
OTHER DATA																		
Revisit-why																		
Revisit-Time	Discrete (in weks)										Discrete (in weeks)							
Follow-uptype											n/i	Office	Phone					
PtResponse											n/i	Motivated	indifferent	Other				
Prognos-ST	n/i	Good	Fair	Poor														
Prognos-LT	n/i	Good	Improving	Guarded														
Planref	No	Yes																
Planlvd	No	Yes																
RecomOT	No	Yes																
RecomTR	No	Yes																
RecomSS	No	Yes																
RecomVR	No	Yes																
MCB	No	Yes																
OtherCS	No	Yes																
MOW	No	Yes																
Hmaker	No	Yes																
Transp	No	Yes																
FamilyS	No	Yes																
ObjSP	No	Yes																
ObjTX	No	Yes																
ObjADL	No	Yes																
ObjCOM	No	Yes																
ObjLEI	No	Yes																
ObjDRV	No	Yes																
ObjMOB	No	Yes																
ObjSEDVIEW	No	Yes																
Diff-side											n/i	No	Yes					
Turn-head											n/i	No	Yes					
Drive											n/i	No	Yes					
PublicTransp											n/i	No	Yes					
In-Outdoor											n/i	No	Yes					
Cane											n/i	No	Yes					
ReadingDev1-3											None	Hhmags	Smags	Read/spec	Telemicros	CCTV	Other	
DistanceDev1-											None	Monocular	Binocs	hand held	Spect-mou	Driving bio	Other	
Filters											No	Noirs						
Lighting											n/i	Positioning	Bulbsize	Other				
Writing1-2											n/i	BoldLPape	Felt tip	Check guic	Signature (	Other		
Accessor1-2											n/i	Hi-marks	Phone dial	LP books	Lap board	Able table	TalkWatch	Jumbo car
Referral1-2											n/i	Talking bk	Direct' assi	DORS/ICB	Ind/Living (	Drivers lice	Legally blir	Other
Eval areas																		

VARIABLES AT SITES 1-7

SITE		Site 3									Site 4								
Variables		Values									Values								
Received-Devs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomO&M	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomDirServ	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Largeprt	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
AphRegistered	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RegdeafBlind	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE			Site 5										Site 6						
Variables			Values										Values						
BACKGROUNI																			
Age	•	•	Discrete (in years)		•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•
Gender	•	•	Female	Male	•	•	•	•	•	•	•	•	Female	Male	•	•	•	•	•
Marital-St	•	•	n/i	Single	Married	Divorced	Widowed	•	•	•	•	•	•	•	•	•	•	•	•
Pt-type	•	•	New	Repeat	•	•	•	•	•	•	•	•	New	Repeat	•	•	•	•	•
Diagnos-P	Aphakia	Other	Amd	Diab. Ret	Cataracts	Acc/Injury	Glaucoma	Nystagmu	Optic atro	H. Myopia	Ret Pigme	Other	n/i	Nystagmu	Optic atro	R.O.P.	Cataracts	Detached	Celebral pa
Diagnos-S	Aphakia	Other	Amd	Diab. Ret	Cataracts	Acc/Injury	Glaucoma	Nystagmu	Optic atro	H. Myopia	Ret Pigme	Other	n/i	Nystagmu	Optic atro	R.O.P.	Cataracts	Detached	Celebral pa
Distance-T	•	•	In-state	Outstate	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Onset	•	•	•	•	•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•
Treated?	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Disability	•	•	No	Yes	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Medication	•	•	No	Yes	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Eye-surgery	•	•	Discrete (in months)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Race	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Pt-categ	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Lastexam	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Religion	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MedHist1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OcularHis1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Network	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Came-with			n/i	Parents	Spouse	Chid(ren)	Sibling	Companion	Self/alone	Friend			•	•	•	•	•	•	•
Living(alone)	•	•	n/i	Parents	Spouse	Chid(ren)	Sibling	Companion	Self/alone	Friend			•	•	•	•	•	•	•
Occupation	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Employ/Retirec	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Insurance	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Understand	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Working	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
School	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diffs(Voc/edu)	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
NameCond'n	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye Medicats	•	•	No	Yes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
HBP	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diabetes	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Stroke	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Heart disease	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Orthopeadic	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Anxiety	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Surghospital	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Referred-By	•	•	Self/Fam/F	OBVSI	EBVSI	PaBSVI	In-house	•	•	•	•	•	•	•	•	•	•	•	•
LaserTX	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye pain	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
FluctuationVis	•	•	•	•	•	•	•	•	•	•	•	•	None	Worse	Better	•	•	•	•
Previous LVE	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Sunlight/Glare	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
PreferredLight	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ProbNightVis	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Guardian	•	•	•	•	•	•	•	•	•	•	•	•	Mother	Father	Both	•	•	•	•
Physical cond'r	•	•	•	•	•	•	•	•	•	•	•	•	Good	Poor	Unstable	•	•	•	•
Hearing loss	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Learning disab	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Balpmove	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
WatchTV	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Seebelt	•	•	•	•	•	•	•	•	•	•	•	•	Unsure	Bright	Overcast	No diff'nce	•	•	•
Glareprobs	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Braille	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Talkbooks	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE			Site 5										Site 6						
Variables			Values										Values						
Travsch	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Schplayg	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Crossstr	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Usepubtr	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Omserv	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Achieve'tlevel	•	•	•	•	•	•	•	•	•	•	•	•	n/i	BelowAver	Average	AtGradeLe	Presch/EOSE	•	•
Grade	•	•	•	•	•	•	•	•	•	•	•	•	n/i	PreschEC	HomeInter	SpecClass	Grade1-4	Grade5-8	Grade9-12
School	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CondinFamily	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Birthorder	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Siblings	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
GOALS, VA, V.																			
Chiefcomplaint	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Goals(1-5)	Hobbies	Other	n/i	Read/write	Mobility	Educ/Voc	Glare cont	ADLs	Driving	Hobbies	Recog fac	Other	n/i	UpdateInf	AssessFI	RecomDe	LearnAda	ParentInfo	NewRx
UseLVaid	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
CurVde1-3	Other	•	n/i	None	Readers	CCTV	Hhmags	Smags	Bi/Monoc	Non-optic	Other	•	None	Glasses	Mags	CCTV	Bi/Monoc	Bifocals	Other
Pres-VA-Od	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•
Pres-VA-Os	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•
Pres-VA-OU	•	•	•	•	•	•	•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•
Vfa-bin	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Corr-VA-Od	•	•	•	•	•	•	•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•
Corr-VA-Os	•	•	•	•	•	•	•	•	•	•	•	•	Discrete (converted to a numerator of 20)				•	•	•
Preferred eye	•	•	•	•	•	•	•	•	•	•	•	•	n/i	OU-same	OD	OS	•	•	•
WearGlasses	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
GlassesHelp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadPrint	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
ReadLprt	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Printsize read	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
What-read	Phone/Pho	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherDifVisTas	ADLs	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ActivityMissed	Hobbies	None	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Prefervision	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Infosought	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Add'lreports	•	•	•	•	•	•	•	•	•	•	•	•	n/i	Reeval'n	CurrentVA	GenAssess	AvailDevs	DriversLic	Any&All
ReadAbil	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
WriteAbil	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Needs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
CategoryVisual	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RESOURCE D.																			
Dr-time	•	•	Discrete (in minutes)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Edu-time	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect1	•	•	Discrete (in minutes)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect2	•	•	Discrete (in minutes)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
TotalTime	•	•	Discrete (in minutes)		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Letters/reports	•	•	Discrete	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Source	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Loaned 1-3	•	•	None	Spectacle	Hh/Smags	Telescope	Non-optic	•	•	•	•	•	•	•	•	•	•	•	•
ServType	•	•	None	Exp'd focus	Low comp	Mod comp	Comp cons	Int'e cons	Comprehe	•	•	•	None	Half eyes	Magnifiers	Telescope	Filters	•	•
DevsPrescribed	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomDEVS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Dispdevice1-3	•	•	No	Yes	•	•	•	•	•	•	•	•	None	Telescope	Half eyes	Magnifiers	Little room	O&M	Other
Vservice	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
VAidTried	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Individ-code	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Exam-office	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OLVdevs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE			Site 5										Site 6						
Variables			Values										Values						
SLVdevs	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Source-letter	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Oconsult	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Social worker	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OTvisittype	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Spec-diagnosti	•	•	No	Comp refraction		•	•	•	•	•	•	•	•	•	•	•	•	•	•
Assessments	•	•	No	Functional	CCTV	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Training in	•	•	No	Vision	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Ophthalmic ser	•	•	No	Hhmag	Spec-mounted mag		Telescope	Other	•	•	•	•	•	•	•	•	•	•	•
Feetype	•	•	Clinic/Diag	Funct'l/Tra	Materials	C/D,F/T	C/D,M	C/D,F/T,M	F/T,M	None	•	•	•	•	•	•	•	•	•
Func-type	•	•	None, n/a	Brief	Comprehe	CCTV ass	•	•	•	•	•	•	•	•	•	•	•	•	•
Service-m	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
O&MEval'n	•	•	•	•	•	•	•	•	•	•	•	•	n/l	EduConsul	O&MEval	•	•	•	•
Event/VisDesc	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Seen By	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OTHER DATA													•	•	•	•	•	•	•
Revisit-why	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Revisit-Time	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Follow-uptype	•		•	•	•	•	•	•	•	•	•	•	Discrete (in years)		•	•	•	•	•
PtResponse	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Prognos-ST	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Prognos-LT	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Planref	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Planlvd	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomOT	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomTR	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomSS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomVR	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MCB	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherCS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
MOW	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Hmaker	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Transp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
FamilyS	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSP	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjTX	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjADL	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjCOM	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjLEI	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjDRV	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjMOB	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSEDVIEW	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Diff-side	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Turn-head	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Drive	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
PublicTransp	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
In-Outdoor	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Cane	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadingDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
DistanceDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Filters	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Lighting	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Writing1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Accessor1-2	Ind.Living t	Other	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Referral1-2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Eval areas	•	•	None	ADLs	CCTV	Reading	Lighting	Handwritin	Filters	Mobility	Other	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE			Site 5										Site 6						
Variables			Values										Values						
Received-Devs	•	•	No	Yes	•	•	•	•	•	•	•	•	None	Half eyes	Magnifiers	Other	•	•	•
RecomO&M	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
RecomDirServ	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
Largeprt	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
AphRegistered	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•
RegdeafBlind	•	•	•	•	•	•	•	•	•	•	•	•	No	Yes	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE				Site 7									
Variables				Values									
BACKGROUNI													
Age	•	•	•	Discrete (in years)		•	•	•	•	•	•	•	•
Gender	•	•	•	Female	Male	•	•	•	•	•	•	•	•
Marital-St	•	•	•	•	•	•	•	•	•	•	•	•	•
Pt-type	•	•	•	New	Repeat	•	•	•	•	•	•	•	•
Diagnos-P	Cortical	In Albinism	Other	n/l	Albinism	Ret Pigme	Amd	Optic atro	Cataracts	Nystagmu	Aphakia	H.Myopia	Other
Diagnos-S	Cortical	In Albinism	Other	n/l	Albinism	Ret Pigme	Amd	Optic atro	Cataracts	Nystagmu	Aphakia	H.Myopia	Other
Distance-T	•	•	•	•	•	•	•	•	•	•	•	•	•
Onset	•	•	•	Discrete (in years)		•	•	•	•	•	•	•	•
Treated?	•	•	•	No	Yes	•	•	•	•	•	•	•	•
Disability	•	•	•	No	Yes	•	•	•	•	•	•	•	•
Medication	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye-surgery	•	•	•	•	•	•	•	•	•	•	•	•	•
Race	•	•	•	•	•	•	•	•	•	•	•	•	•
Pt-categ	•	•	•	In	Outreach	•	•	•	•	•	•	•	•
Lastexam	•	•	•	•	•	•	•	•	•	•	•	•	•
Religion	•	•	•	•	•	•	•	•	•	•	•	•	•
MedHist1-2	•	•	•	•	•	•	•	•	•	•	•	•	•
OcularHis1-2	•	•	•	•	•	•	•	•	•	•	•	•	•
Network	•	•	•	•	•	•	•	•	•	•	•	•	•
Came-with	•	•	•	•	•	•	•	•	•	•	•	•	•
Living(alone)	•	•	•	•	•	•	•	•	•	•	•	•	•
Occupation	•	•	•	•	•	•	•	•	•	•	•	•	•
Employ/Retirec	•	•	•	•	•	•	•	•	•	•	•	•	•
Insurance	•	•	•	•	•	•	•	•	•	•	•	•	•
Understand	•	•	•	•	•	•	•	•	•	•	•	•	•
Working	•	•	•	•	•	•	•	•	•	•	•	•	•
School	•	•	•	•	•	•	•	•	•	•	•	•	•
Diffs(Voc/edu)	•	•	•	•	•	•	•	•	•	•	•	•	•
NameCond'n	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye Medicats	•	•	•	•	•	•	•	•	•	•	•	•	•
HBP	•	•	•	•	•	•	•	•	•	•	•	•	•
Diabetes	•	•	•	•	•	•	•	•	•	•	•	•	•
Stroke	•	•	•	•	•	•	•	•	•	•	•	•	•
Heart disease	•	•	•	•	•	•	•	•	•	•	•	•	•
Orthopeadic	•	•	•	•	•	•	•	•	•	•	•	•	•
Anxiety	•	•	•	•	•	•	•	•	•	•	•	•	•
Surghospital	•	•	•	•	•	•	•	•	•	•	•	•	•
Referred-By	•	•	•	•	•	•	•	•	•	•	•	•	•
LaserTX	•	•	•	•	•	•	•	•	•	•	•	•	•
Eye pain	•	•	•	•	•	•	•	•	•	•	•	•	•
FluctuationVis	•	•	•	•	•	•	•	•	•	•	•	•	•
Previous LVE	•	•	•	•	•	•	•	•	•	•	•	•	•
Sunlight/Glare	•	•	•	•	•	•	•	•	•	•	•	•	•
PreferredLight	•	•	•	•	•	•	•	•	•	•	•	•	•
ProbNightVis	•	•	•	•	•	•	•	•	•	•	•	•	•
Guardian	•	•	•	•	•	•	•	•	•	•	•	•	•
Physical cond'r	•	•	•	•	•	•	•	•	•	•	•	•	•
Hearing loss	•	•	•	•	•	•	•	•	•	•	•	•	•
Learning disab	•	•	•	•	•	•	•	•	•	•	•	•	•
Balpmove	•	•	•	•	•	•	•	•	•	•	•	•	•
WatchTV	•	•	•	•	•	•	•	•	•	•	•	•	•
Seebett	•	•	•	•	•	•	•	•	•	•	•	•	•
Glareprobs	•	•	•	•	•	•	•	•	•	•	•	•	•
Braille	•	•	•	•	•	•	•	•	•	•	•	•	•
Talkbooks	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE				Site 7									
Variables				Values									
Travzch	•	•	•	•									
Schplayg	•	•	•	•	•	•	•	•	•	•	•	•	•
Crossstr	•	•	•	•	•	•	•	•	•	•	•	•	•
Usepubtr	•	•	•	•	•	•	•	•	•	•	•	•	•
Omserv	•	•	•	•	•	•	•	•	•	•	•	•	•
Achieve'tlevel	•	•	•	•	•	•	•	•	•	•	•	•	•
Grade	•	•	•	None, n/a	Presch-nur	Grade1-4	Grade5-8	Form1-4	Univ-colleg	•	•	•	•
School	•	•	•	None, n/a	NIEP	Regular	St. Oda	St. Francis	Kibos	•	•	•	•
CondinFamily	•	•	•	No	Yes	•	•	•	•	•	•	•	•
Birthorder	•	•	•	Discrete	•	•	•	•	•	•	•	•	•
Siblings	•	•	•	Discrete	•	•	•	•	•	•	•	•	•
GOALS, VA, V.													
Chiefcomplaint	•	•	•	•	•	•	•	•	•	•	•	•	•
Goals(1-5)	Other	•	•	n/l	Musc/sing	Reading	Writing	ADLs-coo	Driving	Sports	Socializin	Farmwork	Other
UseLVaid	•	•	•	•	•	•	•	•	•	•	•	•	•
CurVde1-3	•	•	•	•	•	•	•	•	•	•	•	•	•
Pres-VA-Od	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•	•
Pres-VA-Os	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•	•
Pres-VA-OU	•	•	•	•	•	•	•	•	•	•	•	•	•
Via-bin	•	•	•	Discrete (converted to a numerator of 20)				•	•	•	•	•	•
Corr-VA-Od	•	•	•	•	•	•	•	•	•	•	•	•	•
Corr-VA-Os	•	•	•	•	•	•	•	•	•	•	•	•	•
Preferred eye	•	•	•	n/l	OD (RE)	OS (LE)	OU (BE)	•	•	•	•	•	•
WearGlasses	•	•	•	No	Yes	•	•	•	•	•	•	•	•
GlassesHelp	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadPrint	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadLprt	•	•	•	•	•	•	•	•	•	•	•	•	•
Printsize read	•	•	•	•	•	•	•	•	•	•	•	•	•
What-read	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherDifVisTas	•	•	•	•	•	•	•	•	•	•	•	•	•
ActivityMissed	•	•	•	•	•	•	•	•	•	•	•	•	•
Prefervision	•	•	•	•	•	•	•	•	•	•	•	•	•
Infosought	•	•	•	•	•	•	•	•	•	•	•	•	•
Add'lreports	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadAbil	•	•	•	None	CantRYet	ProbswR	AtGradelev	Fluently	Braille	•	•	•	•
WriteAbil	•	•	•	None	CantWYet	ProbswW	AtGradelev	Fluently	Braille	•	•	•	•
Needs	•	•	•	n/i	LVdevice	Training	VisStimul	NIEP	ReadWrite	EduAdapt'r	NewRx	Other	•
CategoryVisual	•	•	•	Discrete (1 - 5)									
RESOURCE D.													
Dr-time	•	•	•	•	•	•	•	•	•	•	•	•	•
Edu-time	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect1	•	•	•	•	•	•	•	•	•	•	•	•	•
Indirect2	•	•	•	•	•	•	•	•	•	•	•	•	•
TotalTime	•	•	•	•	•	•	•	•	•	•	•	•	•
Letters/reports	•	•	•	•	•	•	•	•	•	•	•	•	•
Source	•	•	•	•	•	•	•	•	•	•	•	•	•
Loaned 1-3	•	•	•	No	Yes	•	•	•	•	•	•	•	•
ServType	•	•	•	•	•	•	•	•	•	•	•	•	•
DevsPrescribed	•	•	•	No	Yes	•	•	•	•	•	•	•	•
RecomDEVS	•	•	•	•	•	•	•	•	•	•	•	•	•
Dispdevice1-3	•	•	•	•	•	•	•	•	•	•	•	•	•
Vservice	•	•	•	•	•	•	•	•	•	•	•	•	•
VAidTried	•	•	•	•	•	•	•	•	•	•	•	•	•
Individ-code	•	•	•	•	•	•	•	•	•	•	•	•	•
Exam-office	•	•	•	•	•	•	•	•	•	•	•	•	•
OLVdevs	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE				Site 7									
Variables				**Values**									
SLVdevs	•	•	•	•	•	•	•	•	•	•	•	•	•
Source-letter	•	•	•	•	•	•	•	•	•	•	•	•	•
Oconsult	•	•	•	•	•	•	•	•	•	•	•	•	•
Social worker	•	•	•	•	•	•	•	•	•	•	•	•	•
OTvisittype	•	•	•	•	•	•	•	•	•	•	•	•	•
Spec-diagnosti	•	•	•	•	•	•	•	•	•	•	•	•	•
Assessments	•	•	•	•	•	•	•	•	•	•	•	•	•
Training in	•	•	•	•	•	•	•	•	•	•	•	•	•
Ophthalmic ser	•	•	•	•	•	•	•	•	•	•	•	•	•
Feetype	•	•	•	•	•	•	•	•	•	•	•	•	•
Func-type	•	•	•	•	•	•	•	•	•	•	•	•	•
Service-m	•	•	•	•	•	•	•	•	•	•	•	•	•
O&MEval'n	•	•	•	•	•	•	•	•	•	•	•	•	•
Event/VisDesc	•	•	•	n/i	LVAssess't	Follow-up	Get Device	VisStimul	Ref'nVFiel	Letter-Rep	IntrotoPrt	Training	Other
Seen By	•	•	•	n/i	Therapist	Advisor	Trainee	Th-Tr	Th-Ad	Tr-Ad	Th-Tr-Ad	•	•
OTHER DATA													
Revisit-why	•	•	•	•	•	•	•	•	•	•	•	•	•
Revisit-Time	•	•	•	**Discrete-months**		•	•	•	•	•	•	•	•
Follow-uptype	•	•	•	•	•	•	•	•	•	•	•	•	•
PtResponse	•	•	•	•	•	•	•	•	•	•	•	•	•
Prognos-ST	•	•	•	•	•	•	•	•	•	•	•	•	•
Prognos-LT	•	•	•	•	•	•	•	•	•	•	•	•	•
Planref	•	•	•	•	•	•	•	•	•	•	•	•	•
Planlvd	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomOT	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomTR	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomSS	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomVR	•	•	•	•	•	•	•	•	•	•	•	•	•
MCB	•	•	•	•	•	•	•	•	•	•	•	•	•
OtherCS	•	•	•	•	•	•	•	•	•	•	•	•	•
MOW	•	•	•	•	•	•	•	•	•	•	•	•	•
Hmaker	•	•	•	•	•	•	•	•	•	•	•	•	•
Transp	•	•	•	•	•	•	•	•	•	•	•	•	•
FamilyS	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSP	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjTX	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjADL	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjCOM	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjLEI	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjDRV	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjMOB	•	•	•	•	•	•	•	•	•	•	•	•	•
ObjSEDVIEW	•	•	•	•	•	•	•	•	•	•	•	•	•
Diff-side	•	•	•	•	•	•	•	•	•	•	•	•	•
Turn-head	•	•	•	•	•	•	•	•	•	•	•	•	•
Drive	•	•	•	•	•	•	•	•	•	•	•	•	•
PublicTransp	•	•	•	•	•	•	•	•	•	•	•	•	•
In-Outdoor	•	•	•	•	•	•	•	•	•	•	•	•	•
Cane	•	•	•	•	•	•	•	•	•	•	•	•	•
ReadingDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•
DistanceDev1-:	•	•	•	•	•	•	•	•	•	•	•	•	•
Filters	•	•	•	•	•	•	•	•	•	•	•	•	•
Lighting	•	•	•	•	•	•	•	•	•	•	•	•	•
Writing1-2	•	•	•	•	•	•	•	•	•	•	•	•	•
Accessor1-2	•	•	•	•	•	•	•	•	•	•	•	•	•
Referral1-2	•	•	•	•	•	•	•	•	•	•	•	•	•
Eval areas	•	•	•	•	•	•	•	•	•	•	•	•	•

VARIABLES AT SITES 1-7

SITE				Site 7									
Variables				Values									
Received-Devs	•	•	•	No	Yes	•	•	•	•	•	•	•	•
RecomO&M	•	•	•	•	•	•	•	•	•	•	•	•	•
RecomDirServ	•	•	•	•	•	•	•	•	•	•	•	•	•
Largeprt	•	•	•	•	•	•	•	•	•	•	•	•	•
AphRegistered	•	•	•	•	•	•	•	•	•	•	•	•	•
RegdeafBlind	•	•	•	•	•	•	•	•	•	•	•	•	•

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